RICE UNIVERSITY

Charting the Course: A Test of the Dynamic Implications of the On-Line and Memory-Based Models

by

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# Table of Contents

Abstract ii

Acknowledgements iii

List of Tables ix

List of Figures xi

Chapter 1  1
Introduction

Chapter 2  6
Formalizing Information Processing Models

Chapter 3  40
Simulating Information Environments of Political Campaigns

Chapter 4  76
Testing the Dynamic Implications of the On-Line and Memory-Based Models

Chapter 5  101
Eight Congressional and Gubernatorial Campaigns

Chapter 6  235
Do Our Models of Public Opinion Predict the Actual Course of Public Opinion? Four Reasons Why They Do Not

Chapter 7  270
Conclusion

Bibliography 287
ABSTRACT

Charting the Course:

A Test of the Dynamic Implications of the On-Line and Memory-Based Models

By

Elizabeth J. Miller

The goal of this project is to determine how well our current models of public opinion—the on-line and memory-based—predict the course of public opinion during political campaigns. Unfortunately, the dynamic implications of these public opinion models have not been explored to the point where they can provide an answer to this question and the dynamic implications of these models have not been leveraged in the empirical evaluation or theoretical refinement of the models themselves. My approach to this task is two-pronged. I first formalize the theoretical arguments into mathematical equations to produce dynamic maps of the movement of public opinion. Consequently, I test the theoretical models by collecting data on campaign communications in eight congressional and gubernatorial campaigns and use these data as the inputs in the equations. The result is a predicted course for public opinion over the campaign, given the campaign communications that actually occurred. I then examine public opinion data to evaluate which of the two models accurately predicts the course of public opinion over the campaign. The results suggest that neither model can adequately account for the dynamics of a political campaign; therefore, I suggest a path for future research aimed at understanding the relationship between memory for campaign information and candidate evaluation.
Acknowledgements

I am not one to keep things short, so to no one’s surprise, my acknowledgements will be quite lengthy. However, this is due to the long list of remarkable people playing an instrumental role in my growth as a political scientist and as a person, not to my tendency to ramble.

I have been incredibly lucky to have an amazing dissertation committee. I want to thank each of them for the amount of time they have spent over the last five years in teaching and advising me.

In particular, I wish to thank my advisor, Randy Stevenson, for his unwavering efforts to ensure that I am a successful political scientist, an excellent teacher, and a valuable member of any future department. I do not overstate our relationship by saying that Randy is more than just my mentor, he is my friend. Randy truly deserves much of the credit for my completion of my doctorate. Randy has challenged me to go beyond my academic comfort level and for that I am grateful. Throughout the last five years I have been at Rice, I have thought on multiple occasions how easy it would be to give up and pursue a less challenging career. Randy’s continuous encouragement not only kept me in the program, but made me more successful than I ever envisioned.

What I admire most about Randy is that he never limits his creativity to what other people consider reasonable. He always attempts to answer any research question by considering the answer that is right, not just reasonable. Even though my research interests are not within Randy’s primary area of interest or expertise, he was not only willing to remain my advisor, but he was also willing to work on projects with me in my areas of interest. I also thank Randy for his methodological training. Randy’s ability to
teach empirical methods is unparalleled in the department, and probably in the discipline as well. Next spring, I will teach my own methods course and I can only hope that I will be half as successful as Randy has been in teaching the methods sequence at Rice.

I am grateful for Rick Wilson’s guidance and support over the last five years. He has been an important force in guiding my methodological approach and substantive research interests. To that end, he encouraged me to attend the Summer Institute in Political Psychology at the Ohio State University. This additional training was critical in giving me the resources necessary to be successful in my chosen research area. I appreciate his continued efforts to ensure that I am a credible political psychologist.

I also thank John Alford for providing my committee with much needed humor and intellect. John is a rare breed among political scientists. He is both incredibly smart and incredibly humble. I thank John for reminding me that, in the end, political science is a great life. I thank Jim Pomerantz from the Department of Psychology for his comments on the dissertation and his suggestions for future research.

While my committee has played a very specific role in my dissertation progress, all of the faculty in the Political Science Department at Rice are remarkable and have contributed much to my development as a scholar and a person over the last five years. A few of them deserve special recognition.

Even though Keith Hamm was not an official member of my dissertation committee, I would like to thank him for being my “unofficial member” and for his unrelenting support. The very first “optional” class I took at Rice was Comparative Legislatures. I was a first-year graduate student fresh out of college and much younger than the rest of the class in terms of age and experience, but he expected no less of me than he did
everyone else. His expectations along with the extensive reading I did in the three courses I took with him left me well-prepared for comprehensive exams and to teach my own courses. But, he is more than just an incredible teacher. He is also a caring and involved mentor. I will treasure most our discussions about the profession and his assistance with my interview preparation.

I am grateful to Ashley Leeds for her constant support, both academically and personally. The Introduction to International Relations is a difficult course, but Ashley taught the course so that even non-IR students like me were captivated. I also thank Ashley for her participation in the dissertation workshop and help in preparing me for the job market. Every dissertation defended this year is a better dissertation because of Ashley’s guidance during the prospectus preparation. Finally, I thank her for providing me with a much needed road trip last summer. The American West will never be the same for me without her in the driver’s seat.

I would also like to thank Ray Duch from the University of Houston for providing me with much needed relief from the Houston heat. I will treasure the arguments we had over food, wine, and political science at the dinner table in Monbalen.

There are four graduate students that I cannot lump with everyone else in a general thank you. Michaela, Rosa, Johanna, and Greg are my rocks at Rice. Each of them has supported me on a daily basis through the ups and downs of the last five years. None of them doubted my ability to be successful, even though I myself might have questioned it. They are four of the smartest, most genuinely humble, and hilarious persons that I know. I thank Michaela, Johanna, and Rosa for their ceaseless friendship. I thank Greg for putting up with me over the last year and laughing with, and at, me. He provided a
shoulder to cry on, a hand to hold, and an ear to listen to my complaints, fears, dreams, and even some crazy research ideas. I would not have made it through the job process without him standing next to me, or towering over me.

I owe a debt of gratitude to all those participating in the Dissertation Workshop: Randy, Ashley, Burcu, Johanna, Michaela, Rosa, and Jonathon. Not only did they provide important suggestions for improving my dissertation project, but they also made the dissertation process much less painful. Knowing that there were five people who knew my pain was comforting.

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I also wish to thank Ann Mikus and Lorie Zepeda for their efforts in organizing and mailing job packets. I especially thank Ann for putting up with me for the last five years.

All that I am and all that I will be I owe to my family. They inspire me, amuse me, and accept my peculiar personality. For those of you reading this, you know how much my parents mean to me and how extraordinary they are. My success is completely due to them. They both sacrificed their own wants to provide my sisters and me with a loving and enjoyable childhood. We never had the newest or the nicest clothes and toys growing up, but we had something that many kids never have: undying love and affection from our parents. Even today my parents go to great lengths to shower us with their love and to ensure that we have what we need to be healthy and happy.
My mom is by far the most amazing woman that I have ever met. She never gave up on any of her daughters and constantly encourages us to pursue success. Throughout the last five years, I have thought at various points that graduate school was too much for me and it was time to throw in the towel. But, then I think about my mom struggling to earn a bachelor’s degree with three young girls at home and a masters’ degree with three rowdy teenagers. Picturing my mother studying late into the night, waking early to make us breakfast before school, teaching all day, and going to class at night is enough to encourage me on even my laziest day. George Eliot once wrote: “life began with waking up and loving my mother’s face”. I think she might have been writing about my mom. My mom is not only the most sensitive and loving mother, but she is also my best friend.

Children are often lucky to have one remarkable parent, but I have two. We disagree on almost everything religious or political, but I am grateful for my dad’s constant challenges to my beliefs. His challenges inspire me to become even more informed for the next time he questions my political preferences. My dad is more than just a crazy Republican. My dad might be the most loving and hardworking man. I would be incredibly lucky if my own children had such an amazing father. His temperament and love is the standard I use to evaluate others. Most of my friends will tell you that their fathers rarely say I love you and rarely give them hugs, but this is standard for my dad. My dad has always been there for me, regardless of the insanity of my decisions.

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## List of Tables

<table>
<thead>
<tr>
<th>Table 2.1</th>
<th>Shorthand of Basic Zaller Equations</th>
<th>28</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 2.2</td>
<td>The Influence of New Information on the Updated Tally</td>
<td>35</td>
</tr>
<tr>
<td>Table 3.1</td>
<td>Types of Hypothetical Races</td>
<td>41</td>
</tr>
<tr>
<td>Table 3.2</td>
<td>Information Release in Hypothetical Cases</td>
<td>43</td>
</tr>
<tr>
<td>Table 4.1</td>
<td>Static Elements of the Memory Based Model</td>
<td>78</td>
</tr>
<tr>
<td>Table 4.2</td>
<td>Newspapers for the Eight Campaigns</td>
<td>82</td>
</tr>
<tr>
<td>Table 5.1</td>
<td>Dispersion of Newspaper Coverage in the Arizona Senate Race</td>
<td>104</td>
</tr>
<tr>
<td>Table 5.2</td>
<td>Number of Days of Accurate Prediction for the On-Line and Memory-Based Models in the Arizona Senate Race</td>
<td>112</td>
</tr>
<tr>
<td>Table 5.3</td>
<td>Dispersion of Newspaper Coverage in the Illinois Senate Race</td>
<td>114</td>
</tr>
<tr>
<td>Table 5.4</td>
<td>Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Illinois Senate Race</td>
<td>123</td>
</tr>
<tr>
<td>Table 5.5</td>
<td>Dispersion of Newspaper Coverage in the New Jersey Senate Race</td>
<td>125</td>
</tr>
<tr>
<td>Table 5.6</td>
<td>Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the New Jersey Senate Race</td>
<td>136</td>
</tr>
<tr>
<td>Table 5.7</td>
<td>Dispersion of Newspaper Coverage in the New York Gubernatorial Race</td>
<td>138</td>
</tr>
<tr>
<td>Table 5.8</td>
<td>Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the New York Gubernatorial Race</td>
<td>154</td>
</tr>
<tr>
<td>Table 5.9</td>
<td>Dispersion of Newspaper Coverage in the Pennsylvania Senate Race</td>
<td>156</td>
</tr>
<tr>
<td>Table 5.10</td>
<td>Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Pennsylvania Senate Race</td>
<td>168</td>
</tr>
<tr>
<td>Table 5.11</td>
<td>Dispersion of Newspaper Coverage in the Texas Gubernatorial Race</td>
<td>170</td>
</tr>
<tr>
<td>Table 5.12</td>
<td>Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Texas Gubernatorial Race</td>
<td>180</td>
</tr>
</tbody>
</table>
Table 5.13  Dispersion of Newspaper Coverage in the Utah Congressional Race 185
Table 5.14  Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Utah Congressional Race 197
Table 5.15  Dispersion of Newspaper Coverage in the Virginia Senate Race 205
Table 5.16  Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Virginia Senate Race 227
Table 6.1  Initial Change versus Persistence 241
Table 6.2  Initial Change versus Persistence—Error Correction Model 244
Table 6.3  The Point in the Campaign Season—Memory-Based Model 248
Table 6.4  The Point in the Campaign Season—On-Line Model 250
Table 6.5  Stability—the Memory-Based Model 254
Table 6.6  Volatility—the Memory-Based Model 255
Table 6.7  Mispredicting Stability and Volatility—the Memory-Based Model 257
Table 6.8  Stability—the On-Line Model 260
Table 6.9  Volatility—the On-Line Model 261
Table 6.10  Mispredicting Stability and Volatility—the On-Line Model 262
Table 6.11  Predicting Stability in Public Opinion 263
Table 6.12  Mispredicting Volatility—the On-Line Model 264
Table 6.13  Newspaper Coverage by Incumbency 265
Table 6.14  Incumbency and the Campaign Season 267
Table 6.15  The Interaction between Incumbency and the Campaign Season 268
Table 7.1  Number of Days of Accurate Prediction for Modified Memory-Based Models 279
Table 7.2  Number of Days of Accurate Prediction for Modified On-Line Models 281
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Reception Equation: Altering the Floor Parameter</td>
<td>19</td>
</tr>
<tr>
<td>2.2</td>
<td>Reception Equation: Altering the Intensity Intercept</td>
<td>20</td>
</tr>
<tr>
<td>2.3</td>
<td>Reception Equation: Altering the Awareness Coefficient</td>
<td>21</td>
</tr>
<tr>
<td>2.4</td>
<td>Acceptance Equation: Altering the Familiarity Intercept</td>
<td>23</td>
</tr>
<tr>
<td>2.5</td>
<td>Acceptance Equation: Altering the Awareness Coefficient</td>
<td>24</td>
</tr>
<tr>
<td>2.6</td>
<td>Acceptance Equation: Altering the Ideology Coefficient</td>
<td>25</td>
</tr>
<tr>
<td>2.7</td>
<td>Updating the Tally: the Influence of New Information</td>
<td>36</td>
</tr>
<tr>
<td>2.8</td>
<td>The On-Line Tally Overtime</td>
<td>37</td>
</tr>
<tr>
<td>3.1</td>
<td>Predictions from the Models for Hypothetical Case 1</td>
<td>49</td>
</tr>
<tr>
<td>3.2</td>
<td>Predictions from the Models for Hypothetical Case 2</td>
<td>51</td>
</tr>
<tr>
<td>3.3</td>
<td>Predictions from the Models for Hypothetical Case 3</td>
<td>54</td>
</tr>
<tr>
<td>3.4</td>
<td>Predictions from the Models for Hypothetical Case 4</td>
<td>56</td>
</tr>
<tr>
<td>3.5</td>
<td>Predictions from the Models for Hypothetical Case 5</td>
<td>58</td>
</tr>
<tr>
<td>3.6</td>
<td>Predictions from the Models for Hypothetical Case 6</td>
<td>61</td>
</tr>
<tr>
<td>3.7</td>
<td>Predictions from the Models for Hypothetical Case 7</td>
<td>63</td>
</tr>
<tr>
<td>3.8</td>
<td>Predictions from the Models for Hypothetical Case 8</td>
<td>66</td>
</tr>
<tr>
<td>3.9</td>
<td>Memory-Based Model—Relative Intensity</td>
<td>67</td>
</tr>
<tr>
<td>3.10</td>
<td>Moving the On-Line Tally</td>
<td>68</td>
</tr>
<tr>
<td>3.11</td>
<td>Memory-Based Model—the Role of Incumbency</td>
<td>69</td>
</tr>
<tr>
<td>3.12</td>
<td>Memory-Based Model—The Role of Partisanship</td>
<td>70</td>
</tr>
<tr>
<td>3.13</td>
<td>Memory-Based Model—Overcoming the Role of Incumbency</td>
<td>71</td>
</tr>
<tr>
<td>3.14</td>
<td>Memory-Based Model—Overcoming the Role of Partisanship</td>
<td>72</td>
</tr>
<tr>
<td>Figure</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>----------</td>
<td>------------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>3.15</td>
<td>On-Line Model—Disrupting the Original Tally</td>
<td>73</td>
</tr>
<tr>
<td>3.16</td>
<td>On-Line Model—the Entrenched Tally</td>
<td>74</td>
</tr>
<tr>
<td>4.1</td>
<td>Memory-Based Model’s Predictions for Ann Richards</td>
<td>90</td>
</tr>
<tr>
<td>4.2</td>
<td>Memory-Based Model’s Predictions for George W. Bush</td>
<td>91</td>
</tr>
<tr>
<td>4.3</td>
<td>On-line Model’s Predictions for Coppersmith</td>
<td>94</td>
</tr>
<tr>
<td>4.4</td>
<td>Polling Data vs. Iowa Electronic Market Data for the New York Gubernatorial Race</td>
<td>98</td>
</tr>
<tr>
<td>5.1</td>
<td>Memory-Based and On-Line Models’ Predictions for Coppersmith</td>
<td>105</td>
</tr>
<tr>
<td>5.2</td>
<td>Memory-Based and On-Line Models’ Predictions for Kyl</td>
<td>107</td>
</tr>
<tr>
<td>5.3</td>
<td>Iowa Electronic Market Results for the Arizona Senate Race</td>
<td>108</td>
</tr>
<tr>
<td>5.4</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Coppersmith</td>
<td>109</td>
</tr>
<tr>
<td>5.5</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Kyl</td>
<td>110</td>
</tr>
<tr>
<td>5.6</td>
<td>Memory-Based and On-Line Models’ Predictions for Simon</td>
<td>116</td>
</tr>
<tr>
<td>5.7</td>
<td>Memory-Based and On-Line Models’ Predictions for Martin</td>
<td>118</td>
</tr>
<tr>
<td>5.8</td>
<td>Iowa Electronic Market Results for the Illinois Senate Race</td>
<td>119</td>
</tr>
<tr>
<td>5.9</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Simon</td>
<td>121</td>
</tr>
<tr>
<td>5.10</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Martin</td>
<td>122</td>
</tr>
<tr>
<td>5.11</td>
<td>Memory-Based and On-Line Models’ Predictions for Lautenberg</td>
<td>127</td>
</tr>
<tr>
<td>5.12</td>
<td>Memory-Based and On-Line Models’ Predictions for Haytaian</td>
<td>129</td>
</tr>
<tr>
<td>5.13</td>
<td>Iowa Electronic Market Results for the New Jersey Senate Race</td>
<td>130</td>
</tr>
<tr>
<td>5.14</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Lautenberg</td>
<td>133</td>
</tr>
<tr>
<td>Figure 5.15</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Haytaian</td>
<td>135</td>
</tr>
<tr>
<td>Figure 5.16</td>
<td>Memory-Based and On-Line Models’ Predictions for Cuomo</td>
<td>141</td>
</tr>
<tr>
<td>Figure 5.17</td>
<td>Memory-Based and On-Line Models’ Predictions for Pataki</td>
<td>144</td>
</tr>
<tr>
<td>Figure 5.18</td>
<td>Memory-Based and On-Line Models’ Predictions for Rosenbaum</td>
<td>145</td>
</tr>
<tr>
<td>Figure 5.19</td>
<td>Iowa Electronic Market Results for the New York Gubernatorial Race</td>
<td>146</td>
</tr>
<tr>
<td>Figure 5.20</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Cuomo</td>
<td>148</td>
</tr>
<tr>
<td>Figure 5.21</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Pataki</td>
<td>150</td>
</tr>
<tr>
<td>Figure 5.22</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Rosenbaum</td>
<td>153</td>
</tr>
<tr>
<td>Figure 5.23</td>
<td>Memory-Based and On-Line Models’ Predictions for Wofford</td>
<td>160</td>
</tr>
<tr>
<td>Figure 5.24</td>
<td>Memory-Based and On-Line Models’ Predictions for Santorum</td>
<td>162</td>
</tr>
<tr>
<td>Figure 5.25</td>
<td>Iowa Electronic Market Results for the Pennsylvania Senate Race</td>
<td>163</td>
</tr>
<tr>
<td>Figure 5.26</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Wofford</td>
<td>165</td>
</tr>
<tr>
<td>Figure 5.27</td>
<td>Comparing the Models’ Predictions with Actual Public Opinion—Santorum</td>
<td>167</td>
</tr>
<tr>
<td>Figure 5.28</td>
<td>Memory-Based and On-Line Models’ Predictions for Richards</td>
<td>175</td>
</tr>
<tr>
<td>Figure 5.29</td>
<td>Memory-Based and On-Line Models’ Predictions for Bush</td>
<td>177</td>
</tr>
<tr>
<td>Figure 5.30</td>
<td>Iowa Electronic Market Results for the Texas Gubernatorial Race</td>
<td>178</td>
</tr>
<tr>
<td>Figure 5.31</td>
<td>Memory-Based and On-Line Models’ Predictions for Shepherd</td>
<td>188</td>
</tr>
<tr>
<td>Figure 5.32</td>
<td>Memory-Based and On-Line Models’ Predictions for Greene-Waldholtz</td>
<td>191</td>
</tr>
<tr>
<td>Figure 5.33</td>
<td>Memory-Based and On-Line Models’ Predictions for Cook</td>
<td>195</td>
</tr>
<tr>
<td>Figure 5.34</td>
<td>Iowa Electronic Market Results for the Utah Congressional Race</td>
<td>196</td>
</tr>
<tr>
<td>Figure 5.35</td>
<td>Memory-Based and On-Line Models’ Predictions for Robb</td>
<td>209</td>
</tr>
<tr>
<td>Figure 5.36</td>
<td>Memory-Based and On-Line Models’ Predictions for North</td>
<td>215</td>
</tr>
<tr>
<td>Figure 5.37</td>
<td>Memory-Based and On-Line Models’ Predictions for Coleman</td>
<td>218</td>
</tr>
<tr>
<td>Figure 5.38</td>
<td>Memory-Based and On-Line Models’ Predictions for Miller</td>
<td>221</td>
</tr>
<tr>
<td>Figure 5.39</td>
<td>Memory-Based and On-Line Models’ Predictions for Wilder</td>
<td>223</td>
</tr>
<tr>
<td>Figure 5.40</td>
<td>Iowa Electronic Market Results for the Virginia Senate Race</td>
<td>225</td>
</tr>
<tr>
<td>Figure 6.1</td>
<td>The Memory-Based Model—the Arizona Senate Race—Sam Coppersmith</td>
<td>237</td>
</tr>
<tr>
<td>Figure 6.2</td>
<td>Scatterplot of the Point in the Campaign Season—Memory-Based Model</td>
<td>245</td>
</tr>
<tr>
<td>Figure 6.3</td>
<td>Smoothing Line of the Point in the Campaign Season—Memory-Based Model</td>
<td>246</td>
</tr>
<tr>
<td>Figure 6.4</td>
<td>The Point in the Campaign Season—On-Line Model</td>
<td>249</td>
</tr>
<tr>
<td>Figure 6.5</td>
<td>Stability versus Volatility—Memory-Based Model</td>
<td>252</td>
</tr>
<tr>
<td>Figure 6.6</td>
<td>Stability versus Volatility—On-Line Model</td>
<td>258</td>
</tr>
</tbody>
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Chapter 1: Introduction

In this project, I explore the dynamic impact of different campaign communication strategies on public opinion about political candidates. The premise of the project is that useful models of public opinion should be able to explain the evolution of public opinion during political campaigns and thus provide a guide to the design of optimal campaign communication strategies. Consequently, my goal is to explore both questions of academic interest (e.g., why did public support for Governor Cuomo decline in the last months of the 1994 New York gubernatorial race?) as well as questions that will be of use in practical politics (e.g., is it better to concentrate campaign communications at the beginning or end of a campaign?).

Thankfully, there has, over the last decade, been an explosion of work on the nature and sources of public opinion and so I can begin my project by exploring the dynamic implications of two general models of public opinion that have come to dominate the literature in recent years. The first model I examine is “memory-based”. It suggests that individuals receive campaign information, store the information in long-term memory, recall the information, and integrate the recalled information in some way to make a vote choice or offer a political opinion (Zaller 1992). In contrast, “on-line” models contend that when individuals receive campaign information they have an immediate affective reaction to this information and store this affective response in long-term memory in a “tally” that groups reactions to messages about similar substantive domains. Importantly, it is assumed individuals do not retain a memory for the substance of the message. Finally, when asked to make a choice or state an opinion, the affective tally is recalled and forms the basis of opinion (Lodge et al.1995).
These models have benefited from a number of clear theoretical statements and refinements (Zaller 1996; McGraw 2003; Taber 2003; Morris et al. 2004) as well as various empirical evaluations (Zaller 1996; Redlawsk 2001). Unfortunately, however, most of this work has not directly addressed the dynamic implications of the theories or subjected these implications to appropriate empirical tests\(^1\). To be clear, these models do have dynamic implications; however, the theoretical literature has not fully explicated these implications. Indeed, a close examination of the few available discussions of dynamics in these models makes it clear that most of the dynamic implications of the models that have so far been discussed do not actually flow from the “core” assumptions of the models but result from relatively arbitrary “auxiliary” assumptions that have been adopted to make them more conducive to empirical tests. Even these few tests, however, are limited. The vast majority of the empirical evidence to which these models have been subjected has been static. There has as yet been no large-scale analysis of the dynamic implications of the models (even as they have been explicated so far). Where evidence about the evolution of opinion has been presented, it has been anecdotal or based on single races or events (Zaller 1992, 1996). In this project I will correct the inattention to the dynamics of public opinion in these models both by thoroughly exploring their dynamic implications and providing an empirical evaluation of these implications using detailed data for 3,300 days in eight congressional and gubernatorial campaigns.

My approach to this task is multi-faceted. I first formalize the on-line model’s theoretical argument mathematically and use Zaller’s formalization of the memory-based model to create predictions for the course that public opinion should take in a campaign if

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1 By dynamic implications, I refer to the implications for the study of public opinion throughout the course of a campaign.
one or the other model were right and if the theoretical inputs to the models evolve in various ways. This sort of dynamic map of the models’ implications allows me to explore how different campaign communication strategies (represented by different values for the relevant theoretical parameters in the models – e.g., in Zaller’s model, the volume of campaign messages at each point in time) should impact opinion over time.

Because my formalization of the models allows me to explore their predictions, I can test the theoretical models by collecting data on campaign communications in real world campaigns (e.g., the type and volume of news coverage) and use this data to set the parameters in the simulation. Given the campaign communications that actually occurred, each model will yield a predicted course for public opinion over the campaign. Thus, I can then examine public opinion data to evaluate which of the two models (if any) correctly predicts the course of public opinion throughout the campaign. If neither model is adequate, a careful examination of the ways in which they fail will be the first step in identifying useful theoretical refinements.

The results of this project will be of interest to both political professionals and academics studying public opinion. The design of campaign communications is only the most practical application of this work. The results of this project also speak to academics interested in exploring the nature and sources of public opinion. First, my project provides a new test of the two leading theories of public opinion against each other, as well as against the hypothesis that neither explains the dynamics of public opinion. My prior is that both models will contribute something to the empirical prediction of opinion but that neither will be completely adequate (though, of course, nothing in my design predisposes this to be the result). In this case, the empirical part of
my project provides new stylized facts—in the form of deviations between theoretical predictions and actual opinion—that can be used in modifying and extending the theories in useful ways.

The study should be particularly helpful to campaign managers concerned with conducting effective campaigns at the lowest possible cost. Even a cursory analysis of the dynamic implications of the two models above reveals that they call for different optimal campaign strategies. For example, proponents of the memory-based model argue that opinion statements will respond to the salience of political messages as well as the importance of partisan cues; therefore, a campaign manager should spend money establishing partisan cues and should also spend the majority of funds close to the election to ensure a candidate’s political message remains salient. In contrast, the on-line model implies that early information is more influential than later information on judgment. As a result, campaign managers must ensure that voters are exposed to positive information about their candidate as early as possible. This suggests candidates ought to spend a great deal of money at the beginning of the campaign and progressively less throughout the campaign season. These are broad expectations that flow from the logic of the models, but a more thorough analysis of the models reveals important subtleties and many ambiguities concerning the dynamic properties of opinion.

In the following chapters, I develop the project in more detail. In the second chapter, I review the literature on information processing, discuss the theoretical arguments underlying the memory-based and on-line models, present Zaller’s formalization of the memory-based model, formalize the on-line model mathematically, and discuss the previous empirical tests of the models’ dynamic implications. The third chapter uses the
mathematical equations outlined in Chapter 2 to simulate the course of public opinion across a variety of hypothetical cases. In the fourth chapter, I explain how I conduct that test and describe the data I collected. This data comes from different campaigns and so in Chapter 5, I describe these races in more detail. The sixth chapter provides the results of the empirical analysis. I examine whether there are systematic ways in which the models fail to predict the course of public opinion and propose theoretical refinements to the models informed by their failure. Finally, I suggest possibilities for theoretically modifying the models to more accurately capture the dynamics of public opinion and conclude the dissertation with thoughts on future research in the seventh chapter.
Chapter 2: Formalizing Information Processing Models

While proposed as competing models in the person perception literature (Bassili, 1989), the on-line and memory-based models emerged in political science within separate spheres. The use of the on-line model in political science, initiated by Lodge and his colleagues (Lodge et al. 1995), represented a break from the standard memory-based model prevalent in the voting behavior literature for the last thirty years. The memory-based model represents the approach adopted by much of the traditional voting behavior literature. Voters stand in the voting booth on Election Day, attempt to recall information about the candidates, and use this information to make a decision in an election (Kelley and Mirer, 1974; Zaller, 1992; Zaller, 1996). In contrast, the on-line model developed as a way for political psychologists to explain the way individuals process information about political candidates and use that information to evaluate political candidates in the context of a political campaign. Individuals do not wait until Election Day to evaluate information about political candidates; instead, individuals have an immediate affective reaction to campaign information. The individual retrieves these affective reactions, not the information itself, when asked to evaluate political candidates on Election Day.

These models have been tested in a number of different contexts, yet the dynamic implications of these models remain untested in the context of a political campaign. I am interested in examining the implications each model has for the course of aggregate public opinion in various types of campaign environments, where I think of the campaign environment as encompassing the type of race, the number of candidates running, and the type of candidates running.

In this chapter, I first briefly discuss the historical progression of the models in the
public opinion literature and their foundations in psychology. I then discuss the emergence of the memory-based model, provide a basic outline of Zaller’s memory-based model including its dynamic features, and present Zaller’s mathematical formalization of his model. I then turn to a discussion of the development of the on-line model in the public opinion literature, explore its dynamic features, and formalize Lodge’s theoretical model into mathematical equations suitable for making predictions about movements in public opinion. Each model includes various inputs that the authors assume affect the process of candidate evaluation in various ways.

I am specifically interested in the ability of these models to predict the course of public opinion during a political campaign. To determine this, I need a predicted path of public opinion for each model to compare to the actual path of public opinion during a specific campaign. By formalizing the theoretical models into mathematical equations, I can use data from actual campaigns as inputs in the formalized equations to produce just such a predicted path. I then examine how well these predicted paths of public opinion from each model conform to the actual course of public opinion for each candidate in each race. These “tests” bear directly on whether we should have confidence in either the on-line or the memory-based models.

Public Opinion Literature

In 1960, Campbell et al published The American Voter. In this volume, the authors find that the vast majority of the American public does not maintain a coherent value structure or ideology and pays very little attention to politics. Based on survey data collected by the NES in 1948, 1952, and 1956, this dismal picture of the American public continued with Converse’s extension in 1964. Echoing and expanding the arguments by
Campbell et al (1960), Converse (1964) argues that the American public does not maintain stable attitudes overtime. He explains that this instability from election to election stems from the lack of constraint in the public's belief systems. Belief systems are a configuration of ideas and attitudes. The elements of such a belief system are bound together by constraints or functional interdependence. An important element of Converse's (1964) argument is that the American public is divided according to their ability to organize political events according to a liberal-conservative continuum and the stability of attitudes is dependent upon this ability. Individuals at the very bottom of the continuum are those that fail to have any meaningful opinions. Further, the constraints placed on belief systems are higher among elites; thus, these elites also hold more stable attitudes. Finally, Converse (1964) argues that a good portion of the electorate does not have meaningful opinions concerning the issues underlying American political controversy for a substantial period of time.

The response to this article from public opinion scholars was multifaceted. In particular, Nie and Anderson (1974) argue that attitude consistency has actually increased in the post-1964 period. Further, the authors' find that individuals with low levels of education actually have more constraints; this finding contradicts Converse's link between education and issue constraint. Stimson (1975) disagrees with this assessment finding support for Converse's contention that higher cognitive ability constrains policy evaluation. However, Stimson (1975) argues that attitude stability is increasing with the increase in the cognitive ability of the American public. In contrast, Sullivan, Pierson, and Markus (1978) find, using non-NES surveys, no support for the conclusion that constraints actually increased in the post-1964 world.
Not only have scholars examined the existence and influence of constraints on belief systems, Achen (1975) maintains that the instability witnessed by Converse (1964) is actually an artifact of measurement error. Achen argues that a true opinion should be conceived of as a distribution around a principle position and the objects of choice are the distributions around these main points as opposed to conceiving of an attitude as expressed in a survey questionnaire. Measurement error exists because surveys include vague questions. Bolstering such a claim, Achen (1975) argues that the information level of the environment is not related to the size of the measurement error making it likely that the political involved find the questions just as vague and perplexing as do the uninformed. Once measurement error has been corrected, the lack of correlation between time periods identified by Converse disappears.

If one tentatively accepts Converse’s findings concerning the instability of the American public’s attitudes overtime, the important question to ask is why are attitudes unstable overtime? In answering this question, some scholars focus on the way individuals process information. Scholars interested in information processing argue that the individual mind is limited in its ability to process information. These information-processing models provide distinct explanations for the way individuals use campaign information to formulate evaluations of political candidates and have been considered contending models even before they were discussed in political science. Psychologists developed information processing models to explain the role of memory in the judgment process. Specifically, these scholars focused on the way individuals store information in memory and rely on this information to make judgments about others. Like their psychological predecessors, the two public opinion models make different assumptions
about the use of campaign information and the timing of that usage (Taber 1998). The on-line model assumes that individuals use information immediately upon encountering it while the memory-based model assumes information is stored in memory and only used at a later point when the individual is asked to make a decision, like in an election.

**Memory and Judgment in Psychology**

For years, psychologists interested in the relationship between memory and judgment found that different judgment tasks yield disparate relationships between memory and judgment. A number of classic studies (Tversky and Kahneman, 1973; Beyth-Marom and Fischhoff, 1977; Gabrielck and Fazio, 1984) find a positive relationship between the judgments individuals make and the information they can recall. For example, Ross and Sicoly (1979) ask subjects to make a variety of judgments regarding responsibility for joint tasks and find the attribution of responsibility to be related to the amount of evidence subjects could recall about the task in question. This retrieval of information from memory to make a judgment is termed memory-based processing.

However, a number of studies find that the relationship between memory and judgment was not actually direct; in fact, a variety of studies find this relationship to be direct, indirect, or non-existent (Anderson and Hubert, 1967; Anderson, 1981; Reyes, Thompson, and Bower, 1980). The question plaguing psychologists became how to reconcile these incongruent findings. Hastie and Park (1986) argue that the inconsistent relationship between memory and judgment stems from the type of judgment task asked of subjects. The authors argue that when an individual is faced with a judgment task, in or outside of the laboratory, a judgment operator processes information. This judgment operator can be either memory-based or on-line. There are certain circumstances in
which the individual must, by necessity, rely on information stored in memory to make a judgment; but, Hastie and Park (1986) argue that these situations are limited to those in which an individual does not anticipate making a judgment at a later date. The authors refer to these situations as situations requiring surprising judgments. The example Hastie and Park (1986) give is of a professor who attends a conference and returns home to find that his department has a faculty position available. Because this judgment was not expected, the professor must now search his memory for information about potential candidates. Bassili and his colleagues (1989) concur that individuals are most likely to rely on their recall of information to make judgments in those situations involving spontaneous judgment.

However, Hastie and Park (1986) argue that, in the vast majority of cases involving others, individuals make judgments on-line. That is, individuals form impressions about others as they encounter information about the other (Bassili, 1989). When asked to voice a judgment about the other (like in a survey, experiment, political discussion, voting booth, etc.), the individual retrieves the previously formed judgment. If the individual is also asked to recall information, the relationship between the information recalled and the judgment could be direct, indirect, or unrelated.

In politics, one might suspect that individuals make only on-line judgments because in a political campaign individuals are rarely surprised by the judgment task, particularly in the US where elections operate on a set schedule. Potential voters know, long before Election Day, that an election is to take place, so they make judgments about candidates as the information is encountered. One might be able to make a case that in a

\[2\text{ The reason that the relationship is unequivocal is related to whether the individual has biased encoding, biased retrieval, or neither. After initial information, the individual could encode further information}\]
parliamentary democracy potential voters are not as aware that they will need to make a judgment, because there is no set election schedule. Even in this case Hastie and Park (1986) would likely disagree as they argue that in almost all circumstances of judgment of others, individuals are most likely to operate on-line.

**Fundamentals of the Memory-Based Model**

While Lodge et al.'s (1995) adoption of the on-line model for use in candidate evaluation marks the on-line model's arrival in political science, memory-based models have formed the basis of the voting behavior literature for at least the last three decades. In general, memory-based models argue that individuals make decisions in elections based on the specific combination of campaign information retrievable from memory. Specifically, these models contend that (1) individuals store campaign information in long-term memory at the moment of exposure to such information, (2) retrieve this information from memory when asked to make a decision, (3) and integrate this information into an evaluation of the candidate.

Two different types\(^3\) of memory-based models exist in the voting behavior/public opinion literature: comprehensive-memory models and limited-memory models. Comprehensive models assume that individuals recall (Druckman and Lupia, 2000) all relevant information about a candidate and integrate all information in order to yield an overall evaluation. Limited-memory models recognize the limits of the human mind in arguing that individuals do not recall *all* information to which they were initially exposed; instead, individuals recall a subset of such information. This division between

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\(^3\)This division I have discussed is a division that does not actually exist within the literature itself, but I think it is a useful way to see the evolution of memory-based models in the voting behavior/public opinion literature.
comprehensive and limited models distinguishes between models which conceive of individuals as integrating all related information stored in memory (Kelley and Mirer, 1974), and models which focus on the integration of the most salient information (Zaller, 1992; Zaller, 1996).

Kelley and Mirer's 1974 article exemplifies the comprehensive approach. In this article, the authors propose a way to explain how voters make decisions in elections. Kelley and Mirer (1974) propose, what they call, the Voter's Decision Rule. According to this rule, the voter searches through his likes and dislikes of the candidates and the parties, weighs each consideration equally, and votes for the candidate with the greatest net number of likes. Such a decision rule implies that to make a vote choice the individual searches memory for all considerations about the candidates and parties in an election. After collecting all considerations, the individual combines the considerations to determine which candidate has the more positive net value.

In contrast, limited memory-based models rely implicitly on a particular assumption: political judgments are mediated by information most salient at the time of judgment (Druckman and Lupia, 2000; Kinder 1998). Salient considerations vary across individuals and overtime (Lavine 2001). The instability identified by Converse can therefore be explained by shifts in saliency. The saliency of particular considerations relies on the content of elite discourse, media coverage, political events, chronic accessibility of issue-relevant information, political knowledge and interest, and more general beliefs and predispositions.
Zaller's Memory-Based Model

In the best-known example of the memory-based model, Zaller (1992) proposes a model of the way individuals construct survey attitudes or opinion reports in response to stimuli in their environment. The key to understanding Zaller's model is to understand that it is memory-based; that is, opinion reports rely on memory for substantive information about political candidates, called considerations by Zaller. Zaller defines a consideration as any reason that might influence an individual's decision about a political issue or candidate. In issuing opinion reports, individuals rely on those considerations that are immediately accessible in memory. The accessible considerations are a function of the flow of campaign messages in the media.

These notions are formalized into four axioms (Zaller 1992). The first axiom is hardly controversial—the reception axiom—the higher an individual's level of political awareness the more likely the individual will be exposed to and be able to comprehend\(^4\) political messages. Political awareness is typically conceived of as the extent of an individual's attention to and understanding of politics, also known as an individual's cognitive engagement with politics\(^5\). Political awareness is measured by factual questions concerning politics (also known as political knowledge quizzes). However, individuals are not sponges soaking up all political messages; rather, individuals resist messages inconsistent with their political predispositions (resistance axiom). The ability of individuals to resist political messages is a function of their ability to link political messages to their political predispositions. Zaller defines political predispositions as those individual traits that are stable and have the capacity to regulate an individual's

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\(^4\) In the model, an individual's comprehension of politics is referred to as his/her receipt of politics.

\(^5\) Two important points concerning political awareness: average levels within the population are quite low and variance in awareness in the population is quite high.
acceptance of political messages. Political predispositions can include ideology, religion, party attachment, ethnicity, etc. If we think in terms of partisanship, this axiom suggests that strong partisans would be less likely to accept messages from the opposing party's candidates.

The reception and resistance axioms together imply that political awareness increases the likelihood that an individual will resist political messages inconsistent with his/her political predispositions. To move from the acceptance of messages to an opinion report or a vote choice, two final axioms are necessary. Once an individual has received and accepted messages about political candidates, a vote choice or survey response must be made. This decision is based on the previously accepted information or considerations that are now accessible to the individual. Accessible considerations are those considerations most recently thought about because they are the easiest to retrieve from memory for use in making a decision (accessibility axiom). These considerations must be combined in a particular way—such as averaging or sampling—in order to provide an opinion report or make a vote choice (response axiom).

Combined, the above axioms suggest that opinion reports or vote choices result from a Receive-Accept-Sample (RAS) model. In the RAS model, individuals receive information, decide to accept or reject it based on their political predispositions, and sample from accessible considerations when asked to make a judgment. The probability that an individual receives a message is a function of the individual's exposure to information. Exposure to information is mediated by an individual's political awareness and by the only dynamic element in the model—message intensity. Message intensity is the relative balance and quantity of mass media attention to an issue. Messages have
varying levels of intensity and individuals have varying levels of political awareness; as a result, individuals could receive one message (the dominant message), but not the other message (opposition message). Zaller (1992, 1996) terms this differential reception the reception gap\(^6\). Whether or not an individual has such a reception gap stems from his/her political awareness and the intensity of the campaign messages.

In a low intensity campaign (a campaign in which one message is dominant), the reception gap is greatest among those in the middle range of political awareness. This means that these individuals are most likely to receive the dominant message and fail to receive the opposition message. Because reception is critical for acceptance, they are also less likely to accept the opposition message and more likely then to support the dominant message. As opposing messages increase in intensity, the reception gap shifts left on the political awareness scale to include voters that are in the lower ranges of political awareness. When intensity is high for both messages, the gap all but disappears, as very few individuals do not receive both messages. During such intense campaigns, individuals in the middle range of political awareness change in the direction of the dominant message while highly attentive citizens move in the direction of the opposing message.

The above discussion suggests that instability in public opinion could be likely. As intensity of the messages increases, acceptance is more likely. Two of Zaller's assumptions are relevant: the accessibility axiom and the response axiom. Together these two axioms propose that the most recently thought about considerations are the easiest for individuals to retrieve from memory and bring to the top of the head for use in issuing

\(^6\) The reception gap is simply the difference between the reception of the dominant message and the opposition message.
an opinion report or a vote choice. Such assumptions imply that attitudes then are only
stable if the particular combination of considerations that are salient remains constant. If
the combination of salient considerations at time $t$ is different than the combination of
salient considerations at time $t+1$, then attitudes should not be identical at $t$ and $t+1$.
Zaller (1992) makes it very clear that attitude change is most likely to occur when the
relative salience of dominant and countervailing messages changes. Relative salience is
disrupted by only two sources. Current events or new information increases the salience
of preexisting considerations or new considerations enter elite discourse so that voters
receive and accept new communications.

Formalization of Zaller

In his book, Zaller (1992) formalizes the above discussion into mathematical
equations. Before presenting these equations, a bit of clarification in the terms is
necessary. Zaller distinguishes between considerations and messages. Recall that
considerations can be conceived of as pieces of information that could potentially
influence a vote choice or a survey response. However, messages are the totality of the
considerations valenced in a particular direction. To illustrate, imagine we have a
political candidate, Smith. Assuming Smith is running against an opponent (Jones) in a
political race, two messages exist—a pro-Smith message (or anti-Jones) and an anti-
Smith (or pro-Jones) message. If we ask individuals what they can recall about a
particular candidate, the recalled information are considerations. Considerations could
include statements like Smith is pro-choice, Smith is a lawyer, Smith has two kids, etc.
The pro-Smith message for a given voter would be the totality of those considerations
positively valenced (for that voter) towards Smith.
In order for a given consideration to influence the vote choice or an opinion report, Zaller argues that this consideration must be received and accepted by the individual. Zaller argues that reception and acceptance are both critical to attitude formation and change. He formalizes the probability of reception and acceptance as logistic functions of several variables, like political awareness.

The reception function\(^7\), Equation Z-1, formalizes the relationship between an individual’s political awareness, the intensity of the campaign messages, and receipt of a particular political message in a given time period.

\[
\text{Prob(Reception)}_{ikt} = RE_{ikt} = 1 - \left[1 + f + \exp(a_0 + \alpha_1 \times \text{Awareness}_t)\right]^{-1}
\]

Equation Z - 1

In this and subsequent equations, the subscript \(i\) refers to the individual, the subscript \(k\) refers to the ideological coloration of the message\(^8\), and the subscript \(t\) refers to the time period.

What are the various elements of the reception function? The first element is \(f\), which represents the floor parameter. Zaller’s primary goal is to explain the survey response, not attitudes in some general notion. As a result, he argues that one needs to account for certain peculiarities of survey respondents. In particular, public opinion scholars find that individuals sometimes answer survey questions without any knowledge of the object of the question. For example, subjects might answer a question about George W. Bush without knowing anything about him. As a result, reception will appear

\(^7\)The reception equation looks slightly different than a typical logistic function, but it is mathematically equivalent. In a typical logistic function the exponents of the natural log are negative. In this equation, they are positive and there is a leading 1 that the function is then subtracted from. Zaller argues that reception is an increasing function of awareness and intensity of the campaign. As such, he wants awareness and intensity to have positive coefficients. For this to be mathematically possible, he must subtract this from 1.

\(^8\) When I discuss the formation of opinions, the \(k\) subscript will become either an \(a\) or \(b\) designating the dominant and countervailing messages. In the example of Smith and Jones, Smith will be represented by an \(a\) and Jones by a \(b\).
higher than it actually is. To mitigate this tendency, Zaller starts all individuals with a reception equation of $f$. The $f$ parameter allows Zaller to claim that reception of a message is strongly related to awareness and is not related to the tendency of respondents to answer questions regardless of their actual reception of the information. As is evident in Figure 2.1, the $f$ parameter influences reception only at the lowest levels of political awareness. The probability of reception does not increase if we change the floor parameter from 0 to 0.3 for individuals with higher levels of political awareness (greater than 1).

**Figure 2.1: Reception Equation: Altering the Floor Parameter**

Note: Figure 2.1 displays the floor parameter when the other variables in the reception equation are as follows: $a_0 = 0$ and $a_1 = 2$. Political awareness is scored in standard units from a low of $-3$ and a high of $+3$.

The intercept of the logistic function ($a_0$) represents the intensity of the message. The intensity of a candidate’s message includes the amount and volume of information about the candidate. High intensity campaigns lead to higher levels of reception than low intensity campaigns at all levels of political awareness. This intercept does not move the function up or down; rather, the $a_0$ term moves the function to the left or the right. As intensity increases, individuals at lower levels of political awareness are more likely to
receive the message than at lower levels of intensity. To illustrate this movement, I plot the function at three different levels of intensity when all other elements are held constant in Figure 2.2. In the most intense campaign ($a_0 = 1$; represented by the large dashed line), even individuals scoring at the lowest level of political awareness still have a positive likelihood of reception. Once an individual’s political awareness exceeds -0.5 the individual has a 50% probability of receiving the messages. However, this figure also illustrates that at low levels of intensity, the politically unaware are unlikely to receive such messages. With such non-intense messages, one needs a 0.5 level of political awareness to exceed a 50% probability of reception. This intercept contains two subscripts ($k$ and $t$). These subscripts allow for shifts in the intensity of each message over time. What does this mean for the equation? This means that if there are four time periods and two messages, there could potentially be eight different $a_0$ parameters.

**Figure 2.2: Reception Equation: Altering the Intensity Intercept**

![Graph showing reception equation]

Note: Figure 2.2 displays the intensity coefficient when the other variables in the reception equation are as follows: $f = 0$ and $a_1 = 2$. Political awareness is scored in standard units from a low of -3 and a high of +3.

The coefficient $a_1$ signifies the strength of the relationship between political awareness and reception. As this coefficient increases, the proposed logistic relationship
between awareness and reception strengthens\(^9\). In Figure 2.3, I demonstrate the effect of changing this coefficient from a weak, positive relationship (0.25) to a stronger, positive relationship (1). Altering this coefficient changes the shape of the function reflecting different conceptions of the relationship between awareness and reception. Zaller argues that awareness should be positively related to reception of a political message \((a_1 = 1)\). As awareness increases, the probability of reception should increase, but this relationship should be logistic. However, when the coefficient does not equal 1, reception is an increasing function of awareness, but not necessarily logistic. The final element is the only variable in this equation: political awareness.

**Figure 2.3: Reception Equation: Altering the Awareness Coefficient**

Note: Figure 2.3 displays the awareness coefficient when the other variables in the reception equation are as follows: \(f = 0\) and \(a_0 = 0\). Political awareness is scored in standard units from a low of \(-3\) and a high of \(+3\).

Having received the message, Zaller (1992) argues that an individual must accept the message for it to have an influence on an opinion report or a vote choice. Equation Z-2 is

\(^9\)Zaller indicates that one could consider subscripting this coefficient by time or message if one believed, for example, that the messages were carried by different mediums in different time periods. Given the constraints of his data, this is not necessary.
the acceptance function given that an individual has received a message\footnote{Equation Z-2 appears to be a conditional probability making it odd that one would need both equations when considering attitude change. However, Zaller considers the two functions to be distinct and necessary conditions for attitude change. Notice in the equations that awareness plays a role in each, but a distinct role. In the first equation, awareness determines one’s reception of information while in the second equation awareness allows one to resist persuasion. As will become clear below, the reception function relies on a parameter, two coefficients, and one variable. The acceptance function on the other hand relies on three coefficients and two variables.}. 

\[
\text{Prob} (\text{Accept})_{ikt} = \text{Accept}_{ikt} = 1 + \exp[-b_{0k} - b_{1k} \cdot \text{Awareness}_{ik} - b_{2k} \cdot \text{Distance}_{ik}]^{-1} \quad \text{Equation Z-2}
\]

The intercept (b_{0k}) signifies the familiarity of the message. Zaller indicates that some messages, for whatever reason\footnote{At various times, Zaller refers to this coefficient as capturing difficulty, familiarity, and credibility of the message. He provides two different examples for why this coefficient is important. An anti-war Vietnam era message might face more resistance given that it might be considered anti-patriotic. Or, the anti-war message might run into resistance given that it is contrary to the established policy.}, will face less resistance than others regardless of an individual’s level of political awareness\footnote{Zaller includes this coefficient in this function because he is interested in changes in attitudes on issues, as opposed to candidates. However, we can assume that this coefficient is important in cases in which the candidates we ask subjects to evaluate are very obscure candidates.}. The k subscript on this intercept signals that difficulty can vary by message. In Figure 2.4, I alter the familiarity of a message from 0 to 2. When the familiarity of the message increases (b_{0} = 2), the probability of acceptance of this message also increases at all levels of political awareness. As a message becomes less familiar or more difficult (b_{0} = 0), the probability of acceptance declines across all levels of political awareness.
Figure 2.4: Acceptance Equation: Altering the Familiarity Intercept

Note: Figure 2.4 displays the familiarity intercept when the other variables in the acceptance equation are as follows: $b_1 = -1$ and $b_2 = -1$. I have set ideological distance at 2, which signifies a Democrat. Political awareness is scored in standard units from a low of $-3$ and a high of $+3$.

The second coefficient ($b_1$) represents the effect of political awareness on an individual’s resistance to persuasion. In Figure 2.5, I demonstrate the role of this coefficient in the function by plotting the function when I vary the size of this coefficient. Zaller argues that the relationship between awareness and acceptance ought to be negative; that is, individuals with high levels of political awareness are less likely to be persuaded by any given message than those at the lowest levels of political awareness ($b_1 = -1$). When this coefficient does not equal $-1$, the probability of acceptance is a decreasing function of awareness, but not necessarily logistic. The $t$ subscript allows Zaller to examine if political awareness becomes more important in influencing acceptance in different time periods. Why is this important? In the empirical analysis, Zaller argues that political awareness became more important in the acceptance of

---

13 This subscript does not indicate that awareness changes overtime. This is a subscript on the coefficient that measures the strength of the relationship between awareness and acceptance. What this means is that the relationship itself may become more important in one time period than in another. Awareness should be very consistent from one time period to another and should vary by individual not time.
messages within the context of Vietnam War attitudes after a specific date. As a result, he allows the relationship between awareness and acceptance to vary overtime by subscripting the coefficients by time.

**Figure 2.5: Acceptance Equation: Altering the Awareness Coefficient**

![Graph showing the relationship between awareness and acceptance with different coefficients for b1 and b2.](chart)

Note: Figure 2.5 displays the awareness coefficient when the other variables in the acceptance equation are as follows: \( b_0 = 2 \) and \( b_2 = -1 \). I have set ideological distance at 2, which signifies a Democrat. Political awareness is scored in standard units from a low of -3 and a high of +3.

Finally, the third coefficient (\( b_2 \)) represents the relationship between ideological distance from a message and the probability that an individual resists the message. In Figure 7-6, I vary the strength of the relationship between ideological distance and acceptance from \(-0.25\) to \(-1\). Zaller argues that the relationship between ideological distance and acceptance ought to be negative and logistic. As ideological distance increases, acceptance of the message ought to decrease; however, the relationship is not just negative but logistic. As the graph indicates, individuals at the lowest level of political awareness are unable to determine the distance between the message and their own predispositions. As a result, they are likely to accept the message regardless of ideological distance. At the highest levels of political awareness, ideological distance plays a much greater role. The \( t \) subscript fulfills the same purpose for this coefficient as
it did for the one above\textsuperscript{14}. Zaller argues that ideological distance may become more important in one time period than it was in another time period. The distance variable captures an individual’s ideological distance from the message.

**Figure 2.6: Acceptance Equation: Altering the Ideology Coefficient**

![Graph showing the acceptance equation with different ideology coefficients.](image)

Note: Figure 2.6 displays the ideology coefficient when the other variables in the acceptance equation are as follows: $b_0 = 2$ and $b_1 = -1$. I have set ideological distance at 2, which signifies a Democrat. Political awareness is scored in standard units from a low of −3 and a high of +3.

The above discussion outlines the reception and acceptance functions, but a few additional equations are necessary to move us from reception and acceptance of campaign information to a predicted value for public opinion on any given day. Zaller’s model assumes that individuals sample considerations at the top of their head when asked to issue an opinion or make a vote choice; therefore, one might ask what is the probability an individual can recall any single consideration. Equation Z-3 provides the form of the recall equation\textsuperscript{15}. The probability of recalling a single consideration is only a

\textsuperscript{14} This subscript does not indicate that ideological distance changes overtime. This is a subscript on the coefficient that measures the strength of the relationship between ideological distance and acceptance. This indicates that the relationship between ideological distance and acceptance becomes more important in one time period than in others, but this does not mean that ideological distance itself varies substantially from one time period to another for each individual.

\textsuperscript{15} The recall equation looks slightly different than a typical logistic function, but it is mathematically equivalent. In a typical logistic function the exponents of the natural log are negative. In this equation, they are positive and there is a leading 1 that the function is then subtracted from. Zaller argues that recall
function of awareness. This recall equation does not have any k or t subscripts; therefore, recall of a consideration is not related to when the consideration was formed or the ideological coloration of the consideration. This is not a trivial assumption. Psychologists interested in learning and memory focus much of their attention on various elements of time and on the learning object itself believing that these elements influence one’s ability to recall information. For now, I will maintain Zaller’s functions in their original state. The first element of this equation is simply the intercept of the logistic function and represents the probability of recall of a consideration when an individual has no political awareness. The second coefficient represents the strength of the relationship between political awareness and recall\(^1\). As awareness increases, the probability that an individual can recall any given consideration increases.

\[
\text{Prob (Recall)} = 1 - \left[ 1 + \exp(c_0 + c_1 \times \text{Awareness}) \right]^{-1} \quad \text{Equation Z - 3}
\]

Equation Z-4 combines the above three functions together to explicate the probability that considerations an individual has been exposed to will be accessible. This equation is simply a function of reception, acceptance, and recall of the considerations.

\[
\text{Prob (Accessible)}_{ikt} = AC_{ikt} = RE_{ikt} \times Accept_{ikt} \times R_i \quad \text{Equation Z - 4}
\]

How can we transform this equation such that we can determine the probability that considerations concerning a particular message (pro-Smith) or considerations concerning a different message (pro-Johnson) will be accessible to the individual for use in a vote decision or an opinion report? Imagine we have two particular messages—a pro-Smith

---

is an increasing function of awareness and any other variable that might influence recall. As such, he wants awareness to have a positive coefficient. For this to be mathematically possible, he must subtract this from 1.

\(^1\) Zaller points out that this need not depend only on awareness but could be a function of any variable that also influences an individual’s attention to an issue. To be discussed in detail later, Zaller indicates that Axiom 3 allows for recall ability to be inversely related to the time since the consideration has been formed. He omits it in this discussion he says because it has no observable implications.
message and a pro-Johnson message—what is the probability that a single consideration in favor of Smith will be accessible. To determine the accessibility of considerations concerning Smith, we first need to sum the total number of Smith considerations that have been received, accepted, and recalled. This sum is then divided by the total number of Smith and Johnson considerations that have been received, accepted, and recalled.

Equation Z-5 is the probability that a pro-Smith consideration is accessible.

\[
\text{Prob}(\text{SmithAccess})_{ikt} = \frac{\sum_{i=1}^{N} \text{RE}_{\text{lat}} \cdot \text{Accept}_{\text{lat}} \cdot R_i}{\sum_{i=1}^{N} \text{RE}_{\text{lat}} \cdot \text{Accept}_{\text{lat}} \cdot R_i + \sum_{i=1}^{P} \text{RE}_{\text{tbt}} \cdot \text{Accept}_{\text{tbt}} \cdot R_i}
\]

Equation Z - 5

In this equation, the probability that a Smith message is accessible is equal to the sum of the reception, acceptance, and recall of each Smith consideration divided by the sum of the reception, acceptance, and recall of each Smith consideration and the sum of the reception, acceptance, and recall of each Johnson consideration. The subscripts on the summation signs indicate the considerations for each message.

Zaller simplifies Equation Z-5 in two ways. First, Zaller assumes there are equal numbers of Smith and Johnson messages; therefore, the summation signs are unnecessary. Further, both the numerator and the denominator include the recall function so they cancel each other out. This is possible because the recall function is not subscripted by anything but the individual; this indicates that recall of each consideration at each point in time is identical. This leaves us with Equation Z-6 as the probability that a Smith message is accessible. The probability that a pro-Smith consideration is accessible is then a function of the proportion of all considerations (both pro-Smith and pro-Johnson) received and accepted that are pro-Smith. This accessibility varies across time and individuals.

\[
\text{Prob}(\text{SmithAccess})_{ikt} = \frac{\text{RE}_{\text{lat}} \cdot \text{Accept}_{\text{lat}}}{\text{RE}_{\text{lat}} \cdot \text{Accept}_{\text{lat}} + \text{RE}_{\text{tbt}} \cdot \text{Accept}_{\text{tbt}}}
\]

Equation Z - 6
The reception and acceptance functions along with the accessibility equation are outlined in Table 2.1.

**Table 2.1: Shorthand of Basic Zaller Equations**

<table>
<thead>
<tr>
<th>Shorthand</th>
<th>Meaning</th>
<th>Example</th>
<th>Inputs to the Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE(_{ikt})</td>
<td>The probability of reception of a message k at time t by a given individual i</td>
<td>The probability of reception of a Smith or Johnson message at time t by a given individual i</td>
<td>Floor parameter, intensity of k message at time t, strength of relationship between awareness and reception, individual i’s political awareness</td>
</tr>
<tr>
<td>Accept(_{ikt})</td>
<td>The probability of acceptance of a message k at time t by a given individual i</td>
<td>The probability of acceptance of a Smith or Johnson message at time t by a given individual i</td>
<td>Difficulty of k message, strength of relationship between awareness and acceptance, individual i’s political awareness, strength of relationship between ideological distance and acceptance, individual i’s ideological distance from message</td>
</tr>
<tr>
<td>AC(_{ikt})</td>
<td>The probably that a message k will be drawn out at time t by a given individual i</td>
<td>The probably that information, about the Smith message or Johnson message, will be accessible as a consideration at time t by a given individual i</td>
<td>The result of reception and acceptance functions</td>
</tr>
</tbody>
</table>

The equations outlined above help determine the accessibility of Smith information, but alone are not enough to determine the probability that an individual will issue a pro-Smith response. To determine this, we need to know what the probability is that an individual issues any response. Survey researchers often must deal with individuals that have no opinions on an issue or candidate. Having no opinion can only occur if an individual has no accessible considerations about either Smith or Johnson at time \(t\). In my example of Smith and Johnson, an individual can have up to \(2N\) possible considerations (\(N\) is the number of considerations for each message and 2 is the number of messages—pro-Smith and pro-Johnson—an individual could receive).

Accessibility depends on both acceptance and reception; therefore, an individual could have no opinion if the individual either failed to receive any considerations or did
not accept any considerations\(^{17}\). The probability that an individual has not received or accepted a single consideration would be: \(\text{Prob(NoOpinion)}_{it} = (1 - AC_{ikt1}) \times (1 - AC_{ikt2}) \times \ldots (1 - AC_{ikt2N})\). In this equation, no opinion responses occur when there are no accessible considerations. The subscript on AC denotes the accessibility of a given consideration \((1, 2, \ldots N)\) of a given message \(k\) for a given individual \(i\) at time \(t\). Zaller assumes there are an equal number of considerations for each message, so the subscript signaling the particular considerations is unnecessary. Eliminating the subscript produces the reduction in Equation Z-7.

\[
\text{Prob (NoOpinion)}_{it} = \left( \prod_{j=1}^{N} (1 - AC_{ijt}) \right) \times \left( \prod_{j=1}^{N} (1 - AC_{ijt}) \right) \quad \text{Equation Z-7}
\]

Of course, we are most interested in the probability that an individual \textit{will} have an opinion. The probability that an individual will have an opinion at time \(t\) is one minus the probability that an individual will have no opinion at time \(t\). Equation Z-8 represents the probability that an individual will have any opinion at time \(t\).

\[
\text{Prob (Opinion)}_{it} = 1 - \left( \prod_{j=1}^{N} (1 - AC_{ijt}) \right) \times \left( \prod_{j=1}^{N} (1 - AC_{ijt}) \right) \quad \text{Equation Z-8}
\]

The above equations put us in a position to answer the question posed earlier: what is the probability that an individual will issue a pro-Smith response? This probability is a function of the probability of issuing any opinion (Equation Z-8) and the accessibility of pro-Smith considerations (Equation Z-6). Equation Z-9 is the probability that an individual issues an opinion, and that opinion is a pro-Smith opinion. This equation will be used to produce a predicted value for public opinion for each candidate throughout the campaign season.

\(^{17}\) If one included the recall equation in the appendix, then the probability of having no opinion or having an opinion is also a function of recall.
\[
\text{Prob } (\text{Smith})_{iat} = 1 - \prod_{j=1}^{N} (1 - AC_{iat}) \times \prod_{j=1}^{N} (1 - AC_{ibt}) \times \frac{RE_{iat} \times \text{Accept}_{iat}}{RE_{iat} \times \text{Accept}_{iat} + RE_{ibt} \times \text{Accept}_{ibt}}
\]

Equation 2 - 9

Static versus Dynamic Properties

To produce a predicted path of public opinion from the memory-based model, I modify the above equations slightly to deal with the fact that I am interested in movement of public opinion throughout a campaign season\(^\text{18}\). The focus of Zaller’s book is explaining variation in individual-level opinion; therefore, he emphasizes the role of differences in political awareness and political predispositions in the reception and acceptance of campaign messages. By contrast, I am interested in the course of public opinion for a given candidate throughout a campaign season. As a result, I am concerned with the elements of each model that are dynamic; that is, I am interested in identifying those elements that change throughout the course of a political campaign.

Previous discussions of this model have insufficiently appreciated the dynamic or static properties of the inputs to the model. All inputs to the model appear in the first two equations—reception and acceptance—while the other seven equations are used to produce a predicted value for public opinion. There are four inputs to the model in these two equations—intensity, difficulty, awareness, and political predispositions. These four inputs to the model vary in their dynamic nature.

Of these four inputs, three are static. What does this mean? I mean to suggest that these elements do not change over the course of a campaign, although they might vary across individuals or races. Public opinion research has consistently shown that political awareness and things like partisanship and ideology vary across individuals (cross-
sectional variation), but not over the short time-period of a political campaign. Similarly, difficulty of the message should vary across candidates, but it should not vary across time. When thinking in terms of political campaigns, these three elements set the context in which public opinion can move overtime.

So, what does that leave for doing the dynamic work? The only element in either equation that can move public opinion throughout the course of a campaign is the relative intensity of the campaign messages or the relative quantity and volume of information about the candidates. Throughout a campaign season, the relative flow of campaign information for a given candidate certainly varies (perhaps even on a daily basis). Thus, if public opinion moves overtime, the movement must be related to the flow of campaign information. If the majority of information about a candidate becomes more negative overtime, public opinion ought to become more negative as well. If the information concerning a candidate trend in a positive direction, public opinion should become more positive towards the candidate. So, we have one input to explain the dynamics of public opinion. And, if this element can successfully explain public opinion, then we have an extremely parsimonious model.

**Fundamentals of the On-Line Processing Model**

While the memory-based model was implicitly used in the voting behavior literature for many years and explicitly developed in the psychological literature concerning the relationship between memory and judgment, the on-line model emerged in psychology as a way to explain the lack of a one-to-one relationship between memory and judgment. As Hastie and Park (1986) discuss, in the on-line model information is encountered and enters working memory. Once in working memory, the information flows directly to the
judgment operator. The process is referred to as on-line because judgments are made at the time of information exposure. Further, on-line judgments about others are updated as new information is encountered. Once judgments are made, the model does not suggest whether or not the information itself is stored in any area of long-term memory. This is why the model cannot give an unequivocal supposition concerning the relationship between memory and judgment.

*Lodge et al’s On-Line Processing Model*

In 1995, Lodge and his colleagues introduced the on-line model in political science to explain how individuals can evaluate political candidates, but fail to remember campaign information. There are five important assumptions of the on-line model (Lodge, Steenbergen et al. 1995). Upon receipt of campaign information the individual (1) extracts the affective value of that piece of information and (2) quickly forgets the descriptive content in which it is embedded. A running tally, or on-line tally, (3) integrates these affective components. The tally summarizes the voter’s affective response to the political candidate at the present moment and (4) is stored in long-term memory. The on-line model assumes that (5) the individual retrieves the affective tally from long-term memory when asked to issue an opinion or make a vote decision.

There are three important implications from this model. The first is that responsive voters, upon exposure to negative campaign information, decrease their evaluation of candidates and increase their evaluation when exposed to positive information. The second implication is that we should not necessarily anticipate a strong relationship between exposure to campaign information and recall of campaign information. Finally, the tendency for individuals to forget campaign information is of little consequence in
their ability to evaluate candidates meaningfully.

Both the on-line and the memory-based models make distinct predictions for the stability of attitudes overtime. In the case of candidate evaluation, the "attitude" I am referring to is the survey response or vote choice. What are the dynamic implications for the on-line model? The authors insist that responsive citizens respond to campaign stimuli by forming an on-line tally and, having established this tally, update it as they attend to new information. However, the exact nature of this updating process determines whether or not we should anticipate stability in candidate evaluations overtime in response to new information. The on-line model suggests that preferences for candidates ought to be quite stable and less susceptible to sudden shifts (Druckman and Lupia, 2000). Why might this be the case? Krosnick and Brannon (1993) point out that evaluations formed using an on-line processing approach have quite a bit of inertia. These evaluations are based on large quantities of previously obtained information such that each new piece of information is unlikely to have a substantial impact on the evaluation of a candidate.

Formalization of Lodge et al's On-Line Model

The above discussion sets the background for formalizing Lodge et al's argument. I first formalize the establishment of the on-line tally. While Lodge et al do not explicitly discuss the origination of the tally we can reasonably assume that the on-line tally is instantiated when an individual first has an affective response to information about a candidate. For purposes of this project I assume the on-line tally forms when the individual is first exposed to information about a candidate and knows he/she will need to make an evaluation (McGraw, 2003). Equation L-1 gives a mathematical form to this
process. In this equation, \( i \) represents a piece of information to which an individual is exposed. The tally is formed at time zero from the voter's affective response to each piece of information received at that time. These affective reactions are just summed to generate an online tally. If the individual is asked to evaluate the candidate at this time, this tally is retrieved. If the tally is positive, the individual will issue a positive evaluation of the candidate; if the tally is negative, the individual will issue a negative evaluation.

\[
Tally_{(t=0)} = \sum_{i=1}^{N_0} AffectResponse_{i0} \quad \text{Equation L-1}
\]

This baseline feeling towards the candidate is updated each time new information about the candidate is encountered. Lodge et al. (1995) recognize that the tally, once established, could be updated in a number of different ways (and differences in this process will surely impact the dynamic evolution of opinion); however, they assume a simple additive updating rule. That is, the affective evaluations of information are weighed equally and summed. I present Equation L-2 to represent this updating process. In Equation L-2, the first part of the equation represents the original tally formed in Equation L-1 and new information is added to this tally in the second half of the equation.

\[
UpdatedTally_{(t=1)} = Tally_0 + \sum_{i=1}^{N_1} AffectResponse_{i1} \quad \text{Equation L-2}
\]

To illustrate the updating process, consider Table 2.2 and the resulting graph in Figure 2.7. Imagine we have nine individuals with original tallies set at 5. What happens to the tally if these nine individuals evaluate new information differently? In Table 2.2, I present nine potential combinations of affective reactions to twenty-five
pieces of new information. The final column represents the updated tally. Altering the
affective reactions to new information significantly influences the resulting tally.

| Table 2.2: The Influence of New Information on the Updated Tally |
|---------------------------------|---------------|---------------|
| Original Tally                  | New Information | Updated Tally |
| 5                              | -1, -1, -1, -1, -1, -1, 0, 0, 1, 1, 0, 1, 1, 1, 1 | 3 |
| 5                              | -1, 0, -1, -1, -1, 0, 0, -1, 1, 1, 1 | 14 |
| 5                              | 1, 1, 1, 1, -1, 1, 1, 1, 1, 1, 1, 0, 1, -1, -1, 1, 0 | 14 |
| 5                              | -1, -1, 1, -1, -1, 1, 1, -1, 1, -1, -1, 1, -1, -1, 1, 0 | -3 |
| 5                              | -1, -1, 1, 1, -1, 1, 1, -1, 1, -1, 1, 0, -1, -1, 1, 0 | 4 |
| 5                              | -1, -1, 1, 1, -1, 1, 1, -1, 1, -1, 1, 0, -1, -1, 1, 0 | 4 |
| 5                              | -1, -1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, -1, -1, 1, 0 | 3 |
| 5                              | -1, -1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, -1, -1, 1, 0 | 2 |
| 5                              | -1, -1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, -1, -1, 1, 0 | 2 |
| 5                              | -1, -1, 1, 1, 1, 1, 1, 1, 1, 1, 1, -1, -1, 1, 1, 1 | 7 |
| 5                              | -1, -1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, -1, -1, 1, 0 | 3 |
| 5                              | -1, -1, 1, 1, 1, 0, 1, 1, -1, 1, 1, 1, 1, 1, 1, 1 | 4 |
| 5                              | -1, -1, 1, 1, 1, 0, 1, 1, -1, 1, 1, 1, 1, 1, 1, 1 | 4 |

In Figure 2.7, I illustrate graphically the above discussion. I set the original on-line
tallies for all nine individuals at +5. Using the affective reactions to the twenty-five
pieces of new information outlined in Table 2.2, the tallies are updated. Even though
each individual evaluates the twenty-five new pieces of information differently, only one
tally becomes negative after updating. The original tally is clearly important. Even
though all nine individual react differently to the new information, three of the updated
tallies are identical (+3).
Figure 2.7: Updating the Tally: the Influence of New Information

The above figure illustrates the roles of the original tally and new information in the updating process. This updating process is consistent with Krosnick and Brannon's (1993) discussion of inertia. The updating process does not yield tallies that never change; instead, the updating process produces an inertial tally. As the tally becomes more and more entrenched, it is difficult to move the tally in such a way as to alter the overall evaluation of a candidate (positive or negative). That is, as more and more pieces of information are added to the tally in a given direction, moving the tally such that the individual issues the opposite evaluation is incredibly difficult.

To illustrate this notion, consider Figure 2.8. In this figure, we have an individual with a consistently positive tally for a candidate. When the tally is formed at $t=0$, the ability of new information to alter the tally is greatest. At $t=0$ the tally is equal to 0 and the tally can be moved either positive or negative in $t+1$ by a single piece of information valenced in the particular direction. At $t+1$, the individual receives positive information about the candidate. At each successive time period, the individual has received more and more positive information concerning the candidate. By the time we reach time period 3, it is much more difficult (because of the distance from zero) for the tally to dip
into the negative range. The tally has become entrenched. As such, the individual is much more likely to issue an evaluation in a particular direction as the tally becomes more entrenched. New information at $t=1$ moves the tally the same distance as new information at $t=3$; however, the distance from zero is greater at $t=3$ such that more information is needed to move below zero (or to yield a negative evaluation of a candidate).

**Figure 2.8: The On-Line Tally Overtime**

![Figure 2.8](image)

**Tests of the Memory-Based and On-line Model**

Formalizing the on-line and memory-based models provides an opportunity to examine the implications these models have for the movement of public opinion overtime. In the next chapter, I simulate eight political campaigns and these campaigns demonstrate that, in very simple cases, the two models provide different predictions for the course of public opinion. Before turning to this examination, one final question remains: have the dynamic implications of the models been tested? Unfortunately, the dynamic implications have yet to be tested using detailed data from actual political campaigns. I briefly outline below the previous tests of the two models and discuss the reasons why they fail to examine the dynamic implications of the models.
While the voting behavior literature beginning with Kelley and Mirer (1974) has found that the information an individual recalls about a candidate influences his/her vote choice, the evidence for this argument overlooks a key aspect of political campaigns—in political campaigns, information is presented to voters overtime. Much of the voting behavior research is based on static surveys. That is, surveys conducted at a single point in time. Such surveys cannot provide information about the dynamic relationship between campaign information and public opinion during the course of a political campaign. These studies cannot provide evidence to support the models' predictions for public opinion overtime. Kelley and Mirer's classic findings rely on evidence from the National Election Studies during the 1952, 1956, 1960, and 1964 presidential elections. The authors find that knowing respondents' likes and dislikes of the parties and their candidates makes it possible to accurately predict respondents' vote choices. However, tests of this nature do not provide evidence for the dynamic relationship between campaign information and vote choice.

Like the testing of the more comprehensive models, the tests of the limited-memory models, characterized by Zaller's Receive-Accept-Sample model, rely on survey data. In 1992 and 1996, Zaller indicates that he tests a dynamic two-message memory-based model. His analysis certainly provides evidence that public opinion responds to campaign messages; however, the tests he provides are limited and do not examine the daily change in public opinion throughout a campaign season.

Zaller (1992, 1996) reports two tests that are somewhat dynamic. In particular, Zaller (1992) examines the change in support for the Vietnam War between 1964 and 1970 using election studies conducted by the Center for Political Studies. These surveys
asked the public about their support for the Vietnam War on four different occasions between 1964 and 1970. However, this evidence does not demonstrate the manner in which support for a candidate might change on a daily basis throughout a campaign season.

Focusing more explicitly on the change in support for a candidate during the campaign season, Zaller (1992, 1996) considers the change in support for Mondale and Hart in the 1984 Democratic presidential primary and the support for Ross Perot in the spring of 1992. Neither of these tests examines public opinion as it moves throughout a campaign season in response to campaign stimuli; instead, the tests examine discrete points in time during the campaign season selected by the author as particularly critical. This test does not capture the way that public opinion changes on a daily basis throughout the campaign season in response to daily changes in the relative flow of campaign information. Further, this test does not examine the ability of the on-line model to capture change in public opinion.

On the other hand, Lodge et al. do test versions of the two models. However, like the memory-based model, the on-line model’s dynamic implications have not been fully explored in the context of an actual political campaign. Lodge et al.’s experimental design is static. Candidate information is presented to subjects at a single point in time, in the form of a factsheet of campaign information, and evaluation of the candidates occurs at a second point in time. At no point in the experiment do the authors examine the way changes in campaign stimuli influence opinion overtime. In the empirical test described in Chapter 4, I examine the way in which the daily flow of campaign information influences support for candidates overtime.
Chapter 3:  
Simulating Information Environments of Political Campaigns

The formalization of the memory-based and on-line models presented in the previous chapter provides a unique opportunity to explore the assumptions of the model. In this chapter, I exploit this opportunity by exploring the predicted paths of public opinion that emerge from each model's formalization in a number of hypothetical cases that illustrate the models' strengths and weaknesses. In doing so, I demonstrate that the two models predict different paths of public opinion for a given candidate even though the models rely on the same campaign information as inputs.

To demonstrate this, I construct a series of eight hypothetical campaign seasons with two political candidates. I then use the hypothetical features of the campaign season as inputs in the formalized equations. Each of the eight hypothetical cases involves a race for governor of state X. The races vary according to what "types" of candidates are running for governor: incumbents versus non-incumbents. The cases also vary according to whether the incumbent matches the political party that is most dominant in the state and the extent to which the race is competitive. These three different variables—incumbency, partisanship, and competitiveness—produce eight cases. These eight cases are listed in Table 3.1. The eight cases vary according to whether there is an incumbent in the race, whether Candidate A matches the partisanship of the dominant party in the state, and the extent to which the race is competitive.
Table 3.1: Types of Hypothetical Races

<table>
<thead>
<tr>
<th>State Partisanship</th>
<th>Incumbent, Competitive</th>
<th>Non-Incumbent, Competitive</th>
<th>Incumbent, Non-Competitive</th>
<th>Non-Incumbent, Non-Competitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matches Candidate A</td>
<td>Case 1</td>
<td>Case 3</td>
<td>Case 5</td>
<td>Case 7</td>
</tr>
<tr>
<td>Matches Candidate B</td>
<td>Case 2</td>
<td>Case 4</td>
<td>Case 6</td>
<td>Case 8</td>
</tr>
</tbody>
</table>

In Chapter 2, I presented the formalization of the memory-based and on-line models. For each model, certain theoretical inputs must be measured in order to produce a predicted value for public opinion. The on-line model argues that individuals have affective reactions to campaign information and store these affective reactions in an on-line tally. In contrast, the memory-based model posits a role for four elements: difficulty, political predispositions, political awareness, and intensity of the candidates’ messages. For the hypothetical cases outlined in Table 3.1, I need to “measure” these inputs in order to produce a predicted path of public opinion. I input these hypothetical values into the equations presented in Chapter 2. By inputting these values into the equations for each model, I am able to produce a predicted path of public opinion throughout the campaign season for the two candidates in each race.

In the next section, I describe the way in which I calculate values for each of the concepts included in the mathematical equations. I then turn in the third section to a description of the specifics of the eight hypothetical cases. For each of the cases, I first describe the hypothetical race. I then discuss the way in which I calculated values for each of the concepts in the particular race under discussion. I then discuss the role of the parameter inputs in producing the predicted level of support in each race. I then graphically display the predicted paths and discuss the different predictions the models
make. I conclude the chapter by asking if the models make systematically different predictions even though they rely on the same information environment.

**Simulating Public Opinion**

**On-Line Model**

The on-line model described in Chapter 2 proposes a role for an original tally—constructed from the first information individuals hear about a candidate—and an updated tally—incorporating the affective reactions individuals have to new information about the candidate. For each of the candidates in the eight races outlined in Table 3.1, I need to calculate an original tally and an updated tally.

To construct the original tally and the updated tally, I need a measure of the affective reactions individuals have to information about the candidates. To produce an affective reaction to candidate information, I draw a random value for each piece of candidate information. This value can range from very positive (+5) to very negative (-5). This value is drawn randomly for each piece of information released throughout the campaign season. On each day of the campaign season, these affective reactions can be input into the two equations presented in Chapter 2 to produce a value for the on-line tally at each point in the campaign season. Together, these values produce a predicted path for public opinion extending from the on-line model.

The next question then is how much information is released for each candidate throughout the campaign season. In Table 3.1, I indicate that the eight hypothetical cases vary according to incumbency and competitiveness. I use these two variables to establish the information flow—prior to the start of the campaign season and throughout the campaign season—for each candidate. The amount of information incorporated in the
original tally varies according to the incumbency of the candidate. Incumbent candidates are most likely to have substantial tallies before the beginning of the campaign season. I construct the original tally from the affective reactions to twenty pieces of information. Affective reactions are drawn randomly for each piece of information and range from very positive (+5) to very negative (-5). Non-incumbents are less likely to have substantial original tallies; as a result, I calculate the original tally for the non-incumbent candidates from the affective reactions to five pieces of information.

Tallies are updated throughout the hypothetical campaign season when individuals are exposed to new campaign information. Each day, new information about the candidates is released. In Table 3.2, I outline the number of additional pieces of information that are released on a daily basis for each candidate. The logic behind this daily information flow is based on two features of the campaigns—incumbency and competition. Candidate A in this table is always the incumbent if there is an incumbent. If there is no incumbent in the race, then Candidate A is the dominant candidate. Five pieces of information about incumbents are released each day, three pieces of information are released each day about competitive, non-incumbents or dominant candidates in a non-competitive race, and one piece of information is released each day for non-incumbents in non-competitive races.

**Table 3.2: Information Release in Hypothetical Races**

<table>
<thead>
<tr>
<th>Type of Incumbent</th>
<th>Republican Incumbent</th>
<th>Republican Candidate A</th>
<th>Democratic Incumbent</th>
<th>Democratic Candidate A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Candidate A</td>
<td>5 pieces</td>
<td>3 pieces</td>
<td>5 pieces</td>
<td>3 pieces</td>
</tr>
<tr>
<td>Candidate B</td>
<td>3 pieces</td>
<td>3 pieces</td>
<td>1 pieces</td>
<td>1 piece</td>
</tr>
</tbody>
</table>
Memory-Based Model

The predictions from Zaller’s model are calculated using the equations outlined in Chapter 2. The memory-based model relies on four concepts: difficulty, political awareness, political predispositions, and the intensity of the campaign messages for all candidates. Difficulty is simply the ease with which all individuals regardless of predispositions and awareness can accept a message. To measure difficulty, I turn to the incumbency variable. The messages of incumbents are the easiest to accept because they are the most familiar. Incumbency is coded one if the candidate is an incumbent and zero otherwise. In Chapter 2, I discussed the static nature of political awareness and political predispositions. These elements should not vary across time, so I simply need to set these elements to a specific number to be used in the equations. Political awareness ought not to vary over time, but it also obviously should not vary across evaluations of candidates. However, political predispositions, like difficulty, should vary across candidates. The extent to which an individual accepts a campaign message ought to be related to the distance between the individual’s political predispositions and the message.

One important predisposition is partisanship. I measure partisan distance as the distance from the candidate’s partisanship and the dominant partisanship in the state. Partisanship will vary across candidates and states but not overtime. States that are Republican-dominant receive a score of 1. States that are Democrat-dominant receive a score of 3. Candidates that are Democrat receive a score of 2.5. Candidates that are Republican receive a score of 1.5. I then subtract the state score from the candidate’s score to measure distance from the predisposition of the state and the candidate’s message.

That leaves only intensity left to discuss. The intensity of a candidate’s message is
conceived of as the flow of information about the candidate. To capture this, I use the same schedule for the dispersal of information about the candidates. For example, each day, five pieces of information are released about incumbents. The memory-based model does not have a notion like an on-line tally, so the predictions for each day are based solely on the flow of information about the candidates on that particular day. Information in the memory-based model does not have an affective component, but is simply either for the candidate or against the candidate. To capture this, I draw a random value for each piece of information representing positive (1), neutral (0), or negative (-1).

Inputting this hypothetical data into the formal equations discussed in Chapter 2 produces a set of predicted values for each model for a given candidate. However, the models predictions cannot be directly compared because the on-line model specifies a predicted path for the on-line tally that is cumulative while the memory-based model predicts a level of support that resembles a percentage. In order to compare the two predicted paths of public opinion, I need to standardize the two models predictions. To standardize the predicted values, I calculate z-scores for each predicted value. To do this, I calculate a mean and standard error of the predicted path for each candidate. Each predicted value is then subtracted from this mean. Dividing the difference between the mean for the series and each day’s predicted value by the standard error of the series then creates the z-score for a given day. I use these z-scores as the predicted values from each model.

**Predictions for Eight Hypothetical Cases**

In what follows, I use the above hypothetical data to construct predicted paths of public opinion from each model for the eight races. I first describe the race and discuss
the role of each of the inputs in creating a predicted level of support for each candidate on a given day. I then present the predicted paths produced by inputting the hypothetical data into the formal equations for each model for the two candidates in each race. I conclude each case discussion by highlighting the disparate predictions the models make for the candidates.

*Incumbent, Competitive, Partisan Match*

The first two races ought to be the most competitive by any measure as these races feature incumbents running against competitive challengers. In the first race, Smith, a very popular Republican Senator, is challenging Jones, the Democratic Governor in a state that is marginally Democrat, for her seat. This is a most intriguing race in that both candidates are popular within their respective parties, but the incumbent has relied heavily on out-party members in previous elections. Both candidates win their respective primaries with little effort against fields of lesser-known politicians. This is a cordial race for the most part with both sides running on their respective records; however, a month before the election, Smith hires a new campaign manager that decides to take the race negative. At the time, friends and foes alike predict this to be a hasty and dangerous move in such a tight race, and the election night results tell the same story as Jones defeats Smith by a small margin.

What are the predictions for this campaign from the on-line and memory-based models? I show these predictions in Figure 3.1. The upper panel displays the predicted path for Jones and the lower panel shows the predicted path for Smith. The filled circles represent the on-line model’s predictions while the hollow circles represent the memory-based model’s predictions. The first observation concerning the predicted paths is the
volatility of the memory-based model's predictions for the two candidates. The on-line model also predicts increases and decreases in support for the candidates, but these changes are much more gradual. Interestingly, the models' predictions diverge late in the campaign season as Smith takes the campaign negative. The on-line model responds with a gradual decline in support for Smith and a stable level of support for Jones. The memory-based model on the other hand predicts a series of declines in support for Smith, but then a rebound the last few days before the election.

Corresponding to the above description, Jones begins the race with a tally that is incredibly negative (-18.4771) and Smith begins the race with an overwhelming positive tally (10.49121). This positive tally for Smith remains relatively positive and stable for the first few months of the campaign season as the campaign information concerning Smith is positive. The tally for Smith does not begin to decline until the candidate takes the campaign negative in October. At that point, the on-line model predicts a decline in support for Smith until Election Day. In contrast, the on-line model, predicts a relatively poor start for Jones that is mitigated as the campaign season progresses. Public support is predicted to precipitously decline in early September and continue until Smith takes the campaign negative. Even with the conservative amounts of volatility predicted by the on-line model, the model predicts much more instability for Jones than it does for Smith. Why might this be the case? In updating the on-line tally, I rely on different amounts of information for each candidate. Five pieces of information are released for the incumbent candidates and only three pieces for competitive challengers. Based on this information release, the on-line model could make two different types of predictions: volatility or stability. In general the on-line model is much more stable in its predictions; however,
there are candidates for which information varies dramatically from day to day. Even the stable tendency of the on-line tally cannot overcome this variation.

Turning to the memory-based model, much more volatility is predicted. In this model, stability in prediction only occurs when no information about either candidate is released. There are only a few days of no campaign information. If information about at least one of the candidates is released, the model’s predictions vary. Recall that in the formalization of the model, today’s level of support is not dependent upon information released on any previous days. There is no explicit role for long-term memory in the model. This corresponds to the theoretical notion that the most readily accessible information is that information most recently heard. Further, a candidate’s level of support is dependent upon the intensity of his/her own messages and the intensity of his/her opponent’s messages. For the most part then, the model predicts an increase for one candidate and a simultaneous decrease for the other candidate. In this race, the model predicts many days of positive support for the incumbent candidate, but much less positive support for the challenger. The campaign season stretches from June 1st until November 8th and the memory-based model predicts one hundred days of negative support for Smith and sixty-one days of positive support for Smith. On the other hand, the model predicts only sixty-four days of negative support for Jones and ninety-seven days of positive support for Jones. Both models predict an increase in support for Jones from late September on and a decline in support for Smith from the same point. The predictions for Jones are relatively similar for both models.
Figure 3.1: Predictions from the Models for Hypothetical Case 1

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

*Incumbent, Competitive, Partisan Mismatch*

The second race to discuss, Case 2, features Martinez (the Republican) and Page (the Democrat). Martinez has been the incumbent governor for four years, but is now battling the former State Superintendent, Page, for his re-election bid. Most incumbent governors do well because they do not face any, or at least any *serious* primary challengers, and Martinez is no exception. Such an advantage is short lived given that the extremely popular Page also does not garner any serious primary competition. The general election begins as a relaxed affair with Martinez banking on his incumbency to trounce Page. Such a situation does not emerge, however, as Page's popularity translates into large sums of campaign funds. The state has become increasingly Democratic, so Page's chances of defeating the incumbent Republican could have been relatively high.
The problem Page seems to face throughout the campaign is lack of name recognition among the voters, particularly the voters entering the electorate since Page retired from his former post. Among likely voters who recognize Page’s name, he is overwhelmingly supported. Unfortunately, such name recognition does not come as easily as it does for Martinez. Martinez squeaks out a victory against Page because in the end, being the incumbent governor counts for something, even in a state that is increasingly becoming Democratic.

What do the models predict for the course of public opinion in this race? Figure 3.2 shows the predictions from each model for the course of public opinion for both Martinez and Page. Both models predict substantial positive support for Martinez throughout the campaign season. As is typically the case with incumbents, the on-line tally for Martinez is quite high when the campaign season opens; however, this tally declines substantially during the first month of the campaign. By the end of the campaign season, the tally has returned to a relatively high level for the incumbent.

The memory-based model predicts a few days of substantial positive support for Page in mid-June and mid-August, but these two days are offset by the one hundred and twenty-two days of negative support predicted by the memory-based model. These days of negative support predicted for Page correspond to the equivalent number of positive days predicted for Martinez. While both models predict an increase in support for Page by October, they predict an opposite track for Martinez with the on-line model predicting an increase in support and the memory-based model predicting relative stability in support. Once again, both models predict a victory for Martinez in the November election.
Figure 3.2: Predictions from the Models for Hypothetical Case 2

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

*Non-incumbent, Competitive, Partisan Match*

Also a highly competitive race, the third case pits Thomas against Davis, both current members of the House of Representatives from different sides of the aisle. In this race, there is no incumbent, but both candidates are incredibly popular among their own partisans. Thomas is considered to be an up-and-comer in the Democratic Party and Davis rode the Republican wave into the US House twelve years ago. In this race, Thomas has a slight edge in that the state tends to vote Democrat. An interesting race because both candidates are not only members of the House, but they are also former teammates on Harvard's rowing team and have been friends for most of their lives. Neither expected to win their party's nomination against heavy hitters like the current Lieutenant Governor and a former Senator. Given that both candidates are good friends
the race is mostly congenial with both easily agreeing to avoid negative ads and
denouncing any negative advertising by their respective political parties. In the end, the
state votes Democrat in almost every statewide election and goes blue for the presidency
as well. Thomas slides to a reasonably easy victory given that both candidates are
continuously evaluated positively by majorities of the electorate.

Even though the electorate throughout the campaign evaluates both candidates
positively, the predicted course of public opinion varies by model as shown in Figure 3.3.
The two models diverge for both candidates early in the campaign season. The on-line
model predicts below average support for Thomas and Davis until at least July. In
Chapter 2, I discussed the inertial tendency of the model as time progresses. At the
beginning of the campaign season, the tallies for both candidates are relatively non-
entrenched because they are both non-incumbents. However, as the season progresses,
more and more information about the candidates exist and their tallies become much
more stable. We certainly see this for Thomas. After July, the on-line model predicts
positive and relatively stable support for Thomas with only minor increases or decreases
in support. For Davis, the model predicts a much more unstable progress towards
Election Day. The increases and decreases predicted for Davis from the on-line model
result from daily changes in the flow of information.

While the on-line model makes more volatile predictions for Davis than it does for
Thomas, the memory-based model’s predictions are clearly more volatile than those of
the on-line model. However, there are a number of points in the campaign season when
the two models predict similar directions of support for the candidates. This is especially
true early in the campaign season, which is exactly as we might expect. The memory-
based model does not provide for an explicit role for memory. As a result, the model moves on a daily basis in response to new information. The on-line model’s “memory” is most difficult to change later in the campaign season. At the beginning of the season, the model shifts in response to new information in a way similar to the memory-based model.

Another interesting observation from this race concerns the tendency of the memory-based model to rebound quickly from a change in public opinion. To be clear, look at the predicted paths for Davis in early June. The memory-based model predicts a decline on June 3rd as does the on-line model, but the memory-based model predicts an increase the very next day. The on-line model continues to predict a decline in support for Davis until the model predicts support to rebound on the 8th. As mentioned above, the memory-based model does not have an explicit role for memory, and the memory-based model depends on the relative flow of campaign information. As a result, one candidate’s support can decline or increase without his own campaign coverage changing. Thus the formalization would lead us to suspect that the two models diverge in this way.

The models diverge at the end of the campaign season as the on-line model predicts an increase in support for both candidates while the memory-based model predicts stability for both Thomas and Davis. The memory-based model is relying on the daily flow of information and the on-line model allows an explicit role for memory of the affective value of information.
Figure 3.3: Predictions from the Models for Hypothetical Case 3

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

Non-Incumbent, Competitive, Partisan Mismatch

What happens when you pit two former heavyweights against each other in a race for governor? In this race for the highest office in the state, Wells attempts to paint his opponent, Price, as a Washington insider given his former career as a member of the president’s cabinet, while downplaying his own position as former Speaker of the state’s House of Representatives. Neither candidate can successfully claim they are outsiders as Wells quickly learns in his primary race against true novices. Luckily for both candidates, the primary voters demonstrate their desire to restore professionalism to the state capitol as the only two former officeholders easily trounce their primary opponents. Price’s campaign team realizes quite early that the public mood is pro-Republican and pro-incumbent so the team fashions a media campaign highlighting Price’s activities as a
former cabinet member, but downplays the Democratic aspect. The public responds favorably to this approach, but the partisan mismatch is a difficult battle for Price to overcome. His Republican opponent, Wells, taps into the public mood as well and successfully portrays himself as a former Speaker of a Republican House. This response translates into a predicted victory for Wells on Election Day according to the memory-based model. However, the on-line model does not incorporate such an advantage for Wells and Price’s on-line tally of 21.1 is predicted to be much higher than Wells’ on-line tally of -61.7 on Election Day.

This divergence in predicting which candidate is the frontrunner on Election Day corresponds to a divergence in prediction throughout the campaign season. The partisan advantage for Wells seems to produce more days of predicted positive support for Wells from the memory-based model than for his opponent. However, the on-line model predicts a negative tally for Wells from the first day of the campaign season. As Figure 3.4 illustrates, the tally for Wells decreases precipitously from the beginning of the campaign season and continues to decline throughout the entire season. In contrast, the on-line model predicts a tally for Price that is variously negative from the end of June until the beginning of October. In October, the on-line model predicts a positive tally Price that remains positive throughout the remainder of the race.

On the other hand, the memory-based model predicts much more volatile support for both candidates throughout the campaign season. As the daily flow of information changes, the model’s prediction for the candidates’ level of support also varies. However, the last week of the campaign season features levels of support for Wells unmatched by his opponent. For example, Wells’ support for November 3rd is predicted
to be six points higher (40.2) than Price’s support (34.9). This is an important difference between the two candidates because the memory-based model rarely predicts full point differences between the candidates. Typically, the difference between candidates is closer to one-tenth or even one-hundredth of a point.

Figure 3.4: Predictions from the Models for Hypothetical Case 4

![Case 4 Candidate A—Price](image)

![Case 4 Candidate B—Wells](image)

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

**Incumbent, Non-Competitive, Partisan Match**

The fifth hypothetical campaign I will examine is one in which the incumbent governor, Miller, is running against Johnson, a novice challenger, for re-election. In this campaign, Johnson faces a difficult battle in his effort to unseat the extremely popular Miller. Very little is known about Johnson until he surprises most observers by winning his party’s nomination. While not an upset given the lack of power hitters in the Republican field, his victory is credited to his status as an unknown player in a field of
unpopular regulars. Even though he wins the nomination, the Republican Party decides that expending resources to assist Johnson’s campaign in a state that has been blue for some time is not worth extracting such resources from more realistic campaigns. Having engineered the economic recovery of the state after ten years of recession, Republicans and Democrats alike consider Miller to be their golden girl. While Johnson has had to beg for the media to cover even his key speeches, the media monitor Miller’s daily activities closely. Out of sheer desperation, Johnson invests his own money in a series of media spots aimed at tarnishing Miller’s image. As is characteristic of this campaign, his efforts backfire. The public views the attacks as cheap shots from a floundering novice. Once the votes are tallied, Miller is re-elected with an overwhelming 60% of the vote.

Given such a campaign, what do the two models predict will be the course of public opinion? The overwhelming support for Miller is reflected in the similar predictions that the models make for change in support for Miller throughout the campaign season as displayed in Figure 3.5. When the memory-based model predicts a steep decline in support for Miller on July 23rd, the on-line model also predicts a decline in support for the incumbent. On this date, coverage of Miller is so incredibly negative that the tally is overwhelmed and declines. This decline continues until the tally begins to become more positive after October 10th. The memory-based model predicts additional declines for Miller after July 23rd. In particular, support is predicted to drop dramatically again on September 1st. For an incumbent, the on-line model predicts a tally for Miller that is mostly negative and only slightly positive towards the end of the campaign season; however, this tally is still much higher for Miller than it is for Johnson.

This is an interesting race given the predictions that the two models make. In this
case, Johnson is facing an uphill battle in terms of the memory-based model. Miller is not only an incumbent, but also of the same party as the majority of voters in the state. In order for Johnson to overcome this inherent disadvantage, the relative flow of campaign messages must be in his favor. This is a most difficult task when the simulation allows for incumbents to receive five times the coverage of non-competitive opponents.

Johnson is successful in outpacing Miller in terms of predicted support on only thirty-five of the one hundred and sixty-one days of the campaign season. On these days, coverage of Miller is incredibly negative. However, Johnson is unable to yield greater predicted support during the last three weeks of the campaign season and the memory-based model predicts defeat for Johnson in this race.

**Figure 3.5: Predictions from the Models for Hypothetical Case 5**

![Graphs showing predicted support models for Case 5 candidates Miller and Johnson.](image)

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.
Incumbent, Non-Competitive, Partisan Mismatch

While a novice to politics, Arnold is no newcomer to many of the state’s voters. A former Miss America, Arnold is attempting to defeat a somewhat unpopular incumbent, Democrat Carter, in a state that voted Republican in the last presidential election. While representing the state as Miss America, Arnold demonstrated her ability to move large crowds as she advocated for children’s rights. The big question is whether her natural speaking ability will be enough to defeat a state-level elected officer. Both general election candidates face serious opponents in their primary races and barely squeak out victories. While Carter can easily demonstrate he has previous statewide elected office experience, the state’s current deficit is not something Carter is willing to tout as his greatest victory. As one might anticipate, throughout the campaign Carter continuously paints Arnold as an uneducated beauty queen never mentioning Arnold’s Masters’ degree from Stanford. Arnold has many prime opportunities to question Carter’s ability to manage state affairs given the inability of the governor to increase investment in the state and his inability to work with the legislature to alleviate the state’s deficit. Unfortunately, she fails to capitalize on these opportunities preferring to advertise her own strengths. As a result, Carter skates to an easy victory against a potentially strong opponent.

This is an interesting race in terms of the predictions made by the two models displayed graphically in Figure 3.6. For both candidates, the models predict a substantial amount of stability throughout the campaign season. This is particularly remarkable given the tendency of the memory-based model to predict much volatility in the other races discussed. There is a single dramatic increase for Arnold early in the campaign
season and a simultaneous decrease for Carter. Aside from this one dramatic change, the model predicts only slight increases or decreases throughout the campaign season. At the end of the season, the predictions for both candidates remain stable.

In the end, the models diverge significantly. The memory-based model predicts a higher level of support for Arnold even though the flow of information tends to be much more negative for her than for Carter. There are two likely explanations. The first is that the partisan advantage is difficult for Carter to overcome in the memory-based model. Further, the memory-based model does not have an explicit role for memory. As a result, support can change daily depending on the flow of information on that particular day. On the other hand, the on-line model relies on a cumulative tally that is constantly updated as new information emerges in the campaign season. As a result, the support for a candidate cannot shift dramatically even if the tally becomes slightly more positive or slightly more negative. On November 1st, Arnold’s tally is at -64.8 and increases slightly by Election Day when it equals -56.7. However, Carter’s tally increases slightly from November 1st (76.9) through Election Day (82.9). This increase in the tally for Arnold is not enough for the model to predict a victory for Arnold, as Carter’s tally is substantially more positive throughout the campaign season.
Figure 3.6: Predictions from the Models for Hypothetical Case 6

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

Non-incumbent, Non-Competitive, Partisan Match

A former member of the legislature and leader of the state’s Democratic Party, Cohen, decides to try his luck against Jackman, a novice from the state’s most populous region in the race for the state’s executive office. A very interesting race given that Cohen lost his previous re-election attempt because his opponent advertised his campaign improprieties. This scandal had media gurus predicting the end of Cohen’s public career. To surprise of most, Cohen took an early lead in the primary campaign and maintained his hold on his party’s nomination. Jackman did not have such an easy go in the primary campaign as his opponents painted him as a center-hugging opportunist, but he did successfully win his party’s nomination. Luckily, Jackman’s early difficulties do not translate into general election difficulties as Cohen finds it difficult to paint Jackman as
an extremist and difficult to avoid his own scandal-ridden past. The race comes down to the bitter end and Jackman ekes out a victory against the scandal-ridden Cohen in a state that is increasingly trending Democrat.

In this race, the models predict an almost identical path for Jackman and Cohen at the beginning of the campaign season as visible in Figure 3.7. This is what we would expect in a race in which neither candidate is an incumbent. Neither candidate has an entrenched on-line tally therefore the models' predictions correspond. The models begin to diverge by mid-June as the on-line tallies begin to solidify. The significance of this is that the on-line model reacts more slowly to new information that is negative or positive. The tally moves slightly but does not change its overall direction.

Interestingly, both models also tend to predict increases in support for Jackman, but decreases in support for Cohen. However, the graphs are only useful in demonstrating the directional changes in support. If one looks at the actual numbers, the path appears somewhat misleading in this campaign because the standardized tally for Cohen is more than three times the size of the tally for Jackman. On the other hand, the memory-based model predicts much more variance in support for the two candidates. Let's look at the end of the campaign season for a prime example. On November 1st, the on-line model predicts a more positive tally for Cohen (65.7) than for Jackman (15.2). Even though Cohen's predicted tally declines by Election Day to 60.7, his tally remains higher than Jackman's tally, which actually increases over this period (16.2). By contrast, the memory-based model predicts Cohen to have the greatest amount of support on November 1st, but this declines such that by November 8th, Jackman's predicted support is higher. Because the memory-based model lacks an explicit role for memory, a
candidate can be a frontrunner one day and fall far behind the very next day in response to a change in the relative flow of information.

Figure 3.7: Predictions from the Models for Hypothetical Case 7

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

Non-incumbent, Non-Competitive, Partisan Mismatch

In a last hoorah for Democrats in the South, Representative Ellis is taking on the former Republican Lieutenant Governor Davidson. The South may have turned Republican over the last two decades, but someone forgot to remind Representative Ellis and his campaign team. Capitalizing on the lack of Democratic primary opponents, Ellis looks good, at least monetarily, heading into the general election. Davidson faces a slate of Republican opponents, but no serious competitors in the primary and easily wins his party’s nomination. The general election race is billed as a partisan showdown between a former Baptist minister (Davidson) and a cotton farmer (Ellis). Unfortunately for Ellis,
the South proves too difficult for a Democrat, even King Cotton himself, to win as Davidson easily defeats Ellis to become the state's chief executive.

Both the on-line and the memory-based models predict such a defeat as Figure 3.8 shows Davidson with increasing support and Ellis with decreasing support from mid-September through Election Day. There are a number of points when the on-line model predicts an increase for one of the candidates while the memory-based model predicts a decrease. In particular, the on-line model predicts lower than average support for Davidson in late June, early July; however, the memory-based model predicts increasing support for Davidson on these days. This type of divergence occurs on a number of occasions throughout this race.

This simulation demonstrates the importance the memory-based model places on the relative intensity of campaign messages in predicting support for the candidates. The on-line model does not depend on such a notion and Figure 3.8 demonstrates the implication of this assumption. The memory-based model cannot predict an increase for both candidates on the same day; instead, a predicted increase in support for one candidate corresponds to a predicted decrease in support for the other candidate. The on-line model does not rely on campaign messages in a relative sense. The affective tally for a given candidate can increase on the same day that the affective tally for a different candidate increases. This is illustrated during late August. The on-line model predicts a rise in support for both Ellis and Davidson during this period. The on-line model predicts an increase in Ellis' tally from 25.7 on August 22nd to 68.8 on September 1st. During this same period, the model predicts a simultaneous increase in Davidson's tally from 29.9 on August 22nd to 44.0 on September 1st. The memory-based model by contrast predicts
support for Ellis to increase only on those days when Davidson is predicted to decrease. For example, support is predicted to increase for Davidson on August 23rd and the model predicts a decrease in support for Ellis. When the memory-based model predicts an increase in support for Ellis the very next day (August 24th), predicted support, by necessity, decreases for Davidson.

An interesting pattern that has emerged throughout these races is that the on-line model predicts much more volatility when the candidate is not an incumbent. In this case, the original tally is formed for both candidates from only five pieces of information. As a result, little information is needed to move the predicted path in a negative or positive direction. As a result, we do not see the ever-increasing or ever-decreasing tallies as we saw much more frequently with incumbents in these simulated races.

For Ellis, the partisan hurdle is more than a descriptive component. The memory-based model predicts lower levels of support as the distance from the candidate's message increases. Ellis faces more difficulties in convincing the voters to vote for him. This might also lead us to anticipate a divergence in the two predicted paths because the on-line tally does not provide an explicit role for partisanship.
Figure 3.8: Predictions from the Models for Hypothetical Case 8

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores for the candidates in the first hypothetical case.

**Interesting Patterns**

The above cases demonstrate that the on-line and the memory-based models propose different paths for public opinion even though they both rely on the same campaign messages. Why do the two models make different predictions for the path of public opinion? There are a number of reasons why this is likely the case.

First, the two models posit a different role for information about opponents. In the memory-based model, the level of support for a given candidate is dependent upon the relative intensities of the campaign messages of all candidates. Let me illustrate. In Figure 3.9, I graph the level of support predicted by the memory-based model for a candidate, Candidate A, with a positive intensity. I vary the level of intensity of Candidate B in the two panels. Candidate B’s intensity remains positive in the left panel
and intensity remains negative in the panel on the right.

In these graphs, the partisan distance and the difficulty of the messages of the two candidates are held constant. The predicted level of support for Candidate A is quite low in the first panel and much higher in the second panel. This is completely dependent upon the relative intensity of the candidates’ messages. In the first panel, when the intensity of Candidate A’s message is positive and Candidate B’s intensity is equal to zero, the level of support for Candidate A reaches a high of 37.55%. However, increasing the intensity for Candidate B slightly decreases the support for Candidate A to a low of 37.45% when A’s intensity equals zero.

Turning to the right panel, the level of support for Candidate A varies, but this support is dependent upon the relative intensity of the candidates’ messages. When the intensity of Candidate B equals -10, support for Candidate A approaches 100%. As the intensity of Candidate B’s message approaches zero, the support for A declines to the level of support in the left panel.

**Figure 3.9: Memory-Based Model—Relative Intensity**
In contrast, the on-line model relies only on the campaign messages of a particular candidate. To illustrate, I graph the manner by which support for a candidate can move in the on-line model. The two panels in Figure 3.10 differ according to the level of the original tally and the affective value of new information. In the left panel, the candidate has a positive original tally and new information about the candidate is evaluated positively. As new information is received, the tally is updated in a positive direction.

The candidate in the right panel has an original tally that ranges from very negative (-10) to neutral (0). New information ranges from very negative to very positive. The updated tally reflects this trend toward the negative in that its highest value is substantially lower than the updated tally on the left. For many of the values of the original tally, the new information cannot move the tally into positive territory.

**Figure 3.10: Moving the On-Line Tally**

Second, the memory-based model incorporates two notions that the on-line model does not specify explicitly—the partisanship of the candidates and their incumbency.\(^{19}\)

\(^{19}\) I consider incumbency to be a measure of difficulty, one of the parameters of the memory-based model.
As discussed in Chapter 2, these elements are static, but they do vary across candidates. This suggests that they do not affect the changes in public opinion throughout a campaign season, but both partisan distance and incumbency play a role in determining the difficulty that out party members and non-incumbents face in attempting to win elections. Figure 3.11 displays the role that incumbency plays in the memory-based model. These graphs do not look dramatically different from each other. The panel on the left features the incumbent as Candidate A and there is no incumbent in the panel on the right. The only difference between the graphs concerns the level of support. Incumbents in the memory-based model start with a higher level of support than non-incumbents regardless of the level of intensity.

**Figure 3.11: Memory-Based Model—the Role of Incumbency**

The memory-based model also posits a role for the distance between the voters' partisanship and the partisanship of the candidate. However, I have also argued that partisan distance is a static element of the model that varies only across candidates, not
across time. Figure 3.12 demonstrates the role that partisanship plays in determining the level of support for a given candidate. Like incumbency, partisanship simply alters the level of support that a given candidate has at each point in the campaign season. In the first panel, the candidate is close to the voters in terms of partisanship and in the second panel, the candidate is further away from the voters. As a result, the level of support for the candidate is higher in the left panel, regardless of the relative intensity of the messages.

**Figure 3.12: Memory-Based Model—The Role of Partisanship**

In order for candidates to overcome this bias against non-majority candidates and non-incumbents, these candidates need many more positive messages relative to their opponents. What happens when we grant non-incumbents a greater edge over incumbents in terms of messages? This is what I do in the right panel of Figure 3.13. The left panel represents a non-incumbent candidate facing an incumbent candidate. This is the same as the right panel in Figure 3.11. Increasing the intensity of the non-incumbent’s message leads to higher levels of support for this candidate as long as
Candidate B’s intensity remains low. When I increase the intensity of Candidate B’s message by five units, support declines for the non-incumbent. However, overall support remains higher for the non-incumbent candidate when this candidate’s message is more intense.

Figure 3.13: Memory-Based Model—Overcoming the Role of Incumbency

Turning to the partisan advantage, I graph in Figure 3.14 the ability of intensity to overcome the disadvantage afforded the minority party candidate in terms of support. The left panel is the same graph as the right panel in Figure 3.12. When the intensity of the candidate’s message is increased, the candidate’s level of support increases as well. However, the intensity required to increase this support is such that we would expect the partisan advantage to remain a difficult obstacle to surmount.
The difficulty in overcoming the partisan advantage and the incumbency advantage in the memory-based model is similar to the inability of a candidate to overcome a pre-existing tally in the on-line model. The theoretical specification of the on-line model asserts that the affective tally is continuously updated with affective reactions to new information. At no point in the discussion of the tally do Lodge and his colleagues propose a role for memory decay of the tally. As a result, the on-line tally is cumulative and continues to grow throughout the campaign season. As such, huge shocks play a greater role earlier in the season rather than later. Why is that the case? Mathematically, shocks (like a scandal) would not have a different value earlier in the campaign season than they would later in the season. What has changed is the original tally that they are updating. The on-line tally early in the campaign season can turn positive or negative rather easily. As the season progresses, the tally becomes more entrenched. The more entrenched the tally is, the more affectively-charged information needs to be in order to disrupt the positive or negative pre-existing tally. Let me illustrate.
In Figure 3.15, I graph the situation that might exist at the beginning of a campaign season. The original tally is relatively low, between zero and ten affective reactions. In the left panel, all new information is positive so the tally increases with each additional affective reaction. However, we can easily disrupt this “young” tally with negative information. In the right panel of Figure 3.15, I display the updated tally given various values of a “young” tally and new affective reactions. This graph illustrates the ease with which the “young” tally can be disrupted by new information. If the tally is incredibly young (equal to 1), two pieces of information judged to be negative can yield a negative evaluation of a candidate. Even with a moderately entrenched tally (equal to 10), ten pieces of negative information can disrupt the tally leading to a non-positive evaluation.

**Figure 3.15: On-Line Model—Disrupting the Original Tally**

![Graph showing the process](image)

However, if we had an on-line tally that had developed throughout the campaign season and was clearly more entrenched we could move the tally only with successive periods of incredibly affective information. In particular, Figure 3.16 displays the role of new information when the on-line tally is entrenched. The left panel has a positively
entrenched tally and the right panel has a negatively entrenched tally. In both panels, the entrenched tally cannot be moved in the opposite direction with twenty oppositely charged pieces of information. This would represent a large shock to the system and would still fail to disrupt the tally. One can think of individuals with entrenched tallies as partisans. Campaign advisors often suggest that opposite partisans are impossible to sway, so one should ignore them in calculating a campaign strategy; instead, candidates should focus on the undecided (or in the case of the on-line model, individuals with non-entrenched tallies) in attempting to win elections. Figure 3.16 demonstrates why this is a useful strategy. Importantly, this graph also demonstrates why candidates might consider ignoring partisans of their own party as well. Unless the opposition reveals incredibly negative information about a candidate, an entrenched tally is unlikely to move such that the individual issues a negative evaluation of the candidate.

Figure 3.16: On-Line Model—the Entrenched Tally
**Conclusion**

In this chapter, I explored the differences in prediction made by the two models for a series of hypothetical races. In doing so, I highlighted a number of interesting patterns in the predictions. In the next three chapters, I evaluate the ability of each model to predict the course of public opinion for eight actual gubernatorial and congressional races occurring between 1990 and 1994. These chapters provide empirical evidence suggesting that the models fail to accurately predict public opinion during the course of a campaign. These chapters, in combination with this chapter, provide the impetus for the research program suggested in the final chapter.
Chapter 4:  
Testing the Dynamic Implications  
of the On-Line and Memory-Based Models

In this chapter, I describe the proposed empirical test of the two models outlined in  
the previous chapters and highlight the ways in which the test I propose would build upon  
the previous tests—both static and dynamic. In Chapter 3, I showed how the equations  
from the formalization of the on-line and memory-based models could be used to  
simulate courses of public opinion given a set of hypothetical inputs. In this chapter, I  
propose to test the models by substituting the hypothetical inputs for measured inputs  
from eight real campaigns with twenty-one candidates. Substituting these measured  
inputs into the models produces two predicted paths of public opinion for each candidate  
in each race. In the first section of this chapter, I describe the measurement of these static  
and dynamic inputs. Substituting these measured inputs produces two predicted paths of  
public opinion for each of the twenty-one candidates. To determine how well these two  
models predict the actual course of public opinion, the predicted paths need to be  
compared to an actual path of public opinion. So, in the second section of this chapter, I  
discuss the measurement of the actual path of public opinion. Once I have both the  
predicted path of public opinion and the actual path of public opinion, I can then turn to a  
comparison of the two paths to determine how useful the models are for predicting public  
opinion during the course of a political campaign. The third section of this chapter  
describes the way I intend to test the two models in Chapters 5 and 6 by comparing the  
predicted courses of public opinion to the actual course of public opinion.
Measuring the Models' Theoretical Inputs

Specifically, I use eight campaigns in 1990 and 1994 for a total of twenty-one candidates. The races that I examine are the Illinois Senate Race in 1990, the Arizona, Virginia, New Jersey, and Pennsylvania Senate Races in 1994, the 1994 2\textsuperscript{nd} Congressional District Race in Utah, and the New York and Texas Gubernatorial Races in 1994. There are three different types of races: five senate races, two gubernatorial races, and one US House race. The number of candidates for each race varies as well. I have five races with two candidates from the two major parties, two races with three candidates, and one race with five candidates. In the next chapter, I describe each campaign in detail.

In order to test the two models using these actual campaign environments, I need to measure the inputs in the mathematical formalization of the two models. In this section, I lay out the theoretical inputs in need of measurement, how I operationalize these concepts, and the data I use in the tests conducted in Chapters 5 and 6.

Memory-Based Model

The memory-based model argues that opinion relies on campaign information that is immediately accessible in memory. What information is immediately accessible is a function of the relative flow of campaign messages in the mass media (the intensity of the campaign messages). However, opinions are also a function of three additional elements: the difficulty of the message, political awareness, and political predispositions. The formalization of these relationships was outlined in Chapter 2. At the aggregate level, it seems reasonable to argue that awareness, predispositions, and the difficulty of the candidates' messages do not change dramatically over a period of a few months. That is,
we should not anticipate that the average level of political awareness in a state or district alters dramatically from day to day during the campaign. As a result, I do not collect daily measures of these variables; instead, I rely on static measures of these inputs. Therefore, the only dynamic property in the model is the intensity of campaign messages or relative quantity and volume of information about the candidates.

To produce the predicted path of public opinion for the model, both static and dynamic elements need to be measured. To capture the static components—political awareness, political predispositions, and difficulty of the message—I rely on static measures of these variables. Table 4.1 provides a quick reference for the description and measurement of each of these concepts. The dynamic element of the model is the intensity of campaign messages, which I measure using daily newspaper coverage.

<table>
<thead>
<tr>
<th>Table 4.1: Static Elements of the Memory Based Model</th>
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<tbody>
<tr>
<td><strong>Inputs</strong></td>
</tr>
<tr>
<td>Political awareness—average level of political awareness for each state</td>
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<tr>
<td>Political predispositions—average distance from candidate’s message</td>
</tr>
<tr>
<td>Difficulty/Familiarity of Messages—the difficulty with which a message can be accepted</td>
</tr>
</tbody>
</table>

Turning to the static elements, the first input to be measured is political awareness. Political awareness appears in both the reception and acceptance equations. In the reception equation, reception of a message increases as political awareness increases. However, acceptance of the message declines as a function of political awareness because individuals who are politically aware are capable of deciphering whether a candidate’s message is at odds with their predispositions. Because I am focusing on the movement of aggregate public opinion, I need a measure of the level of political awareness in a given state during a given campaign season.
Political awareness, or the extent to which an individual attends to and understand politics, is typically measured in three different ways. In some cases, scholars have used education as a proxy for political awareness. As Zaller (1992) points out, the use of education to capture political awareness is a reasonable proxy; however, this is not exactly what is intended by the term political awareness. Not only does one need to be able to understand politics (be educated enough to understand political concepts), but one also needs to attend to politics (that is, be interested in politics). Another proxy scholars have used to measure political awareness is self-reported measures of media usage. That is, surveys often ask respondents how often they read a newspaper each week. The idea is that more politically aware individuals are also likely to read the newspaper more times per week than less politically aware individuals. Finally, scholars typically assess political awareness by using objective knowledge scales. Surveys often ask respondents a number of questions aimed at tapping their knowledge of features of the American political system. These political knowledge questions are considered to be a reasonable measure of political awareness—interest and understanding of politics.

I need a state-level measure of political awareness for each race that will be used in the empirical analysis. For each of the eight states included in the study, I use the average of the responses to questions from the National Election Studies to capture political awareness and predispositions. I use the National Election Study conducted in the same year as the campaign. I measure political awareness by creating an objective knowledge scale based on five questions asking respondents to recall factual information. The first question asks respondents to recall the names and parties of the House candidates in their district. The value for this question can range from no correct names,
no correct parties (0) to three correct names, three correct parties (6). The second question asks respondents to name the candidates the incumbents running in their district. The value for this question ranges from 0 (incorrect) to 1 (correct). The third question asks respondents to recall the names and parties of the Senate candidates in their district. The value for this question can range from no correct names, no correct parties (0) to three correct names, three correct parties (6). The last three questions ask respondents to name the most conservative political party, the majority party in the Senate, and the majority party in the House. This question can range from 0 (correct) to 1 (incorrect). The individual-level measure varies from 0 to 17. I calculate a state-level measure by taking the mean of the scores of the respondents from each state.

Zaller argues that an individual rejects or accepts a message based on the distance between that message and the individual’s own political predispositions. Partisanship is certainly the most important of such political predispositions, so I need a state-level measure of partisan distance from a candidate’s message. I once again turn to the National Election Study for the year of the campaign. The NES asks respondents for their partisan affiliation ranging from Democrat (1), an Independent (2), or Republican (3). I take the average for the respondents of each state. The state level partisanship measure varies from 1 to 3.

To capture partisan distance, I calculate a measure of the distance between the average partisanship of the state and the partisanship of the candidate. Democratic candidates are given a 1, Independent candidates a 2, and Republican candidates a 3. I then subtract the average state level partisanship from the partisanship of the candidate. This produces a measure of distance for each candidate. For example, the average
partisanship in Illinois in 1990 is 1.87. The distance from Simon’s message (a Democrat) is 0.87 and the distance from Martin’s message (a Republican) is 1.13.

The final static input is difficulty. Difficulty is simply the ease with which a message can be accepted, so I measure difficulty with incumbency. When a candidate is not the incumbent officeholder, that candidate must convince voters to accept the message—vote for me—even though this message is not familiar. An incumbent running for re-election is much more familiar to voters than a novice candidate; therefore, the message of the incumbent is less difficult to accept. Current officeholders running for a new office are more familiar than novice candidates, but less familiar than the incumbent. Finally, candidates that are former officeholders have an advantage, in terms of difficulty, over novice candidates, but not over current officeholders or the incumbent. Therefore, I measure incumbency as a categorical variable taking the following values: 4 (novice candidate), 3 (former officeholder), 2 (current officeholder), and 1 (incumbent officeholder). For example, in the Illinois Senate Race in 1990, Simon is the incumbent officeholder (difficulty=1) and Martin is a current member of the U.S. House (difficulty=2).

Together these three elements set the context in which public opinion can vary throughout the campaign season. The dynamic element of the model is the intensity of campaign messages or the relative quantity and volume of information about political candidates. Zaller’s model posits an important relationship between public opinion and the relative flow of campaign messages, or the intensity of campaign messages. The argument is that intense campaigns will lead to greater reception of campaign messages
ceteris paribus. Intensity or the relative flow of campaign messages certainly varies throughout the campaign season.

I rely on daily headline and article coverage from two main newspapers for each race throughout the campaign season to measure the intensity of campaign messages. For each race, I collect the newspaper coverage at the beginning of the month that the actual public opinion data begins\(^{20}\). For example, I have public opinion data for the 1994 Virginia Senate race that begins at the end of January 1994, so I collect newspaper data for this race beginning on January 1, 1994. I then continue collecting newspaper coverage for the race until the election. For six of the eight campaigns, I am able to collect all of the newspaper coverage for the entire campaign season from two major newspapers. For the remaining two races, only one newspaper is available. Table 4.2 lists the newspapers for each campaign.

<table>
<thead>
<tr>
<th>State</th>
<th>Newspaper 1</th>
<th>Newspaper 2</th>
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</thead>
<tbody>
<tr>
<td>Arizona</td>
<td>Tucson Daily Star</td>
<td></td>
</tr>
<tr>
<td>Illinois</td>
<td>Chicago Sun-Times</td>
<td>Chicago Tribune</td>
</tr>
<tr>
<td>New Jersey</td>
<td>Atlantic City Press</td>
<td>The Record</td>
</tr>
<tr>
<td>New York</td>
<td>New York Times</td>
<td>Buffalo News</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>Philadelphia Inquirer</td>
<td>Pittsburgh Post-Gazette</td>
</tr>
<tr>
<td>Texas</td>
<td>Houston Chronicle</td>
<td>Dallas Morning News</td>
</tr>
<tr>
<td>Utah</td>
<td>Deseret News</td>
<td></td>
</tr>
<tr>
<td>Virginia</td>
<td>Virginia Pilot</td>
<td>Richmond Times-Dispatch</td>
</tr>
</tbody>
</table>

While television coverage of campaigns and television advertising by campaigns has increased dramatically over the last twenty years, newspapers continue to cover such campaigns. Furthermore, newspapers also cover television advertising by candidates. All of the newspapers I examined for this project include descriptions and analyses of television ads as part of their typical campaign coverage. There is also a practical reason

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\(^{20}\) I do this in order to create a base for establishing the original tally prior to the start of the public opinion data.
for not using television coverage of campaigns. It is simply not available for past campaigns as stations destroy broadcasts more than a few months old. Determining the affective nature of television news coverage is not possible for the set of elections I consider in this project.

Each article or headline is coded positive, neutral, or negative using a coding scheme\(^{21}\). The coding scheme asks a number of questions about each article. The first set of questions—date, section, page, and words—are simply used to distinguish an individual article from other articles. The next question asks for the candidate for which the article is being coded.

In order to code the articles positive, neutral, or negative, I ask a series of questions about the substance of the article or headline (i.e. is a scandal mentioned) to determine whether the coverage is conveying a positive (1), negative (-1) or neutral (0) message about the candidate. The questions can be answered no (0) or yes (1). The first question is simply whether or not a scandal is mentioned that involves the candidate. Scandals can include, but are not limited to, sexual activities, illicit drug use, embezzlement, and illegal activity in any capacity. The second question concerns the coverage of issues. Does the article/headline cover a candidate’s position in a positive way or make a negative judgment about the candidate's issue positions?

Moving to the third question, I ask if the article discusses the candidate’s personal life or personal characteristics in a positive or negative way. For example, an article might discuss that a particular candidate is known for his devotion to his family. Such an article would be coded a 1. On the other hand, the article might discuss the bankruptcy

\(^{21}\) I use the same coding of the newspaper articles and headlines for both the on-line and memory-based models.
rate of the businesses in which the candidate has been involved. As such, the article would be coded a \(-1\).

Not only do I ask about a candidate's personal life, but I also ask about a candidate's professional life. If the article makes a positive judgment or uses positive language about the candidate's professional life, the article is coded 1. For example, if the article discusses how the candidate was able to propose a bill and win passage of that bill, I would consider this to be positive for the candidate. Conversely, the article is coded \(-1\) if the article makes a negative judgment or uses negative language concerning the candidate's professional life.

The next two questions are very similar and attempt to gauge the candidate's level of political and interest group support. I code the two questions—political support and interest group support—as 1 if the article mentions the endorsement of a candidate or the support for the candidate by another politician, political party, or well-known figure (political support) or interest group (interest group support). I code the two questions \(-1\) if the article mentions the unwillingness of another politician, political party, or well-known figure (political support) or interest group (interest group support) to support or endorse the candidate. Newspaper endorsements are also captured in this category.

I also ask whether or not the article discusses the candidate's electoral fortune. I code the article 1 if the article mentions that the candidate is likely to win, doing well, making up ground, etc. I want to know if the newspaper article considers the candidate's chances of winning to be high or whether the article considers the candidate to have improved his/her chance of winning. I code the article \(-1\) if the article mentions that the candidate is unlikely to win, doing poorly, losing ground, etc. I want to know if the
newspaper article considers the candidate’s chances of winning to be low or whether the article considers the candidate to have decreased his/her chance of winning. In some cases, candidates, particularly governors, are linked to the economic situation of their particular state. As such, I code the article 1 if the candidate is linked to a positive economic situation, -1 if the candidate is linked to a negative economic situation and 0 otherwise.

The answers to these questions are used to create a measure for whether the article is conveying a positive, negative or neutral message about the candidate. Each question is scored -1, 0, or 1. I sum the answers to the questions for each article/headline for each candidate. I sum the answers to the questions for each article/headline for each candidate: a positive sum is coded 1, a negative sum is coded -1, and a neutral sum is coded 0.

I also weight the coverage such that articles and headlines appearing on the first page of the newspaper get a higher value for intensity. The weight is 0.25. Articles and headlines appearing in the front section of the newspaper receive an additional weight of 0.25. Further, all headlines also receive a weight of 0.25. The reason that I weight the coverage is because individuals are more likely to receive messages that are displayed prominently in a newspaper. When a candidate is mentioned in the front section of a newspaper, an individual is more likely to be exposed to the message. Exposure is critical to receipt of a message. The candidate’s message is even more likely to be read if the message appears on the front page of the newspaper. The goal of headlines is to grab the attention of readers and encourage them to read the article. As a result, the inclusion
of a candidate in the headline of a newspaper provides more exposure than if the
candidate’s name appears in the body of the article.

For each day in the campaign season, I add up the intensity values for the articles and
headlines from each newspaper and then take the average of the two newspapers. This
produces a measure of intensity for each day in the campaign season and can range from
very positive to very negative. For example, the Chicago Sun Times published one
article and one headline for Martin on June 2. The Chicago Tribune did not publish any
articles or headlines for Martin on June 2. The intensity measure for the Chicago Sun
Times’ headlines on June 2 is 1.5625 and the intensity measure for the articles is 1. The
intensity for the Sun Times’ coverage on June 2 is 2.5625. Because the Tribune did not
publish any articles on this date, the intensity of coverage for Martin on June 2 is 2.5625.

I input this static and dynamic data into the equations described in Chapter 2 to
produce a predicted value for public opinion for each day in the campaign season for
each candidate. Together these predicted values form a predicted path of public opinion
for the memory-based model. Remember that the probability that an individual issues a
positive response for a given candidate is a function of the reception and acceptance of
the messages of each candidate. The reception of a candidate’s message is a function of
the intensity of the message and the individual’s level of political awareness (Equation Z-1).
Higher levels of political awareness lead to higher levels of reception of campaign
messages.

\[
\text{Pr(Reception)} = 1 - \frac{1}{1 + \exp(\text{Intensity} + a_1 \cdot \text{Awareness})}^{-1}
\]

Equation Z-1

But, the probability of support for a candidate is also a function of the acceptance of the
candidates’ messages (Equation Z-2). Acceptance of a message increases as the
difficulty of a message declines, but acceptance decreases as political awareness increases and as the partisan or ideological distance from the candidate’s message increases. Individuals that are more politically aware are able to reject messages that are inconsistent with their predispositions.

\[ 
\text{Pr (Accept)} = 1 + \exp(-\text{Difficulty} - b_1 \cdot \text{Awareness} - b_2 \cdot \text{Distance}^{-1}) \quad \text{Equation Z-2} 
\]

There are more equations that are necessary to move from these notions of reception and acceptance to a predicted path of public opinion, but none of the other equations require additional inputs aside from these four elements—intensity, awareness, difficulty, and predispositions. The final equation, Equation Z-8, produces a predicted value for support for a given candidate on a given day.

\[
\text{Prob (CandidateA)} = 1 - \prod_{j=1}^{N} \frac{\text{Recept}_A \cdot \text{Accept}_A}{\text{Recept}_A \cdot \text{Accept}_A + \text{Recept}_B \cdot \text{Accept}_B} \cdot \frac{\text{Recept}_B \cdot \text{Accept}_B}{\text{Recept}_A \cdot \text{Accept}_A + \text{Recept}_B \cdot \text{Accept}_B + \text{Recept}_B \cdot \text{Accept}_B} \quad \text{Equation Z-8}
\]

For example, suppose we were interested in the Texas gubernatorial race in 1994. In 1994 there were two candidates, the Democratic incumbent Ann Richards and the Republican challenger George W. Bush. I would then input the data for each day in the Texas gubernatorial race into Equation Z-8 to produce a predicted value for public opinion for each day in the Texas gubernatorial race. Here is what the final equation would look like for the probability of support for Richards on a given day.

\[
\text{Prob (Richards)} = 1 - \prod_{j=1}^{N} \frac{\text{Recept}_{\text{Richards}} \cdot \text{Accept}_{\text{Richards}}}{\text{Recept}_{\text{Richards}} \cdot \text{Accept}_{\text{Richards}} + \text{Recept}_{\text{Bush}} \cdot \text{Accept}_{\text{Bush}}} \cdot \frac{\text{Recept}_{\text{Richards}} \cdot \text{Accept}_{\text{Richards}}}{\text{Recept}_{\text{Richards}} \cdot \text{Accept}_{\text{Richards}} + \text{Recept}_{\text{Bush}} \cdot \text{Accept}_{\text{Bush}}} \quad \text{Equation Z-8}
\]

What does this equation mean for opinion? In this race, the probability of support for Richards is a function of the reception and acceptance of Richards’ message and the
reception and acceptance of Bush's message. Remember that the reception equation is equal to a dynamic component—intensity—and a static component—political awareness while the acceptance equation is equal to three static components—difficulty, awareness, and distance. So, if we are interested in the way that support for a candidate changes throughout a campaign season, this equation makes it clear that the intensities of both candidates' messages are important in determining the movement of opinion throughout the campaign season. However, this equation also makes clear that intensity does not affect opinion the same way in all contexts. The static elements capture the context in which intensity is operating.

If I input the data for a given day in the Texas Gubernatorial race into this final equation, I can produce a predicted value for Richards on this particular day. Let's take May 5th. The static and dynamic components are measured as described above. The average level of political awareness in the state of Texas equals 4 (out of a possible seven) and the average partisanship is 1.84 out of 3. The partisan distance from the Richards message is 0.84 and the distance from the Bush message is 1.16. The difficulty of the messages varies because Richards is a very well known incumbent governor and George W. Bush has never held office.

The dynamic component of the model—intensity of the message—varies across candidates and across time. On this particular day, there is more information about Richards, but it is universally negative. Richards' intensity value is -2.53. There is less information about Bush, but it is universally positive and his intensity value is 1.88.

The last elements of the equations to discuss are the parameters. If you recall from the reception and acceptance equations, there are a few parameters. These parameters
would be necessary if I was interested in estimating the reception and acceptance functions. That is, if I was interested in determining the relationship between the inputs and reception/acceptance of messages. However, I am not interested in the causal relationships in the equations. I am interested in producing an overall prediction for public opinion based on the theoretical model’s assertion that these variables are related. As a result, I set the parameters equal to one. What impact does this have? It means that I cannot talk about Richards’ level of support being, for example, equal to 50% on May 5th, but only increasing or decreasing on May 5th. Further, in the empirical analysis, I standardize the predictions and the actual path of public opinion in terms of z-scores so that public opinion is scale-free. I calculate a mean and standard error of each series for each candidate. Each predicted value is then subtracted from this mean. Dividing the difference between the mean for the series and each day’s value by the standard error of the series then creates the z-score for each series for a given day.

Given these inputs, the predicted value for a pro-Richards response is displayed below and is only equal to one-third. This is the predicted value for a particular day in the campaign season.

\[
\text{Probability (Richards) } = 0.337 = 1 - \frac{\left(1 - \frac{1}{1 + \exp(-1.88 + 1*4)}\right)^{-1} \times 1 + \exp(-4 - 1*4 - 1*0.84)^{-1}}{\left(1 - \frac{1}{1 + \exp(-2.53 + 1*4)}\right)^{-1} \times 1 + \exp(-4 - 1*4 - 1*0.84)^{-1}} + \left(1 - \frac{1}{1 + \exp(-1.88 + 1*4)}\right)^{-1} \times 1 + \exp(-4 - 1*4 - 1*1.16)^{-1}}{\left(1 - \frac{1}{1 + \exp(-2.53 + 1*4)}\right)^{-1} \times 1 + \exp(-4 - 1*4 - 1*0.84)^{-1}} + \left(1 - \frac{1}{1 + \exp(-1.88 + 1*4)}\right)^{-1} \times 1 + \exp(-4 - 1*4 - 1*1.16)^{-1}}
\]

However, in the empirical test, I examine the predicted path of public opinion for each candidate throughout the campaign season. I produce a predicted path of public opinion for both Bush and Richards. Turning to the incumbent, Ann Richards, this graph
shows the predicted path for Richards when I input real data into the equations.

Remember that these graphs are the predicted paths of public opinion based on the fact that intensity of the campaign messages varies across the two candidates and across time.

**Figure 4.1: Memory-Based Model’s Predictions for Ann Richards**

![Graph showing predicted public opinion for Ann Richards]

This graph shows the predicted path of public opinion for the Republican challenger, George W. Bush, throughout the campaign season.
The On-Line Model

In order to produce predictions for the on-line model, I need only one input: the affective value of campaign messages. No other inputs are necessary to test the original formulation of the on-line model. The on-line model posits that individuals have an immediate affective reaction to candidate information. An on-line tally integrates this affective information and is stored in long-term memory. The on-line tally is continuously updated as voters are exposed to new information. These “new” affective reactions are incorporated into the preexisting or original on-line tally.

Therefore, to produce a predicted path for public opinion for the on-line model I need a measure of the preexisting tally as well as a measure of the updated tally at each point in the campaign season. How might I calculate a pre-existing tally as well as the on-line tally throughout the campaign season? Because an on-line tally consists of the affective reactions to campaign information, I need campaign information for each of the
eight campaigns included in this study. To measure the affective reaction to campaign information, I once again turn to the coverage of each of the eight campaigns in the newspapers included in this study.

In coding the newspaper articles and headlines for the memory-based model, I asked a series of questions aimed at capturing whether the article or headlines was providing a positive, neutral, or negative message about the candidate. To measure affect, I once again turn to these questions. However to measure affect, I want to know what type of reaction a typical individual would have to a given piece of information about a political candidate. I add up the answers to each question for each article/headline. For the memory-based model, I collapse this score to positive (1), neutral (0), or negative (-1), but for the on-line model, an affective reaction of -3 is very different from an affective reaction of -1. As a result, I let the affective value for each candidate for each article or headline range from -8 to +8 (each question can be answered positively (1), neutrally (0), or negatively (-1)). For the articles and headlines that I code, the score actually ranges from -3 to +5.

These affective reactions are used to create the original tally and update the tally as new information is encountered. To create the original tally, I collect newspaper coverage a month before the campaign season begins and code these articles and headlines for affect. I add up the affective reactions to all articles and headlines published in each newspaper and take the average of the two newspapers. This average is

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22 Ideally I would want to average the reactions of multiple individuals to all articles and headlines. Unfortunately, this was not possible for my study.
23 I recode this score slightly. In this coding scheme, a zero means neutrality. This means that the affective reaction is zero; however, making neutrality equal to zero would make neutral coverage equivalent to no coverage. I think this is a false notion of neutrality. Neutral campaign coverage is not only “better” for the candidate than negative coverage, but it is also better than no coverage. Neutral coverage increases name recognition of candidates ceteris paribus.
24 The start of the campaign in my study occurs when trading opens for the IEM price data.
the original tally. After the campaign begins, the affective value of new information is added to the tally. I add up the affective reactions to all articles and headlines published in each newspaper on day $t$ and take the average of the two newspapers. This value is the daily affective reaction to a particular candidate on day $t$. I calculate the value for the updated tally on day $t$ by adding the daily affective reactions to articles and headlines on day $t$ to the previously established tally from day $t-1$. This updated tally becomes the original tally for day $t+1$. I then add the daily affective reaction for day $t+1$ to the tally updated on day $t$. This updated tally becomes the initial tally for day $t+2$, and so on.

In this way, the on-line tally for each candidate is created and then updated throughout the campaign season. For each day in the campaign season, the on-line model predicts a particular value for the tally. This value changes throughout the campaign season as new information is encountered. Together, these predicted values produce the on-line model's predicted path of public opinion for each candidate.

In Chapter 2, I formalized the on-line model's theoretical argument into two mathematical equations. The first equation (L-1) represents the initial tally.

$$Tally_{(t=0)} = \sum_{i=1}^{N_0} \text{AffectResponse}_{i0} \quad \text{Equation L-1}$$

Once an on-line tally has been formed, new information must be incorporated into the tally. The second equation (L-2) represents the updating process.

$$\text{UpdatedTally}_{(t+1)} = Tally_t + \sum_{i=1}^{N_1} \text{AffectResponse}_{i1} \quad \text{Equation L-2}$$

Let's take an example. In 1994, the Arizona Senate race featured two members of the U.S. House of Representatives running against each other. Figure 4.3 displays the predicted path of the on-line model for Sam Coppersmith and Jon Kyl. I have
standardized this predicted path so that it is comparable to the predicted path of the memory-based model and the actual path of public opinion for these two candidates. To interpret Figure 4.3, and all figures presented in the next two chapters, the standardization should be kept in mind. Each point in the graph should be interpreted as the extent to which support for a given candidate is increasing or decreasing. If the path is decreasing, this suggests that public opinion for the candidate is declining from the previous day’s level. If the path is increasing, then public opinion is increasing for the candidate from the previous day’s level. For example, November 5th represents a day when Coppersmith’s support is predicted to decline substantially from what it was the previous day and Kyl’s support is predicted to increase from the support he had on November 4th.

**Figure 4.3: On-line Model’s Predictions for Coppersmith**

![Graph showing predicted public opinion over time]

**Measuring Actual Public Opinion**

Because I am interested in determining if the models can explain the path public opinion takes during the course of a political campaign, I need a measure of the actual
path that public opinion took during the campaign season. Ideally, I would like daily public opinion data for a large number of campaigns. There are two potential measures of this concept: polling data and the Iowa Electronic Market.

The first option, polling data, has certain problems of comparability that make it not the best choice for my purposes. First, polling data does not exist for a wide variety of cases below the presidential level. Where polling data does exist below the presidential level, it must be constructed from polls conducted by many different polling organizations. A number of comparability problems arise when one uses more than a single polling organization to construct a time-series. Different polling organizations use different questions and different universes from which to draw their sample. For example, a polling organization could choose to survey all individuals over the age of 18 in California, or registered voters in California, or likely voters in California. Even though the respondents might be in the same location, the universes are often different; therefore, the sample drawn for each polling organization will be dissimilar. Even within the same polling organization, different samples are used and question wording differs as the campaign proceeds. Candidates come in and out of races and polling organizations structure their questions to include certain candidates and exclude others as the campaign proceeds. Further, different samples tend to be used as the election nears the end.

Polling organizations often switch from all adults to likely voters.

An alternative data source for daily public opinion is the Iowa Electronic Market. The market has daily public opinion data for twenty-one candidates in eight elections occurring between 1990 and 1994. In 1988, the University of Iowa established the Iowa Electronic Market (IEM). The IEM is a futures market. Futures markets are markets that

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25 Scholars have found that question wording can play an important role in structuring responses.
trade assets in which the value of those assets is based on the outcome of a future event. I use this market for my project because its reward structure is conducive to gauging dynamic public opinion.

Once the election is over, payoffs are determined by the percentage of the total popular vote a candidate receives in the November election. Basically, participants are paid according to how well they were able to predict the percent of the vote a given candidate acquired. The incentive in the market, then, is to accurately predict the support for a given candidate.

Given the reward structure and the incentives, participants ought to be encouraged to follow the campaign to determine the level of support for each candidate prior to betting. Further, the questions polling organizations ask respondents to answer essentially require them to make such a judgment. These questions are usually worded something like this: if the election were held today, which of the following candidates would you most likely support? The IEM basically asks participants to determine the answers that their fellow citizens would make to such polling questions, which is exactly my interest in this project. In the end, I am interested in the way public opinion shifts in response to changes in the flow of candidate messages.

Even though the market seems a useful tool for this project, is it really a "better" or more effective measure of public opinion than polling data? I believe it is the case for a number of very different reasons. The fundamental advantage of the market is that it is a daily measure of public opinion producing 2800 time points for the twenty-one candidates in the eight campaigns. This allows me to study the way public opinion
changes overtime and whether these changes correspond to the models’ predicted changes.

Further, these markets are amenable to studying specific events. For example, imagine a campaign strategy that exposes a scandal involving the other candidate. Given that the IEM is a daily measure of public opinion, we would be able to evaluate the instantaneous impact of such exposure on the public. As Gromme (2003) points out, polling data are often a few days old when reported and are constructed from interviews conducted across a number of days. This makes it difficult to gauge the instantaneous impact of events. Finally, the market avoids problems associated with comparability: question wording, different universes, etc.

What is also reassuring about the market measure is that it moves together with polling data. Both are measures of the same concept: public opinion. One of the cases for which I have IEM data and polling data is the New York Gubernatorial race in 1994. Figure 4.4 shows the paths of public opinion using IEM data and polling data from the Harris poll for the two major party candidates: Cuomo on the left and Pataki on the right. The IEM data is measured daily so I have dropped all the days for which polling data does not exist.

How well do the series move together? From September until November, the two series move together quite well making me comfortable that either measure is capturing the underlying concept of public opinion.
Empirical Test

I approach testing these two models in a slightly unconventional manner. I am not simply interested in whether or not these models can predict the end result of a campaign season—that is, which candidate wins the election—but in the ability of the models to correctly predict the course public opinion takes during the campaign. As a result, in the previous chapters I formalized the theoretical arguments into mathematical equations. Doing this allows me to take actual campaign data as inputs for the two models thereby producing a predicted path of support for each candidate from each model. I then compare this predicted path with the actual path of support for each candidate during the campaign season. The empirical analysis then is for the purpose of determining if and how the models fail to predict actual public opinion.

To determine this, I use a graphical strategy alongside a statistical analysis in the next two chapters. In Chapter 5, I describe the eight political campaigns used in the
analysis. In describing the campaigns, I outline the type of race, the candidates running for the particular office under discussion, and any interesting facets of the campaign. I also present the predicted paths of public opinion as well as the actual path of public opinion. Finally, I compare the predicted paths with the actual paths of public opinion for all twenty-one candidates to determine if the models are capturing the course of public opinion during these eight campaigns. In Chapter 6, I explore the ways in which the models fail to predict the movement of public opinion.

For example, the models might do better at predicting public opinion early in the campaign season, but become progressively worse as the season continues. Further, the models might be able to predict volatility in public opinion but have difficulty predicting public opinion when it is more stable. The models might also do better at predicting public opinion with certain types of candidates (incumbents versus non-incumbents). Finally, the models might do better at predicting initial change in public opinion but do worse at predicting persistence after change.

Once I identify the ways in which the models seem to be failing, I then use a series of statistical tests to determine if the models actually do fail at those points. To be clear, the goal of these statistical tests is not the goal of a typical statistical test. I am not looking for a causal relationship between two variables. Rather, I would like to know if the predicted path of public opinion deviates from the actual path of public opinion in a specific way.

**Conclusion**

Previous tests of the on-line and memory-based model do not address the way in which public opinion changes throughout the course of a political campaign. As a result,
I propose an additional test of the two models based on the need to examine the dynamic nature of public opinion during a political campaign. In the next two chapters, I turn to a description of the eight campaigns and examine the ability of the models to predict actual public opinion.
Chapter 5:
Eight Congressional and Gubernatorial Campaigns

In this chapter, I describe the eight political campaigns used to explore the dynamic implications of the on-line and memory-based models. For each of the eight races, I use a consistent approach. I first describe the campaign season. In describing the campaign, I discuss the race, the candidates, and any interesting facets of the campaign. Because of the importance of the newspaper coverage for the predictions of both models, each race has a table depicting the overall dispersion of newspaper coverage, in terms of headlines and articles, from each newspaper. This table highlights both the absolute number of headlines/articles mentioning each candidate and the proportion of headlines/articles valenced in a positive or negative direction for each candidate. I then present the predictions from the on-line and memory-based models and display the actual movement of public opinion, in terms of price data from the Iowa Electronic Market, for each candidate throughout the campaign season. Finally, I compare this actual path of public opinion to the path predicted by the two models for each candidate in the race. The goal of this comparison is to determine whether the models' predictions conform to the actual path of public opinion during the eight political campaigns.

For this comparison, I need to be able to compare the ability of the models' predictions to track actual public opinion. In order to make this possible, I need to standardize the predicted values and the actual values of public opinion. The on-line model's predicted value is the daily level of the tally for each candidate. The memory-based model's predicted value is the daily level of support for the candidate. As such, I need to standardize the two models predictions and the actual values of public opinion to make them comparable. To achieve this, I standardize the price data and the predictions
for each model in terms of z-scores. For the predicted values, I calculate a mean and
standard error of the series for each candidate. Each predicted value is then subtracted
from this mean. Dividing the difference between the mean for the series and each day’s
predicted value by the standard error of the series then creates the z-score for a given day.
I construct the z-score for the price data similarly. In the graphical and statistical
analyses in this chapter and the next, I use the z-scores for each candidate-day.

**Arizona Senate Race: Coppersmith versus Kyl (1994)**

The first case is the 1994 race between Democrat Sam Coppersmith and Republican
Jon Kyl for the open Arizona Senate seat. Both candidates were current members of the
U.S. House of Representatives running for an open seat held by the retiring Democrat,
Sen. Dennis DeConcini. Consistent with the tone of other 1994 congressional races, both
candidates appeared to be running more against the national party leaders, Newt Gingrich
and Bill Clinton, than each other. The younger candidate, Sam Coppersmith, served a
single term in the U.S. House before running for this Senate seat. His Republican
opponent, in contrast, was serving his third term in the U.S. House.

Unlike Kyl, Coppersmith faced two serious opponents in the September 13th
Democratic primary. This was no ordinary primary contest. The Arizona Secretary of
State Richard Mahoney and state Senator Cindy Resnick challenged Coppersmith for
their party’s nomination. Seventeen days after the primary election, Coppersmith
officially won the Democratic primary by fifty-nine votes over Mahoney after an official
statewide recount.

The disadvantage facing Coppersmith given his late start in the general election was
further exacerbated by Kyl’s fundraising edge. The combination of the two, along with a
national trend against the Democrats, led to a resounding Kyl victory. With fifty-four percent of the vote, Jon Kyl became Arizona’s junior senator.

Newspaper Coverage

As discussed in the previous chapter, I relied on newspaper coverage to measure the models’ dynamic inputs in order to produce the predicted values of public opinion for each model. As one might anticipate in an open race for the U.S. Senate with two incumbent members of the U.S. House, the number of articles and headlines mentioning the candidates was roughly equivalent. The dispersion of coverage is displayed in Table 5.1. The second column in this table provides the number of headlines mentioning each candidate while the fifth column provides the number of articles mentioning each candidate. The difference between the number of articles and headlines mentioning each candidate was insignificant. In fact, one might have anticipated a greater disparity between the two candidates given the unusual nature of Coppersmith’s primary contest. However, when discussing the Democratic primary the newspaper also discussed the edge Kyl gained from not participating in such a primary. These two columns provide evidence for parity in absolute coverage; however, there is much disparity in the valence of the coverage. In columns three and four, I provide the percentage of the total headlines mentioning each candidate that are positive and negative. Similarly, columns six and seven display the positive and negative nature of the articles for each candidate. In this race, there is a difference in the valence of the headlines and articles. The newspaper published more positive headlines about Jon Kyl than it published negative headlines. In contrast, the headline coverage of Coppersmith was more negative than positive. The articles tell a different story. The newspaper published many more positive
articles about Coppersmith while it published equal numbers of positive and negative articles about Kyl.

Table 5.1: Dispersion of Newspaper Coverage in the Arizona Senate Race

<table>
<thead>
<tr>
<th></th>
<th>Number of Headlines</th>
<th>Positive Headlines (%) Total</th>
<th>Negative Headlines (%) Total</th>
<th>Number of Articles</th>
<th>Positive Articles (%) Total</th>
<th>Negative Articles (%) Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tucson Daily Star</td>
<td>28</td>
<td>33.3</td>
<td>58.3</td>
<td>178</td>
<td>34.1</td>
<td>27.5</td>
</tr>
<tr>
<td>Coppersmith</td>
<td>12</td>
<td>33.3</td>
<td>58.3</td>
<td>91</td>
<td>34.1</td>
<td>27.5</td>
</tr>
<tr>
<td>Kyl</td>
<td>16</td>
<td>43.8</td>
<td>31.3</td>
<td>87</td>
<td>29.9</td>
<td>29.9</td>
</tr>
</tbody>
</table>

Predictions

The public opinion data for this race does not begin until mid-October, so I do not calculate predicted values until this period. Figure 5.1 depicts the predicted paths of the memory-based model and the on-line model produced from inputting actual campaign data into the formalized equations. Inputting this data produces a predicted value for each day in the campaign season for each of the models. As I mention in the introduction, comparing the models’ predictions to actual opinion requires standardizing the predicted and actual values into z-scores. Given this standardization, the predicted value of public opinion on any given day is not meaningful; instead, what is important is the extent to which the models predict stability in opinion or changes in a positive or negative direction. And, whether these predicted changes conform to actual changes in public opinion.

As is evident in Figure 5.1, the models’ predicted paths are very similar for Coppersmith. One might expect such similarity given that both models rely on newspaper coverage as the dynamic input to the formalized equations. However, there are quite a few points of divergence between the two models. On October 23rd, the memory-based model predicts a dramatic increase in support for Coppersmith. The on-line model also predicts this increase in support but it is much less dramatic. On this
date, the newspaper included in this study, the Tucson Daily Star, endorses Coppersmith for the Senate seat. Both models predict an increase resulting from this endorsement, but the very next day the models diverge. On this date, the memory-based model predicts the greatest decline in support in the entire series while the on-line model predicts no change in support (or stability) for Coppersmith. A further divergence in prediction occurs at the end of the campaign season. The on-line model yields a predicted increase in support for Coppersmith, but the memory-based model suggests support will remain stable for Coppersmith.

**Figure 5.1: Memory-Based and On-Line Models’ Predictions for Coppersmith**

![Graph showing predictions for Coppersmith](image)

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

The models’ predictions for Jon Kyl diverge to an even greater extent than do their predictions for Coppersmith. In Figure 5.2, I display the paths of public opinion predicted by the memory-based and on-line models for Kyl. Both models predict the same days of stability in opinion, albeit at different levels—the on-line model predicts
stable negative support in both the beginning of October and the end of October while the memory-based model predicts stability that is more neutral. This predicted stability results from a lack of newspaper coverage of the two candidates during these periods.

What is particularly interesting and highlights the different formulations of the two models is that the on-line tally remains in its negative position when there is no new coverage but the memory-based model jumps to the mean. Because the on-line tally at time $t$ is a function of the tally’s value at $t-1$ and information received on day $t$, the value of the tally cannot jump to the mean level when the media fails to cover the campaign. Instead, the value of the tally continues at the value on day $t-1$ until new information updates the tally. On the other hand, the memory-based model, as formalized by Zaller, does not include a role for previously received information. As a result, the lack of coverage for a candidate makes the level of support dependent upon coverage of the opponent and the stable elements in the model.

This divergence in terms of predicted support for Jon Kyl is even more visible at the end of the campaign season. The on-line model predicts a steady increase in support for Kyl beginning on November 1st that continues until Election Day. However, the memory-based model continues to predict much more volatility in support for Kyl through Election Day. Again, this difference is a function of the importance of the tally formed at $t-1$ for the level of the tally at $t$. Without incorporating the value of the candidate’s previous level of support, the memory-based model cannot easily predict an ever-increasing or ever-decreasing path of public opinion.
Figure 5.2: Memory-Based and On-Line Models’ Predictions for Kyl

<table>
<thead>
<tr>
<th>Date</th>
<th>Memory-Based</th>
<th>On-Line</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 Oct 1994</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19 Oct 1994</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26 Oct 1994</td>
<td></td>
<td></td>
</tr>
<tr>
<td>02 Nov 1994</td>
<td></td>
<td></td>
</tr>
<tr>
<td>06 Nov 1994</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

**Actual Public Opinion**

In the next section, I compare the predicted paths depicted above with the actual path of public opinion created from the Iowa Electronic Market (IEM) data to determine if there are systematic divergences between the predicted paths and the actual paths of public opinion. To set this comparison, I graph in Figure 5.3 the movement in support for Coppersmith and Kyl using the IEM data. The IEM data for this race begins on October 13th. Through mid-October, the support for both candidates was very similar. Coppersmith’s support plunged around October 22nd, rebounded the next day, but continued to remain much lower than the initial value of support for the rest of the campaign season. Kyl’s support remained consistently positive for the entire campaign season and increased steadily from late October until Election Day. The end level of
support for both candidates corresponded well to their election results: the end price for Coppersmith was 0.40 and the end price for Kyl was 0.58.

**Figure 5.3: Iowa Electronic Market Results for the Arizona Senate Race**

![Graph showing price trends for Coppersmith and Kyl over the campaign season.](image)

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate's price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

**Comparing the Models' Predictions with Actual Public Opinion**

In this section, I compare the actual paths of opinion for Sam Coppersmith and Jon Kyl with the models' predicted paths. The public opinion data for this race begins in mid-October, so I calculate the predicted values of public opinion from October 12th until Election Day. The important question is whether the models increase or decrease in concert with actual public opinion. In Figure 5.4, for example, do the models predict stable support for Coppersmith for the first six days of the campaign season or do they predict more volatile support? Both models predict stable support early in the campaign season, but the memory-based model predicts this support for four of the six days while the on-line model predicts stable support for only three of the six days. After this initial
conformity, the models' predictions diverge from actual public opinion, but the memory-based model does a better job of matching the actual path of public opinion. For example, towards the end of the campaign season, the on-line model diverges to a great extent from actual public opinion and the memory-based model more closely predicts public opinion. On November 5th, actual public opinion begins to decline for Coppersmith and the models capture this decline, but the on-line model’s predicted path rebounds and steadily increases through Election Day. The memory-based model also rebounds but then stabilizes for the remainder of the campaign season.

**Figure 5.4: Comparing the Models’ Predictions with Actual Public Opinion—Coppersmith**

![Graph comparing predictions with actual opinion](image)

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

Turning to the predictions for Jon Kyl, the graphical depiction in Figure 5.5 demonstrates that both models do worse at predicting changes in support for Kyl than they did for Coppersmith in Figure 5.4. Something that is particularly striking in this graph is the stability in actual support for Kyl throughout the campaign season. The IEM price
for Kyl remains higher than the price for Coppersmith throughout the campaign season. There are only two periods of declining support for Kyl in the actual opinion data: October 19th through 20th, and October 31st through November 3rd. The memory-based model accurately predicts the first decline while the on-line model actually predicts stability in opinion for four days after predicting an increase on the 18th of October. Again the on-line model mispredicts the decline in support for Kyl on the 31st as it predicts support for Kyl to steadily increase through Election Day. The memory-based model is able to predict this decline in support and the rebound that follows. While the memory-based model appears more capable of capturing volatility than the on-line model, Figure 5.5 demonstrates the model is also likely to mispredict stability in opinion by predicting it to be volatile (i.e. an increase on October 22nd and a decrease on 23rd).

**Figure 5.5: Comparing the Models’ Predictions with Actual Public Opinion—Kyl**

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

A further way to examine the models’ predictive capacity is to examine the number of days each model accurately predicts stable opinion days, and accurately predicts the
increases and decreases in support for the candidates. For the Arizona Senate race, I display this evidence in Table 5.2. The second and fourth columns show the number of days of each type that each model predicts accurately. For example, the on-line model correctly predicts six changes in opinion (two increases and four decreases) and five days of stability for Sam Coppersmith. The memory-based model predicts four days of change and seven days of stable support for Jon Kyl. The third and fifth columns in this table display the percentage of total days of each type that the models accurately predict. For example, the memory-based model is able to predict the direction of support for Coppersmith on 44% of the change days, but when we turn to the direction of the change the model is able to predict 50% of the days for which support increased and only 40% of the days for which support declined. The model does slightly better at predicting the days of stability for Coppersmith. The on-line model by contrast does much better at predicting the days of declining support for Coppersmith than it does for increasing support, and is much better at predicting stable opinion than it is at predicting volatile opinion.

When we turn to Jon Kyl, the on-line model does equally well predicting days of volatility and days of stability. However, the on-line model is incapable of predicting the days of declining support for Kyl, but does capture half of the increases in support for Kyl. The memory-based model does much better at predicting volatility (50% accuracy rate) than stable days (~37% accuracy rate) for Kyl. Further, the memory-based model correctly predicts the two days of declining support for Kyl.
Table 5.2: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Arizona Senate Race

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>6</td>
<td>37.5</td>
<td>7</td>
<td>43.8</td>
</tr>
<tr>
<td>Increase</td>
<td>2</td>
<td>33.3</td>
<td>3</td>
<td>50.0</td>
</tr>
<tr>
<td>Decrease</td>
<td>4</td>
<td>40.0</td>
<td>4</td>
<td>40.0</td>
</tr>
<tr>
<td>Stability</td>
<td>5</td>
<td>45.5</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>Kyl</td>
<td>3</td>
<td>37.5</td>
<td>4</td>
<td>50.0</td>
</tr>
<tr>
<td>Increase</td>
<td>3</td>
<td>50.0</td>
<td>2</td>
<td>33.3</td>
</tr>
<tr>
<td>Decrease</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>100.0</td>
</tr>
<tr>
<td>Stability</td>
<td>8</td>
<td>42.1</td>
<td>7</td>
<td>36.8</td>
</tr>
</tbody>
</table>

**Illinois Senate Race: Martin versus Simon**

Being a candidate in an open race for the U.S. Senate is challenging, but being a challenger facing an incumbent in a race for the U.S. Senate has been an almost impossible battle. Political scientists for years have taken note of the overwhelming tendency for the American public to return their incumbent Congressmen and Congresswomen to office. Nowhere has incumbency been heralded as more vital than in the U.S. Senate. Such a situation faced Republican Lynn Martin as she attempted to oust incumbent Sen. Paul Simon in Illinois in 1994.

Lynn Martin, an incumbent Representative in the U.S. House, certainly had a better shot at defeating Simon than a non-incumbent would have had, but the task was daunting nonetheless. Simon had been a familiar face in Illinoisan politics for the last three decades and was a current member of the Senate Judiciary Committee and the Senate Foreign Relations Committee. Both committees gained prominence during the 1994 campaign season because of the impending war in the Middle East and the nomination of a Supreme Court justice by the Bush Administration.

A number of interesting developments took place during this campaign. The Illinois branch of the National Organization for Women endorsed Simon for re-election, but to
his dismay the president of the national NOW issued a statement assuring Martin that
NOW's political action committee would not be making an endorsement in the Illinois
Senate race. Few will soon forget former President George Bush's campaign pledge of
"Read my lips: No new taxes" and his subsequent abandonment of such a pledge. Martin
is probably among the few that would like to forget this abandonment. Campaigning on a
similar pledge, Martin was left campaigning on a pledge that the President had deemed
impossible to uphold. Rep. Martin was left insisting that Bush, and his team of economic
advisers, were wrong about the impossibility of such a pledge.

More memorable than Martin's anti-tax pledge was the relationship between this
race and the Savings-and-Loan disaster. During campaigns, dirty deals or perceived
improprieties typically surface to the detriment of one candidate, but in this race, both
candidates were susceptible. First, Rep. Martin accused Sen. Simon of intervening on
behalf of campaign contributors—a culinary school and a minority-oriented Chicago
college—under investigation by regulators. Unfortunately for Rep. Martin, a few weeks
later information surfaced indicating that she took donations and honorariums from a
corporation and intervened on behalf of this corporation with the Defense Department.
The problem was that the corporations' former executives were put on trial for cheating
that very department.

Newspaper Coverage

Incumbency played a significant role in the dispersion of newspaper coverage in this
race as Simon eclipsed Martin in terms of headlines and articles. Table 5.3 follows the
same format as Table 5.1 above. One explanation for the disparity in the amount of
coverage stems from Simon's free publicity for his membership on a number of key
Senate committees that became relevant while the campaign was underway. Simon was a member of the Senate Judiciary Committee during a time period in which President Bush nominated a justice for the Supreme Court. Further, Simon was also a member of the Senate Foreign Relations Committee during a time when hostilities were growing in the Middle East. The news media continuously sought comments from Simon granting him free publicity and an enhanced public perception that he was an influential senator. This last point corresponds to the direction of the coverage. In this race, Sen. Simon received much more positive coverage, in terms of both headlines and articles, than his Republican opponent.

**Table 5.3: Dispersion of Newspaper Coverage in the Illinois Senate Race**

<table>
<thead>
<tr>
<th></th>
<th>Number of Headlines</th>
<th>Positive Headlines (% Total)</th>
<th>Negative Headlines (% Total)</th>
<th>Number of Articles</th>
<th>Positive Articles (% Total)</th>
<th>Negative Articles (% Total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tribune</td>
<td>74</td>
<td></td>
<td></td>
<td>334</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Martin</td>
<td>34</td>
<td>5.9</td>
<td>20.6</td>
<td>148</td>
<td>18.2</td>
<td>37.8</td>
</tr>
<tr>
<td>Simon</td>
<td>40</td>
<td>20.0</td>
<td>32.5</td>
<td>186</td>
<td>36.0</td>
<td>22.0</td>
</tr>
<tr>
<td>Sun-Times</td>
<td>77</td>
<td></td>
<td></td>
<td>305</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Martin</td>
<td>30</td>
<td>10.0</td>
<td>43.3</td>
<td>137</td>
<td>19.7</td>
<td>40.2</td>
</tr>
<tr>
<td>Simon</td>
<td>47</td>
<td>25.5</td>
<td>48.9</td>
<td>168</td>
<td>35.1</td>
<td>28.0</td>
</tr>
</tbody>
</table>

**Predictions**

The public opinion data for the Illinois Senate race begins much earlier than it did for the Arizona Senate race. As a result, there are significantly more datapoints in the predicted paths for Simon and Martin than there were for Coppersmith and Kyl. In Figure 5.6, I display the memory-based and on-line models' predicted paths for Simon. An important observation is the fluctuation predicted by the memory-based model. The lowess line remains relatively flat as the path dips and rebounds throughout the campaign season. Turning to the on-line model, the prediction for support for Simon is one of ever-increasing support from July until mid-September and then increasing support again from
early October until Election Day. The significant decrease in support occurring between these two periods of stability results from the extremely negative coverage surrounding Simon’s role in the Savings and Loan scandals. However, the value of Simon’s tally is so high that even this overwhelmingly negative coverage is mitigated by intense positive coverage from October onward.

The on-line model suggests that an on-line tally is formed when individuals first encounter information about a candidate and is updated throughout the campaign season with new information. In this race, the initial tally for Simon starts at 37\(^{26}\), which is over twice his opponent’s initial tally (17.5). Coverage for Simon continues to be incredibly positive and continues to feed this tally. Simon benefits from increased coverage depicting his stature as an incumbent Senator on two important committees: Judiciary and Foreign Relations. This increase in Simon’s stature is evident in the more positive coverage he receives throughout the campaign season.

In contrast, the memory-based model predicts much greater volatility in support for Simon. Not only does the memory-based model fail to account for the previous level of support for Simon, but the memory-based model also emphasizes the relative flow of information as the key factor in producing change in support for a candidate during a campaign season. This relativity notion means that support for Simon is dependent upon not only the intensity of his campaign message, but also the intensity of Martin’s campaign message. As a result, Simon’s predicted support fluctuates in response to changes in his own coverage and changes in coverage of his opponent.

\(^{26}\) In Chapter 2 I outlined the formalization of the on-line tally and in the previous chapter, I discussed the way that the initial tally is calculated. The actual value of the tally does not hold any meaning except in comparison to the value for the opponent. In this case, Simon’s tally is much higher than that of Martin.
Figure 5.6: Memory-Based and On-Line Models' Predictions for Simon

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Because of the memory-based model relies on the relative flow of campaign information to predict support for candidates, the predicted path for Lynn Martin fluctuates just as frequently as the predicted path for Simon. At the beginning of the campaign season, both models predict only slight fluctuations in support for Martin. However, the models diverge in their predictions after this point.

Given that the on-line model includes a role for previous information, the value of the initial tally plays an important role in shaping predicted support for Martin. As discussed above, the initial value of Martin's tally is much more negative than Simon's tally. Unlike the on-line model's predicted path for Simon, Martin's predicted path from the on-line model is not a steadily increasing path of support. Instead, support is predicted to increase until reaching a high at the end of September. During this time, coverage was much more positive towards Martin as the newspapers discussed President
Bush’s attendance at a fundraiser for Lynn Martin’s election campaign. Predicted support begins to decline as newspapers reported on October 8th that Martin encouraged a lawsuit settlement for a company facing sexual discrimination charges. Further, it was reported that Martin was unable to continue campaign advertising on television because of a lack of funds. Finally, new polling data was released demonstrating that Martin was severely trailing Simon in support among the electorate. All of this information contributed to a predicted steady decline in support for Martin continuing until Election Day.

Why does the memory-based model not predict the same corresponding increase and decrease in support? The memory-based model predicts very little variation in late September when the on-line model predicts a significant bump from Bush’s support. Remember that the relativity notion in the memory-based model means that the model can only predict this significant bump if positive coverage increases for Martin and coverage of Simon becomes even less positive. If so, then Martin gets the bump in predicted support. If not, then Martin’s support could even be predicted to decline substantially relative to Simon’s support. The negative predictions from the on-line model do correspond somewhat to the memory-based model’s predicted support for Martin in early October.
Figure 5.7: Memory-Based and On-Line Models’ Predictions for Martin

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Actual Public Opinion

I graph above the predicted paths of opinion for each candidate. The actual paths of opinion as measured by the Iowa Electronic Market data are depicted in Figure 5.8. The paths of opinion for the two candidates illustrates the difficult battle Martin faced in attempting to overcome the support for Simon in the 1990 Illinois Senate race. Aside from a steep increase in mid-September, Simon’s support remained quite consistent and high throughout the campaign season. Similarly, Martin’s support remained consistent, but consistently lower than Simon’s support from September until Election Day.
Figure 5.8: Iowa Electronic Market Results for the Illinois Senate Race

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

Comparing the Models’ Predictions with Actual Public Opinion

The models predict very different paths of public opinion for the candidates. The memory-based model predicts much fluctuation in opinion and this does not correspond well to the much more stable path predicted by the on-line model. How well do these predictions correspond to the actual path opinion took for these candidates? I plot the memory-based model’s predictions against actual opinion for Simon in the upper panel and the comparison between actual opinion and the on-line model’s predictions in the lower panel of Figure 5.9.

Similar to the results from the Arizona Senate race, actual public opinion in this race is much more stable than the memory-based model predicts. There are substantial stretches of time in which opinion for both candidates does not fluctuate. The most extreme of the stable periods stretches from July 31st until August 23rd. During this time
period, the memory-based model predicts almost daily fluctuation in opinion. For the
most part, these fluctuations are minor until August 19th when the memory-based model
predicts a substantial increase in support for Simon. On this date, Simon held a news
conference to discuss his sponsorship of an anti-profiteering bill aimed at eliminating
excessive gasoline and oil pricing. Martin heard of the proposed news conference and
showed up; however, she was virtually ignored by Simon. The press covered this
exchange as a desperate effort by Martin to get attention. However, this exchange does
not appear to resonate with the public, as public opinion remains stable for both
candidates. Interestingly, the on-line model actually predicts a decline in support for
Simon on this same date. This occurs in part because the coverage of Simon was not
necessarily positive, but coverage was simply less negative for Simon than for Martin.
The divergence between the models occurs because the memory-based model relies on
the relative coverage of the candidates to calculate its predictions for support while the
on-line model relies on the absolute coverage of a candidate.

Another interesting series of dates is September 27th through 29th. An increase in
coverage of Simon on September 27th leads to a predicted increase in support for the
memory-based model corresponding to an actual increase in opinion. In contrast, the on-
line model predicts a decline in support on these days. This predicted decline actually
begins much earlier than the 27th as the model predicts the decline to begin on September
14th and continue well into October when predicted support rebounds.

In general, the correspondence between the predictions of the on-line model and
actual public opinion shown in Figure 5.9 is not as great as with the memory-based model
and actual opinion. However, the on-line model does a better job predicting changes in
opinion prior to the end of September. During this period, the model predicts much more stability corresponding to a greater extent with the actual path of opinion. Further, the on-line model’s predictions for an increase in support for Simon conform to the actual increase in support for Simon at the end of the campaign season.

Figure 5.9: Comparing the Models’ Predictions with Actual Public Opinion—Simon

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

The Illinois Senate race also featured Republican Lynn Martin, a freshman representative. Do the models do a comparable job predicting public opinion for Martin as they do for Simon? Figure 5.10 indicates that both models do much worse at predicting support for Martin. Not only is actual public opinion much more volatile for Martin, but the ability of the models to predict that volatility declines. I do not mean to suggest that the models predict stability; Figure 5.10 demonstrates that they do not.

However, the models simply predict volatility on days when public opinion is actually quite stable. In discussing Simon, I gave August 19th as an interesting day in which the models predict different directions of support. In Martin’s case, the impromptu
appearance at Simon’s press conference yields no change in actual support for Martin but the models both predict a decline in support for the Republican on this date. A few days later, on August 23rd, support for Martin actually does decline and the models fail to capture this decline.

As the campaign season progresses, actual public opinion becomes more volatile and the models appear to do worse at predicting public opinion. As one might anticipate, the memory-based model diverges at the end of the campaign season in predicting an increase in support for Martin immediately preceding the election. The on-line model in contrast accurately predicts the decline in support for Martin.

**Figure 5.10: Comparing the Models’ Predictions with Actual Public Opinion—Martin**

![Graph comparing models with actual data]

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

To further illustrate the ability of the models to predict public opinion, Table 5.4 outlines the ability of each model to predict stability and the direction of the volatility for the two candidates in the Illinois Senate Race. Overall, the on-line model does slightly
better at predicting changes in support for Simon than the memory-based model (~53 percent of the days in the campaign season to 50 percent). However, the memory-based model more accurately predicts the changes in support for Martin throughout the campaign season (~56 percent to ~39 percent).

Breaking the support down into increases and decreases in support, an interesting pattern emerges. For Simon, the on-line model does much better at predicting increases in support than the memory-based model does, but the memory-based model outpaces the on-line model when support for Simon starts to decline. For Martin, the memory-based model does better at predicting changes, both increases and decreases. For both candidates, the on-line model captures stable public opinion to a greater extent; however, both models do poorly in predicting stable public opinion when compared to their ability to predict volatile public opinion.

Table 5.4: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Illinois Senate Race

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simon</td>
<td>16</td>
<td>53.3</td>
<td>15</td>
<td>50.0</td>
</tr>
<tr>
<td>Increase</td>
<td>12</td>
<td>60.0</td>
<td>10</td>
<td>50.0</td>
</tr>
<tr>
<td>Decrease</td>
<td>4</td>
<td>40.0</td>
<td>5</td>
<td>50.0</td>
</tr>
<tr>
<td>Stability</td>
<td>16</td>
<td>21.3</td>
<td>5</td>
<td>6.67</td>
</tr>
<tr>
<td>Martin</td>
<td>14</td>
<td>38.9</td>
<td>20</td>
<td>55.6</td>
</tr>
<tr>
<td>Increase</td>
<td>5</td>
<td>31.3</td>
<td>9</td>
<td>56.3</td>
</tr>
<tr>
<td>Decrease</td>
<td>9</td>
<td>45.0</td>
<td>11</td>
<td>55.0</td>
</tr>
<tr>
<td>Stability</td>
<td>14</td>
<td>20.3</td>
<td>4</td>
<td>5.80</td>
</tr>
</tbody>
</table>

New Jersey Senate Race: Haytaian versus Lautenberg

Returning to the 1994 campaign season, the third race to discuss is between the incumbent, Democrat Frank Lautenberg, and the challenger, Republican Garabed “Chuck” Haytaian for one of New Jersey’s Senate seats. The successful campaign waged by Christie Todd Whitman against incumbent Governor Jim Florio the year before
encouraged New Jersey Assembly Speaker Haytaian to wage his own battle against the incumbent Senator Lautenberg. In a year that would soon become known as the anti-incumbent year, both candidates portrayed themselves as the non-incumbent (a difficult task given that Lautenberg was asking for his third term as U.S. Senator, and Haytaian was the current Speaker of the New Jersey Assembly).

A number of interesting events took place during this campaign. One such event occurred when a group of African-American ministers accused New York radio host, Bob Grant, of making racist comments. They identified a number of instances in which he called Rev. Martin Luther King Jr. a “scumbag”, wished AIDS upon HIV-infected Ervin “Magic” Johnson, referred to Los Angeles rioters as "savages", and proposed that Haitian boat people be left to drown. The ministers called on the candidates to denounce Bob Grant, but Haytaian refused to denounce Bob Grant, even though he denounced racism, because of their friendship. This was a particularly glaring act because another Grant friend, Gov. Whitman did repudiate the radio host. Such action encouraged the Lautenberg campaign to make race an issue in the campaign.

Even with Whitman’s late-season appearances, Haytaian was unable to muster the funds necessary to compete against the incumbent Senator. With fifty-one percent of the vote, Lautenberg resisted the national anti-incumbent/anti-Democratic trend to defeat Haytaian.

Newspaper Coverage

Turning to the candidate’s messages, the dispersion of newspaper coverage for this campaign is displayed in Table 5.5. Surprisingly, the incumbent, Sen. Lautenberg, did not receive the majority of coverage by both newspapers. In fact, Haytaian did a good
job eclipsing the Senator in terms of coverage for both the Atlantic City Press and the Record. While at first glance this seems quite strange, much of the additional coverage received by Haytaian concerned one specific issue: Megan’s law. During the campaign season, seven-year old Megan Kanka was raped and murdered. As Speaker of the Assembly, Haytaian was instrumental in pushing through a number of new laws aimed at convicted sex offenders that did not go through the normal committee review process in the Assembly. Such action led to much publicity for Haytaian. However, the article coverage of Lautenberg tended to be positive or neutral. In both newspapers, less than twenty percent of the articles could be considered negative towards Lautenberg. On the other hand, the negative coverage of Haytaian was either greater or equivalent to his positive coverage in terms of articles and headlines.

<table>
<thead>
<tr>
<th></th>
<th>Number of Headlines</th>
<th>Positive Headlines (% Total)</th>
<th>Negative Headlines (% Total)</th>
<th>Number of Articles</th>
<th>Positive Articles (% Total)</th>
<th>Negative Articles (% Total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic City</td>
<td>92</td>
<td>32.7</td>
<td>32.7</td>
<td>315</td>
<td>27.7</td>
<td>28.9</td>
</tr>
<tr>
<td>Press</td>
<td>Haytaian</td>
<td>55</td>
<td>32.7</td>
<td>166</td>
<td>27.7</td>
<td>28.9</td>
</tr>
<tr>
<td></td>
<td>Lautenberg</td>
<td>37</td>
<td>29.7</td>
<td>149</td>
<td>28.9</td>
<td>14.1</td>
</tr>
<tr>
<td>The Record</td>
<td>111</td>
<td>22.6</td>
<td>29.0</td>
<td>448</td>
<td>18.6</td>
<td>39.6</td>
</tr>
<tr>
<td>Haytaian</td>
<td>62</td>
<td>32.7</td>
<td>16.3</td>
<td>220</td>
<td>36.0</td>
<td>17.5</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>49</td>
<td>22.6</td>
<td>29.0</td>
<td>228</td>
<td>18.6</td>
<td>39.6</td>
</tr>
</tbody>
</table>

Predictions

The above table highlights the limits of the incumbency advantage. Typically, incumbents have the early advantage in terms of coverage, but Senator Lautenberg, facing an incumbent Speaker of the New Jersey Assembly, receives less coverage on average than his challenger. In fact, Haytaian receives much more coverage than Lautenberg in terms of headlines in this race. Given this interesting finding, what are the models’ predictions for public opinion, which both rely on this coverage? In Figure 5.11,
I graph the predictions from the memory-based and on-line model for Lautenberg. What is immediately apparent from this graph is that the on-line model’s predictions are very similar to the predictions for Simon, another incumbent senator running for reelection. As the campaign season moves forward, the on-line model predicts Lautenberg’s support to increase so that by Election Day his support is predicted to be greater than his opponent’s support. An important question to ask is how it is that the on-line model predicts a consistently increasing level of support for Lautenberg even though his opponent receives more newspaper coverage. Both candidates receive both positive and negative coverage throughout the campaign season and such variance is evident in the graphs. In the end, the coverage for Lautenberg is slightly more positive than the coverage for Haytaian.

Again the memory-based model predicts more fluctuations in public opinion for Lautenberg. The memory-based model predicts a positive change in support for Lautenberg on October 13th corresponding to an announcement by the national Democratic Party that it would focus resources on the New Jersey Senate race. Support for Lautenberg is predicted to decline on October 18th, but it is not immediately obvious why Zaller’s model predicts a decline in support for Lautenberg as his coverage actually becomes more positive on this date. A likely reason for this mismatch is the importance of Zaller’s notion of a relative flow of information. An individual candidate’s level of support is determined not only by his/her own coverage, but also by the amount of coverage for his/her opponents. In late October, the memory-based model predicts a sharp increase in support for Lautenberg. During this period, Haytaian refused to disassociate himself from a controversial radio talk show host who had been accused of
making racist statements on his show and there was also a discussion of Lautenberg’s likely probability of winning the election. The coverage of these events increased the predicted level of support for Lautenberg. Just prior to the election, Zaller’s model predicts a slight decrease (November 7th) in support for Lautenberg. This decline in support corresponds to the fact that only one article was published about the campaign on November 7th while there was many more articles the previous day.

**Figure 5.11: Memory-Based and On-Line Models’ Predictions for Lautenberg**

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

I graph the models’ predictions for change in public opinion for Assembly Speaker Chuck Haytaian in Figure 5.12. One immediate conclusion that can be drawn from this graph is that Haytaian’s level of support is quite high, but one should notice that the scale is different from the scale for Lautenberg. Importantly, the graphs are also displayed in terms of z-scores so the direction of change is important but the level of change is only comparable within a series, not across series.
The tally that Haytaian begins with is substantially lower than his opponent’s tally (23 vs. 86). Even though his path of public opinion is also predicted to increase throughout the campaign season, the on-line model does not predict Haytaian’s level of support to surpass Lautenberg at any point in the campaign season. There are a few points in which the on-line model predicts a downturn or upswing in support that are noteworthy. On October 20th, both models predict a decline in support for Haytaian. This decline in support corresponds to negative coverage concerning Haytaian’s recent statements on his record of tax cuts and spending.

As the campaign approaches Election Day, the on-line model predicts an increase in support for Haytaian on October 29th. The model then predicts a decline the very next day. Coverage for Haytaian is not necessarily all that positive on the 29th, but it is substantially more positive than on the 30th. On the 30th, the New Jersey Record published a series of editorials that were severely critical of Haytaian concerning his professional record as speaker of the New Jersey Assembly and his position on the issues in the campaign.

However, the memory-based model predicts a significant decline in support and then a rebound for Haytaian. The decline, on November 3rd, corresponds to Lautenberg’s endorsement by one of the newspapers. For the most part, Haytaian’s coverage is high on this date but the coverage is either negative or neutral. The very next day Haytaian rebounds (November 4th), but it is not because his coverage becomes positive. In fact, his coverage happens to simply be neutral coverage instead of negative coverage. The on-line model also predicts the decline on November 3rd, but its predicted impact is tempered more than the memory-based predicts.
Figure 5.12: Memory-Based and On-Line Models’ Predictions for Haytaian

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Actual Public Opinion

The New Jersey Senate race is an interesting race in that the two candidates were both very popular incumbents, but Lautenberg had the edge in being the incumbent for the office in question. I graph the IEM data for this race in Figure 5.13. The public opinion data for this race begins on October 5th. Throughout the month of October, Lautenberg led Haytaian in terms of public opinion; however, the graph below illustrates the dramatic movement in public opinion throughout the campaign season. Note that the path of public opinion is displayed in terms of z-scores, so this figure should not suggest that Haytaian had more support at the end of the race. In fact, Haytaian never reached above 0.50 while Lautenberg remained above 0.50 for the entire campaign. What the graph illustrates are the highs and lows in terms of support for each candidate. So, in early October, Lautenberg’s level of support was much lower than his mean level of
support throughout the campaign season. On the day before the election, Lautenberg’s level of support was almost ten points greater than Haytaian’s level of support.

**Figure 5.13: Iowa Electronic Market Results for the New Jersey Senate Race**

![Graphs showing price changes for Lautenberg and Haytaian](image)

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

**Comparing the Models’ Predictions with Actual Public Opinion**

How well do the models predict the movement of public opinion for the two candidates in this race? I compare the predicted paths of public opinion from the two models for the New Jersey Senate race between Chuck Haytaian and Frank Lautenberg with the actual path of public opinion for these candidates in Figures 5.14 and 5.15.

In this race, the incumbent Senator, Democrat Frank Lautenberg, is running against the incumbent Speaker of the New Jersey Assembly, Republican Chuck Haytaian. Coming off of a Republican victory in the New Jersey gubernatorial race in the previous election cycle, the Republican Party was confident that they would be able to oust the two-term senator. Unfortunately for the Republican Party, Senator Lautenberg was able
to hold off Haytaian and win re-election. How well do the models predict the course of public opinion for the incumbent?

In Figure 5.14, I show the models' predictions for the course of public opinion for Frank Lautenberg. The predictions from both models conform during the first few days of the campaign season; however, the on-line model clearly predicts an ever-increasing level of support for Lautenberg while the memory-based model predicts much more instability in prediction. Both models diverge from Lautenberg's actual path of public opinion. In particular, the models predict a decrease on October 13th while actual public opinion increases on this date. The next day, the models converge with actual opinion as support is expected to increase on this date. On October 13th, coverage of Lautenberg tended to be negative as the Democratic Party announced it would spend substantial resources on the New Jersey Senate race suggesting that the three-term incumbent risked losing his seat. Further, there was discussion concerning the extent to which either candidate's message was ringing true for urban voters or whether the campaign messages were simply additional empty promises. Both models capture this negative coverage, and the memory-based model predicts an even-greater decline in support than the on-line model because Haytaian's coverage on this day is much more positive.

However, the models do accurately predict public opinion on certain days. In particular, the on-line model accurately predicts the stability in public opinion that occurs on October 20th while the memory-based model predicts a substantial increase on this date. The coverage for Lautenberg on October 20th was not substantially different than it was the previous day; however, on this date, the coverage for Haytaian was incredibly negative. The memory-based model relies on a relative flow of information, so an
individual candidate's level of support is determined not only by his/her own coverage, but also by the amount of coverage for his/her opponents. The on-line model does not have such a relativity notion, so support for Lautenberg is not expected to increase on this date.

The large spike in public opinion for Lautenberg predicted by the memory-based model on November 2nd corresponds to a slight predicted increase for the on-line model and a larger increase in actual public opinion. On this date, Lautenberg received the endorsement from a variety of groups: Democratic Black Caucus of the New Jersey Legislature, the South Jersey Building Trades Council and members of United We Stand, Ross Perot's group.

The above discussion suggests that there is much more convergence between the models themselves; however, the discussion in one of the previous sections makes it clear that the models not only diverge from actual public opinion but also from each other. In particular, actual public opinion is predicted to be completely stable during four different periods (October 6th through 12th, October 14th through 15th, October 21st through 24th, and October 28th through 31st), but the models do not correctly predict such stability. The on-line model predicts an ever-increasing level of support for Lautenberg with only a few moments of almost stability. The memory-based model on the other hand predicts a number of almost stable days (October 14th through 15th), but also predicts volatility during days of actual stability in public opinion (October 28th through 31st).
Figure 5.14: Comparing the Models' Predictions with Actual Public Opinion—Lautenberg

![Graph showing predicted vs. actual public opinion]

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

I graph the change in actual support for Speaker Haytaian against the changes predicted by the two models in Figure 5.15. These graphs are interesting because the models appear to do substantially worse at predicting changes in support in either direction for Haytaian than they did for Lautenberg. At the beginning of the campaign season, the memory-based model does a great job predicting stability that conforms to actual stability in support for Haytaian. The on-line model also predicts relatively stable opinion at the beginning of the campaign season, yet these predictions are substantially more negative than those made by the memory-based model. But, both models diverge from the substantial decline in actual opinion on October 12th, the stability on the 13th, and the decline again on the 14th. The memory-based model predicts a slight decline on the 12th, a substantial increase on the 13th, and then accurately captures the decline on the 14th. In contrast, the on-line model predicts an increase on the 12th, correctly predicts...
stability on the 13\textsuperscript{th}, and diverges with an increase on the 14\textsuperscript{th}. As I mentioned in the previous discussion, the divergence of the models from each other is likely a function of the memory-based model's reliance on relative information flows.

Similarly, the models differentially predict the amount of stability in public opinion for Haytaian. This was a point discussed in the previous section concerning Lautenberg, but it emerges again in the predictions for Chuck Haytaian. We ought to expect this from the memory-based model. Because a candidate's support is dependent upon his/her coverage and his/her opponent's coverage in the memory-based model, stability in opinion can only occur when both candidates' coverage remains unchanged. As a result, stability for one candidate will be coupled with stability for his/her opponent. For example, the memory-based model predicts stability for Haytaian and Lautenberg at the beginning of the campaign season. This is not true of the on-line model. The on-line model predicts stability during the first few days for Haytaian, but the first few days for Lautenberg is a period of increasing support.

As the campaign approaches Election Day, the models diverge from actual public opinion and each other one final time. The on-line model predicts a decline on November 3\textsuperscript{rd} and then a further decline for Haytaian on November 4\textsuperscript{th}. The memory-based model, by contrast, predicts the decline on November 3\textsuperscript{rd}, but then predicts an increase on November 4\textsuperscript{th}. Actual public opinion declines as well on the 3\textsuperscript{rd}, but increases slightly on the 4\textsuperscript{th}. This decline on the 3\textsuperscript{rd} corresponds to Lautenberg's endorsement by one of the newspapers. Why is there a divergence on the 4\textsuperscript{th}? The coverage of Haytaian does not become positive on this date, but it is less negative than on the 3\textsuperscript{rd}. As a result, the memory-based model would predict more positive opinion on the
4th than it did on the 3rd. The on-line model, however, is an accumulation of the coverage for the entire campaign season and each additional day of negative coverage decreases the tally even if it is only slightly negative coverage.

**Figure 5.15: Comparing the Models’ Predictions with Actual Public Opinion—Haytaian**

![Graph showing public opinion trends](image)

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

I compare the predicted direction of support from the on-line model and memory-based model with the actual direction of support for Lautenberg and Haytaian in Table 5.6. The two models make very different predictions for support for Lautenberg as we saw in Figure 5.11. The on-line model proposes that Lautenberg’s level of support will continue to increase throughout the campaign season while the memory-based model predicts much more fluctuation. How do the two models’ predictions correspond to the actual direction of support for Lautenberg? In this race, the memory-based model does a substantially better job predicting change in public opinion than does the on-line model. However, the on-line model does a much better job predicting increases in support for
Lautenberg while the memory-based model does better at predicting decreases in support for Lautenberg. The memory-based model more accurately predicts both types of change in support for Haytaian to a greater extent than the on-line model. Interestingly, neither model can predict stability for either candidate.

Table 5.6: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the New Jersey Senate Race

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lautenberg</td>
<td>8</td>
<td>47.0</td>
<td>10</td>
<td>58.8</td>
</tr>
<tr>
<td>Increase</td>
<td>6</td>
<td>75.0</td>
<td>5</td>
<td>62.5</td>
</tr>
<tr>
<td>Decrease</td>
<td>2</td>
<td>22.2</td>
<td>5</td>
<td>55.6</td>
</tr>
<tr>
<td>Stability</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Haytaian</td>
<td>7</td>
<td>43.8</td>
<td>9</td>
<td>56.3</td>
</tr>
<tr>
<td>Increase</td>
<td>4</td>
<td>50.0</td>
<td>5</td>
<td>62.5</td>
</tr>
<tr>
<td>Decrease</td>
<td>3</td>
<td>37.5</td>
<td>4</td>
<td>50.0</td>
</tr>
<tr>
<td>Stability</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**New York Gubernatorial Race: Cuomo versus Pataki versus Rosenbaum**

In 1994, incumbent governor, Mario Cuomo, did the seemingly impossible: he sought a fourth term as governor of New York. Coming at a time when his popularity within New York was lower than Bill Clinton’s and the economy was just emerging from a deep recession, many Republicans and Democrats alike perceived him to be vulnerable to any viable Republican candidate. However, the Republican Party in New York had attempted to deny Cuomo re-election in each of his previous two campaigns and had been unsuccessful due a substantial divide between the conservative and moderate wings of the party. To avoid such a disaster in 1994, some of the leaders of the Republican Party chose a candidate, George Pataki, strongly supported by Senator Alfonse M. D’Amato. However, for many New Yorkers, Pataki was a virtual unknown as a State Senator from Westchester County.
As an unknown state senator selected by the Republican leadership, Pataki faced two charges time after time. First, Pataki was simply running as the “not Cuomo” candidate and lacked any substance. Second, Sen. D’Amato was a “puppet master” pulling Mr. Pataki’s strings. Neither charge was strong enough to overcome the sheer Cuomo-exhaustion felt in many areas of the state, including traditional Democratic strongholds.

Pataki was able to easily dispose of his Republican primary opponent, Richard Rosenbaum, by winning over seventy-five percent of the primary votes. Further, Rosenbaum immediately supported Pataki over Cuomo in the general election. Pataki continued to lead Cuomo in the polls until late October when the incumbent mayor of New York City, Republican Rudolph Giuliani, crossed party lines to support Governor Cuomo’s re-election campaign. Many pundits perceived this to be the key to stopping the anti-Cuomo tide washing over New York. While holding on to New York City and its boroughs, Cuomo was unable to muster enough votes to counter Pataki’s upstate surge. With forty-nine percent of the vote to Cuomo’s forty-five percent, Pataki became New York’s first Republican governor since the 1970s. In the end, Cuomo was unable to communicate to the voting public the ways in which his fourth term would be different from his previous three terms.

Newspaper Coverage

Focusing on the candidate’s messages, Table 5.7 outlines the dispersion of newspaper coverage from the New York Times and the Buffalo News. Given that Cuomo was a nationally renowned incumbent governor, he received much more coverage than either Pataki or Rosenbaum throughout the campaign season. Further, Pataki’s frontrunner status in the Republican primary was clearly evident by his eclipsing
Rosenbaum in terms of newspaper coverage. After he lost to Pataki on September 13th, Rosenbaum's newspaper coverage plummeted. The coverage from both newspapers tended to be much more negative for Pataki than it was for Cuomo. In fact, the headlines from the Buffalo News were almost 50% negative. For Rosenbaum, the coverage tended to be neutral from the New York Times and more negative from the Buffalo News.

<table>
<thead>
<tr>
<th></th>
<th>NY Times</th>
<th>Cuomo</th>
<th>Pataki</th>
<th>Rosenbaum</th>
<th>Buffalo News</th>
<th>Cuomo</th>
<th>Pataki</th>
<th>Rosenbaum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Headlines</td>
<td>365</td>
<td>220</td>
<td>141</td>
<td>4</td>
<td>233</td>
<td>141</td>
<td>84</td>
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</tr>
<tr>
<td>Positive Headlines (% Total)</td>
<td>24.6</td>
<td>31.2</td>
<td>26.2</td>
<td>50.0</td>
<td>31.2</td>
<td>37.5</td>
<td>37.5</td>
<td>37.5</td>
</tr>
<tr>
<td>Negative Headlines (% Total)</td>
<td>36.4</td>
<td>37.6</td>
<td>48.8</td>
<td>0</td>
<td>37.5</td>
<td>37.5</td>
<td>37.5</td>
<td>37.5</td>
</tr>
<tr>
<td>Number of Articles</td>
<td>1263</td>
<td>678</td>
<td>489</td>
<td>96</td>
<td>770</td>
<td>449</td>
<td>244</td>
<td>78</td>
</tr>
<tr>
<td>Positive Articles (% Total)</td>
<td>27.3</td>
<td>27.0</td>
<td>27.1</td>
<td>16.7</td>
<td>31.7</td>
<td>31.7</td>
<td>31.7</td>
<td>31.7</td>
</tr>
<tr>
<td>Negative Articles (% Total)</td>
<td>29.4</td>
<td>37.6</td>
<td>42.6</td>
<td>14.6</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
</tr>
</tbody>
</table>

Predictions

The predicted paths of public opinion from the two models for the incumbent, Mario Cuomo, are displayed in Figure 5.16. The lowess lines for the two models indicate that the predictions for the paths of public opinion are different. The memory-based model remains quite stable during early September, but the predictions begin to fluctuate by mid-September and continue throughout the campaign season until mid-October. This stability is a function of the fact that the primary challenges were being waged during this period and Cuomo faced very little opposition. Pataki's coverage was much greater and more positive during this period as he was successful in his efforts to defeat his primary opposition.

There is a stretch of five days in which the memory-based model predicts support to remain unchanged for Cuomo. This is an interesting finding because the on-line model predicts declining support for Cuomo during this exact time period. Support for Cuomo
is not predicted to change because coverage remains consistently negative. On October 17\textsuperscript{th}, coverage was particularly negative. Polls were released suggesting that Cuomo’s attempts to explain his record for the last twelve years have had little success in dampening the electorate’s discontent with his lengthy tenure. The coverage improves somewhat on October 18\textsuperscript{th}, but remains negative. By October 24\textsuperscript{th}, this negative prediction ends as a result of two separate events. President Clinton arrived in New York to mobilize Democratic voters and raise money for Cuomo’s reelection efforts. Even more significant, was Cuomo’s endorsement by the Republican Mayor of New York City, Rudy Giuliani. After weeks of remaining neutral in this contentious campaign, Giuliani announced that he would be crossing party lines to support the reelection efforts of Governor Cuomo.

Again, public support for Cuomo is predicted to decline in early November and remain stable through Election Day. The predictions for support for Cuomo from the memory-based model remain quite stable after declining from a relative high on November 3\textsuperscript{rd}. Interestingly, the intensity of coverage for Cuomo fluctuates from 4.625 to 0.625 from November 3\textsuperscript{rd} through Election Day. However, this does not lead to fluctuating predictions because the memory-based model also relies on the intensity of Pataki’s and Rosenbaum’s campaign messages to calculate the predictions for support for each candidate. The coverage for Pataki is quite negative during this time period, which yields the spike in support for Cuomo on November 3\textsuperscript{rd}. Because of this extremely negative coverage, Cuomo’s support spiked upward, but after Pataki’s coverage turns toward the positive, Cuomo’s support stabilizes.
By contrast, the on-line model never predicts rapid fluctuation for Mario Cuomo. This is consistent with the predictions for the other candidates examined above. The on-line model’s role for previous information makes rapid shifts in public opinion virtually impossible. The model predicts quite a bit of stability in terms of predicted support until early October when it predicts a steady decline through Election Day. This decline in support corresponds to two changes in coverage. During this time period, there was much more emphasis on the economy and the jobs that had been lost during the Cuomo administration. Further, there was much coverage of the fact that the Governor was having trouble securing support in his own Queens borough. Importantly, Pataki also began to attack Cuomo on the issue that he was least secure on: the death penalty. Many New Yorkers were finding it hard to accept Cuomo’s perceived switch on the death penalty. For years, he had argued that he could not, with a clear conscious, re-instate the death penalty. During the campaign, however, he began to indicate that he would support re-instatement if the public supported it.

An upswing in support is predicted by the on-line model for Cuomo beginning on October 24th that continues through Election Day. This is similar to the memory-based model’s predictions. Coverage becomes much more positive with President Clinton’s visit to New York and Giuliani’s endorsement.
Figure 5.16: Memory-Based and On-Line Models’ Predictions for Cuomo

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Cuomo’s Republican challenger, George Pataki, had to overcome a primary challenge from Richard Rosenbaum, before emerging victorious to face Cuomo in the general election. As a result of his success against Rosenbaum, both models predict positive support for Pataki until at least September 21st as seen in Figure 5.17. After this date, fluctuation in predicted support begins with the memory-based model and the online model begins to predict a downward track of support for Pataki. Focusing first on the memory-based model’s predictions, support for Pataki is predicted to be positive for many of the days of the campaign season. However, there are days predicted to be substantially negative and these predictions pull the lowess line downward. In particular, September 30th, October 14th, and October 24th are predicted to be days of particularly negative support. On September 30th, coverage for Pataki focused on the issues discussed in the campaign and was universally negative towards his issue positions. In particular,
the newspaper coverage focused on the tax cut proposal by Pataki. The discussion concerned the likelihood that Pataki’s plan to cut income taxes would lead the state to cut aid to local governments; this, it was argued, would lead local officials to raise their own property taxes to make up for the loss of state support.

Predicted support becomes more positive after this discussion until October when support is predicted to decline again dramatically. On October 14th, the newspapers again turned to the issues in the campaign and Pataki’s positions were judged in a much more negative light than those of Cuomo. In this case, the discussion concerned Cuomo’s attempts to buy the Long Island Lighting Company. The proposed buyout was an attempt to lower electricity rates for Lilco customers who paid among the highest rates in the country. Further, coverage surrounded Cuomo’s proposals to reduce crime, and a series of editorials criticized Pataki’s misconstrual of an anti-bias law. Again, support is predicted to increase and stabilize for a number of days in October. Recall that this was also a time of stability for Cuomo. The predicted level of support for Pataki is a function of the negative coverage Cuomo received during this period. However, the endorsement by Giuliani and the Clinton visit led to a dramatic decline in support for Pataki by October 24th.

By Election Day, predicted support falls into positive territory. After a few impressive negative dips, Pataki’s predicted level of support skyrockets on November 4th. This results from the fact that on November 1st and 3rd Pataki’s newspaper coverage is more negative than at any other point in the campaign season. On November 1st, Mayor Rudy Giuliani urged other Republicans to support Cuomo’s re-election bid. Further, Pataki reportedly misconstrued the state’s Medicaid policy by claiming that it included
funds for hair replacement. On November 3rd, coverage of the campaign was also negative as a number of articles questioned Pataki's attempt to show the voters who he really is. Even though coverage is still negative on the 4th and continues through Election Day, it is still less negative than on previous days and more positive than Cuomo's coverage; therefore, support is predicted to increase during this period.

Turning to the on-line model's predictions in Figure 5.17, it is obvious that there is much less fluctuation in predicted support for Pataki throughout the campaign season. Public opinion is predicted to take a logarithmic form. Predicted support is positive and relatively stable throughout September, but starts to take a more negative track in late September-early October. The negative tally emerges when Pataki's tax cut plan received heavy criticism from various quarters. The tally continues its negative track over the next week as the newspapers published additional articles critical of Pataki's issue positions. Further, Pataki was continuously questioned about his professional qualifications for the highest office in New York State.

By October 7th, support turns slightly more positive and the negative track is mitigated somewhat for about a week. The first day in this predicted upswing featured a series of articles discussing Pataki's successful fundraising efforts as well as his success in recent polls. Further, one of the newspapers published a series of articles discussing Pataki's issue positions and his experience as state senator and mayor of Peekskill. However, predicted support begins to slope downwards from October 23rd until Election Day. After Giuliani issued his endorsement of Cuomo, predicted support for Pataki enters a freefall and continues to decline with only a slight upswing on November 4th.
Figure 5.17: Memory-Based and On-Line Models' Predictions for Pataki

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

While Pataki handily defeated Rosenbaum, Rosenbaum’s name remained on the ballot as a minor party candidate so I display the predictions each model makes for Rosenbaum throughout the campaign season in Figure 5.18. This is an interesting case for the two models because Rosenbaum was really only a contender for ten days of the campaign season (from September 5 until the Republican primary in mid-September). In general, we would anticipate that support would be predicted to drop off significantly as coverage of Rosenbaum becomes all but extinct by late September. However, this truly only happens for the on-line model. Because the memory-based model relies on the notion of relative intensity, Rosenbaum’s level of support corresponds not only to the intensity of his own campaign, but also to the intensity of his opponent’s campaigns. The lowess line for the memory-based model’s predictions in Figure 5.18 illustrates that the memory-based model actually predicts increasing support for Rosenbaum even though he
was rarely mentioned by either newspaper, and, has a ballot line as a third party candidate. This suggests that the relativity notion might be problematic with third party candidates.

As the newspaper coverage of Rosenbaum dropped off, the on-line model predicts a continuous decline in support for the candidate particularly once he lost the Republican primary in mid-September. The period prior to the Republican primary is interesting because the on-line model predicts very positive support for Rosenbaum. Coverage during this time period tends to be either positive or neutral. Remember that neutral coverage is considered to be positive in my measure of affect as it increases name recognition of a candidate. The negative turn for Rosenbaum is predicted the day before the Republican primary as the articles discussed Rosenbaum’s insurmountable obstacle (namely, George Pataki) in trying to win the primary.

Figure 5.18: Memory-Based and On-Line Models’ Predictions for Rosenbaum

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.
Actual Public Opinion

Turning to the actual public opinion data for these three candidates, I depict the support, in terms of the IEM data, for each candidate in Figure 5.19. In this race, the actual public opinion data begins on September 6th. Throughout the campaign season, Cuomo’s support remained quite high and consistently above Pataki’s until the day before the election when Cuomo’s popularity plummets. While Pataki’s support was more varied, it remained below 0.50. Pataki’s support remained above 0.40 but never reached above 0.50. Rosenbaum received very little support throughout the campaign season particularly after he lost the Republican line to Pataki. He remained on the ballot because he won a third party line, but he did not do well in the election. This is one case in which the IEM data did not correspond well to the end result of the election.

Figure 5.19: Iowa Electronic Market Results for the New York Gubernatorial Race

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.
Comparing the Models' Predictions with Actual Public Opinion

How well do the models predict the course of public opinion for the three candidates presented in Figure 5.19? The first candidate in the New York gubernatorial race to be discussed is the incumbent, Mario Cuomo. Figure 5.20 displays the comparison between the actual course of public opinion and the courses predicted by the on-line and memory-based models.

The actual course of public opinion for Cuomo does not start until September 21st. After this date, support is incredibly stable. There are only very minor increases and decreases throughout the campaign season. Surprisingly, the models do equally well at predicting the direction of these minor increases and decreases and the number of these accurate predictions is relatively high, as I show in the next section (Table 5.8).

After declining on October 10th, the actual course of public opinion remains stable until October 19th. However, the memory-based model predicts substantial deviation in public opinion during this period predicting increases on some days and decreases on others. In fact, the memory-based model predicts an increase in support for Cuomo on October 10th when actual support declined while the on-line model does capture this decrease in support for Governor Cuomo. On this date, much of the coverage focused on Cuomo’s opponent, George Pataki, and the differences between a Pataki administration and a Cuomo administration. Unlike the stability in actual opinion, the on-line model continues to predict additional decreases.

Actual support for Cuomo increases on the 21st and continues to be high until Election Day. This positive change is captured somewhat by each model. The on-line model catches this directional change by the 24th, and by the 28th, the tally reaches
positive territory and stays there until Election Day. The memory-based model catches this changing support by the 23rd, but by the 25th the memory-based model predicts a decline in support diverging from the actual flow of support for Cuomo. The positive change for Cuomo during this period corresponds to coverage of President Clinton’s visit to New York. Further, Giuliani, the Republican mayor of New York City, endorsed Cuomo for re-election during this period.

Figure 5.20: Comparing the Models’ Predictions with Actual Public Opinion—Cuomo

![Graph comparing models' predictions with actual public opinion for Cuomo.]

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

Having defeated Richard Rosenbaum, Pataki must then face the three-term incumbent Mario Cuomo to win the general election contest for governor of New York. Figure 5.21 highlights the accuracy of the two models in predicting the course of public opinion for Pataki during the campaign season.

The comparison between the models’ predictions and actual public opinion for Cuomo in mid-October was interesting, and a similar divergence occurs for Pataki in
mid-October. In this case, the two models predict an increase in public opinion on the 10th while actual public opinion decreases substantially. Actual opinion then remains stable on the 11th and the memory-based model predicts a decrease while the on-line model predicts an increase. On the 12th, both models predict a decrease while actual public opinion increases. By the 13th, actual opinion decreases, but the models predict an increase. This divergence continues on the 14th when the models predict a decrease and actual opinion remains stable. The memory-based model predicts a rebound on the 15th conforming to a slight increase in actual public opinion while the on-line model diverges with a predicted decrease in public opinion.

What was the media covering during this period? As described above, much of the coverage on the 10th focused on the differences between a Pataki administration and a Cuomo administration. On the 11th, media coverage of Pataki was not negative even though the memory-based model predicts a decline in support. The coverage was actually positive, but it was substantially less intense than the previous days, so support is predicted to decline. Because the on-line model does not rely on an intensity measure, each additional piece of information is added to the on-line tally. As a result, the positive coverage of Pataki on this date contributes to an increase in the on-line model’s predictions. The following day, the models converge again to predict a decline in support corresponding, among other reasons, to the endorsement of Cuomo for re-election by a group of 50 ministers representing the most prominent black churches in New York City. The predicted decline on October 14th corresponds to a series of editorials criticizing Pataki’s misconstrual of an anti-bias law. A divergence occurs the very next day as coverage is universally negative, but is less negative than the previous day so the
memory-based model predicts an increase in support. The on-line model is cumulative so yesterday's negative coverage is included along with today's negative coverage in the predictions for today's level of support.

The ability of the models to predict the course of public opinion for Pataki becomes clearer at the end of the campaign season. From mid-October until Election Day, the on-line model predicts a continuous decline in support. In contrast, the memory-based model predicts much more volatile support for Pataki from October until Election Day. Both models perform similarly in predicting actual public opinion during these last few weeks of the campaign season. During the period from October 21st until Election Day, the on-line model accurately predicts thirteen days of support for Pataki while the memory-based model accurately predicts twelve days of support for Pataki.

Figure 5.21: Comparing the Models' Predictions with Actual Public Opinion—Pataki

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.
Republican George Pataki faced a primary challenge from Richard Rosenbaum, but emerged victorious to face Cuomo in the general election. However, Rosenbaum’s name remained on the ballot as a minor party candidate so I will focus on the ability of the models to predict the change in support for Rosenbaum throughout the campaign season.

For this candidate, the models do equally well in predicting the course of public opinion although Figure 5.22 may not make this completely obvious. This is particularly interesting because Figure 5.22 demonstrates the key difference between the two models. The memory-based model proposes that support for a given candidate is a function of the relative flow of campaign messages. What is important is not the absolute coverage of the candidate, but the candidate’s coverage in relation to the other candidates. As a result, the memory-based model predicts volatile support for Rosenbaum even though there are periods of time when Rosenbaum is not mentioned in either of the newspapers. With the on-line model, such a situation is impossible. The on-line tally will not move in either direction if there is no new information about the candidate.

The above discussion explains why the memory-based model does a better job of predicting changes in support while the on-line model does a much better job predicting stability for Rosenbaum. By October 1\textsuperscript{st}, coverage ceases to exist for Rosenbaum and this corresponds to stability in the on-line model from this point until October 27\textsuperscript{th} when a negative article is published. The memory-based model continues to predict changes in public opinion for the month of October based on the coverage of Pataki and Cuomo.

However, early in the campaign season, both models do a good job predicting the significant declines in support for Rosenbaum. In particular, the predictions from the two models and the actual support for Rosenbaum decline on September 14\textsuperscript{th}, the day before
the Republican primary. On this date, coverage of Rosenbaum tended to be particularly negative as the newspapers discussed the impossible feat Rosenbaum faced in attempting to defeat Pataki. Again on the 18th the two models converge with each other and actual public opinion in predicting a decline in support for Rosenbaum. What did the newspapers cover on this date? The two articles published on September 18th were also negative and argued that Rosenbaum’s bid was a losing battle from the start and questioned why he ran in the first place. A final interesting point to discuss occurs on October 27th. On this date, actual public opinion and the prediction from the memory-based model increase while the on-line model predicts a further decline. Recall from the above discussion that this was the day that Giuliani announces his support of Cuomo’s re-election effort. Only one article discussing Rosenbaum was published on this date.

When Rosenbaum ran for the Republican nomination, he also won the nomination of a number of small parties. The article discussed whether Rosenbaum’s loss to Pataki in the Republican primary hurt the chances of these small parties.
Figure 5.22: Comparing the Models’ Predictions with Actual Public Opinion—Rosenbaum

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

In Table 5.8, I outline the tendency of each model to accurately predict the direction of support for the three candidates throughout the campaign season. What are the important conclusions concerning the models’ ability to predict public opinion? Overall, the memory-based model does a much better job than the on-line model at predicting change in support for Cuomo (60 percent to 40 percent). Further, the memory-based model more accurately predicts increases and decreases in support for Cuomo than the on-line model. The ability of the models to accurately predict change in support for Pataki is less distinct. The on-line model accurately predicts more days of change than the memory-based model, but this distinction is driven by the greater performance of the on-line model in predicting increases in support. The two models correctly predict the same number of days of decreasing support for Pataki. The on-line model does abysmally in predicting changes in support for Rosenbaum, but does incredibly well at
predicting stability for Rosenbaum. The on-line model predicts over sixty-five percent of stable days correctly while the memory-based model predicts no stable days for Rosenbaum. Neither model predicts a single day of stability for Cuomo or Pataki.

Table 5.8: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the New York Gubernatorial Race

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cuomo</td>
<td>6</td>
<td>40.0</td>
<td>9</td>
<td>60.0</td>
</tr>
<tr>
<td>Increase</td>
<td>4</td>
<td>50.0</td>
<td>6</td>
<td>75.0</td>
</tr>
<tr>
<td>Decrease</td>
<td>2</td>
<td>28.6</td>
<td>3</td>
<td>42.9</td>
</tr>
<tr>
<td>Stability</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pataki</td>
<td>9</td>
<td>50.0</td>
<td>8</td>
<td>44.4</td>
</tr>
<tr>
<td>Increase</td>
<td>5</td>
<td>50.0</td>
<td>4</td>
<td>40.0</td>
</tr>
<tr>
<td>Decrease</td>
<td>4</td>
<td>50.0</td>
<td>4</td>
<td>50.0</td>
</tr>
<tr>
<td>Stability</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>3</td>
<td>17.7</td>
<td>11</td>
<td>64.7</td>
</tr>
<tr>
<td>Increase</td>
<td>1</td>
<td>11.1</td>
<td>5</td>
<td>55.6</td>
</tr>
<tr>
<td>Decrease</td>
<td>2</td>
<td>25.0</td>
<td>6</td>
<td>75.0</td>
</tr>
<tr>
<td>Stability</td>
<td>31</td>
<td>66.0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Pennsylvania Senate Race: Santorum versus Wofford**

Few remember the way in which the healthcare debate ushered in the Clinton administration and made Democrats admit in 1994 that reform might be impossible, but Pennsylvanians do. Incumbent Senator, Democrat Harris Wofford, turned his 1991 election campaign into a plea for healthcare reform. With the apparent inability of Democrats to put together a healthcare proposal acceptable to enough moderate Republicans to ensure passage, Sen. Wofford, so closely tied to the healthcare debate and President Clinton, was considered one of the most vulnerable Democratic senators in 1994. His opponent, Rick Santorum, a Representative in the U.S. House from Mt. Lebanon, was a darling of the conservative wing of the Republican Party. The two opponents not only differed in ideology, but the two men represented two distinct generations. Wofford was a liberal in the 1960s, government-is-useful vein while
Santorum was a young, conservative, relentlessly driven, professional coming of age in the late 1970s.

Surprising many analysts, one of the most contentious issues in this race was the candidates’ attendance records in Congress. This was a surprising issue because questioning an opponent’s attendance record does not typically bring voters to the polls and this race was ripe for a serious ideological showdown as it pitted a liberal Democratic against a conservative Republican. There were a few key incidents from the campaign that had the potential to alter the outcome. First, Santorum was caught on tape suggesting that he might consider increasing the age at which Americans become eligible for social security benefits. Further, a fundraiser for Santorum, held at a sportsmen’s club, used targets with the phrase “gun owners...let’s target the real problem” and Wofford’s name appearing in the bull’s-eye. Santorum denied his campaign had any part in the development of the targets and denied he knew anything about their use in raising money for his campaign. While bizarre and slightly tasteless, the targets were no match for Teresa Heinz’s remarks about Santorum. In a speech at the University of Pittsburgh, Heinz, wife of former Sen. John Heinz, emphatically condemned Santorum as the “antithesis” of her late husband and a "challenger who is short on public service and even shorter on accomplishments. He is articulate, full of sound bites, overflowing with glib ideology - in short, good TV, good entertainment". In what could have been a critical mistake, Santorum responded to this critique by claiming that Heinz criticized him because she was dating a certain Democratic senator from Massachusetts.

Given such incidents, one might assume that Wofford won re-election with little trouble. In fact, the Republican tide proved too much for an incumbent Senator so
closely tied to President Clinton and the failure to enact health-care reform. Further, Santorum showed the tenacity on the campaign trail that he had displayed in the House by making five or six campaign appearances daily. With a one percent edge, Harris Wofford lost to his challenger, Rick Santorum, after only two years in office.

*Newspaper Coverage*

Table 5.9 displays the amount of newspaper coverage for both candidates as well as the valence of that coverage. The coverage of the candidates from both newspapers was quite comparable; however, the valence of that coverage differed more dramatically. The Philadelphia Inquirer’s coverage of Wofford in terms of headlines tended to be neutral, but the articles tended to be either positive or neutral for Wofford. The Philadelphia Inquirer’s coverage of Santorum tended to be much more negative in terms of articles and headlines. By contrast, the Pittsburgh Post-Gazette covered Wofford more negatively in terms of headlines and articles than the Philadelphia Inquirer. However, this newspaper covered Santorum more positively in both articles and headlines than the Philadelphia Inquirer. Why was there a difference in coverage of Santorum from the two newspapers? This disparity likely stems from the fact that Pittsburgh is the hometown of Santorum.

**Table 5.9: Dispersion of Newspaper Coverage in the Pennsylvania Senate Race**

<table>
<thead>
<tr>
<th></th>
<th>Number of Heads</th>
<th>Positive Heads (% Total)</th>
<th>Negative Heads (% Total)</th>
<th>Number of Articles</th>
<th>Positive Articles (% Total)</th>
<th>Negative Articles (% Total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Philadelphia Inquirer</td>
<td>73</td>
<td>18.4</td>
<td>36.8</td>
<td>192</td>
<td>20.7</td>
<td>46.0</td>
</tr>
<tr>
<td>Santorurn</td>
<td>38</td>
<td>14.3</td>
<td>22.9</td>
<td>87</td>
<td>35.2</td>
<td>30.5</td>
</tr>
<tr>
<td>Wofford</td>
<td>35</td>
<td>14.3</td>
<td>22.9</td>
<td>105</td>
<td>35.2</td>
<td>30.5</td>
</tr>
<tr>
<td>Pittsburgh Post-Gazette</td>
<td>63</td>
<td>46.0</td>
<td>24.3</td>
<td>294</td>
<td>28.5</td>
<td>27.1</td>
</tr>
<tr>
<td>Santorurn</td>
<td>37</td>
<td>46.0</td>
<td>24.3</td>
<td>144</td>
<td>28.5</td>
<td>27.1</td>
</tr>
<tr>
<td>Wofford</td>
<td>26</td>
<td>23.1</td>
<td>30.8</td>
<td>150</td>
<td>28.7</td>
<td>31.3</td>
</tr>
</tbody>
</table>
**Predictions**

Figure 5.23 and 5.24 display the predicted paths of public opinion for the two candidates in the Pennsylvania Senate Race. Starting with the incumbent, Harris Wofford, the two models predict divergent paths. The on-line model predicts support for Wofford to increase steadily throughout the campaign season with only minor reversions. In contrast, the memory-based model predicts much more fluctuation and many more negative shifts in support. In particular, the memory-based model predicts a slight increase in support on September 26th, but then a dramatic decrease in support the very next day. Both models capture this decrease in support on September 27th, but the on-line model’s prediction is not as dramatic as the memory-based model. Remember that the on-line model has a previous tally to which the negative coverage is added. As a result, the on-line model does not predict such a dramatic decrease in support, but only a slight decrease. On this particular day, the newspaper coverage included a discussion of a recent television ad by Wofford focusing on Santorum’s lack of attendance in committee hearings. The ad claimed that Santorum was too busy campaigning to attend his House duties. However, the newspaper articles argued that the facts of this ad were misleading. Further, Wofford was criticized for attacking Santorum on something he did himself in his previous election. The conclusion of one article was: “Wofford's ads take nuggets of truth and weave them into an out-of-context portrayal of Santorum's attendance record and fund raising” (Pittsburgh Post-Gazette, September 27, 1994). Coverage also concerned the inability of Congress to pass comprehensive health care reform and Wofford’s particular role in that failure. Wofford was proposing a series of small
reforms for which there was majority support, but the newspapers reported that there was no indication that the leadership of either party would support Wofford's proposals.

Predicted support from the memory-based model for Wofford remains somewhat static throughout much of October until a series of spikes, both positive and negative, occur in late October. On October 28th, support for Wofford is predicted to increase dramatically. Remember that support for a given candidate in the memory-based model is also a function of the relative coverage of the two candidates. In this case, Wofford's predicted support increases dramatically when Teresa Heinz criticized Santorum. In a speech at the University of Pittsburgh, Teresa Heinz called Santorum "short on public service even shorter on accomplishments" and "the antithesis of John Heinz", her late husband. She also referred to Wofford as "a dignified, noble human being". While Heinz stopped short of endorsing him, predicted support for Wofford increases in response to her words. When Santorum responds by attacking Heinz's personal life, predicted support for Wofford increases further.

The predicted support for Wofford emerging from the memory-based model fluctuates for the next six days, but on November 6th support is predicted to increase dramatically. What produces such a predicted increase? On this date, the Pittsburgh Post-Gazette endorsed Harris Wofford for re-election arguing that he combined experience in and out of government with personal characteristics that his opponent could not rival. The Philadelphia Inquirer also chose to endorse Wofford for re-election citing his continued efforts on healthcare reform and his support for the national service law, economic reforms, the crime bill, and the family-leave act.
Turning to the on-line model, the predictions remain negative for Wofford until October 18th. On this date, predicted support for Wofford enters positive territory and remains so until the election. There is a slight dip on October 25th, but support then increases steadily for the next five days and remains high until Election Day. Remember that Teresa Heinz’s comments concerning Santorum were issued in late October. Santorum’s response to her comments was considered to be very negative by the press. Wofford received a spike in positive coverage at the same time that Teresa Heinz issued her condemning statements about Santorum. As such, the negative coverage increased dramatically for Santorum during this time period. Support is predicted to continue to increase throughout the remaining days of the campaign season. This is an interesting case in that Wofford’s tally is triple the value of Santorum’s tally yet Santorum wins the election. Why? This was one of the races in which one might easily argue that the victor, Santorum, benefited from the national Republican tide that swept incumbent Democrats out of office. One might tentatively propose that the two models fail to consider the national landscape in which the two candidates find themselves.
Figure 5.23: Memory-Based and On-Line Models’ Predictions for Wofford

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

In this race, Wofford, the champion of health care reform, faced, and fell victim to, a darling of the conservative wing of the Republican Party in a state that had become a key battleground for Republicans and Democrats. How well do the two models compare in their predictions for Santorum? The predictions for Rick Santorum from the on-line model display more variance than the predictions the model makes for all other candidates. In contrast, the predicted support for Wofford does not vary as dramatically throughout the campaign season. This is most likely due to Wofford’s positive coverage just prior to the start of the campaign season. The fluctuations begin very early on in the campaign season with a slight increase and then decrease in predicted support for Santorum. In the description of the case, I mentioned a mistake by the Santorum campaign: the shooting targets bearing Wofford’s name. The coverage for Wofford was much more positive concerning the situation than it was for Santorum. Santorum
received a decrease in positive coverage resulting in a decrease in the model’s predicted opinion on this date.

In contrast, the memory-based model predicts stability in support for Santorum until a sharp increase on September 27th. This corresponds to a dramatic decrease in support for Wofford with the newspapers’ negative analysis of a Wofford campaign ad. An editorial was also published suggesting that Wofford ought to consider focusing more on substantive issues and answer questions concerning failed efforts at healthcare reform.

The models deviate in their predictions for Santorum in late October with the comments by Teresa Heinz. The newspapers reported the incident on October 28th and 29th. The memory-based model predicts a large decline in support on the 28th followed by a slightly less negative level of support on the 29th. The on-line model predicts the opposite situation. A decrease is predicted on the 28th followed by an additional decrease on the 29th when Santorum responded to Heinz’s comments. Both models also capture the rebound in public opinion the very next day. Following Teresa Heinz’s announcement, polling data was released indicating Santorum’s level of support had increased across the state. Further, the Christian Coalition stepped up its involvement in the race by endorsing Santorum, Senator Phil Gramm endorsed Santorum, and a number of positive editorials were published.

Both models decrease their predicted support for Santorum on November 6th in response to the endorsements of his opponent by the two newspapers. Given that the on-line predictions rely on a previous tally, the decrease is only a slight decrease. The memory-based model, in contrast, predicts a much more dramatic decline in support for Santorum in response to the endorsements.
Figure 5.24: Memory-Based and On-Line Models’ Predictions for Santorum

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Actual Public Opinion

The actual paths of support for the candidates in the Pennsylvania Senate race are displayed in Figure 5.25. The IEM data for this race began on September 22nd. An immediately evident feature of this graph is the steep spike in support for Santorum at the beginning of October. From examining the data, I would caution placing too much importance on this spike as it lasted only a day and then Santorum’s support returned to the pre-spike position. Santorum’s support remained relatively consistent after this early spike, as did Wofford’s support. However, the election ended with Wofford’s support in the negative region and Santorum’s just slightly positive.
Figure 5.25: Iowa Electronic Market Results for the Pennsylvania Senate Race

![Graph showing the price data for Wofford and Santorum with dates from 21 Sep 1994 to 06 Nov 1994.]

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

Comparing the Models’ Predictions with Actual Public Opinion

I graph the predictions each model makes for the course of public opinion for Harris Wofford and Rick Santorum in the Pennsylvania Senate race in Figures 5.26 and 5.27. In this senate race, the incumbent Democrat Wofford was closely associated with President Clinton during a campaign season in which Democrats were actively running away from the president. This is an interesting case because the on-line model does substantially better in predicting support for both candidates as is demonstrated in the next section.

In Figure 5.26, I compare the predictions the on-line and memory-based models make for Harris Wofford to the actual support Wofford receives throughout the campaign season. An obvious observation from these graphs is that actual support for Wofford is incredibly stable with only a few changes throughout the campaign season. One of these changes occurs early in the campaign season on September 28th as actual public opinion...
is predicted to increase. Both models capture this increase in public opinion. When public opinion falls on October 2\textsuperscript{nd}, the models also capture this decrease.

The above discussion suggests that the models accurately predict the course of support for Wofford, but there are multiple points when the models fail to accurately predict public opinion. In particular, public opinion for Wofford remains constant until the end of October after increasing on October 4\textsuperscript{th}. The models accurately capture this increase, but they do not predict stability for the remainder of October. The on-line model certainly does not predict much volatility at any point in the campaign season, but public opinion is predicted to fluctuate for the first two weeks of October. After this fluctuation, support for Wofford becomes more stable, only increasing slightly each day. However, this continuous increase in support for Wofford does not correspond to the actual support for Wofford. Wofford’s support remains quite high until late October when it begins to decline quite rapidly. The memory-based model by contrast predicts fluctuations throughout October, but only slight fluctuations. Interestingly, during the last week of the campaign season, the memory-based model predicts support for Wofford to fluctuate rapidly.
Figure 5.26: Comparing the Models’ Predictions with Actual Public Opinion—Wofford

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

The Pennsylvania Senate race in 1994 also featured an incumbent representative, Rick Santorum. This was one of the races in which one might easily argue that the victor, Santorum, benefited from the national Republican tide that swept incumbent Democrats out of office because the newspaper coverage of this candidate was not overwhelmingly positive. How well do the models predict the path of Santorum’s victory?

Turning to Figure 5.27, the memory-based model has difficulty predicting changes increases or decreases in support for Santorum. In the lower panel, the on-line model’s predictions for change are graphed alongside the actual changes in public opinion. The on-line model is able to predict a few more directional points than the memory-based model. Let’s look at a few of those points. An obvious increase in public opinion occurs on October 4th. Recall from the discussion of Wofford, this was a day when public
opinion for Wofford also increased. The reliance in the memory-based model on a relative flow of campaign information makes it impossible for the memory-based model to predict an increase for both candidates; instead, the model predicts an increase for Wofford and a decrease for Santorum. By contrast the on-line model can predict dual increases in support, but in this case the model also predicts a decrease for Santorum. The coverage on this date concerned protests by activists from the Philadelphia chapter of Act Up. These activists were protesting Rick Santorum’s lack of support of legislation advancing gay and lesbian rights. As a result, the on-line model predicts a decline in support for Santorum on this date.

The models do diverge in terms of the accuracy of their predictions late in the campaign season. On October 29th, actual public opinion declines and so does the prediction from the on-line model. In contrast, the memory-based model predicts an increase on this date. This increase in predicted support is interesting because this is the date that the newspapers reported the remarks made by Teresa Heinz criticizing Santorum as someone whose motivations and personality were at odds with those of her late husband.

By the 31st, actual public opinion rebounds, as does the on-line model’s prediction of support for Santorum. Once again, the memory-based model diverges in that it predicts a decrease in support. Following Teresa Heinz’s announcement, polling data was released indicating Santorum’s level of support had increased across the state. Further, the Christian Coalition stepped up its involvement in the race by endorsing Santorum, Senator Phil Gramm endorsed Santorum, and a number of positive editorials were published.
Figure 5.27: Comparing the Models’ Predictions with Actual Public Opinion—Santorum

Note: These two panels are the comparison between the predicted paths of public opinion for the on-line and memory-based models and the actual path of public opinion in terms of z-scores.

In this Pennsylvania Senate race, both models do a good job predicting changes in public opinion, but fail to accurately predict the days of stability in public opinion as evidenced in Table 5.10. The on-line model does a slightly better job predicting stable public opinion for both candidates (~5 percent to ~3 percent for Wofford, and ~10 percent to ~2 percent for Santorum). Throughout the campaign season, Harris Wofford’s level of public opinion is much more stable than it is volatile, but the models do a poor job predicting that stability. The models are capable of predicting all four increases in public opinion, but do much worse predicting decreases in public opinion for Harris Wofford.

The models diverge substantially in their overall ability to accurately predict the course of public opinion for the Republican candidate, Rick Santorum. The on-line model correctly anticipates over seventy percent of the changes throughout the campaign season.
while the memory-based model falls short at accurately predicting only forty-three percent. For Santorum, the on-line model produces accurate predictions seventy-five percent of the time when public support is heading in a positive direction and almost sixty-seven percent when public opinion is declining. The memory-based model predicts half of the increases in public opinion, but the model can only predict a third of the decreases in public opinion.

**Table 5.10: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Pennsylvania Senate Race**

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wofford</td>
<td>5</td>
<td>55.6</td>
<td>6</td>
<td>66.7</td>
</tr>
<tr>
<td>Increase</td>
<td>4</td>
<td>100.0</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>Decrease</td>
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<td>20.0</td>
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<td>40.0</td>
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<td>Stability</td>
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<td>2.56</td>
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<tr>
<td>Santorum</td>
<td>5</td>
<td>71.4</td>
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<td>42.9</td>
</tr>
<tr>
<td>Increase</td>
<td>3</td>
<td>75.0</td>
<td>2</td>
<td>50.0</td>
</tr>
<tr>
<td>Decrease</td>
<td>2</td>
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<tr>
<td>Stability</td>
<td>4</td>
<td>9.76</td>
<td>1</td>
<td>2.44</td>
</tr>
</tbody>
</table>

**Texas Gubernatorial Race: Bush versus Richards**

Also in 1994, the two sons of former President George Bush ran for governor in Texas and Florida. George W. Bush ran against the darling of the Democratic Party, incumbent Texas governor, Ann Richards. Known for her sense of humor and distinctive hairdo, Ann Richards began the 1994 campaign season with high favorability ratings, a growing economy, and a decline in crime. George W. Bush was known in Texas for being the son of the former president and being an owner of the Texas Rangers baseball team, but his lack of experience in public office led many to predict a Richards’ victory.

A series of gaffes provided comedians across the country with fodder for their stand-up routines. At the time, candidates interested in holding statewide office in Texas found it useful to portray themselves as avid hunters. Dove season opened in Texas in time for
both candidates to take their first shot at each other. To avoid any dangerous mishaps, Richards, posing for reporters with her gun, shot into the air. Bush, not so cautious, took aim at what he perceived was a dove. Unfortunately for Bush, he shot a killdeer (or killdee) a protected bird in Texas. Richards, not to be outdone by Bush’s gaffe, engaged in a few of her own. In speaking to a group of teenage girls, Richards encouraged the girls to be prepared if life does not turn out the way they expect, warning that marriage can end in a disaster as their Prince Charming might have “a beer gut and a wandering eye”. Conservatives throughout the state chided her for offering such “anti-marriage” rhetoric to teenage girls. On a different occasion, Richards referred to Bush as “some jerk” for criticizing the state of education in Texas.

In a very tight race, Bush was able to capitalize on such gaffes and emerge victorious with fifty-three percent of the vote. Most observers of the election concluded that the Bush victory resulted from Bush’s clearly articulated message that Texas was being led in the wrong direction and only he could lead Texas in the right direction. While Richards’ first term was successful by many counts, she failed to provide a vision for the future of Texas and relied too often on her previous experience and accomplishments. Further, she focused much attention in the campaign on what she perceived as the failed business experience of George W. Bush. Bush, for the most part, kept his arguments to the issues facing Texans and capitalized on the growing and violent nature of juvenile crime in Texas.

Newspaper Coverage

Once again, being the incumbent proved useful in terms of the amount of newspaper coverage Richards received in this campaign versus the amount of coverage of the non-
incumbent Bush. Interestingly, there was little disparity between the newspapers in terms of which candidate received the most coverage in terms of headlines and articles. Both newspapers covered Richards to a greater extent than Bush; however, the valence of that coverage did differ. The Dallas Morning News tended to publish many more neutral headlines and articles about both candidates although the articles concerning Richards tended to be more negative than positive. In contrast, the Houston Chronicle published twice as many negative articles and headlines than positive headlines and articles concerning Richards. This newspaper also published more negative headlines than positive headlines about Bush, but the article coverage tended to be equivalent in terms of negative or positive valence of the articles.

| Table 5.11: Dispersion of Newspaper Coverage in the Texas Gubernatorial Race |
|---------------------------------|----------------|----------------|-----------------|----------------|----------------|----------------|
|                                 | Number of Headlines | Positive Headlines (% Total) | Negative Headlines (% Total) | Number of Articles | Positive Articles (% Total) | Negative Articles (% Total) |
| Dallas Morning News             | 325              | 22.2           | 29.9           | 792            | 21.7          | 18.5          |
| Bush                            | 144              | 22.2           | 29.9           | 351            | 21.7          | 18.5          |
| Richards                        | 181              | 23.2           | 26.0           | 441            | 22.2          | 28.6          |
| Houston Chronicle               | 219              | 17.2           | 38.7           | 709            | 27.0          | 28.0          |
| Bush                            | 93               | 17.2           | 38.7           | 318            | 27.0          | 28.0          |
| Richards                        | 126              | 19.1           | 46.8           | 391            | 19.2          | 42.7          |

Predictions

The incumbent Ann Richards faced a formidable challenge from her Republican opponent. The on-line model’s predictions and the memory-based model’s predictions for Ann Richards appear in Figure 5.28 and for George W. Bush in Figure 5.29. The memory-based model’s predictions are particularly interesting in the Texas gubernatorial race. The days predicted to be extremely negative for Ann Richards are predicted to be extremely positive for George W. Bush, and vice versa. In the other races, this
sometimes occurs, but never to the extent that it occurs in this race. I will discuss the precipitous declines and upswings for the two candidates predicted by the memory-based model simultaneously. The predictions from the on-line model do not follow such a pattern, so I will continue to discuss the predictions from this model for the candidates separately.

Starting with the dramatic negative predictions for Richards (or, the dramatic positive predictions for Bush), May 1st is a day when much of the coverage is focused on Governor Richards. In particular, ten articles were published from the two newspapers used in this study. However, the coverage for Bush in these articles is neutral explaining in part the positive upswing for Bush on this date. Many of the articles are also neutral for Richards, but there are three articles published that are particularly negative. These articles focused on what critics have argued are Richards’s shortcomings—she is long on style but short on substance. Many fault her for not taking any risks by pursuing innovative or controversial programs. This criticism is not restricted to May 1st, but is something the Richards campaign must deal with throughout the campaign season. An additional article pleaded for more than just rhetoric surrounding juvenile crime and education and criticized the Richards administration for the lack of programs aimed at reducing juvenile crime and improving education. Finally, the governor’s promises to reduce insurance rates on cars and homes when she ran for governor in 1990 were evaluated to determine if they had been achieved. Unfortunately for Richards, the evidence was not promising. This negative coverage of Richards assists in raising the predicted level of public opinion for George W. Bush. Remember the memory-based model relies heavily on the notion of a relative flow of campaign information.
Not only does George W. Bush benefit from negative coverage of Governor Richards, but Richards also receives a bump in her predicted level of support when Bush's support is predicted to decline in late July. From July 29th through the 31st, newspaper coverage for Richards was either neutral or positive. The positive articles focused on Richards' effort to bring the Hollywood film industry to Texas and the reduction in the crime rate during Richards' administration. For Bush, no positive articles were published on these dates, but three negative articles were published. All three articles focused on Bush's business relationship with Richard E. Rainwater, an individual whose company has invested in a casino and gambling machine company. This was controversial because Mr. Rainwater had been pressuring the state to lift the ban on casinos and gambling. The Richards camp argued that this was a conflict of interest.

At the end of August, the tables turn and Bush's support is predicted to increase while Richards' support is predicted to decrease. On August 31st, coverage for Richards was universally negative with articles highlighting demeaning ads prepared for the Richards campaign in which she referred to her opponent as "that young Bush boy". Also, new polling data was released indicating that the race was a virtual tie and highlighting the vulnerability of the incumbent.

However, this coverage turns more negative for Bush on September 1st. These articles focused on a lawsuit in which Bush was named as a party. In this lawsuit, individuals owning property surrounding the Texas Rangers stadium sued the Texas Rangers managing partners. The case argued that the owners conspired with their law firm to negotiate a lower price for the property and conspired to have the city condemn the property for private use. There was no positive coverage for Richards on this date,
but the negative coverage for Bush led to a predicted decrease for Bush and a predicted increase for Richards from the memory-based model.

Turning to the on-line model's predictions for Governor Richards in Figure 5.17, an interesting pattern emerges. The on-line model predicts relatively stable support for the incumbent throughout the race. The most negative support occurs in late-April, early May. What happened in the campaign during this time period that led to a predicted decrease in support from the on-line model? This week of negative support predicted by the on-line model corresponds to a week of negative substantive coverage for the governor, particularly with respect to her job performance. The first in a series of articles focused on the promise by Richards that she would lower insurance rates if elected in 1990, but car and home insurance were reported to be higher now than when Richards took office. Not only did Richards promise insurance reform, but a series of articles criticized Richards' lack of action on teacher pay raises she also promised in her 1990 campaign. The governor also faced a number of criminal justice criticisms coupled with the endorsement of her opponent by the Dallas County Sheriff. He argued that Bush would be best able to handle the jail overcrowding issue since the governor's administration had waited until recently to do anything to alleviate county jail overcrowding. While the governor oversaw a crime rate drop in Texas during her administration, reports concerning crime among juveniles had the potential to be Richards' albatross. The Bush campaign seized upon this issue and Richards could do little to mitigate it because juvenile crime, particularly violent crime, had increased during her tenure. Richards also faced harsh criticism over a series of Washington fundraisers, particularly one that President Clinton attended. Republicans argued that she
held Washington fundraisers because she was afraid to bring Clinton to Texas. One of the articles summed up the chorus of the negative coverage: Richards’ “record is long on style and short on substance”.

The most positive time period predicted for Governor Richards by the on-line model stretches from August 11 through August 18th. During this time period, Richards ran a series of “positive” campaign advertisements aimed at increasing support in East Texas. The newspapers covered these advertisements in a positive way leading to a correspondence between newspaper coverage and the positive change predicted by the on-line model. Richards also visited a Lancaster tornado victim and helped replace the young boy’s special computer that had been destroyed by the tornado. This positive tenor continued with Governor Richard’s speech at the funeral of one of Texas’ most well known voting rights activists. Further, the Texas Secretary of State, Ron Kirk, encouraged African Americans to turn out and vote for Richards. The only negative publicity during this time came when her opponent tried to criticize the governor for a failed multimillion-dollar juvenile detention center project, but the governor’s campaign cited evidence that one of Bush’s own business partners approved construction on the jail. However, towards the end of that week, Richards’ positive coverage began to decline as she likened her opponent to “some jerk” for his critique of education in Texas. This comment received much publicity and marked the beginning of a decline in predicted support for Richards.
Figure 5.28: Memory-Based and On-Line Models' Predictions for Richards

![Graph showing Memory-Based and On-Line models' predictions for Richards.]

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

In 1994, incumbent Governor Ann Richards faced non-incumbent George W. Bush in her first re-election campaign. A few missteps and a lack of a plan for the future of Texas by Richards made it a competitive race and George W. Bush became the governor of Texas in November 1994. What predictions does the on-line model make for the course of public opinion for Bush during this campaign? The low point for Bush according to the on-line model should be in early to mid-September. In early September, Bush made a Texas-sized error; he accidentally shot a protected bird while posing for photographs on the opening day of dove season. This predictably led to quite a bit of coverage, particularly in the editorial section of the newspapers. Another editorial focused on Bush's latest campaign advertisement concerning crime in Texas. The claim in the ad is that crime has actually increased in Texas, but the reality was that the crime rate was down in Texas. On a personal note, individuals owning property surrounding
The Ballpark in Arlington sued the Texas Ranger's managing general partner, and other team affiliates, for conspiring to illegally obtain the land. The argument was that the law firm representing the property owners worked with the Rangers to drive down the land and coerced officials to condemn the land for private use. At the same time, the owners of the Texas Rangers as well as the ballplayers received negative publicity concerning the ongoing baseball strike. Finally, a third party candidate criticized Bush for allowing the Texas Rangers to use taxpayer money to finance The Ballpark in Arlington.

Consistent with the election results, the on-line model predicts a precipitous increase in support for Bush after this low point in mid-September. From this point until Election Day, Bush's on-line tally continues to increase and reaches its height the last week of October and the first week in November. One of the newspapers in the sample, the Dallas Morning News, endorsed George W. Bush for governor. This contributes to the upswing in support predicted for Bush in early November. The slight decline apparent in the graph results from Bush's criticism of a few of Richards' appointments. One particular criticism, that of Lena Guerrero, reportedly angered members the Hispanic community. Lena Guerrero resigned as chairwoman of the Texas Railroad Commission in 1992 after evidence emerged that she had misstated her educational background. However, Bush's coverage rebounded again when a series of editorials discussed Bush's refusal to respond to Richards' personal attacks and focus the debate on the issues. Finally, the newspapers reported that Bush had a slight advantage over Richards in a statewide poll released the day before the election.
Figure 5.29: Memory-Based and On-Line Models' Predictions for Bush

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

*Actual Public Opinion*

The actual public opinion data corresponds well to the case description as displayed in Figure 5.30. The IEM data for this race begins on April 29, 1994. Through the end of July, the race was quite close in terms of the support each candidate received. At the end of July and the beginning of August, both candidates' support declined dramatically, but rebounded by October. After mid-October, Bush's support continued to increase while Richards' support showed much more variance until a few days before the election. The end price for the candidates corresponded quite well to the election results with Bush receiving 0.574 and Richards receiving 0.462.
Figure 5.30: Iowa Electronic Market Results for the Texas Gubernatorial Race

![Graph showing Richards and Bush's market results with price on the y-axis and dates from April 1994 to November 1994 on the x-axis.]

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

Comparing the Models’ Predictions with Actual Public Opinion

How well do the two models predict the actual course of public opinion depicted in the previous section? The last three races—the Texas Gubernatorial race, the Utah Congressional race, and the Virginia Senate race—are races for which the public opinion data start in at least April (in the last two cases, the data starts in January 1994) and extends through November 1994. I collect newspaper coverage to follow this lengthy campaign season. As one might anticipate, this leads to 194 candidate-days in the case of Texas, 276 candidate-days in the case of Utah, and 300 candidate-days in the case of Virginia. Comparing the models’ predictions with the actual course of public opinion in a graphical sense would make it difficult to distinguish when the models are accurately predicting public opinion and when the models are diverging from actual public opinion.
Instead of presenting the graphs for each candidate, I will proceed directly to the table highlighting the ability of the model to accurately predict stability and the direction of changes in public opinion. I will then discuss a few points in the campaign season in which the models accurately predict public opinion.

While political pundits predicted the election night results to be quite close, the actual support for the two candidates was much more disparate. In Table 5.12, I compare the predictions the two models make for Richards and Bush to the actual path of public opinion. The on-line model does not perform as well as the memory-based model in terms of predicting changes in support for the two candidates, but the on-line model does more accurately predict stability in public opinion for the candidates. The on-line model correctly predicts over forty-seven percent of changes for Richards while the memory-based model correctly predicts fifty percent of the changes in support for Richards. The on-line model does equally well predicting increases and decreases in support for Richards. In contrast, the memory-based model overwhelmingly predicts declines in support (sixty-three percent) for Richards, but does less well predicting increases (thirty-five percent). The ability of the memory-based model to accurately predict support increases with Bush. Interestingly, the on-line model does a much better job predicting downturns in public opinion for Bush while the memory-based model more accurately predicts upswings for Bush.
Table 5.12: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Texas Gubernatorial Race

<table>
<thead>
<tr>
<th>Model</th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Richards</td>
<td>17</td>
<td>47.2</td>
<td>18</td>
<td>50.0</td>
</tr>
<tr>
<td>Increase</td>
<td>8</td>
<td>47.1</td>
<td>6</td>
<td>35.3</td>
</tr>
<tr>
<td>Decrease</td>
<td>9</td>
<td>47.4</td>
<td>12</td>
<td>63.2</td>
</tr>
<tr>
<td>Stability</td>
<td>16</td>
<td>10.1</td>
<td>12</td>
<td>7.59</td>
</tr>
<tr>
<td>Bush</td>
<td>14</td>
<td>43.8</td>
<td>17</td>
<td>53.1</td>
</tr>
<tr>
<td>Increase</td>
<td>7</td>
<td>38.9</td>
<td>10</td>
<td>55.6</td>
</tr>
<tr>
<td>Decrease</td>
<td>7</td>
<td>50.0</td>
<td>7</td>
<td>50.0</td>
</tr>
<tr>
<td>Stability</td>
<td>28</td>
<td>17.3</td>
<td>10</td>
<td>6.17</td>
</tr>
</tbody>
</table>

Throughout the campaign season, the models converge and diverge with the actual course of public opinion during the 1994 Texas Gubernatorial race. Starting with the models ability to accurately predict declines in public opinion, the on-line and memory-based models accurately predict retrenchment of support for Richards on May 18th. On this date, there was one article published about the campaign. In this article, Governor Richards was criticized for lacking a statewide economic development plan, and the article cited a State Auditor's report that questioned whether the state effectively invested $216 million in the previous year to increase business development.

The models also accurately predict various decreases in support for Bush. Not only did coverage of George W. Bush decline on May 26th, the coverage that did exist was universally negative. In particular, an editorial was published urging voters to avoid voting for another Bush. A different editorial questioned whether Bush, the baseball owner, should be entrusted with the state government if he was incapable of running a decent baseball team.

There are also a number of points during the campaign season when the models accurately predict upswings in public opinion for the two candidates. For example, the models predict that Governor Richards will increase her level of support at the end of
summer (August 11th through 12th). What was happening during these points in the campaign season that might contribute to this increase in predicted support for Governor Richards? The articles that mentioned Governor Richards (5) eclipsed those that mentioned George W. Bush (2) on August 11th through 12th leading to an increase for Governor Richards during this time period. During this time period, Richards also ran a series of “positive” campaign advertisements aimed at increasing support in East Texas. The newspapers covered these advertisements in a positive way leading to a correspondence between the actual positive change in public opinion and the positive change predicted by the on-line model.

The models also accurately predict an increase in support for Bush on September 9th. An interesting observation from this graph is that much of the increase in support or coverage follows a time-period of negative support or negligible coverage. During the week prior to September 9th, Bush accidentally shot a protected bird while posing for photographs on the opening day of dove season. This predictably led to quite a bit of coverage, particularly in the editorial section of the newspapers. While coverage on September 9th was not particularly positive, it was much less negative than the previous week.

The above discussion suggests that the models do a great job predicting support for the two candidates; however, Table 5.12 suggests that there are a number of days when the models mispredict changes in support for the candidates. In particular, the memory-based model predicts a decline in support for Richards on July 16th corresponding to an actual decline on July 16th. In contrast, the on-line model predicts an increase for Richards on this date. Interestingly, coverage for Richards was positive on this date.
However, the decline in support predicted by the memory-based model likely stems from the fact that the intensity of Bush’s coverage is identical to Richards. When this happens, the memory-based model relies on the static components of the model to drive the predicted level of support. The partisanship of Texas tends to be Republican during this time. As a result, Bush is predicted to have a higher static level of support than Richards; therefore, the memory-based model predicts a decline in support for Richards on this date.

The memory-based model also diverges from actual public opinion on a number of occasions. In particular, the memory-based model predicts an increase in support for Bush at the beginning of August, yet actual public opinion and the on-line model predict a decline in support for Bush on this date. At the beginning of August 1994, news surfaced indicating that one of Bush’s partners, a Fort Worth multimillionaire, was working to legalize casino gambling in Texas. The gambling issue appeared to be a non-issue prior to this information given that both candidates opposed the idea. The negative publicity from this discovery was probably a contributing factor to Bush’s decline in support at the beginning of August. The divergence likely occurs because coverage of Richards was also negative on this date, and the coverage was more negative than Bush’s coverage. Because of the relativity notion inherent in the memory-based model, the model predicts an increase for Bush corresponding to his less negative coverage.

**Utah Congressional Race: Cook versus Shepherd versus Waldholtz**

The penultimate case is the 1994 congressional race between Independent Merrill Cook, Democrat Karen Shepherd, and Republican Enid Greene-Waldholtz for the 2nd congressional district in Utah. Karen Shepherd was the incumbent in this race, a
freshman congresswoman from this Salt Lake county district. A businesswoman, Shepherd ran and won a Utah Senate seat in 1990 before running and winning the 2nd district congressional seat in 1992. Running against Shepherd in 1992, and again in this election year, was the Republican, Enid Greene-Waldholtz. Greene-Waldholtz ran on a very simple theme—that she could better represent the 2nd District’s conservative voters. Perennial candidate, Independent Merrill Cook, rounded out the general election field of candidates as he competed in his sixth campaign in under a decade. Cook’s congressional bid was coupled with his sponsorship of Initiative A, a ballot proposition aimed at limiting the terms of public officials in Utah and establishing runoff elections for general elections in which no candidate garnered more than 50 percent of the vote.

This was an extremely close race and the choice for the vast majority of voters was between Shepherd and Greene-Waldholtz. Cook lost much credibility during the campaign when it was made apparent to the public that his candidacy would be the most likely campaign to benefit from Initiative A (because of the runoff provision). Further, a group of current officeholders launched a direct assault on the term limits portion of his initiative. Like many of the previous races, Greene-Waldholtz successfully linked Shepherd to the unpopular democratic president even though Shepherd tried to distinguish her record from that of President Clinton. In what was touted as a must win for the Republicans to gain control of the House, Greene-Waldholtz captured forty-six percent of the vote to Shepherd’s thirty-six percent. Independent Merrill Cook was able to garner eighteen percent of the vote, but lost his term limits initiative thereby securing the seat for Greene-Waldholtz.
Newspaper Coverage

In this race, the coverage corresponded quite well to the above description. The race involved an incumbent officeholder, a challenger without previous public office experience, and an independent coupling his congressional race with a ballot initiative. Based on this description, I would expect the coverage for the incumbent, Shepherd, to be greater than that for the other two challengers. Further, I would also expect Independent Cook to receive more coverage, given his ballot initiative, than the Republican challenger. This was indeed the case as displayed in Table 5.13. Shepherd received twice the coverage in terms of headlines than Cook and over three times the coverage of Waldholtz. The disparity between the coverage of Cook and Waldholtz was narrower in terms of articles, and the newspaper published two hundred additional articles only mentioning Shepherd. Turning to the valence of that coverage, Shepherd tended to receive slightly more positive coverage in terms of headlines and articles than she did negative coverage. Similarly, the coverage of Waldholtz also tended to be positive. In contrast, the newspaper’s coverage of Cook was twice as negative as it was positive in terms of articles and headlines.

Given that incumbent Karen Shepherd lost her bid for re-election, it is interesting that her coverage by this newspaper was greater than the combined coverage of her two opponents. For a freshman representative, Shepherd was unusually active during her first session in Congress. Such activity corresponded to the amount of coverage she received before the other candidates received any coverage. This may be a case of no news was good news as Waldholtz won the election with the least amount of newspaper coverage. While Shepherd received the most coverage (given her incumbency), the coverage was
not necessarily positive throughout the time period. In fact, even with the tendency for incumbents to receive neutral coverage, Shepherd still did not eclipse Enid Greene-Waldholtz in positive coverage. Both major party candidates received much more positive coverage than the Independent Merrill Cook. An interesting facet of this coverage was the paucity of coverage for both Cook and Greene-Waldholtz prior to the fall campaign.

<table>
<thead>
<tr>
<th>Table 5.13: Dispersion of Newspaper Coverage in the Utah Congressional Race</th>
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</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Deseret News</td>
</tr>
<tr>
<td>Cook</td>
</tr>
<tr>
<td>Shepherd</td>
</tr>
</tbody>
</table>

**Predictions**

What do the models predict the paths of public opinion to be for these three candidates? In Figure 5.31, I plot the predictions for Shepherd emerging from the formalization of the memory-based and on-line models. Starting with the memory-based model, the model predicts a number of days with very negative levels of public opinion. The first precipitous decline in public opinion is predicted on March 18th. On this date there were three negative articles and only a single neutral article highlighting the incumbent. One of the negative articles focused on Shepherd's lack of qualms concerning land reform proposals supported by the Secretary of the Interior, Bruce Babbitt, amidst criticism from the entire Utahan delegation. A further article mentioned that Shepherd was facing much trouble in attempting to win re-election. The final article focused on Shepherd's support for a failed balanced-budget amendment to the Constitution.
In late October, the memory-based model predicts much more negative support for Shepherd through Election Day. On October 25\textsuperscript{th}, three articles published in the Deseret News mentioned Shepherd and all three were coded as negative for Shepherd. In particular, two editorials indicated that Shepherd would like Utahans to forget her broken promises and to forget that she was a Democrat, but that Enid Greene-Waldholtz was the clear choice for Representative. In addition, another article cited a Congressional Quarterly Weekly Report that said that Shepherd was the sole endangered congressional incumbent in Utah. The article went on to cite that the Report indicated that her race was a toss up between Greene-Waldholtz and Cook. This negative coverage continued as Ross Perot’s United We Stand gave Shepherd a C+ (the lowest among the candidates for the Second Congressional District) in their report card on the major candidates for the 1994 elections. Other interest groups were just as negative towards Shepherd as the National Right to Life organization argued that she contradicted herself on abortion in order to win more conservative voters.

There were, however, a number of days for which the memory-based model predicts increases in support. The sharpest increases in support occur in early February and late in the campaign season. Beginning with February 7\textsuperscript{th}, the memory-based model predicts a large increase in support as three positive articles were published. One of the articles highlighted Shepherd’s issue positions on a variety of issues that would face Congress in the next term. This coverage of the issues was done to the exclusion of the issue positions of her opponents. One editorial highlighted the poor choice the Republican Party had made in putting Greene-Waldholtz against Shepherd as Shepherd beat her in the 1990 election. The second editorial thanked Shepherd for her efforts to protect the
environment in her first term. Again on February 13\textsuperscript{th} the model predicts an increase in support for Shepherd. This corresponds to positive coverage concerning Shepherd’s lead over her opponents. The final positive spike occurs in mid-September (18\textsuperscript{th}). This is a curious day because there was only one positive article and two neutral articles focusing on Shepherd; however the model predicts a sharp increase. Because the memory-based model relies on the relative intensity of the campaign message, the negative articles discussing Greene-Waldholtz contribute to the positive spike for Shepherd. The single article highlighted Shepherd’s attendance at a campaign debate and Greene-Waldholtz’s absence.

The on-line model predicts a different path of support for Shepherd. Support is predicted to steadily increase throughout the campaign season. The deviation from this trend occurs in early October. On October 2\textsuperscript{nd}, support for Shepherd is predicted to reach a high and then recede until October 9\textsuperscript{th}. The high for Shepherd came when coverage of the candidate focused on her lead in newly released polls. The precipitous decline begins the very next day when coverage became less positive and highlighted a number of negative features of the candidate. Further, Shepherd faced harsh criticism in the editorial pages throughout this period. Readers indicated that Shepherd should be ousted because she continuously supported the Democratic leadership, and could no longer claim to be an independent while voting seventy-nine percent of the time with Clinton—“in reality, instead of a flag-waving independent, she is a Clinton lackey”. Not only was Shepherd criticized generally for her voting record, but also the readers attacked her on specific issues as well, including the crime bill for which she voted. Unfortunately for Shepherd, that week of editorial criticism came simultaneously with reports that her
efforts to seek congressional reform were unlikely to yield actual reform. Support is then predicted to rebound on the 10th. On this date, Shepherd received the Clinton Merriam Memorial Liberty Award for giving up a cost-of-living increase to help offset the national debt.

Figure 5.31: Memory-Based and On-Line Models' Predictions for Shepherd

![Memory-Based](image)

![On-Line](image)

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

The second candidate to discuss in this race is the Republican challenger, Enid Greene-Waldholtz. I display the predictions from the two models for the course of public opinion for Greene-Waldholtz in Figure 5.32. For Shepherd and Cook, the memory-based model predicts volatility throughout the campaign season, but for Greene-Waldholtz the memory-based model predicts more volatility later in the season rather than earlier. However, the model does predict two days of more negative support in February (the 7th and the 13th). On the first of these days, February 7th, a single editorial was published criticizing Greene-Waldholtz for her inability to manage her campaign.
budget during her 1990 campaign against Shepherd. Her campaign debt topped $100,000 and was carried over to the 1994 campaign. The article on the 13\textsuperscript{th} indicated that Shepherd held the lead in the three-way race as determined by a newly released poll.

Again in mid-September (the 18\textsuperscript{th}), the model predicts a sharp decline in support. On this date, the Utah Women's Forum sponsored a debate between the three candidates for the 2\textsuperscript{nd} Congressional District. However, Enid Greene Waldholtz was absent because she was entertaining a freshman Representative from Oklahoma who was helping her campaign. Shepherd and Cook used her absence as an opportunity to point out that Greene-Waldholtz had challenged her opponents to a public debate in a letter she wrote in August. An editorial was also published criticizing fellow readers for their support of the Republican candidate citing her mounting campaign and personal debt. The editorial also mentioned that twenty percent of Republicans were already supporting Shepherd because of her leadership on fiscal responsibility.

The most precipitous increase predicted by the memory-based model occurs in October (the 5\textsuperscript{th}, 8\textsuperscript{th}, and 22\textsuperscript{nd}). What does the coverage look like on these dates? On October 5\textsuperscript{th}, a single article was published. This editorial urged voters to vote for Greene-Waldholtz in order to rid themselves of the liberal voting of Shepherd. The coverage on the 8\textsuperscript{th} again turned to the need to rid the country of Liberal Democrats, including Shepherd who was unfailing in her loyalty to the Democrats, particularly Clinton. Voters were urged to vote for Waldholtz, instead of Cook, to avoid giving Clinton a further opportunity to attempt to “continue his crusade to move the country further into socialism”. On October 22\textsuperscript{nd}, the discussion returned to the extent to which the other two candidates Shepherd and Cook represented the people of Utah. The editorials concluded
that Shepherd voted too often with the Clinton administration and Greene-Waldholtz truly represented the interests of the district.

Turning to the on-line model, the most negative period predicted for Greene-Waldholtz occurs in late February through early March as one can see in Figure 5.32. During this period, there was very little coverage for Greene-Waldholtz. From February 25th until March 18th, only one article was published mentioning the candidate. This single article was a negative article criticizing the candidates for what the author considered to be unwarranted attacks on Shepherd. The negative predictions must then stem from the previous tally for Waldholtz. The on-line model predicts that support for Greene-Waldholtz will increase only slightly throughout the campaign season, but will increase dramatically in mid-October and steadily increase until Election Day. During this period, coverage of the candidate was mixed, but tended to be neutral. Of the thirty-seven articles that mentioned Greene-Waldholtz published from October 15th through Election Day, seventeen were neutral articles. The rest were evenly split between positive and negative articles. A polling of the local schools found that the vast majority of school children supported the election of Greene-Waldholtz to the 2nd Congressional District seat. Not only were children more likely to vote for Greene-Waldholtz, but a poll also released on November 4th indicated that Greene-Waldholtz had surpassed both Shepherd and Cook among adult respondents. As mentioned above, a number of editorials were published supporting Waldholtz over Shepherd for the congressional seat. In particular, these editorials focused on the question of Shepherd’s independency and emphasized that Greene-Waldholtz was the true conservative in the race and held opinions on the issues more in-line with the district.
Figure 5.32: Memory-Based and On-Line Models’ Predictions for Greene-Waldholtz

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

The last candidate in the Utah Congressional race to discuss is Merrill Cook, the perennial Independent candidate. Figure 5.33 highlights the models’ predictions for the path of opinion for Cook. Unlike the coverage of Greene-Waldholtz, Cook’s coverage remained relatively plentiful throughout the campaign season. This resulted in part from his term-limits initiative. This plan received much coverage and reactions from current officeholders that were publicized in the newspaper. This figure makes it clear that the memory-based model’s predictions for support for Cook vary dramatically throughout the campaign season. The most dramatic increases or decreases in predicted support occur during the fall campaign. In particular, September 1st was a day with relatively positive coverage of Cook. His term limits initiative was discussed in detail and given a very
neutral treatment. More importantly, Shepherd’s vulnerability in this three-way race was also highlighted in the newspapers on this date.

By mid-September (the 15th), support is predicted to decline dramatically for Cook. This stems from the newspapers publishing of two negative editorials discussing Cook’s term limit initiative. Cook’s term limit initiative included a majority vote initiative that allowed for runoff elections when a candidate for public office did not receive a majority of the vote. Many, including the writer of this editorial, throughout the campaign season criticized this addition to the initiative as being in Cook’s self-interest. Facing a likely non-majority outcome in the 2nd Congressional District, Cook chose to tack on the majority vote requirement to benefit him in his election efforts. The second criticism with the initiative concerned the constitutionality of imposing qualification requirements on federal legislators by a state. The final critique surrounded the lack of power term-limited states would have as congressional leadership is decided through seniority. States without term limits would hold all the leadership positions. Another editorial highlights the possibility that Cook’s initiative preempted the rights of the electorate to choose its representatives.

This negative level of predicted support is mitigated in early October (7th) with a predicted increase in support from the memory-based model. Only two articles were published on this date and both articles were neutral towards Cook. However, the upswing in support is a function of the extremely negative coverage that Shepherd and Waldholtz received on this date. However, Cook’s support is predicted to decline on two successive days in mid-October (the 22nd and 23rd). This decline in predicted support is a function of the negative coverage Cook received on this date. For the most part, Cook’s
negative coverage resulted from his sponsorship of the term-limits/runoff ballot proposition. On October 22\textsuperscript{nd}, the Utah League of Cities and Towns, and the Salt Lake Area Chamber of Commerce announced their opposition to his initiative. Further, the organized group opposing the initiative, Utahns for Responsible Term Limits, was started and began running radio ads against the measure. The editorials on this date were also less pro-Cook than on previous occasions. In particular, one editorial pointed out that Cook would have more trouble than he anticipated in rallying support for proposals in Congress without party affiliation, and he would likely find himself without important committee appointments.

By October 29\textsuperscript{th}, support for Cook is predicted to rebound to its highest level in the entire campaign season. Like the 7\textsuperscript{th}, this positive support is not a result of positive coverage of Cook as there were four articles and three were neutral and one was negative. The coverage for Shepherd on this date was extremely negative, as was the coverage of Greene-Waldholtz, contributing to the increase in support predicted by the memory-based model for Cook.

Similar to the memory-based model, the on-line model predicts less stable support for Cook than it did for the other two candidates. This volatility results from mixed coverage concerning Cook the candidate and Cook the initiative sponsor. The initiative tended to receive much more negative coverage than Cook himself. The on-line model does predict high levels of support for Cook throughout much of August, but this support declines precipitously by September. This upswing in support corresponds to more positive coverage on August 2\textsuperscript{nd}, but this coverage was positive because a single article highlighted the fact that Cook’s initiative received enough signatures to make the
November ballot. Coverage for the next four days was non-existent for Cook and support is predicted to decline after this until mid-October when support is predicted to pick up again for Cook.

In mid-October, an increase in support is predicted on the 21st with four neutral articles and one positive article. The positive article focused on Cook's positions on the issues in the campaign. The neutral articles focused on Shepherd's battle with her opponents and the likelihood of Shepherd losing the election. This increase ends the very next day as support plummets with the publication of three negative articles on the 22nd and two negative articles on October 23rd. As discussed above, opposition to Cook's term-limits initiative was increasing in terms of money and momentum. A number of interest groups were opposing the candidate's initiative and speaking out against its tenets. This negative coverage of the initiative continued throughout the campaign season and is captured in the declining tally for Cook.
Figure 5.33: Memory-Based and On-Line Models’ Predictions for Cook

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Actual Public Opinion

The panels in Figure 5.34 display the IEM data for the Utah congressional race. In this race, the data series starts in January, but there is no data for the challengers until April. While there was much variation in Cook’s support, it rarely increased above 0.15 and hovered near zero throughout the fall campaign season with periodic increases. Shepherd’s support remained quite high throughout the period, only briefly dipping below 0.50 when the other challengers entered the race. On the other hand, Greene-Waldholtz’s support remained quite low only reaching 0.50 towards the end of the campaign. Illustrating the closeness with which this race was touted, the end price for the two major candidates, Shepherd and Greene-Waldholtz, was almost equivalent. On the other hand, Cook’s support plummeted by the final tracking day. The results vary from the actual election results as Cook received many more votes than one would anticipate.
from this measure of support and the closeness of the race was not as great as was anticipated.

Figure 5.34: Iowa Electronic Market Results for the Utah Congressional Race

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate's price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

Comparing the Models' Predictions with Actual Public Opinion

The Utah Congressional race is the longest campaign season in the dataset with two hundred and ninety three days. As a result, the models have many more days to predict than for the other cases. How well do the models' predict the direction of support for the three candidates in this race? The ability of the models to accurately predict public opinion for all three candidates is depicted in Table 5.14. Overall, the models do much worse predicting changes in public opinion during this race than in the other six races discussed so far.

This is an interesting race because the memory-based model significantly outperforms the on-line model in terms of predicting changes in support for the three
candidates. As we saw in the other six races, the on-line model outpaces the memory-based model in predicting stable public opinion in this race. In fact, the on-line model correctly predicts over seventy percent of the stable days of public opinion for Greene-Waldholtz and Cook. Focusing on the specific direction of the changes, the on-line model accurately predicts increases in support to a greater extent than the memory-based model for Shepherd. Where the model fails to correctly anticipate changes in support is when public support for all three candidates decreases. The on-line model also fails to predict increasing support for the other two candidates: Enid Greene-Waldholtz and Merrill Cook.

Table 5.14: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Utah Congressional Race

<table>
<thead>
<tr>
<th></th>
<th>On-Line Model</th>
<th>Percentage of Total Days Correct</th>
<th>Memory-Based Model</th>
<th>Percentage of Total Days Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shepherd</td>
<td>32</td>
<td>36.8</td>
<td>35</td>
<td>40.2</td>
</tr>
<tr>
<td>Increase</td>
<td>26</td>
<td>47.3</td>
<td>21</td>
<td>38.2</td>
</tr>
<tr>
<td>Decrease</td>
<td>6</td>
<td>18.8</td>
<td>14</td>
<td>43.8</td>
</tr>
<tr>
<td>Stability</td>
<td>74</td>
<td>35.9</td>
<td>51</td>
<td>24.8</td>
</tr>
<tr>
<td>Greene-Waldholtz</td>
<td>15</td>
<td>21.1</td>
<td>32</td>
<td>45.1</td>
</tr>
<tr>
<td>Increase</td>
<td>9</td>
<td>25.7</td>
<td>18</td>
<td>51.4</td>
</tr>
<tr>
<td>Decrease</td>
<td>6</td>
<td>16.7</td>
<td>14</td>
<td>38.9</td>
</tr>
<tr>
<td>Stability</td>
<td>167</td>
<td>75.2</td>
<td>62</td>
<td>27.9</td>
</tr>
<tr>
<td>Cook</td>
<td>12</td>
<td>21.8</td>
<td>20</td>
<td>36.4</td>
</tr>
<tr>
<td>Increase</td>
<td>8</td>
<td>27.6</td>
<td>12</td>
<td>41.4</td>
</tr>
<tr>
<td>Decrease</td>
<td>4</td>
<td>15.4</td>
<td>8</td>
<td>30.8</td>
</tr>
<tr>
<td>Stability</td>
<td>169</td>
<td>71.0</td>
<td>61</td>
<td>25.6</td>
</tr>
</tbody>
</table>

We can examine a few specific days to get a feel for the days when the models' predictions converge with actual public opinion and the days when the models' predictions diverge. In particular, the models' predictions for Shepherd converge with an increase in actual public opinion on June 17th. On this date, coverage of Shepherd was more positive as the articles discussed the approval of a House transportation bill that included increased funding pushed by Karen Shepherd, Shepherd’s position on the A to Z
bill, and Shepherd’s role as a member of the Utah Senate. Again on October 14th, the models predict a decrease in public opinion corresponding to an actual decrease in public opinion. Two negative articles, editorials, argued that Utah could not afford to re-elect Shepherd as she voted for big government and against the people on every issue related to property rights, and pointed out that Shepherd was facing a difficult battle in her effort to win reelection.

Both models also accurately predict May 8th. On this date, public opinion is predicted to increase for Greene-Waldholtz and this conforms to an actual increase in support for the candidate. There were two articles published, up from one negative article the day before. One of the articles on this day was neutral and the other was positive. The positive article focused on the candidate’s victory over her opponents in the Republican primary. The other article on this date concerned Merrill Cook and only mentioned his opponents in the congressional race.

As one might anticipate from Table 5.14, the models frequently diverge from public opinion. For example, on April 27th, a few articles were published focusing on Shepherd, but these articles were neutral. As a result, they are not coded in a particular direction for the memory-based model, but in the on-line model, these articles are coded as having a small positive affect. This leads to the increase in support predicted by the on-line model conforming to an actual increase in support on this date. The memory-based model by contrast predicts a decrease in support on this date, as coverage was non-existent for the other two candidates. Because coverage was not valenced in a particular direction, the model reverts to the static prediction. In Chapter 4, I discussed the coding of the static
elements in the memory-based model for Utah. Utah tends to be a conservative, Republican state, so the static elements are predisposed against Shepherd.

On September 10th, the memory-based model predicts a decline in support for Greene-Waldholtz matching actual public opinion. This decline coincides with a lack of coverage on this date. There was no coverage of Greene-Waldholtz on the 10th, but there was coverage of her opponents. By contrast, the on-line model predicts stable public opinion for Greene-Waldholtz on this date, as there was no new coverage to move the tally up or down. While the on-line model is clearly superior in predicting no change in public opinion for Greene-Waldholtz during the course of this campaign, it does not do as well predicting directional change in public opinion.

On July 8th, actual public opinion for Utah’s perennial Independent, Merrill Cook, increases. However, the on-line and memory-based models predict a decrease in support for Cook. This decline corresponds to a single article concerned with Cook’s report, a week prior, that eight to ten Republicans would be taking out a newspaper advertisement indicating their support for Cook, but the advertisement had yet to appear in the newspaper.

Finally, April 18th is an interesting date. The on-line model predicts stable public opinion on this date, as there was no newspaper coverage of the candidate to move the tally in either direction. However, the memory-based model predicts a decline in support and the actual support for Cook increased. The decrease in public support predicted by the memory-based model must therefore stem from the coverage of other candidates or the static elements in the model. There was no coverage of Shepherd or Greene-
Waldholtz on this date; thus, the decline in predicted support for Cook stems from the static elements.

**Virginia Senate Race**

The Virginia Senate race in 1994 became the most watch, most discussed, and most intriguing race of the 1994 campaign season. The race pitted incumbent Senator Charles "Chuck" Robb against Republican Oliver "Ollie" North, independent J. Marshall Coleman, and independent L. Douglas Wilder. How was it possible that a man (Oliver North) so tied to the Iran-Contra scandal could be a leading candidate for nomination to the very institution he had defied? It was possible because Chuck Robb was himself battle scarred. During Robb’s first term as Senator from Virginia, stories emerged linking him to scandalous parties held at Virginia Beach during his term as Virginia’s governor. Rumors of extramarital affairs and drug use began to pop up all over the news media and culminated in a Playboy spread in which former beauty queen Tai Collins exposed claims of an affair with Robb while he was governor. Robb’s refusal to admit to the affair led to much speculation and late-night talk-show jokes after he finally admitted to receiving a nude massage. Further, in 1992 three of Robb’s aides pled guilty to distributing an illegally made tape of a conversation between Robb’s nemesis, Wilder, and a third party. Robb appeared before a grand jury, but avoided an indictment in the situation. While North’s actions led many to decry him as a man defiant of the Constitution, he had become a hero to some for his role in defying Congress. This hero-status allowed him to tap into a ready-made base of support, in terms of both votes and fundraising, for his Senate campaign.
In the primary race, Robb easily defeated his three opponents while North had a much more tumultuous race for the Republican nomination against former Reagan budget director James Miller, III. While not the dynamic personality that North was, Miller had the backing of the vast majority of former Reagan officials, military and civilian, in the Republican primary. Unfortunately for Miller, he could not overcome North's celebrity status, the support of conservative Christians, or North's grass-roots organization. North emerged from the June nominating convention victorious and ready for a head-to-head contest with Robb. However, two independent candidates pledged to run if Robb and North won their respective party's nomination. Former Attorney General J. Marshall Coleman bucked the Republican Party by pursuing an independent campaign aimed at being the anti-North anti-Clinton candidate. On the Democratic side, former Governor L. Douglas Wilder entered the Senate race as an independent to prevent both North and Robb (his old nemesis) from succeeding in the general election.

J. Marshall Coleman, the once golden boy of the Republican Party decided to run after being recruited by Virginia's other senator, Republican John Warner. Warner argued that North was not fit to hold office given his involvement in the Iran-Contra scandal. Wilder pledged that he would not enter the race for Robb's Senate seat in January of 1994 after he insisted that the Democratic Party hold a primary instead of a nominating convention. He then decided to file as an independent in the race by gathering the necessary signatures. The independent candidates failed to capture the lead during the campaign season, so one of them, Wilder, dropped out of the race in mid-September after steadily losing support. Coleman refused to drop out of the race
believing that by the end of October North and Robb would have damaged each other to such an extent that voters would be looking for an alternative.

The gaffes highlighting the Texas gubernatorial race pale in comparison to some of the comments candidates made in this race. Senator Robb made two gaffes that he quickly argued were a function of the questions he was asked. In one of the debates, Robb, agitated by his opponents unwillingness to demonstrate what spending cuts they would be willing to make to balance the budget and cut taxes, claimed that he would be willing to “take food from the mouths of widows and orphans” if it meant he could cut the deficit. The hyperbole did not go over so well with the audience, his opponents, or the news media. In a second “policy” gaffe, Robb claimed to be leaning towards the federal regulation of nicotine. Robb quickly rescinded such a claim given that Virginia is the fourth largest tobacco producing state. Vice President Al Gore also made an important error in support of Robb when he claimed that North was counting on the fact that he could raise money from the extreme right wing, or the “extra-chromosome right-wing”, to overcome the truth. Gore quickly apologized when it was pointed out to him that Down syndrome was a genetic condition characterized by an extra chromosome.

For a couple of weeks in October, North voiced a series of gaffes that led his campaign to pull him away from the press for a number of days. At one point, North advocated making social security optional and suffered a similar fate as Santorum when he was found arguing that the federal government should consider increasing the age of eligibility for social security benefits. Discussing the military readiness of U.S. Armed Forces, North claimed that President Clinton and Robb had succeeded in destroying troop readiness and morale making it likely Saddam Hussein could run through Kuwait with
impunity if he decided to do so again. Unfortunately for North, he uttered this statement, along with a claim that President Clinton was not his commander-in-chief, at the exact moment when U.S. troops were amassing in the Middle East in response to actions by Hussein. Finally, Nancy Reagan spoke out against North’s misrepresentation of his interaction with former President Reagan during Iran-Contra and called him a liar. In response, North argued that he would not respond because his mother had taught him to “never get in a fight with a lady”. His opponents immediately accused North of being condescending to women. Coleman argued that North would have difficulty with such an approach given that the next senator would be dealing with female senators and female members of the Clinton’s Cabinet.

Newspaper Coverage

Newspaper coverage in such an election was much more extensive than it was in any of the other seven cases. The description above highlights the reasons why that might have been the case. As one might anticipate, Robb and North received much more coverage than their opponents. Robb and North received roughly the same amount of article coverage from the two newspapers, but North’s headline coverage overwhelmed Robb’s, particularly from the Virginian-Pilot. Obviously Miller received the least as he received no coverage after losing to North in the Republican primary. Interestingly, Wilder and Coleman’s coverage was roughly equivalent (in terms of articles and headlines) from the Virginian-Pilot, but Wilder still received more coverage, even though he dropped out of the race, than Coleman from the Times-Dispatch. As one might expect from the description of the race, the coverage of Miller, while substantially lower than that of the other candidates in terms of quantity, tended to be either positive or neutral.
The headline coverage for Coleman from both newspapers was equivalent, but the article coverage tended to be more negative than positive. Interestingly, the coverage, in terms of headlines and articles, of Wilder tended to be overwhelmingly neutral or negative as less than 15% of the articles in both papers were positively valenced towards Wilder. In terms of headlines, Robb’s coverage tended to be more positive than negative; however, the coverage in terms of articles tended to be more negative than positive. North’s coverage from both newspapers in terms of both articles and headlines was overwhelmingly negative; nearly half of the articles were negatively valenced towards North.

This table makes it clear that the article coverage of the two major party candidates was almost equivalent. For the most part, articles that mentioned North also mentioned that he was running for the senate seat currently held by Chuck Robb. The coverage of Miller during the primary season was very consistent from day to day rarely exceeding two articles. Of the minor candidates, Wilder did the best in terms of receiving article coverage. Much of this resulted from his coverage at the beginning of the campaign season as he ended his term as governor of Virginia. Coleman tended to receive much more coverage towards the end of the campaign season as he was mentioned along with Robb when North was discussed. Article coverage for Coleman prior to late May was almost zero as he does not indicate his desire to run until this point.
Table 5.15: Dispersion of Newspaper Coverage in the Virginia Senate Race

<table>
<thead>
<tr>
<th></th>
<th>Number of Headlines</th>
<th>Positive Headlines (% Total)</th>
<th>Negative Headlines (% Total)</th>
<th>Number of Articles</th>
<th>Positive Articles (% Total)</th>
<th>Negative Articles (% Total)</th>
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<td>18.8</td>
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<td>11.4</td>
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<td>43.3</td>
<td>584</td>
<td>19.0</td>
<td>49.1</td>
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<td>28.2</td>
<td>541</td>
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<td>28.8</td>
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<td>30.1</td>
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<td>30.5</td>
<td>456</td>
<td>14.5</td>
<td>20.8</td>
</tr>
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</table>

Predictions

The Virginia Senate Race in 1994 is interesting simply for the fact that four candidates competed for the position against an incumbent Senator. What the figures displayed below make clear is that the two models make different predictions for the course of public opinion for all five candidates in the race. The incumbent candidate in this race, Democrat Chuck Robb, and his primary opponent, Oliver North, provide an extensive period of time for the models to predict changes in public opinion. Both candidates are included in the public opinion data from the end of January through Election Day. I display the predicted paths of support for Sen. Robb in Figure 5.35.

The on-line model provides fewer dates on which there are precipitous changes in predicted support. In fact, the graph makes it quite clear that the on-line model predicts positive support for the incumbent from the beginning of the campaign season until mid-April. After April, support begins to decline, but not as rapidly as that predicted by the memory-based model. There are a few dates predicted by the on-line model to be days of extremely negative support. The first of these days is September 10th. The articles on
this date focused on Robb’s withdrawal from a joint appearance with the other candidates, which led to the cancellation of the function.

Turning to the period of October 20-24, the on-line model predicts support for Robb to trend toward the negative. What was happening on these dates? The first story that received much publicity was the apparent conversion of Robb and Wilder from foes to allies. This led to much ribbing discussion of Senator Robb. The press emphasized that the bitter feud remained an undercurrent even though the two former opponents smiled and embraced. Robb also campaigned at James Madison University where he was greeted by protestors carrying signs and chanting slogans concerning his past marital infidelities. Further, Robb accused North of ignoring evidence that the pilots flying supplies to the contras were also smuggling drugs into the US on the return flights. However, this damaging accusation was muffled by North’s retort about Robb partying with drug dealers when he was governor of Virginia and statements by two high ranking Reagan officials that North did report his suspicions, but there was never any evidence of to support this suspicion. Polling data also indicated that Robb’s support was stagnating at thirty-three percent and North was leading the incumbent by four points. Finally, accusations began to emerge during this time that Clinton “bribed” Wilder to drop out of the race and support Robb in exchange for an ambassadorship.

Turning to the memory-based model, there are many days of dramatic changes in predicted support for Senator Robb. While the on-line model predicts positive support for Robb throughout the first months of the election, the memory-based model predicts a decline in mid-March that follows an increase in predicted support. On March 19th, support for Robb is predicted to increase. This increase is a function of positive coverage
of Robb including reports that a lawsuit against Robb’s re-election committee had been dropped. This positive spike also results from a dramatic decrease in support for North as Reagan administration officials began to line up behind North’s opponent in the Republican nominating contest, Miller. Further, Reagan wrote a letter to a friend indicating that he was particularly upset by North’s continued misstatements about the president’s participation in, and knowledge about, the Iran-Contra scandal. By March 23rd, the memory-based model predicts a sharp decline in support corresponding to an announcement that state Senator Virgil Goode and ex-governor Douglas Wilder would likely enter the Senate campaign. Polling data was also released on March 23rd indicating that Miller would likely win a general election contest against Robb. Finally, a glaring editorial was published berating Robb for attempting to reinvent himself as “Saint Chuck” after years of shenanigans.

By April 29th, the potential negative ramifications of additional candidates in the Democratic primary had receded. Robb handily defeated his primary opponents in the first debate of the season. Further, his main opponent, Goode, faced a setback when NARAL not only endorsed Robb, but indicated that Goode was a detriment to women’s rights. The memory-based model predicts negative support for Robb to return May 23-25. This time, a televised debate did not go well for Robb. Robb was continuously confronted with the womanizing and drug tolerance charges that he seemed unable to escape. Goode asked Robb a very pointed question—“Sen. Robb, I ask you this question: Have you exhibited the character, the judgment and the lawful conduct that Virginians deserve from the elected officials”—and Robb promptly changed the subject. Importantly, Robb also lost an important ally to his primary opponent in the form of a
defeated Democratic gubernatorial candidate, Mary Sue Terry. Terry justified her
decision to endorse Robb’s opponent by citing the likelihood that North would defeat
Robb. One of Robb’s primary opponents, Sylvia Clute, also criticized his record on
women’s issues—particularly his private activities and his Clarence Thomas vote.

The most negative period predicted in the entire season occurs from September 7th
through the 8th. What happened during this period to lead to such a negative prediction?
The first incident included Wilder picking up the support of 19 black ministers. Robb
also announced that he would likely never debate again if the two independent candidates
were included. He spent the debate attempting to deflect personal shots from all three
candidates, and ended up offhandedly arguing that he would be willing to do whatever it
took to cut the deficit including taking “food from the mouths of widows and orphans”.

However, this predicted negative support wanes as one of Robb’s main obstacles,
Doug Wilder, pulled out of the race on September 16th. Most analysts argued that Robb
would receive quite a bump, as Wilder’s supporters became Robb supporters. A poll
conducted a week earlier found that Robb would be boosted to a tie with North if Wilder
simply left the campaign.
Figure 5.35: Memory-Based and On-Line Models' Predictions for Robb

![Graphs showing Memory-Based and On-Line models' predictions for Robb]

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Senator Robb's primary opponent, Oliver North, successfully defeated his opponent, Jim Miller, in the Republican primary to face Robb, Coleman, and Wilder in the general election. The predictions from the memory-based model and the on-line model are displayed in Figure 5.36. While Robb's predicted support from the on-line model declined early in the campaign season and then remained consistent with only minor dips, North's predicted support from the on-line model starts off relatively high but begins to decrease soon after. By the time of North's victory at the Republican convention in June, the on-line model predicts negative support for North that remains stagnant until September when in plummets for the remainder of the campaign season.

Once North made it clear he would run for the Republican nomination in the Virginia Senate race, the newspapers began to discuss North's involvement in the Iran-Contra scandal. This coverage contributed to the predicted decline in support for North
throughout the campaign season. In fact, there were only seventy-six days out of the
two-hundred and eighty-three day campaign season in which North’s involvement in the
Iran-Contra scandal was not mentioned. This is important because even Robb’s
scandalous past (which includes three different scandals—Tai Collins, beach parties, and
the Wilder taping incident) was mentioned on fifty fewer days. These are numbers that
the tally has difficulty overcoming even if coverage were to turn positive.

As discussed in the previous chapter, the on-line tally is a function of not only
scandals but also discussions of the candidate’s personal and professional life. In this
race, much publicity was made about North’s character and whether his lying to Congress
was a matter of integrity or a sign of a lack of integrity. Political support also plays a key
role in determining the level of the tally. Each time that a Reagan associated criticized
North, his predicted tally declines. The combination of these elements leads to a
consistently negative tally for North throughout the campaign season.

So, why did the on-line model predict stagnation throughout the summer months and
then plummeting support in September? In part this stagnation was due to Senator
Robb’s absence from the campaign trail. The Senate was in session far longer than it
normally is during a campaign season to tackle healthcare reform and the crime bill. As a
result, much of the coverage of North’s campaign was somewhat positive or neutral.
However, the Iran-Contra scandal was always in the background of North’s campaign
coverage. This was due in part to Marshall Coleman and Doug Wilder’s presence on the
campaign trail during these summer months.

Robb’s return to the campaign trail by late September corresponded to an increase in
the negative coverage of the North campaign. The on-line model predicts that by
September 30th North’s support is in a negative free-fall. The newspaper coverage began to focus on a series of misstatements North made including denying that he lied to Congress, backed away from statements he made earlier about the Confederate flag, and misstated Robb’s position on abortion. The articles also emphasized North’s misstatements about Reagan in his book, the denunciation by Reagan of North’s false statements regarding Reagan’s role in Iran-Contra, voters being turned off by their scandal-ridden candidates for Senate, and an editorial discussing North’s lack of credibility.

Additional negative articles criticized North for the negativity between him and Robb, and emphasized former Secretary of State Lawrence Eagleburger’s statement that North was a man of "no moral character whatsoever" who "wouldn't recognize the truth if it hit him over the head with a baseball bat". Other negative articles included one quoting Eagleburger as calling North a "pipsqueak lieutenant colonel" and former governor Holton arguing that he was "a dangerous unguided missile", one criticizing North for his most recent misstatements and inability to harness his tongue, and one criticizing his religious tactics by the Interfaith Alliance. Such coverage continued to contribute to the growing negative tally throughout the campaign season even though more positive coverage attempted to mitigate the tally. This positive coverage could not overcome the ever-growing negative tally.

The predictions for the memory-based model are also displayed in Figure 5.36. The memory-based model obviously predicts greater variance in support for North than the on-line model. As a result, I cannot discuss all points, but I will focus on a few dramatic negative points and the three extreme increases in support.
The three positive points correspond to April 20th, May 23rd, and September 8th. The first positive point is a curious one because there was not a single article published on this date that mentions North. Instead, there was one article concerning a scandal involving Robb. Reports began to surface that aides to then-Governor Chuck Robb used their influence to overrule a Virginia Beach panel's decision against a wealthy businessman, allowing the businessman to develop an environmentally sensitive strip of beachfront. This is a situation in which the memory-based model's predictions for a candidate are dependent on the coverage of other candidates in the campaign.

This situation occurs again on May 23rd. In this case, there was an article published discussing Oliver North; however, this article was negative. The only reason that there is an increase predicted for North on this date is because May 23rd was one of the more negative coverage days for Chuck Robb. Robb was confronted in a televised debate with charges that he engaged in womanizing and drug tolerance from his primary opponents. He also refused to answer charges that his character was questionable for a U.S. Senator. This contributed to an increase in predicted support for all of the other candidates in the race on this date.

The final increase in support for North to be discussed occurs on September 8th. The coverage on this date concerned the candidates' performance at a debate the night before at Hampden-Sydney College. The coverage tended to be more positive for North because the college was overwhelmingly Republican and the debate amounted to a North rally with cheers for North and jeers for his opponents. Importantly, Robb committed a serious gaffe when he was asked about balancing the federal budget. Robb answered that he was willing to "take food from the mouths of widows and orphans" in an offhanded
way. The negative coverage of Robb’s statements contributed to the prediction for positive support for North on this date.

There are a number of incredible declines in support for North predicted by the memory-based model (those with z-scores greater than -3.5): March 19th, April 29th, July 1st, October 12th, October 19th, October 22nd, and October 29th. While there are minor dips predicted in support for North, serious negative support is not predicted until March 19th. The coverage rehashed Reagan’s violation of his vow to stay out of intraparty races the previous Thursday by writing a letter arguing that North lied in his book about Reagan’s role in the Iran-Contra scandal. Further, the articles reiterated that over twenty members of the Reagan administration were supporting North’s opponent, Jim Miller, in the primary contest.

Again on April 29th, predicted support declines precipitously. This time predicted support declines in response to North’s absence at a United We Stand America-sponsored candidate forum annoying members of the organization that had previously supported him. The articles continued to mention Reagan’s letter and Warner’s accusation of North’s lack of qualifications for the Senate. A poll was also released indicating that fifty percent of respondents considered North an unacceptable candidate.

Even after winning the June primary, the memory-based model predicts a sharp decline in support for North on July 1st. On this date, the first in a series of articles attacking North’s image and professionalism were published including an attack by Marshall Coleman concerning North’s claim that he was an outsider. Further, Warner issued a statement that North had forfeited his right to serve in the Senate when he lied to that very body concerning Iran-Contra. Importantly, North’s opponents also accused him
of attempting to manipulate the proposed debate before the Virginia Bar Association later that month. North refused to participate unless his needs were met.

Fluctuations in support continue until Election Day, but October in particular contributed a number of serious declines in predicted support from both models. In particular, the memory-based model predicts extreme declines in support from October 12th until the end of the month. On October 12th, Vice President Al Gore issued a statement arguing that North should apologize for the statements he made about military preparedness. North had commented that the Clinton administration had made defense cuts that produced a "hollow military" unable to resist Saddam Hussein if he should invade Kuwait. The criticism of this comment surrounded the fact that the US military and its allies were building up troops in the Persian Gulf in response to reports that Iraqi troops were massing on the border with Kuwait. Support is predicted to become relatively more positive for the next week until it is predicted to sink again on the 19th. On this date, North was forced to pull a campaign ad to which his supporters reacted negatively. The ad featured a Playboy cover reviving tales accusing Robb of womanizing and drug parties. Further, the comic strip Doonesbury continued to portray North as paranoid and reactionary. Further, North was criticized for continuing to argue that debt was an albatross around the necks of our children, but failing to offer in specific ways to eliminate the albatross.

Only three days later on October 22nd, support again is predicted to decline rapidly as a Virginia Beach real estate agent filed a defamation lawsuit against North. In a campaign ad, North portrayed this man as a cocaine dealer. Further, Wilder finally decided to endorse Senator Robb for re-election to avoid a North win and in response to
Clinton’s request. Also, an exposé was published attempting to delineate what North knew and when about the Iran-Contra scandal including potential drug smuggling. Just days before the election, the memory-based model predicts one final precipitous decline in support for North. On this date, former first lady Nancy Reagan said explicitly that she considered North to be a liar in his statements of his relationship with Reagan and Reagan’s involvement in Iran Contra. The final blow for North came when the state Republican Party chairman said that it would not be “cost-effective” for North to campaign for black votes so late in the campaign season. This led to outraged responses from the NAACP and North’s opponents.

Figure 5.36: Memory-Based and On-Line Models’ Predictions for North

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

The first of the independent candidates to enter the race was Marshall Coleman. Figure 5.37 displays the memory-based and on-line models’ predictions for change in support for Coleman throughout the course of the campaign. As will be evident in the
discussion of Miller and Wilder, the predicted support for the independent candidates from the memory-based model fluctuates considerably. However, this support fluctuates mostly between neutral support and positive support. There are only a few cases of extremely negative support for these three candidates. Further, the on-line model predicts ever-increasing positive tally for these candidates, particularly as the campaign season progresses. This increasing support likely occurs because of the newspaper coverage and the structure of the on-line tally. The newspapers tended to cover the major party candidates to a greater extent and the coverage of the minor candidates tended to be non-existent or neutral. None of these candidates had scandalous pasts that received extremely negative coverage. As a result, there coverage tended to be neutral or positive. Negative coverage only occurred when the candidates engaged in serious gaffes or polling/fundraising numbers were released. But unlike the other candidates, Marshall Coleman remained in the race for the duration of the general election campaign.

Turning to the predicted paths for Coleman, the memory-based model predicts three periods of extremely negative support: June 23-25, September 3-4, October 30-31, and November 4-6. Starting on June 23rd, coverage for Coleman turned decidedly negative. The Republican leadership of the Virginia General Assembly sent a signed letter to Coleman telling him that he was considered a traitor to the party and would be responsible for the re-election of Senator Robb. The Coleman camp suffered a further setback when the Virginia Board of Elections rejected a plea by Ross Perot organizers to make Coleman the nominee of a group called the Virginia Independent Party. Finally, a number of editorials were published in which voters voiced their support of ousting Warner and Coleman from the Republican Party.
At the same time that support was starting to wane for Wilder and speculations started to emerge concerning his withdrawal, Marshall Coleman’s support also begins to receive a setback. On September 3rd through 4th, coverage of Coleman highlighted the long shot hopes of Coleman voters. Polls released indicated that Coleman was trailing the major party candidates by at least fifteen percentage points.

This negative support is predicted to turn positive until late October when newspapers discussed Coleman’s eroding level of support. The conclusion by the newspapers was that individuals were starting to fear the strong possibility that their support of Coleman might elect North. Many articles postulated the possibility that Warner and Coleman would need to make a decision as to whether Coleman’s continued campaign efforts best served their purposes. Further, the newspapers interviewed voters who indicated that Coleman was a worthy candidate, but had no possibility of winning the election. Finally, one of the newspapers in my study endorsed Oliver North for the Virginia Senate seat on October 30th.

The final set of dates is the days leading up to the Election Day: November 4th through 6th. As one expects, there were many articles published discussing Marshall Coleman’s campaign and the predicted support for Coleman is universally negative during this period. A number of articles discussed independent Marshall Coleman’s flip-flopping on many of the important campaign issues including abortion, his inability to garner the poll numbers to make him a formidable force in the election, and the fact that his support peaked in late June and has plateaued ever since.

As one might expect, predicted support for Coleman from the on-line model does not begin to change until he announced his intention to run for the Virginia Senate race as an
independent. After this, the on-line model predicts an ever-increasing level of support for Coleman. However, the on-line model does not predict support to pick up for Coleman until after the Republican convention in June. Once it was decided that North would be the Republican nominee, Coleman received an outpouring of support from various quarters. The inertial tendency of the tally makes it difficult for the on-line model to predict the dramatic declines in support that the memory-based model predicts in response to changing poll numbers, criticisms by the media and the endorsement by the newspapers of the other candidates in the race.

Figure 5.37: Memory-Based and On-Line Models’ Predictions for Coleman

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<th>Date</th>
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</tr>
<tr>
<td>08 Nov 1994</td>
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</table>

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate’s predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

Before facing Robb, Coleman, and Wilder in the general election campaign, it was necessary for Oliver North to convince the Republican base that he was the right candidate for the job and that Jim Miller was not. North’s efforts were successful and Miller was defeated at the Republican convention in June. Figure 5.38 shows the
predicted paths of public opinion for Miller emerging from the memory-based and online models over the course of the campaign.

Support for Miller is predicted to vary dramatically over the campaign season according to the memory-based model. Interestingly, there are very few extremely negative changes in support. For the most part, support is predicted to fluctuate between neutral and positive support. However, there are a few days of extremely negative support. The first period of dramatic negative support occurs early in the season on February 1st and 2nd. On February 1st the newspaper coverage included articles discussing Miller's lack of campaign funds and notoriety in comparison to his Republican primary opponent, Oliver North. Further, the articles on February 2nd included poll numbers indicating that Senator Chuck Robb would defeat both North and Miller in a head-to-head contest. Unfortunately for Miller, polling data also indicated that he would lose in the Republican primary to North.

The second set of severely negative predictions for Miller from the memory-based model occurs from April 6th through April 19th. Coverage on these dates varied from non-existent to extremely negative. The topics discussed included survey results indicating that the majority of the religious right supported North over Miller for the Republican primary bid. Also, Republican John Warner, the other Virginia Senator, was criticized by his fellow Republicans for condemning North and supporting Miller. But, the most negative of all the coverage during this period surrounded Miller's criticism of North for not releasing details of medical records included his hospitalization for marital problems and combat service in Vietnam. The problem with this criticism was that
Miller had sought psychiatric counseling himself to deal with the death of his father and a mood disorder, and most importantly, refused to release his own medical records.

The on-line model predicts an ever-increasing level of support for Miller. However, similar to the memory-based model, the on-line model predicts a decline in support in April when coverage of Miller became much more negative. At the end of April coverage began to become less and less negative. Support is predicted to rebound and enter positive territory for the remainder of the campaign season in mid-May. Coverage included a series of articles discussing the improbability of a North victory in a general election and the probability of a Miller victory in the general election. The articles also continued to add former Reagan and Bush officials to the list of supporters of Miller. Specifically, Desert Storm commander H. Norman Schwarzkopf attacked North on issues of integrity. He joined former President Reagan and retired Joint Chiefs of Staff chairman Colin L. Powell, Reagan associates Edwin Meese III and Caspar Weinberger of California and Paul Laxalt of Nevada, and Robert C. McFarlane, Reagan's national security adviser and North's boss in criticizing North.
Figure 5.38: Memory-Based and On-Line Models' Predictions for Miller

![Graphs showing memory-based and on-line models' predictions for Miller.](image)

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

The final candidate to be discussed is former governor Doug Wilder. The Virginia Senate race would have been less than complete without Wilder's surprising announcement that he would not be seeking Robb's seat in January, his late entry after pledging to not enter the race in June and his early withdrawal in September after insisting he would remain in the race until Election Day. The predictions for support for Wilder from the two models appear in Figure 5.39.

For the memory-based model, there are a number of dramatic predictions for change throughout the campaign season. The on-line model however predicts a continuous increase in support even through Election Day. This ever-increasing level of support results in part from the mostly positive coverage of Wilder at the start of the campaign season. At the beginning of January, Wilder was the sitting governor of Virginia, and his exit from office was widely positive. Once he decided to enter the race, the model has
difficulty predicting negative support for Wilder because of the value of the previous tally as well as the fact that most of the articles concerning him tended to be neutral or positive. As a result, slightly negative coverage led to only a minor bump for Wilder.

Turning to some of the more dramatic predictions for support for Wilder, the memory-based model predicts a large decline in support on April 20th. Coverage on this date highlighted Wilder’s prospective independent bid for the Virginia Senate seat. The chairman of the state Democratic Party was quoted as criticizing Wilder, a lifelong Democrat, for foregoing the Democratic primary and potentially splitting the Democratic vote thereby electing North. Further, the Rev. Jesse Jackson refused to endorse Wilder. The final discussion of the day surrounded the conclusion by the Federal Election Commission that Wilder’s presidential campaign owed the federal government money due to federal matching funds received as a result of prohibited and excessive contributions. Support enters positive territory the very next day on April 21st even though coverage continued to focus on Warner’s criticism of Wilder’s potential independent bid. This rebound most likely then results from the more negative coverage of his opponents on this date. Again support decreases in mid-June, but rebounds quickly. On June 10th, the coverage once again turned to Democratic Party leaders urging Wilder not to run as an independent. On this date, Democratic National Committee Chairman David Wilhelm urged Wilder to stay out of the Senate race.

The predicted level of support for Wilder remains quite positive with minor fluctuations throughout the next two months. Wilder’s level of support begins a rapid descent on September 15th and then freefalls to its second lowest level on September 16th. This corresponds to the announcement by Wilder that he would be pulling himself out of
the contest. One article focused on how candidates could defeat the religious right and simply mentioned Wilder as being in the race while another article emphasized Wilder's canceling of his campaign after two polls showed he was trailing the other candidates. The next day, September 16th, support for Wilder continued to decline as eight articles were published discussing Wilder's unlikely bid and eventual withdrawal from the campaign. Once Wilder pulled himself out of the race, his support is predicted to fluctuate between zero and positive values.

**Figure 5.39: Memory-Based and On-Line Models' Predictions for Wilder**

![Graph showing memory-based and on-line models' predictions for Wilder's public opinion from July 1 to September 17, 1994.]

Note: These two panels are the predicted paths of public opinion for the on-line and memory-based models in terms of z-scores. The line is a locally weighted regression of the candidate's predicted public opinion on the dates of the campaign season to provide an indication of the direction of change in the predicted path of public opinion.

**Actual Public Opinion**

Turning to the IEM results, I depict graphically the fluctuation in public opinion for each candidate throughout the campaign season in Figure 5.40. Because of the volatility of this race, the public opinion series began much earlier than in the other races. Trading opened on January 21st and candidates were picked up less than ten days later on January
31st. Robb maintained a high level of support even with opponents in the Democratic primary. This support declined by late March as his primary opponents began to attack his character and performance. His support picked up slightly in May but then continued to remain quite low throughout the summer months. This result was consistent with activities on the campaign trail. Robb spent much of the summer in Washington attending to his senatorial duties. Figure 5.40 suggests that North’s level of support was greater than Robb’s towards the end of the campaign season. However, that is not what the graph suggests. Because the numbers are z-scores, they simply indicate the direction of change in support. North’s level of support was initially quite low, so even a significant increase in support does not surpass Robb’s support.

Figure 5.40 also displays the levels of support for the three “minor” candidates. Miller’s level of support remained positive until he was defeated by North in the Republican primary. Unfortunately, his lack of name recognition meant that, while positive, his support was far below that of North. Few held out any hope that Miller would defeat North in the Republican primary as indicated by Miller’s support. North succeeded in defeating Miller in June and turned to the general election campaign against Robb, Coleman, and Wilder. Neither of the independent candidates—Coleman and Wilder—garnered much support. Coleman did quite well for a stretch prior to mid-September. By September, North’s support had increased substantially and hovered around 0.40 for the rest of the campaign season. The end price for the candidates indicates how close the race between North and Robb truly was. Robb’s price ended at 0.428 while North’s price stood at 0.413.
Figure 5.40: Iowa Electronic Market Results for the Virginia Senate Race

Note: The thin line in this graph is the path of the price data throughout the campaign season. The graph has been standardized in terms of z-scores. The thick line is a locally weighted regression of the candidate’s price on the dates of the campaign season to provide an indication of the direction of change of public opinion.

Comparing the Models’ Predictions with Actual Public Opinion

In Table 5.16, I outline the number of days each model accurately predicts support for each candidate in the Virginia Senate race. Interestingly, the models do equally well predicting overall change for Robb and North. In contrast, the memory-based model more accurately predicts changes in support for the three minor candidates: Wilder, Coleman, and Miller. In fact, the memory-based model correctly predicts over fifty-seven percent of the days of change for Miller to the on-line model’s thirty-six percent. However, the on-line model does substantially better at predicting stable public opinion than the memory-based model. For example, the on-line model correctly predicts over
thirty-five percent of the stable public opinion days for Miller while the memory-based model correctly predicts only a single day of stability.

Not only does the on-line model outperform the memory-based model in this campaign, but also the on-line model predicts support for Coleman and Wilder to a greater extent than Robb and North. Interestingly, the two models are more accurate on opposing days. Turning to the direction of the changes, the on-line model does a much better job predicting decreases in support for Robb and North (over fifty percent for Robb and over sixty-two percent for North) than it does in predicting the increases in support for these candidates. The opposite is true for the memory-based model. For the minor candidates, the memory-based model outperforms the on-line model in all types of change for all three candidates, except increases in support for Miller. The on-line model accurately predicts over seventy-seven percent of these increases.
Table 5.16: Number of Days of Accurate Prediction for the On-line and Memory-Based Models in the Virginia Senate Race

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<tr>
<th></th>
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<th>Percentage of Total Days Correct</th>
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<td>Stability</td>
<td>21</td>
<td>35.3</td>
<td>1</td>
<td>1.69</td>
</tr>
</tbody>
</table>

Are there specific examples of convergence and divergence in the predictions the models make for public opinion and actual public opinion in this race? The Virginia Senate Race in 1994 is interesting simply for the fact that four candidates competed for the position against an incumbent Senator. What the tabular results make clear is that it is an interesting race also because it supports the finding from the Utah congressional race—the on-line model predicts stable public opinion better than the memory-based model and better than it predicts change in public opinion. The opposite is true for the memory-based model as it predicts directional change much better than it predicts stability.

Early in the season, a match between the on-line model’s prediction and actual public opinion occurs on February 10th and 11th. On February 10th, the online model
captures the increase in public support for Senator Robb. In contrast, the memory-based model predicts a decrease in public opinion on this date. One positive article was published. The positive article discussed Senator Robb's efforts to acquire additional police officers for Virginia's communities through a grant program passed the year before. The decrease predicted by the memory-based model stems from the decline in intensity of Robb's message on February 10th. On the previous day, February 9th, five articles were published discussing Senator Robb and these articles were mostly neutral and positive. As a result, the decline in intensity from these five articles to a single article leads to a predicted decline in support. The next day, February 11th, public opinion decreases and both models capture this decrease. Three negative articles were published. These articles focused on the scandals plaguing Robb.

Another interesting series of dates occurred early in the campaign season from February 1st through 3rd. On January 31st, three articles were printed: one neutral and two negative. The next day three articles were published: two positive and one negative article. The positive articles focused on North's huge fund-raising lead over his opponents, but the negative article emphasized North’s unwillingness to debate Jim Miller in the Republican primary. Both models predict an increase in support for North on this date conforming to an actual increase in support for North as the positive articles outweighed the one negative article. Negative coverage of North picked up as three negative articles were published on February 2nd. These articles highlighted North’s declining support and fitness for the U.S. Senate. Both the on-line and the memory-based model pick up this negative turn in support for North. Support for North continues to plummet as three additional negative articles were published on the last day of the series
(February 3rd). These articles again mentioned that, according to results released by Mason-Dixon, Robb would easily defeat North if the election were held today. However, the models’ predictions diverge. The on-line model accurately predicts a decline in support for North, but the memory-based model predicts an increase in support. The reason for this divergence is that the negative coverage was less intense for North than it was on the 2nd. As a result, the memory-based model predicts an increase for North on this date. However, the negative support continues to feed the on-line tally and the on-line model predicts a decrease in support for North.

Moving to the fall campaign season, there is a three day series in which actual public opinion for Robb matches the predictions of support for Robb from both models. Seven articles were published on September 9th, but this amount of coverage declined to two negative articles and a single neutral article on September 10th as public opinion declines as well. The neutral article discussed Robb in the context of a question he posed to Oliver North that led to a misstep by North as he claimed that Norfolk schools had a dropout rate of 63% (the dropout rate was actually 6.1%). The two negative articles focused on Robb’s withdrawal from a joint appearance with the other candidates, which led to the cancellation of the function. On the 11th, support increased for Robb in and the predictions from the models capture this increase. On this date, a number of positive articles were published. One particular article discussed the financial assistance former President Johnson’s loyalists in Texas were giving his son-in-law, Robb. Support continued to increase on the 12th and the models are able to capture this. The articles on this date discussed Robb’s endorsement by legendary civil rights leader Oliver Hill.
By the Republican convention, another series of dates emerges: June 8th through 10th. Both models accurately predict the decline in actual support for North on the first date of this series, June 8th. The coverage of the North campaign became more negative on the June 8th as six articles were published: four negative, one positive, and one neutral. The positive article discussed the endorsement of North by a Reagan associate who helped obtain the former president's letter criticizing North, and the neutral article focused on one of the Democratic primary opponents. Unfortunately for North, these two articles were paired with four negative articles concerned with the ability of the three Democratic primary candidates to defeat North, an editorial mocking all the candidates in the campaign, North's lack of respect for and lack of respect from Virginia's politicians, and North's inability to win the general election. The next day coverage did not rebound as more negative articles were published. This results in a negative prediction for the on-line model matching the actual support for North on this date. In contrast, the memory-based model predicts an increase in support for North on June 9th. Interestingly, the intensity measure for the memory-based model was negative for this date and more negative than the previous day. As I discuss at various points above, this mismatch between absolute coverage and the predictions of the memory-based model is reasonable given Zaller's insistence on a relative flow of campaign information. That is, a candidate's support is a function of not simply his own messages but also the messages of his opponents. However, on June 10th, the on-line model diverges from the actual support of North by predicting a decrease.

The models also diverge from actual public opinion when we consider the minor candidates. On July 8th, both models converge with reality by predicting an increase in
support for Coleman. The articles on July 8\textsuperscript{th} focused their attention on Marshall Coleman’s call for a non-specific middle-class tax cut and mentioned that Coleman would be speaking to the American Legion later in the week to discuss military policy, but on July 9\textsuperscript{th} the article concerned the candidate’s military service record in a positive light. As a result, the on-line model accurately predicts an increase in support. The memory-based model diverges in predicting a decline in support for Coleman. This divergence again stems from the intensity measure. The coverage of Coleman was more intense in a positive direction on July 8\textsuperscript{th}, and so on July 9\textsuperscript{th}, support declines from its level on the 8\textsuperscript{th}.

The on-line model identifies less points of actual directional change for Wilder in this race than the memory-based model. On July 6\textsuperscript{th}, the models diverge from actual support for Wilder. Wilder’s support is predicted to remain constant from its level on the 5\textsuperscript{th}. However, coverage on the sixth was more positive than it was on the 5\textsuperscript{th} (there was actually no coverage of Wilder); thus, the models predict an increase in support for Wilder. The newspaper coverage on July 6\textsuperscript{th} included a single positive article discussing the first debate of the general election campaign. The article itself was highly critical of the debate, but offered the kindest words for Wilder in judging him to be the candidate showing the most promise in the debate.

The final series of dates occurs just prior to Wilder’s withdrawal from the Virginia Senate race. On September 12\textsuperscript{th}, only three articles were published mentioning Wilder: one negative and two neutral. The models correctly predict support to increase on this date. The next day support increased for Wilder according to the on-line model while it decreased according to the memory-based model and the actual public opinion data.
Three articles were published including an article highlighting Wilder's support among 40 black ministers, an article discussing Wilder's endorsement by Richmond's Mayor Leonidas Young, and an article mentioning Wilder's campaign activities for the day. However, the coverage of Wilder's opponents was much more intense on this day than it was for Wilder. As a result, the memory-based model predicts a decrease in support for Wilder.

**Conclusion**

In the next chapter, I explore the systematic ways in which the models fail to predict public opinion at all points in the campaign season. My goal in this chapter was to provide a glimpse of the races in a variety of ways. First, I outlined the race in terms of the players in each race and any events, planned or otherwise, that provided one candidate with an edge. Turning to the data to be used in the next chapter, I depicted graphically the predictions from the on-line and memory-based models when I use the actual campaign data described in Chapter 4 as inputs in the equations for each model. I also graphed the actual path of public opinion data for each candidate using data from the Iowa Electronic Market. Finally, I compared the predicted paths of public opinion and the actual path of public opinion for each candidate to determine how well the models can predict public opinion across these eight races.

What I hope is clear from this chapter is that these are very different races. The races differ in terms of the type of race: two races are gubernatorial races (New York and Texas), one race is a U.S. House race (Utah), and five races are for seats in the U.S. Senate (Arizona, Illinois, New Jersey, Pennsylvania, and Virginia). Further, the races are different in terms of the incumbent nature of the candidates. In one race, the Arizona
Senate race, both candidates were officeholders but neither candidate was an incumbent for the seat in question. In a number of cases—Texas, Pennsylvania, Utah, etc.—single-term incumbents were running for re-election. In one case, the New York gubernatorial race, incumbent Governor Mario Cuomo was running for his fourth-term as governor of New York.

An additional feature distinguishing the races is the number of candidates vying for the seat in question. In Arizona, Texas, New Jersey, New York, Illinois, and Pennsylvania, only two viable candidates were competing for governor and senator, respectively. For Utah's 2nd congressional district, three candidates were competing for the position: a democrat, a republican, and an independent. At the extreme, four candidates were competing in the general election in Virginia, two major party candidates and two independents.

Finally, the races vary in terms of the primary challenges that the major party candidates face. In Texas, Ann Richards and George W. Bush easily won the nomination of their respective parties for governor. On the other hand, Sam Coppersmith had to wage a difficult battle and suffered through a recount in his primary in order to win the Democratic Party's nomination for the Arizona Senate seat. In Virginia, both major party candidates won their parties' nominations, but faced two independents bolting their own parties (Wilder—Democratic Party and Coleman—Republican Party). Such differences make these cases particularly interesting.

Not only are the eight campaigns very different in the ways described above, the predictions that the two models make for the paths of public opinion during these

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27 In a number of races, third party candidates compete for the office, but are not competitive in the sense that they do not acquire more than two or three percent of the vote.
campaigns also differs. In the next chapter, I explore the systematic divergences between the predicted paths and the actual paths. But to preview, the above figures highlight the tendency of the on-line model to be susceptible to inertia. History plays an important role in the on-line model in the sense that previous affective reactions continue to play a role in the on-line tally long after new information has been received. However, the memory-based model shows much more fluctuation in its predictions. Today’s level of support can vary dramatically from the levels of support of yesterday and tomorrow. I focus in the next chapter on these divergences examining specific instances from the political campaigns and illustrating certain contentions that emerge from these divergences. I then statistically test these contentions to determine if they are prevalent for all candidates in all races.
Chapter 6:
Do Our Models of Public Opinion Predict the Actual Course of Public Opinion? Four Reasons Why They Do Not

In the previous chapter, I described the eight campaigns and the predicted paths of public opinion emerging from the on-line and memory-based models. I also compared the actual path of public opinion with the predicted paths for the memory-based and on-line models. Interestingly, the two models predict different paths of public opinion for each candidate even though I rely on the same newspaper coverage to construct the inputs to the formalized equations.

Neither model perfectly predicts the actual path public opinion took for the twenty-one candidates. The important question to ask is in what ways are the two models failing to predict public opinion in these eight campaigns. From the simulated campaigns in Chapter 3 and the actual campaigns presented in the previous chapter, I have identified a number of potential failures that might make it difficult for the models to accurately predict the course of public opinion during these eight campaigns.

To be clear, this is a slightly different approach than is often used in political science research. Typically we propose a relationship between two variables and use statistical tests to determine whether a causal, or correlational, relationship exists between the variables. I could use such an approach by considering the models' predictions to be the explanatory variables and determine whether predicted public opinion "explains" actual public opinion. This approach would make it clear which model predicted "better", but it would make it impossible to determine in what systematic ways the models fail to predict public opinion across a series of campaigns. Instead, I want to determine whether the paths of public opinion predicted by the two models deviate from actual public opinion in
very specific ways. By comparing the predicted paths to the actual paths of public opinion in the previous chapter, I have identified a number of ways that the models might consistently fail to predict public opinion across races.

First, the models might do better at predicting initial change in public opinion but be much worse at predicting persistence after change. Second, the models might do better at predicting public opinion early in the campaign season, but become progressively worse at predicting public opinion as the season continues. Third, the models might be able to predict volatility in public opinion but have difficulty predicting public opinion when it is more stable. Further, the models might be relatively better or relatively worse at coping with incumbent candidates.

In what follows, I describe these potential deviations in greater detail. I use a consistent approach I first discuss the potential failure and illustrate the failure graphically by providing a comparison between the predicted paths and the actual paths of public opinion. After identifying where the models might be failing to predict public opinion, I then use statistical tests to determine if this is a consistent failure across candidates and races. The statistical tests are followed by a discussion of why the models’ predictions might deviate from actual public opinion in the particular ways I identify. In the next chapter, I discuss modifying the models to improve the fit between the actual path of public opinion and the predicted paths of public opinion emerging from the formalization of the on-line and memory-based models.
Initial Change versus Persistence

The first potential failure is that perhaps one or both of the models are better at predicting initial change in public opinion but have difficulty in predicting the days following such change. Let me illustrate what I have in mind. Let’s look at one of the candidates in the Arizona Senate Race—Sam Coppersmith. In Figure 6.1, I plot the actual path of public opinion against the predictions for Sam Coppersmith from the memory-based model. The circular points represent the predicted path of public opinion and the triangular points signal the actual path of public opinion. What is evident from the graph is that there are multiple points of correspondence between actual public opinion and the predicted values for public opinion from the memory-based model. However, the model also deviates at a number of points from the actual path of support for Coppersmith.

Figure 6.1: The Memory-Based Model—the Arizona Senate Race—Sam Coppersmith
Look at the area inside the black circle. On Oct 22nd, represented by the solid arrow, the memory-based model predicts a decline in public opinion. This corresponds to an actual decline in public opinion. The coverage on this date was quite negative for Coppersmith as it discussed his inability to garner public support, and reported polling data finding Coppersmith sixteen points behind Kyl, and argued that Coppersmith had failed to capture support among a diverse group of potential supporters. As a result of this negative coverage, the memory-based model predicts a decrease in support.

However, the very next day the flow of information became much more positive with an article critiquing his opponent’s stance on abortion. Further, Coppersmith also received an endorsement from the newspaper used in this study. This newspaper endorsement highlighted Coppersmith’s favorable personal characteristics as well as his professional qualifications. The memory-based model predicts an increase in public opinion (represented by the upper dotted arrow) corresponding to an actual increase in public opinion for Coppersmith (the lower dotted arrow). At this point the predicted path and the actual path correspond, but an important disjoint occurs on the 24\textsuperscript{th} when the memory-based model predicts a decline in support. However, actual public opinion increases slightly for Coppersmith. This disjoint continues for at least five days after the initial change (the decline on the 22\textsuperscript{nd}).

The model predicts the initial change in public opinion, but fails to predict the persistence in public opinion after this initial change. This type of disjoint occurs throughout the races. This is not an isolated case of failure as the memory-based model consistently fails to predict persistence in public opinion. Why does this disjoint occur? The answer lies within the theoretical model. While the memory-based model is
considered a “memory” model, Zaller is not talking about long-term memory. The accessibility axiom argues that the information most accessible to the individual for use in making a decision is that information that was most recently heard. The model does not rely on information stored in long-term memory. So, when the newspaper endorsed Coppersmith, the memory-based model captures this endorsement with an increase matching an increase in actual support for Coppersmith; however, this increase does not carry over to the next day (the 24th) in the model while the increase does carry over to the next day in actual public opinion.

Does the model consistently fail in this particular way? In order to answer this question, we need to turn to a statistical test. The most straightforward way to test whether the model consistently predicts initial change but mispredicts the days after this change is to focus on the distance between the predicted path for public opinion and the actual path for public opinion. If actual public opinion does not rebound as quickly as the memory-based model predicts, then we would anticipate that the distance between the two paths would be greatest the day after this initial change and decline as time passes.

The unit of analysis in this test is the candidate-day; that is, the unit of analysis is support for a given candidate on a given day. The dependent variable for this test is the distance between the two paths. I create the distance variable by taking the absolute value of the difference between the predicted level of support for a candidate at time $t$ and the actual level of support for that candidate at time $t$. The distance captures the disparity between the two paths. Distance ranges from a minimum of 0.0003 to a maximum of over 8 units. If the memory-based model predicts initial change well, but then fails to predict support after this change, then the expectation is that the distance between the two
paths would be greatest the day after initial change. The distance between the two paths should become substantially less as time progresses after the initial change.

To determine whether the distance between the two paths decreases over time, I create a series of dichotomous variables to capture whether a particular day is the day after an initial change, two days after an initial change, three days after an initial change, four days after an initial change, and five days after an initial change. If a change occurs on Monday, then that day is coded as a day with initial change. Tuesday then would score a one on the day-after-change variable and zero for the other day variables. Wednesday would score a one on the second-day variable, and so on.

After these variables have been created, I regress these dummy variables on the distance variable to determine if distance actually decreases as time elapses. For this regression, I use all twenty-one candidates in the eight races. This produces 2800 timepoints for use in the analysis.

Before discussing the results, remember that I am not looking for a causal relationship between the distance variable and the time variables. I am just looking for evidence that the two paths—predicted public opinion and actual public opinion—diverge in the way I have described above. I display the results from this regression in Table 6.1. The results indicate that distance declines as time after initial change increases. All of the dummy variables are universally positive and three of the five dummy variables are significant. This indicates that the distance between the two series does increase, as one gets further away from the initial change. It seems to be that the memory-based model has trouble predicting public opinion after initial change.
Table 6.1: Initial Change versus Persistence

<table>
<thead>
<tr>
<th>DV = Distance</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Day After</td>
<td>0.073*</td>
<td>0.043</td>
</tr>
<tr>
<td>Two Days After</td>
<td>0.049</td>
<td>0.043</td>
</tr>
<tr>
<td>Three Days After</td>
<td>0.077*</td>
<td>0.044</td>
</tr>
<tr>
<td>Four Days After</td>
<td>0.073*</td>
<td>0.044</td>
</tr>
<tr>
<td>Five Days After</td>
<td>0.026</td>
<td>0.043</td>
</tr>
<tr>
<td>Constant</td>
<td>0.982***</td>
<td>0.028</td>
</tr>
</tbody>
</table>

No. of Observations 2700  
R-Squared 0.009

* p<0.10, **p<0.05, ***p<0.01

The above test is telling, but a more nuanced way to capture the notion that the memory-based model does a good job predicting initial change but much worse at predicting the days after that initial change is with an error correction model. The error correction model was developed to model the way that some time-series tend to track each other overtime. If two time-series move together overtime, one might use an error correction model because it allows for shocks to this tracking (King 1998). If in one period the dependent variable receives a "shock" and no longer moves with the independent variable, the two series would continue to diverge for the remaining time periods without a correction.

The error correction model, given by Equation 6.1, corrects this situation such that after a shock in one time period the two time-series return to their previous tracking state in the next time period. Importantly for my purposes, the error correction model allows one to model the immediate effect of the independent variable on the dependent variable as well as the long-term effect of the independent variable on the dependent variable.

Using the ECM allows me to determine the extent to which the memory-based model’s predictions deviate in response to shocks in such a way that the predictions need to be corrected to bring them back in line with actual public opinion.

\[
\Delta Y_t = \alpha_0 - \alpha_1 (Y_{t-1} - \beta_1 X_{t-1}) + \beta_0 \Delta X_t + \epsilon_t \quad \text{Equation 6.1}
\]
In Equation 6.2, I substitute the variables in Equation 6.1 with the predicted path of public opinion from the memory-based model and the actual path of public opinion.

\[ \Delta \text{Opinion} = \alpha_0 - \alpha_1 (\text{Opin}_{t-1} - \beta_1 \text{PredOpin}_{t-1}) + \beta_0 \Delta \text{PredOpin}_t + \epsilon_t \quad \text{Equation 6.2} \]

In this equation, the current change in \( Y \) is a function of the current change in \( X \) and the extent to which the two time-series are not tracking one another. The term \( \alpha_0 \) is the constant in the equation and the term \( \epsilon_t \) is the error term. The term \( \beta_0 \) represents the contemporaneous effect of \( X \) on \( Y \) while the \( \beta_1 \) term captures the long-term effect of \( X \) on \( Y \). The part inside the parentheses is positive when the paths diverge from each other. The \( \alpha_1 \) term measures the error correcting rate or the time it takes for the paths to move together again. This coefficient represents the rate at which prediction errors are corrected. After the memory-based model mispredicts a day, this rate tells us how long it takes the model to start predicting accurately again. If this coefficient is large (close to \(-1\)) then correction is very quick. If the model mispredicts a day, it very quickly gets back on track. If the coefficient is small, then this suggests that it takes a long time for the model to get back on track after misprediction. If this coefficient is equal to zero, then this indicates that the two time-series are not related in the long term. I have argued that when opinion changes, the memory-based model tends to mispredict for a substantial period of time, but eventually predicts accurately again. As a result, my expectation is that the adjustment process will take at least some time, so the \( \alpha_1 \) coefficient will be non-zero but small.

To test this expectation, I actually use a lagged dependent variable model because a number of scholars (i.e. Keele and De Boef, 1994) have demonstrated that the error
correction model can be derived from a lagged dependent variable model. The lagged dependent variable model that I use is displayed as Equation 6.3.

\[
\text{Opinion}_t = \beta_0 + \beta_1 \text{Opinion}_{t-1} + \beta_2 \text{PredOpin}_t + \epsilon_t \quad \text{Equation 6.3}
\]

The memory-based model's predicted value of support for each candidate \( i \) at time \( t \) is the main explanatory variable in the lagged dependent variable model. The dependent variable in this model is actual support at time \( t \) for a candidate \( i \). The second explanatory variable is actual support for candidate \( i \) at time \( t-1 \). Using the coefficients produced from the lagged-dependent variable model for each candidate \( i \), I calculate the short-term effect and the correction rate or the time it takes for the two time-series to track each other again. The short-term effect is simply the \( \beta_2 \) coefficient on the predicted values of public opinion. The correction rate is calculated by subtracting the coefficient on the lagged dependent variable from one. Such a process provides the leverage I need to determine if the evidence supports the notion that the model does a much better job predicting initial change, but diverges after such initial change.

The results in Table 6.2 support this contention. The short-term effect is not significant, but the key to this contention lies with the correction rate. The correction rate is both non-zero and significant, as I anticipated given the argument. Further, the size of the rate implies a correction period of eight days after a misprediction for the model to correctly predict again. These analyses indicate that the deviation in the graph is a general one across cases and worthy of our attention. My explanation for why this deviation is occurring is that the memory-based model fails to capture long-term memory in any explicit way.
Table 6.2: Initial Change versus Persistence—Error Correction Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short Term</td>
<td>-0.0116</td>
</tr>
<tr>
<td>Correction Rate</td>
<td>-0.1482***</td>
</tr>
</tbody>
</table>

* p<0.10, **p<0.05, ***p<0.01

Point in the Campaign Season

The second potential failure relates to the point in the campaign season in which the two models make more accurate predictions. I anticipated that the memory-based model would be more accurate in making predictions early in the campaign season rather than later. Why? The memory-based model fails to capture long-term memory in any explicit way, so at the beginning of the season the public should look the way the memory-based model perceives individuals to look—no long term memory for campaign information. As the campaign proceeds, individuals acquire memory for campaign information but this is not captured by the memory-based model. As a result, divergence between the actual path of public opinion and the predicted path should occur as the season progresses.

Let me illustrate this notion graphically. I draw the example for this deviation from the Virginia Senate race in 1994. In this race, five candidates compete for this seat. In Figure 6.2, I graph the predicted path of public opinion and the actual path of public opinion for one of the candidates, the Republican nominee, Oliver North.
Figure 6.2: Scatterplot of the Point in the Campaign Season—Memory-Based Model

North

Given the number of datapoints, almost 300 candidate-days, it is quite difficult to discern if the paths diverge later in the campaign season to a greater extent than earlier. To get a handle on whether the paths diverge, I replace the scatter plot with a smoothing line in Figure 6.3. The solid line represents the predicted path of public opinion and the dashed line represents the actual path of public opinion for Oliver North. This graph makes it evident that the lines are much further apart at the end of the campaign season than they were at the beginning. By September, actual public opinion begins to rise dramatically while the memory-based model predicts a dramatic decline beginning on this date. At the end of the campaign season, actual public opinion and the memory-based model diverge to a great extent.
Figure 6.3: Smoothing Line of the Point in the Campaign Season—Memory-Based Model

Is the tendency for the model to predict public opinion more accurately at the beginning of the campaign season than at the end of the campaign season consistent across the twenty-one candidates in the eight campaigns? The hypothesis is that as the season progresses, the distance between the two paths should become greater.

To answer this question, I rely once again on the distance between the two paths as the dependent variable, to capture the divergence between the predicted and actual paths. To measure the point in the campaign season, I create a categorical variable ranging from 0 to 3. For each race, I create three cutpoints to produce the four categories. The first cutpoint is one-fourth of the way through the campaign season, the second cutpoint is halfway through the campaign season, and the third cutpoint is three-fourths of the way through the campaign season. Dates in the campaign season are coded as 0 if they occur before the first cutpoint, 1 if they occur after the first cutpoint and before the second cutpoint, 2 if they occur after the second cutpoint and before the third cutpoint, and 3 if
they fall after the third cutpoint. I have over 2800 timepoints for the twenty-one candidates in the eight races. To test this hypothesis, I regress the season variable on the distance between the memory-based model's predicted path and the actual path of public opinion for all twenty-one candidates. Table 6.3 presents the results of this analysis.

The first model presents the results of the full sample of races. I find that there is indeed a positive relationship between distance and the point in the campaign season. As the campaign season proceeds, distance between the predicted path and the actual path increases. Nonetheless, this result is not statistically significant as the p-value is 0.159. This suggests that the model likely does no better or worse as the season progresses. However, this should not be the immediate conclusion. In Models 2 and 3, I divide the races into those races that have a lengthy campaign season (~200 days) and those that have a shorter campaign season (<200 days). The length of the campaign season is unfortunately not determined by the actual length of the campaign season; in my dataset, the campaign season begins when the public opinion data begins. As a result, some races in the dataset are incredibly short in that they start in the fall while others are much longer as they start in the spring. Does this make a difference for this test? The results presented for Models 2 and 3 suggest that it does. In the shorter races, the point in the campaign season is actually negatively related to distance. As the campaign season approaches Election Day, the actual path and the predicted path converge. In the longer races, the distance between the two paths increases as the campaign season progresses.
Table 6.3: The Point in the Campaign Season—Memory-Based Model

<table>
<thead>
<tr>
<th>DV = Distance</th>
<th>Model 1 All Races</th>
<th>Model 2 Races 1-5</th>
<th>Model 3 Races 6-8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Point in Campaign Season</td>
<td>0.0239 (0.0168)</td>
<td>-0.0807*** (0.0345)</td>
<td>0.0539*** (0.0191)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.0570*** (0.0318)</td>
<td>1.1440*** (0.0651)</td>
<td>1.0313*** (0.0363)</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>2805</td>
<td>622</td>
<td>2183</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.0007</td>
<td>0.0087</td>
<td>0.0036</td>
</tr>
</tbody>
</table>

* p<0.10, **p<0.05, ***p<0.01

While the on-line model is predicted to fail in a similar way, the explanation for the failure is much different. In Chapter 2, I argued that the on-line model is much more susceptible to inertial problems. That is, the model cannot easily be moved from one direction once it has built up a substantial tally in that direction. As a result, the model likely has difficulty responding to “shocks” to the system the longer the campaign season has been going on (like newspaper endorsements or scandals). Therefore, I anticipate that the model will be least accurate at predicting public opinion later in the campaign season. To illustrate, I plot the predictions from the on-line model for Oliver North in Figure 6.4. The on-line model is most inaccurate in its prediction late in the campaign season.
Figure 6.4: The Point in the Campaign Season—On-Line Model

While the above graph is demonstrative, it does not provide evidence that this phenomenon is consistent across the eight races for all twenty-one candidates. To grapple with this, I conduct the same test for the on-line model as I did for the memory-based model. The results are displayed in Table 6.4. Like the results for the memory-based model, the results in Model 1 indicate that as time passes the distance between the predicted value of public opinion and the actual value of public opinion becomes greater. However, this is not a significant relationship. Further, Models 2 and 3 demonstrate that the lengthy campaign seasons of Races 6, 7, and 8 drives the positive relationship in Model 1. In the shorter races, the point in the campaign season is negatively related to distance, but it is insignificant.
Table 6.4: The Point in the Campaign Season—On-Line Model

<table>
<thead>
<tr>
<th>DV = Distance</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Races</td>
<td>Races 1-5</td>
<td>Races 6-8</td>
</tr>
<tr>
<td>Point in Campaign Season</td>
<td>0.0183</td>
<td>-0.0261</td>
<td>0.0317*</td>
</tr>
<tr>
<td></td>
<td>(0.0151)</td>
<td>(0.0299)</td>
<td>(0.0174)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.9635***</td>
<td>1.1313***</td>
<td>0.9144***</td>
</tr>
<tr>
<td></td>
<td>(0.0286)</td>
<td>(0.0565)</td>
<td>(0.0329)</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>2805</td>
<td>622</td>
<td>2183</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.0005</td>
<td>0.0012</td>
<td>0.0015</td>
</tr>
</tbody>
</table>

* p<0.10, **p<.05, ***p<.001

**Stability versus Volatility**

A further contention is that the models vary in their ability to predict public opinion when it is stable or volatile. I anticipated that the memory-based model ought to have difficulty predicting stable public opinion because the model lacks a role for long-term memory. The memory-based model can only predict stability when the relative intensity of campaign messages does not change and in only two ways is this possible given the formalization of the memory-based model. If there is no newspaper coverage for two or more days for all candidates, stability will be possible. In this case, the model will simply rely on the contextual attributes—political partisanship, political awareness, and difficulty—to produce a predicted value for the candidates. Given that these attributes are static, two or more days without coverage will yield a stable prediction. The second way that stability can be produced is if there are successive days with consistent coverage for all candidates. Imagine a situation in which the newspapers publish three positive articles for candidate a and two negative articles for candidate b on day t, and three positive articles for candidate a and two negative articles for candidate b on day t+1. In this case, the model would predict the same level of public opinion for both candidates on day t and t+1.

Using the real campaign data, I demonstrate the conditions under which stability can
emerge in Figure 6.5 for Jon Kyl in the Arizona Senate Race and Enid Greene-Waldholtz from the Utah Congressional Race. In the first panel, the periods of predicted stability for Jon Kyl emerge from a lack of coverage of both Kyl and Coppersmith in the Arizona Senate race on these dates. The stretch from October 24th through the 29th was a period in which there was no coverage for either candidate from the newspaper included in this study. The same was true of the two additional periods of stability: October 13th through 14th and October 19th and 20th. The same was not true however of the coverage of the candidate in the second panel, Enid Greene-Waldholtz from the Utah Congressional Race. In this case, stability emerges not from a lack of coverage but from identical coverage of the candidates in the race. The stretch from March 3rd through 6th is stable because Greene-Waldholtz’s coverage and that of her opponents remained constant. Greene-Waldholtz and the independent candidate, Cook, were not covered in the newspaper during this period, but Karen Shepherd, the Democratic candidate had consistent coverage throughout the period. A similar pattern emerges on a number of occasions, such as the period from April 11th through the 14th and July 25th through 27th.
Figure 6.5: Stability versus Volatility—Memory-Based Model

While the above graphs provide evidence that the memory-based model can predict stability under certain conditions, the graphs also indicate that the model tends to predict instability for substantial periods of time. To determine the accuracy with which the memory-based model predicts stability and volatility, I turn to the predicted values for the twenty-one candidates in the eight races included in the study. Table 6.5 and Table 6.6 include a number of interesting findings. Focusing first on Table 6.5, Column 2 represents the number of days the memory-based model predicts to be stable. The memory-based model predicts only 278 days of stability for all twenty-one candidates across all eight campaigns. An important caution is that the memory-based model, by its formalization, must predict the same number of stable days for all candidates in a given race; this is a constraint imposed by the relative intensity notion of the memory-based model. When the model predicts stability for one candidate, by definition, it also must predict stability for all other candidates in the race. However, the exception to this rule is
the Virginia Senate race. In the Virginia Senate race, Miller, Coleman, and Wilder have different frequencies of stability. This is a result of these candidates entering the race late (Coleman and Wilder) or leaving the race before November (Miller and Wilder).

The third column in the table lists the number of days public opinion is actually stable for each candidate. Across the eight races, actual public opinion is stable on ~1800 days. How well does the memory-based model predict stability? The fourth column represents the number of days of stable public opinion the memory-based model accurately predicts while the fifth column represents the percentage of days of stable public opinion the memory-based model accurately predicts. The answer to the above question is not very well. The memory-based model fails to accurately predict stability in public opinion. The only two races in which the memory-based model accurately predicts more than one-fourth of the days of stable public opinion are the Arizona Senate race and the Utah Congressional race. However, these are the two races in which only one newspaper was available for coding. Because the memory-based model predicts stability only when there is no news coverage of either candidate or if news coverage for both candidates remains static, I would expect the number of accurate predictions to drop even lower if I had more coverage of these two races. This is interesting because it seems to indicate that the more accurately I capture the coverage of a race, the less accurately the memory-based model predicts the stability of public opinion. This suggests that the formalization of the model might be wanting.
Table 6.5: Stability—the Memory-Based Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Days Predicted to be Stable</th>
<th>No. of Stable Public Opinion Days</th>
<th>No. of Stable Opinion Days Predicted Accurately</th>
<th>% of Stable Opinion Days Predicted Accurately</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>10</td>
<td>11</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>Kyl</td>
<td>10</td>
<td>19</td>
<td>7</td>
<td>36.8</td>
</tr>
<tr>
<td>Martin</td>
<td>5</td>
<td>69</td>
<td>4</td>
<td>5.80</td>
</tr>
<tr>
<td>Simon</td>
<td>5</td>
<td>75</td>
<td>5</td>
<td>6.67</td>
</tr>
<tr>
<td>Haytaian</td>
<td>0</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cuomo</td>
<td>0</td>
<td>49</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pataki</td>
<td>0</td>
<td>46</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>0</td>
<td>47</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Santorum</td>
<td>1</td>
<td>41</td>
<td>1</td>
<td>2.44</td>
</tr>
<tr>
<td>Wofford</td>
<td>1</td>
<td>39</td>
<td>1</td>
<td>2.56</td>
</tr>
<tr>
<td>Richards</td>
<td>12</td>
<td>158</td>
<td>12</td>
<td>7.59</td>
</tr>
<tr>
<td>Bush</td>
<td>12</td>
<td>162</td>
<td>10</td>
<td>6.17</td>
</tr>
<tr>
<td>Cook</td>
<td>71</td>
<td>238</td>
<td>61</td>
<td>25.6</td>
</tr>
<tr>
<td>Shepherd</td>
<td>71</td>
<td>206</td>
<td>51</td>
<td>24.8</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>71</td>
<td>222</td>
<td>62</td>
<td>27.9</td>
</tr>
<tr>
<td>Robb</td>
<td>3</td>
<td>120</td>
<td>1</td>
<td>0.83</td>
</tr>
<tr>
<td>North</td>
<td>3</td>
<td>112</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Miller</td>
<td>3</td>
<td>59</td>
<td>1</td>
<td>1.69</td>
</tr>
<tr>
<td>Coleman</td>
<td>0</td>
<td>70</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wilder</td>
<td>0</td>
<td>48</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>278</strong></td>
<td><strong>1828</strong></td>
<td><strong>221</strong></td>
<td><strong>12.1</strong></td>
</tr>
</tbody>
</table>

The second column represents the number of days in the campaign season that the memory-based model predicts to be stable. The third column represents the number of stable public opinion days. The total in column three represents the total number of stable opinion days. The fourth column represents the number of stable opinion days that the memory-based model accurately predicts. The fifth column represents the percentage of stable opinion days that the memory-based model accurately predicts.

Turning to the predictions for volatility, the model does incredibly well at accurately predicting volatility in public opinion for all candidates. The memory-based model predicts many more days of volatility (2527) across the eight races than it predicted stability. Table 6.6 displays the number of days predicted by the memory-based model to be volatile, the number of actual days of volatility, and the accuracy of the memory-based model's predictions for volatility. Column 2 represents the number of days of volatility predicted by the memory-based model for each candidate while Column 3 represents the number of days that public opinion is actually volatile. As one might have expected, the memory-based model predicts much more volatility for all candidates than it predicted
stability. In particular, the model predicts volatility throughout the entire campaign season for the New Jersey Senate and New York Gubernatorial races.

In the final two columns, I list the number of days and the percentage of volatile public opinion days that the memory-based model accurately predicts. Given the high levels of volatility predicted by the memory-based model, it is little surprise that the model correctly predicts over fifty percent of the days in which there are increases or decreases for eleven of the twenty-one candidates.

### Table 6.6: Volatility—the Memory-Based Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Days Predicted to be Volatile</th>
<th>No. of Volatile Public Opinion Days</th>
<th>No. of Volatile Opinion Days Predicted Accurately</th>
<th>% of Volatile Opinion Days Predicted Accurately</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>17</td>
<td>16</td>
<td>7</td>
<td>43.8</td>
</tr>
<tr>
<td>Kyl</td>
<td>17</td>
<td>8</td>
<td>4</td>
<td>50.0</td>
</tr>
<tr>
<td>Martin</td>
<td>100</td>
<td>36</td>
<td>15</td>
<td>50.0</td>
</tr>
<tr>
<td>Simon</td>
<td>100</td>
<td>30</td>
<td>20</td>
<td>55.6</td>
</tr>
<tr>
<td>Haytian</td>
<td>35</td>
<td>16</td>
<td>9</td>
<td>56.3</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>35</td>
<td>17</td>
<td>10</td>
<td>58.8</td>
</tr>
<tr>
<td>Cuomo</td>
<td>64</td>
<td>15</td>
<td>9</td>
<td>60.0</td>
</tr>
<tr>
<td>Pataki</td>
<td>64</td>
<td>18</td>
<td>8</td>
<td>44.4</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>64</td>
<td>17</td>
<td>11</td>
<td>64.7</td>
</tr>
<tr>
<td>Santorum</td>
<td>47</td>
<td>7</td>
<td>3</td>
<td>42.9</td>
</tr>
<tr>
<td>Wofford</td>
<td>47</td>
<td>9</td>
<td>6</td>
<td>66.7</td>
</tr>
<tr>
<td>Richards</td>
<td>182</td>
<td>36</td>
<td>18</td>
<td>50.0</td>
</tr>
<tr>
<td>Bush</td>
<td>182</td>
<td>32</td>
<td>17</td>
<td>53.1</td>
</tr>
<tr>
<td>Cook</td>
<td>222</td>
<td>55</td>
<td>20</td>
<td>36.7</td>
</tr>
<tr>
<td>Shepherd</td>
<td>222</td>
<td>87</td>
<td>35</td>
<td>40.2</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>222</td>
<td>71</td>
<td>32</td>
<td>45.1</td>
</tr>
<tr>
<td>Robb</td>
<td>279</td>
<td>162</td>
<td>79</td>
<td>48.8</td>
</tr>
<tr>
<td>North</td>
<td>279</td>
<td>170</td>
<td>75</td>
<td>44.1</td>
</tr>
<tr>
<td>Miller</td>
<td>139</td>
<td>83</td>
<td>48</td>
<td>57.8</td>
</tr>
<tr>
<td>Coleman</td>
<td>131</td>
<td>61</td>
<td>28</td>
<td>45.9</td>
</tr>
<tr>
<td>Wilder</td>
<td>79</td>
<td>31</td>
<td>15</td>
<td>48.4</td>
</tr>
</tbody>
</table>

| Total      | 2527                                  | 977                                | 469                                              | 48.0                                          |

The second column represents the number of days in the campaign season that the memory-based model predicts to be volatile. The third column represents the number of volatile public opinion days. The fourth column represents the number of volatile opinion days that the memory-based model accurately predicts. The fifth column represents the percentage of volatile opinion days that the memory-based model accurately predicts.

An important question remains—when the model mispredicts stability versus volatility in public opinion, what is the nature of this misprediction? Does the model tend
to predict volatility when actual public opinion is stable or does the model tend to predict stability when actual public opinion is volatile? The answer is probably quite obvious from the discussion above and from the discussion of the model’s formalization in Chapter 2. Table 6.7 makes it clear though that the model consistently mispredicts public opinion when public opinion is stable rather than when public opinion is volatile.

Column two represents the number of stable public opinion days that the memory-based model predicts to be volatile and Column 3 represents the percentage of stable public opinion days predicted to be volatile. The fourth column represents the number of volatile public opinion days that the memory-based model predicts to be stable and Column 5 represents the percentage of volatile days that are mispredicted. The model consistently mispredicts public opinion when opinion is stable rather than when public opinion is volatile. The model commits the first error of predicting volatility when public opinion is stable to a greater extent (eighty-seven percent) than it commits the second error of predicting stability when actual public opinion is volatile (six percent).
Table 6.7: Mispredicting Stability and Volatility—the Memory-Based Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Mispredicted Stable Opinion Days</th>
<th>Mispredicting Stability %</th>
<th>No. of Mispredicted Volatile Opinion Days</th>
<th>Mispredicting Volatility %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>6</td>
<td>54.6</td>
<td>5</td>
<td>31.3</td>
</tr>
<tr>
<td>Kyl</td>
<td>12</td>
<td>63.2</td>
<td>3</td>
<td>37.5</td>
</tr>
<tr>
<td>Martin</td>
<td>65</td>
<td>94.2</td>
<td>1</td>
<td>2.78</td>
</tr>
<tr>
<td>Simon</td>
<td>70</td>
<td>70.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Haytaian</td>
<td>19</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>18</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cuomo</td>
<td>49</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pataki</td>
<td>46</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>47</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Santorum</td>
<td>40</td>
<td>97.6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wofford</td>
<td>38</td>
<td>97.4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Richards</td>
<td>146</td>
<td>92.4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bush</td>
<td>152</td>
<td>93.8</td>
<td>2</td>
<td>6.25</td>
</tr>
<tr>
<td>Cook</td>
<td>177</td>
<td>74.4</td>
<td>10</td>
<td>18.2</td>
</tr>
<tr>
<td>Shepherd</td>
<td>155</td>
<td>75.2</td>
<td>20</td>
<td>23.0</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>160</td>
<td>72.1</td>
<td>9</td>
<td>12.7</td>
</tr>
<tr>
<td>Robb</td>
<td>119</td>
<td>99.2</td>
<td>2</td>
<td>1.23</td>
</tr>
<tr>
<td>North</td>
<td>112</td>
<td>100</td>
<td>3</td>
<td>1.76</td>
</tr>
<tr>
<td>Miller</td>
<td>58</td>
<td>98.3</td>
<td>2</td>
<td>2.41</td>
</tr>
<tr>
<td>Coleman</td>
<td>70</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wilder</td>
<td>48</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>1607</td>
<td>87.9</td>
<td>57</td>
<td>5.83</td>
</tr>
</tbody>
</table>

The second column represents the number of stable days that the memory-based model predicts as volatile. The third column represents the percentage of stable days that the memory-based model predicts as volatile. The fourth column represents the number of volatile days that the memory-based model predicts as stable. The fifth column represents the percentage of volatile days that the memory-based model predicts as stable.

Turning to the on-line model, I anticipate that the model will predict stability to a greater extent than the memory-based model and do worse at predicting volatility. The formalization of the on-line model is such that it cannot easily be moved from a particular direction once the tally has been built up. As a result, one would predict that the on-line model would have much more difficulty responding to “shocks” in the campaign. Therefore, the model should more accurately predict the total number of stable days throughout the campaign season than does the memory-based model. Unlike the memory-based model, the on-line model does not rely on the intensity of opponent’s messages. As a result, the on-line model can predict stability for candidate a and at the same time predict immense volatility for other candidates in the race. To illustrate the
tendency of the model to predict stability, the graphical examples I use are displayed in Figure 6.6. This figure plots the actual path of public opinion against the on-line model’s predicted path of public opinion for Merrill Cook in the Utah Congressional Race and Richard Rosenbaum in the New York Gubernatorial Race.

The actual path of public opinion for both candidates is represented by the dashed line and the predicted path is represented by the solid line. The on-line model predicts periods of stability interspersed with days of volatility. At various points, the on-line model predicts stability for the two candidates that matches the actual stability in public opinion. Unlike the memory-based model, the on-line model does not rely on the intensity of opponent’s messages. As a result, the on-line model can predict stability for candidate a and at the same time predict immense volatility for other candidates in the race. The on-line model predicts stability in support for a given candidate only when there is no coverage of that candidate on a given day.

**Figure 6.6: Stability versus Volatility—On-Line Model**
In Table 6.8, I show the stability numbers for the on-line model across all twenty-one candidates in the eight campaigns. Column 2 represents the number of days of stability predicted by the on-line model. The on-line model triples the memory-based model’s accuracy with respect to predicting days of stability. The on-line model predicts stable public opinion on 777 days in the campaigns. This is much higher than the number of days of stability predicted by the memory-based model (<300). The third column in the table lists the number of days public opinion is actually stable for each candidate (~1800 days).

The fourth column represents the number of days of stability in public opinion the on-line model accurately predicts while the fifth column represents the percentage of days of stable public opinion the on-line model accurately predicts. Of the ~1800 days of stability, the on-line model captures over 500 of these days accurately yielding it an accuracy rate of thirty percent. However, the on-line model mispredicts almost two-thirds of the days of stability. While this misprediction is substantially lower than the memory-based model’s misprediction, it is higher than suggested by the formalization. The on-line model triples the memory-based model’s accuracy with respect to predicting days of stability. However, the on-line model mispredicts almost two-thirds of the days of stability. While this misprediction is substantially lower than the memory-based model’s misprediction, it is higher than what the formalization suggests. Interestingly, the on-line model does a much better job predicting stability for certain candidates than it does for others. For five of the candidates—Cook, Greene-Waldholtz, Rosenbaum, Coppersmith and Kyl—the model predicts at least forty fifty percent of the days of stability.
Table 6.8: Stability—the On-Line Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Days Predicted to be Stable</th>
<th>No. of Stable Public Opinion Days</th>
<th>No. of Stable Opinion Days Predicted Accurately</th>
<th>% of Stable Opinion Days Predicted Accurately</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>13</td>
<td>11</td>
<td>5</td>
<td>45.5</td>
</tr>
<tr>
<td>Kyl</td>
<td>13</td>
<td>19</td>
<td>8</td>
<td>42.1</td>
</tr>
<tr>
<td>Martin</td>
<td>19</td>
<td>69</td>
<td>14</td>
<td>20.3</td>
</tr>
<tr>
<td>Simon</td>
<td>18</td>
<td>75</td>
<td>16</td>
<td>21.3</td>
</tr>
<tr>
<td>Haytaian</td>
<td>0</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cuomo</td>
<td>0</td>
<td>49</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pataki</td>
<td>1</td>
<td>46</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>44</td>
<td>47</td>
<td>31</td>
<td>66.0</td>
</tr>
<tr>
<td>Santorum</td>
<td>5</td>
<td>41</td>
<td>4</td>
<td>9.76</td>
</tr>
<tr>
<td>Wofford</td>
<td>2</td>
<td>39</td>
<td>2</td>
<td>5.13</td>
</tr>
<tr>
<td>Richards</td>
<td>18</td>
<td>158</td>
<td>16</td>
<td>10.1</td>
</tr>
<tr>
<td>Bush</td>
<td>32</td>
<td>162</td>
<td>28</td>
<td>17.3</td>
</tr>
<tr>
<td>Cook</td>
<td>196</td>
<td>238</td>
<td>169</td>
<td>71.0</td>
</tr>
<tr>
<td>Shepherd</td>
<td>101</td>
<td>206</td>
<td>74</td>
<td>35.9</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>211</td>
<td>222</td>
<td>167</td>
<td>75.2</td>
</tr>
<tr>
<td>Robb</td>
<td>23</td>
<td>120</td>
<td>11</td>
<td>9.17</td>
</tr>
<tr>
<td>North</td>
<td>23</td>
<td>112</td>
<td>7</td>
<td>6.25</td>
</tr>
<tr>
<td>Miller</td>
<td>38</td>
<td>59</td>
<td>21</td>
<td>35.6</td>
</tr>
<tr>
<td>Coleman</td>
<td>12</td>
<td>70</td>
<td>7</td>
<td>10.0</td>
</tr>
<tr>
<td>Wilder</td>
<td>8</td>
<td>48</td>
<td>4</td>
<td>8.33</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>777</strong></td>
<td><strong>1828</strong></td>
<td><strong>584</strong></td>
<td><strong>32.0</strong></td>
</tr>
</tbody>
</table>

The second column represents the number of days in the campaign season that the on-line model predicts to be stable. The third column represents the number of stable public opinion days. The fourth column represents the number of stable opinion days that the on-line model accurately predicts. The fifth column represents the percentage of stable opinion days that the on-line model accurately predicts.

The volatility predicted by the on-line model is much lower than that predicted by the memory-based model at 2028 volatile days to 2527 volatile days, respectively. The accuracy in predicting volatility is lower for the on-line model than for the memory-based model. The memory-based model correctly predicted forty-eight percent of the volatile days of public opinion while the on-line model only predicts forty percent. Again, this is exactly what we would expect from the discussion of the formalization of the on-line model. In fact, what is surprising is how well the on-line model predicts volatility.
### Table 6.9: Volatility—the On-Line Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Days Predicted to be Volatile</th>
<th>No. of Volatile Public Opinion Days</th>
<th>No. of Volatile Opinion Days Predicted Accurately</th>
<th>% of Volatile Opinion Days Predicted Accurately</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>14</td>
<td>16</td>
<td>6</td>
<td>37.5</td>
</tr>
<tr>
<td>Kyl</td>
<td>14</td>
<td>8</td>
<td>3</td>
<td>37.5</td>
</tr>
<tr>
<td>Martin</td>
<td>86</td>
<td>36</td>
<td>14</td>
<td>38.9</td>
</tr>
<tr>
<td>Simon</td>
<td>87</td>
<td>30</td>
<td>16</td>
<td>53.3</td>
</tr>
<tr>
<td>Haytaian</td>
<td>35</td>
<td>16</td>
<td>7</td>
<td>43.8</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>35</td>
<td>17</td>
<td>8</td>
<td>47.1</td>
</tr>
<tr>
<td>Cuomo</td>
<td>64</td>
<td>15</td>
<td>6</td>
<td>40.0</td>
</tr>
<tr>
<td>Pataki</td>
<td>63</td>
<td>18</td>
<td>9</td>
<td>50.0</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>20</td>
<td>17</td>
<td>3</td>
<td>17.7</td>
</tr>
<tr>
<td>Santorum</td>
<td>43</td>
<td>7</td>
<td>5</td>
<td>71.4</td>
</tr>
<tr>
<td>Wofford</td>
<td>46</td>
<td>9</td>
<td>5</td>
<td>55.6</td>
</tr>
<tr>
<td>Richards</td>
<td>176</td>
<td>36</td>
<td>17</td>
<td>47.2</td>
</tr>
<tr>
<td>Bush</td>
<td>162</td>
<td>32</td>
<td>14</td>
<td>43.8</td>
</tr>
<tr>
<td>Cook</td>
<td>97</td>
<td>55</td>
<td>12</td>
<td>21.8</td>
</tr>
<tr>
<td>Shepherd</td>
<td>192</td>
<td>87</td>
<td>32</td>
<td>36.8</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>82</td>
<td>71</td>
<td>15</td>
<td>21.1</td>
</tr>
<tr>
<td>Robb</td>
<td>259</td>
<td>162</td>
<td>81</td>
<td>50.0</td>
</tr>
<tr>
<td>North</td>
<td>259</td>
<td>170</td>
<td>74</td>
<td>43.5</td>
</tr>
<tr>
<td>Miller</td>
<td>104</td>
<td>83</td>
<td>30</td>
<td>36.1</td>
</tr>
<tr>
<td>Coleman</td>
<td>119</td>
<td>61</td>
<td>25</td>
<td>41.0</td>
</tr>
<tr>
<td>Wilder</td>
<td>71</td>
<td>31</td>
<td>10</td>
<td>32.3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2028</strong></td>
<td><strong>977</strong></td>
<td><strong>392</strong></td>
<td><strong>40.1</strong></td>
</tr>
</tbody>
</table>

The second column represents the number of days in the campaign season that the on-line model predicts to be volatile. The third column represents the number of volatile public opinion days. The fourth column represents the number of volatile opinion days that the on-line model accurately predicts. The fifth column represents the percentage of volatile opinion days that the on-line model accurately predicts.

In what way does the on-line model mispredict the course of public opinion? Does the on-line model predict volatility when actual public opinion is stable or does the on-line model predict stability when actual public opinion is volatile? Table 6.10 highlights the two different types of misprediction and makes it clear that the on-line model tends to make the same error as the memory-based model—predicting volatility when there is stability. But, the on-line model commits this error to a lesser extent than the memory-based model. On sixty-eight percent of the days that public opinion is stable, the on-line model predicts it to be volatile. Further, the on-line model (~20%) triples the rate at which the memory-based model (~5.8%) makes the second error—predicting stability when public opinion is volatile.
Table 6.10: Mispredicting Stability and Volatility—the On-Line Model

<table>
<thead>
<tr>
<th>Candidate</th>
<th>No. of Stable Opinion Days Predicted to be Volatile</th>
<th>% of Stable Opinion Days Predicted to be Volatile</th>
<th>No. of Volatile Opinion Days Predicted to be Stable</th>
<th>% of Volatile Opinion Days Predicted to be Stable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coppersmith</td>
<td>6</td>
<td>42.9</td>
<td>8</td>
<td>50.0</td>
</tr>
<tr>
<td>Kyl</td>
<td>11</td>
<td>78.6</td>
<td>5</td>
<td>62.5</td>
</tr>
<tr>
<td>Martin</td>
<td>55</td>
<td>79.7</td>
<td>5</td>
<td>13.9</td>
</tr>
<tr>
<td>Simon</td>
<td>59</td>
<td>78.7</td>
<td>2</td>
<td>6.67</td>
</tr>
<tr>
<td>Haytaian</td>
<td>19</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>18</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cuomo</td>
<td>49</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pataki</td>
<td>46</td>
<td>100</td>
<td>1</td>
<td>5.56</td>
</tr>
<tr>
<td>Rosenbaum</td>
<td>16</td>
<td>34.0</td>
<td>13</td>
<td>76.5</td>
</tr>
<tr>
<td>Santorum</td>
<td>37</td>
<td>90.2</td>
<td>1</td>
<td>14.3</td>
</tr>
<tr>
<td>Wofford</td>
<td>37</td>
<td>94.9</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Richards</td>
<td>142</td>
<td>89.9</td>
<td>2</td>
<td>5.56</td>
</tr>
<tr>
<td>Bush</td>
<td>134</td>
<td>82.7</td>
<td>4</td>
<td>12.5</td>
</tr>
<tr>
<td>Cook</td>
<td>69</td>
<td>29.0</td>
<td>27</td>
<td>49.1</td>
</tr>
<tr>
<td>Shepherd</td>
<td>132</td>
<td>64.1</td>
<td>27</td>
<td>31.0</td>
</tr>
<tr>
<td>Waldholtz</td>
<td>55</td>
<td>24.8</td>
<td>44</td>
<td>62.0</td>
</tr>
<tr>
<td>Robb</td>
<td>109</td>
<td>90.8</td>
<td>12</td>
<td>7.41</td>
</tr>
<tr>
<td>North</td>
<td>105</td>
<td>93.8</td>
<td>16</td>
<td>9.41</td>
</tr>
<tr>
<td>Miller</td>
<td>38</td>
<td>64.4</td>
<td>17</td>
<td>20.5</td>
</tr>
<tr>
<td>Coleman</td>
<td>63</td>
<td>90.0</td>
<td>5</td>
<td>8.20</td>
</tr>
<tr>
<td>Wilder</td>
<td>44</td>
<td>91.7</td>
<td>4</td>
<td>12.9</td>
</tr>
<tr>
<td>Total</td>
<td>1244</td>
<td>68.1</td>
<td>193</td>
<td>19.8</td>
</tr>
</tbody>
</table>

The second column represents the number of stable days that the on-line model predicts as volatile. The third column represents the percentage of stable days that the on-line model predicts as volatile. The fourth column represents the number of volatile days that the on-line model predicts as stable. The fifth column represents the percentage of volatile days that the on-line model predicts as stable.

The above analysis suggests that the on-line model ought to do a better job of predicting days of stability than the memory-based model. To test this contention statistically, I construct a measure of stable public opinion and stable predicted opinion for each model. The stable public opinion measure assigns a one to any day that has a value for public opinion identical to the previous day’s value. The stable predicted opinion measure assigns a one to any day that has a predicted value for public opinion identical to the previous day’s predicted value. I expect the on-line model to predict stability in actual public opinion to a greater extent than the memory-based model. I conduct a logistic regression because the dependent variable—stability of actual public opinion—is a dichotomous variable. The results in Table 6.11 suggest that both models
perform similarly in their ability to predict stable public opinion. When the models predict stability, actual public opinion tends to be stable. However, the results do not distinguish if the models outperform each other.

**Table 6.11: Predicting Stability in Public Opinion**

<table>
<thead>
<tr>
<th>DV = Stability</th>
<th>Memory-Based Model</th>
<th>On-Line Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stability</td>
<td>0.797***</td>
<td>0.646***</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.558***</td>
<td>0.462***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>2805</td>
<td>2805</td>
</tr>
<tr>
<td>Pseudo R-Squared</td>
<td>.0083</td>
<td>.0135</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-1798.04</td>
<td>-1788.63</td>
</tr>
</tbody>
</table>

* p<0.10, **p<0.05, ***p<0.01

Importantly, there is an additional test that should be conducted with respect to the on-line model. In the discussion concerning the point in the campaign season, I argued that the on-line model is much less susceptible to shocks as the campaign season progresses. However, actual public opinion is more capable of responding to shocks than the on-line model as it lacks the expansive affective memory of the on-line model. This suggests that the distance between the on-line model's predictions and actual opinion should be greatest when actual opinion is volatile rather than stable.

To test this contention, I use the measure of volatility created above and regress it on the distance between the predicted and actual paths of public opinion. On those days of volatility in actual public opinion, I expect the on-line model to perform poorly, so volatility should be positively related to distance. The results in Table 6.12 suggest that distance is indeed greater when public opinion is more volatile than when it is stable. The coefficient is both positive and significant suggesting that the on-line model has difficulty accurately predicting volatile public opinion. The on-line model is handicapped by the inertial tendency of the on-line tally.
Table 6.12: Mispredicting Volatility—the On-Line Model

<table>
<thead>
<tr>
<th>DV</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
<td>0.2746***</td>
<td>0.0350</td>
</tr>
<tr>
<td>Constant</td>
<td>0.8959***</td>
<td>0.0207</td>
</tr>
</tbody>
</table>

No. of Observations 2805
R-Squared 0.0215

*p<0.10, **p<0.05, ***p<0.01

**Incumbency**

Political scientists of all stripes have consistently proposed an advantage for incumbents in running for re-election. These candidates have name recognition, a fundraising advantage, and an established relationship with the voters. As a result, incumbents enter a political campaign season with a decisive advantage. The two models discussed in this project do not discuss incumbency explicitly, but I believe they do provide an indirect role for incumbency in predicting the course of public opinion. The formalization of the memory-based model proposes an input known as difficulty or lack of familiarity. In this project, I have operationalized this as incumbency arguing that incumbent messages are more familiar, or less difficult, for voters to accept than are messages of newcomers. I use a four-point scale ranging from candidates with no prior political office, candidates that are also former officeholders, candidates that currently hold a different political office, and incumbent candidates. This parameter is a static measure that varies only across candidates. As a result, it does not contribute to the movement of public opinion throughout a campaign season; rather, incumbency helps establish the initial point from which public opinion can then move. As such, the model should be no less or no more likely to accurately predict the movement of public opinion for incumbents than for newcomers.
This static component, however, does not take into consideration the advantage incumbents receive from additional campaign coverage, particularly neutral campaign coverage. As a result, to what extent do incumbent candidates receive more coverage during a campaign season than non-incumbents? Table 6.13 displays the average coverage for each candidate in the eight races. The amount of coverage certainly varies by race and candidate, but the average coverage for all seven incumbents is 2.18 articles per day while the mean coverage of non-incumbents is 1.89 articles per day. Similarly, incumbents receive more headline coverage than non-incumbents across the eight races. This suggests that the advantage of incumbency is not necessarily an advantage that the formalization of the model itself takes explicit consideration of, but instead is an artifact of the way that the news media covers incumbent candidates.

<table>
<thead>
<tr>
<th>Incumbents</th>
<th>Mean Article Coverage</th>
<th>Mean Headline Coverage</th>
<th>Non-Incumbents</th>
<th>Mean Article Coverage</th>
<th>Mean Headline Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simon</td>
<td>1.64</td>
<td>1.14</td>
<td>Coppersmith</td>
<td>1.69</td>
<td>1</td>
</tr>
<tr>
<td>Lautenberg</td>
<td>1.98</td>
<td>1.22</td>
<td>Kyl</td>
<td>1.61</td>
<td>1</td>
</tr>
<tr>
<td>Cuomo</td>
<td>2.63</td>
<td>1.53</td>
<td>Martin</td>
<td>1.51</td>
<td>1.08</td>
</tr>
<tr>
<td>Wofford</td>
<td>1.95</td>
<td>1.20</td>
<td>Haytaian</td>
<td>2.02</td>
<td>1.19</td>
</tr>
<tr>
<td>Richards</td>
<td>2.32</td>
<td>1.46</td>
<td>Pataki</td>
<td>2.45</td>
<td>1.46</td>
</tr>
<tr>
<td>Shepherd</td>
<td>1.8</td>
<td>1.23</td>
<td>Rosenbaum</td>
<td>1.22</td>
<td>1</td>
</tr>
<tr>
<td>Robb</td>
<td>2.34</td>
<td>1.36</td>
<td>Santorum</td>
<td>1.94</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Bush</td>
<td>2.14</td>
<td>1.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Cook</td>
<td>1.61</td>
<td>1.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Greene-</td>
<td>1.53</td>
<td>1.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Waldholtz</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Coleman</td>
<td>1.97</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Miller</td>
<td>1.34</td>
<td>1.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>North</td>
<td>2.35</td>
<td>1.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Wilder</td>
<td>1.80</td>
<td>1.19</td>
</tr>
<tr>
<td>All Incumbents</td>
<td>2.18</td>
<td>1.37</td>
<td>All Non-Incumbents</td>
<td>1.89</td>
<td>1.29</td>
</tr>
</tbody>
</table>

On the other hand, the on-line model proposes a distinct advantage for incumbents that might structure the extent to which it can accurately predict public opinion. The theoretical argument suggests that individuals initially form an on-line tally upon
exposure to information about a politician, update this tally as they come into contact with new information, and use the tallies of all candidates to make a choice on Election Day. The longer a candidate has been in the public eye, the more entrenched is the candidate’s tally. As a result, on-line tallies for incumbents will be much more difficult to move than tallies for non-incumbents.

Further, from the discussion of the point in the campaign season, I found that the on-line model tends to mispredict to a greater extent at the end of the campaign season than it does at the beginning of the campaign season. The logic was that the on-line model is less capable of dealing with shocks as the tally becomes more entrenched. This logic can be extended to the role of incumbency. Incumbents start the campaign season with on-line tallies at a higher rate than non-incumbents. Because both real public opinion and the predicted public opinion from the on-line model provide an important advantage to incumbents, I expect that the accuracy of prediction should increase with incumbency. However, the point in the campaign season should mitigate this relationship. As the incumbent’s tally becomes more and more entrenched with the progression of the campaign season, the model’s predictions ought to deviate to a greater extent for the incumbent than they do for non-incumbents. As a result, the on-line model should predict public opinion more accurately for incumbents than for non-incumbents but this advantage should reverse as the campaign season progresses.

To examine whether the data bear this out, I create a measure for incumbency coded one if the candidate is the incumbent in the race and zero otherwise. To make the dates of the campaign season more distinguishable, I also create a campaign midpoint coded 1 if a day falls after the midpoint in the campaign season. The description of these
variables appears in Table 6.14. Two-thirds of the candidates are non-incumbents while only one-third are incumbents. Given that the campaign marker was constructed to represent the halfway point, almost exactly half of the days in the campaign seasons are classified as before the campaign midpoint and about half are classified as occurring after the cutoff mark.

**Table 6.14: Incumbency and the Campaign Season**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incumbency</td>
<td>0.3640</td>
<td>0 (63.60%)</td>
<td>1 (36.40%)</td>
</tr>
<tr>
<td>Last Half of Campaign</td>
<td>0.5098</td>
<td>0 (49.02%)</td>
<td>1 (50.98%)</td>
</tr>
</tbody>
</table>

I regress incumbency and the point in the campaign season on the distance variable discussed previously. The hypothesis is that distance should decrease with incumbency, but that this relationship should reverse by the end of the campaign season. The results of this test are displayed in Table 6.15. There are a few important points to note. Remember that this is a regression with an interaction term. As a result, we cannot think of the two explanatory variables as additive. Instead, the relationship between incumbency and distance is negative and significant when the campaign midpoint equals zero. In the first half of the campaign season, incumbency decreases the distance between the predicted values of public opinion and the actual values of public opinion. The relationship between distance and the point in the campaign season, captured by the campaign midpoint variable, is positive and significant for non-incumbents. When incumbency equals zero, the distance between the predicted values of the on-line model and the actual values of public opinion is greater during the first half of the campaign season than it is in the second half of the campaign season. So, what information does the interaction term provide? The interaction term is significant and negative, but it is
smaller than the coefficient on the incumbency variable. This suggests that
distance declines with incumbency at the end of the campaign season but to a lesser extent than it
did at the beginning of the campaign season. The on-line model is much better at
predicting the path of public opinion for incumbents, but this is mitigated somewhat at
the end of the campaign season as the distance between the actual path of public opinion
and the on-line model increases.

| Table 6.15: The Interaction between Incumbency and the Campaign Season |
|-----------------|-----------------|-----------------|
| DV = Distance   | Coefficients    | Standard Error  |
| Incumbent       | -0.210***       | 0.0491          |
| Last Half of Campaign Season | 0.081*         | 0.0417          |
| Incumbent* Last Half of Campaign Season | -0.168**       | 0.0692          |
| Constant        | 1.057***        | 0.0300          |
| No. of Observations | 2805            |                 |
| R-Squared       | 0.0275          |                 |

* p<0.10, **p<0.05, ***p<0.01

**Conclusion**

The purpose of this chapter was to demonstrate the utility of both models for
explaining the course of public opinion during a political campaign. The results, from
both the graphical analysis and the statistical tests, demonstrate that the models fail in
particular ways in predicting the course of public opinion for the twenty-one candidates
across the eight races. The models do tend to predict public opinion to a greater extent
early in the campaign season rather than later. The logic behind this contention varies by
model. I argued that the on-line model by design makes it difficult to move the tally for a
candidate once it has become entrenched; thus, the model has difficulty responding to
shocks in the campaign season. This inertial tendency also contributes to the tendency of
the on-line model to do worse at predicting support for candidates when it is volatile than
the memory-based model. Finally, I also discuss a potential interactive effect of
incumbency and the campaign season on the accuracy of the on-line model. The model
predicts more accurately for incumbents at the beginning of the campaign season and more accurately for non-incumbents as the season progresses.

The memory-based model, on the other hand, lacks an explicit role for memory and so voters resemble the voters of the memory-based model world only at the beginning of the campaign season when they are "clean slates". This lack of memory also leads the memory-based model to mispredict a series of days after matching an initial change in public opinion. Further, the model is much less capable of predicting stable public opinion than it is at predicting volatile public opinion.

In the next chapter, I address why the models are failing in these particular ways and discuss how we might go about modifying the models to overcome these particular failures.
Chapter 7: Conclusion

The ultimate goal of this project was to determine how well our current models of public opinion predict the course public opinion takes during political campaigns. To achieve this goal, I first focused in Chapter 2 on a discussion of the evolution of the on-line and memory-based models in the public opinion literature. I then discussed the theoretical underpinnings of Zaller’s memory-based model, presented Zaller’s (1992) formalization of the memory-based model, and specified the static and dynamic components of his model. The on-line model had yet to be formalized mathematically, so I discussed the theoretical foundations of the on-line model, explored the dynamic implications of the on-line model, and formalized the model mathematically.

This formalization set the stage for an examination of the extent to which each model could explain the movement in public opinion throughout a campaign season. In Chapter 3, I explored the predictions the on-line and memory-based models make when I vary the information environment of a political campaign. This chapter suggested that even with the same information environment, the models predict a different path of support for a variety of candidates.

In Chapter 4, I proposed an empirical examination of the dynamic properties of the two public opinion models within the auspices of eight contested congressional and gubernatorial campaigns with twenty-one candidates occurring in 1990 and 1994. I described the specific data that would be used as inputs to the mathematical equations in the empirical test presented in Chapters 5 and 6. I construct the dependent variable from public opinion data from the Iowa Electronic Market. In order to calculate the predicted course of public opinion, I need measures of the inputs for each model. To measure the
dynamic inputs, I collect newspaper coverage for each of the eight campaigns for the entire campaign season, and used data from the National Election Studies to set the static inputs in the models. The test involved examining the predictions each model makes for the course of public opinion during a given campaign and comparing these predictions to the actual course of public opinion during that campaign.

The goal of Chapter five was to provide a description of the eight campaigns in terms of the players in each race and any issues or events, planned or otherwise, which had the potential to alter the outcome of the election. What is clear from this chapter is that these are very different races, in terms of the office the candidates were competing for, the incumbency of the candidates, and the number of candidates vying for the seat. After describing the campaigns and presenting the actual path and the predicted paths of public opinion, I then compare graphically the ability of the models to accurately predict the path of public opinion during the eight campaigns. The graphical analysis made it clear that neither model perfectly predicts support for the twenty-one candidates. In fact, for a number of candidates, the models do quite poorly. For example, the on-line model predicts only seventeen percent of the changes in support for Rosenbaum in the New York Gubernatorial race; however, the on-line model is able to predict seventy-one percent of the stable days of support for Merrill Cook in the Utah Congressional race. In contrast, the memory-based model correctly predicts sixty-four percent of the changes in support for Rosenbaum in the New York Gubernatorial race; yet, in this very race, the memory-based model does not predict a single day of stability for any of the candidates.

Using the graphical analysis in Chapter 5, I focused in Chapter 6 on considering four ways in which the models fail to capture public opinion throughout the campaign season.
In line with the above discussion, I considered how well the models predicted days of stability and how well the models predicted days of volatility. Overall, the on-line model correctly predicts forty percent of the volatile days while the memory-based model predicts forty-eight percent. In contrast, the on-line model outpaces the memory-based model in predicting stability in support for a candidate (thirty-two percent to twelve percent accuracy rate). Both models mispredict support for the candidates when that support is actually stable. However, the memory-based model commits this mistake to a greater degree than the on-line model. Eighty-seven percent of the stable days of public opinion are mispredicted as volatile by the memory-based model. In contrast, the on-line model only mispredicts sixty-eight percent of these days. On the other hand, the memory-based model only mispredicts six percent of the volatile days while the on-line model mispredicts twenty percent of these days.

I also focused on whether the models do better at predicting public opinion at different points in the campaign season. I found this to be the case for both models. The models are much better at predicting public opinion early in the campaign season and become progressively worse as the campaign season proceeds. In the world according to a memory-based model, individuals do not have any long-term memory. The only considerations relevant to a survey response or a vote decision are those considerations that are most salient. However, we know from memory research that individuals do store campaign information in long-term memory. As a result, the model will likely diverge from the actual path of public opinion as the campaign season progresses and individuals begin to store information in memory and use this to make their decisions. I found that the divergence between the actual path of public opinion and the memory-based model is
greater as the season progresses. For the on-line model, I found slightly less supportive results—the model does better at predicting public opinion at the beginning of the campaign season although this finding receives less statistical support. However, the explanation for this divergence differs. The on-line model relies on an ever-accumulating on-line tally. At the beginning of the campaign season, the tally is more susceptible to directional shifts in public opinion. However, at the end of the campaign season any new piece of information is unlikely to shift the tally in the opposite direction.

Incumbency is a topic that has fascinated political scientists for years. Incumbent candidates benefit from a number of advantages that are difficult for a challenger to overcome: name recognition, financing, and free advertising from the news media. Both models provide a role for incumbency although it is not explicitly included in the models. One of the inputs to the memory-based model is a concept Zaller terms difficulty or familiarity. This is simply the ease with which individuals can accept a message regardless of political predisposition or political awareness. I considered this a static input in this analysis so it does not move public opinion during the campaign season. However, I did find that the newspapers themselves cover incumbent candidates to a greater extent than non-incumbents. As such, these candidates receive an advantage in terms of coverage. In contrast, the on-line model allows for the existence of a pre-existing tally. Incumbent candidates will have more entrenched pre-existing tallies than non-incumbents. As a result, the model should do better at predicting support for incumbents because actual public opinion is likely to take the incumbent advantage into consideration. However, as the season progresses, this entrenched tally will make it very difficult for the on-line model to accurately predict changes in public opinion. As a
result, the model ought to do worse at predicting support for incumbents later in the campaign season. This is exactly what I found in Chapter 6.

I also considered a failure that was unique to the memory-based model. The memory-based model does a good job capturing initial change in public opinion, but does much worse at predicting the persistence in public opinion after that change. To examine this contention, I conducted a simple statistical analysis using dummy variables for the days after initial change. I also conducted a more sophisticated analysis using an error correction model. The results of both of these tests provide support for this type of failure of the memory-based model.

In this closing chapter, I turn to the question of why the models fail in these particular ways. Are there particular assumptions in these theoretical models that make them inherently likely to fail in this particular ways regardless of the particular campaign under consideration? Do these features get translated into the formalization of the theoretical models? After considering these questions, I also focus in this chapter on the question of where we go from here. If we know where the models fail and why the models fail in these particular ways, how do we “fix” the models so that they can explain the way support for a candidate changes throughout a campaign season. I conclude this chapter by focusing on the importance of this project for guiding future research on the relationship between memory and public opinion.

**The Role of Memory**

In Chapter 6, I outlined four different circumstances when the models fail to predict public opinion. Given this discussion, the next step is to ask why these failures might be occurring. In working on this project, one feature of both the on-line and memory-based
models strikes me as significant—the relationship between memory for campaign information and candidate evaluation. Specifically, the models make particular assumptions about recall. At their most fundamental, the two models rely in different ways on the notion that individuals are incapable of recalling campaign information.

By accepting this assumption, the on-line model argues that individuals instead rely on an affective tally to make decisions about political candidates. Upon encountering campaign information, these individuals extract the affective value of the information and discard the descriptive information. The manner in which that information is discarded is left vague. However, there is no discussion as to why the tally can be recalled intact, but campaign information itself cannot.

The memory-based model also starts with the assumption that individuals cannot recall substantial amounts of campaign information; however, individuals do use what they can recall to make political decisions. Vote choices are not based on the entire array of campaign information an individual has been exposed to, but only on that information that has been most recently heard. Do these assumptions about recall of campaign information play an important role in whether the models can explain the course of public opinion during a political campaign? I believe that they do. In the two sections below, I consider the ways in which the models’ assumptions about memory influence their ability to predict the course of public opinion during political campaigns.

Memory-Based Model

The memory-based model does not take explicit consideration of the role of memory in the availability of campaign information. The only potential role afforded to memory in the formalization is in the recall equation, but Zaller (1992) argues that recall ability is
not that important to opinion formation because the ability to recall a message is dependent only upon the individual’s political awareness. Importantly, recall ability in the model is neither a function of when the individual received and accepted the information nor a function of the extent to which the information matches the individual’s political predispositions. Memory, then, does not play a role in moving public opinion throughout a campaign season.

If public opinion moves overtime, the model posits that this movement is due to changes in the relative flow of campaign information. In testing the model, I tried to stay true to the model’s lack of a role for memory; thus, today’s predicted value for public opinion is dependent upon today’s relative flow of campaign messages. Previously received information is not used to predict today’s value for public opinion. However, we could incorporate memory into the current formalization of the model. How likely is it that including ad hoc memory functions in the formalization of the memory-based model would improve the accuracy of its predictions of actual public opinion?

To evaluate this question, I examine the improved prediction rate of the model when I assume that memory behaves in a few simplistic ways. In particular, I consider the improved fit between the predicted path and the actual path of public opinion when I incorporate a simple decay function into the equation. In this case, support for a candidate remains a function of the three static components—political awareness, political predispositions, and difficulty—but the dynamic component—intensity—is no longer simply a function of today’s relative flow of campaign messages. Instead, support on any given day is a function of previously accepted information, but this previously accepted information declines in relevance as each day passes. As each day passes,
information declines in contributing to the intensity of a message at a rate of 20%. This means that on Day 2 messages heard on Day 1 are only eight percent as strong as they were on Day 1. In this way, previous information plays a role in support for a candidate, but it does not overwhelm new information.

This notion is displayed in Equation 7.1. In this equation, the modified intensity of a candidate’s message at time $t$ is a function of the intensity of the candidate’s message at time $t$, and a declining percentage of the intensity of the candidate’s message in the previous three time periods.

$$Modified Intensity_t = Intensity_t + 0.8 \times Intensity_{t-1} + 0.6 \times Intensity_{t-2} + 0.4 \times Intensity_{t-3} \quad \text{Equation 7.1}$$

Rather than think of the previous messages as declining in importance, one could also argue that the intensity of a campaign message ought to be measured as the sum of the intensity of the message at time $t$ and the average of the intensity of the message in previous time periods. I consider two different average measures. I consider whether the predictive ability of the model improves if intensity of a message is on any given day is a function of the intensity of that day’s messages as well as the average of the intensity of the messages on the previous three days or the average of the intensity of the messages on the previous two days. In Equation 7.2, I assume that the modified intensity of a message on any given day is a function of the intensity of that day’s messages as well as the average of the intensity of the messages on the previous three days.

$$Modified Intensity_t = Intensity_t + \frac{Intensity_{t-1} + Intensity_{t-2} + Intensity_{t-3}}{3} \quad \text{Equation 7.2}$$

In Equation 7.3, I modify the intensity of the message on any given day to be a function of that day’s intensity as well as the average of the intensity on the previous two days.
ModifiedIntensity\textsubscript{t} = Intensity\textsubscript{t} + \frac{Intensity\textsubscript{t-1} + Intensity\textsubscript{t-2}}{2} \quad \text{Equation 7.3}

I could also assume that the intensity of a candidate’s message on any given day is a function of intensity of the candidate’s message on that particular day and the intensity of the message for the last few days. In Equation 7.4, I assume that the intensity of a candidate’s message is a function of the intensity of the message on a given day and the intensity of the message on the previous three days

ModifiedIntensity\textsubscript{t} = Intensity\textsubscript{t} + Intensity\textsubscript{t-1} + Intensity\textsubscript{t-2} + Intensity\textsubscript{t-3} \quad \text{Equation 7.4}

The second summation function, Equation 7.5, considers intensity to be a function of the intensity of the message at time \( t \) and the intensity on the previous two days.

ModifiedIntensity\textsubscript{t} = Intensity\textsubscript{t} + Intensity\textsubscript{t-1} + Intensity\textsubscript{t-2} \quad \text{Equation 7.5}

The final summation measure considers the intensity at time \( t \) to be function of the intensity at time \( t \) and the intensity of the message at time \( t-1 \) (Equation 7.6).

ModifiedIntensity\textsubscript{t} = Intensity\textsubscript{t} + Intensity\textsubscript{t-1} \quad \text{Equation 7.6}

These functions are incredibly simplistic, but I think the results suggest a few important points. In Table 12, I display the number of days in terms of stable and volatile public opinion that each of these simplistic memory functions accurately predicts for a few of the races included in this project. An immediate observation from this table is that no simplistic function of memory does better at predicting both stable days and volatile days than does the original memory-based model. However, a number of the models do better at accurately predicting either stable support or volatile support. In particular, the decay function and the average functions are the only techniques that exceed the original model in terms of accurately predicting volatile support. Interestingly, no manipulation can more accurately predict stability than the original model; however, the summation
functions come close. The advantages these simplistic techniques make in predicting stability are offset by the simultaneous decline in their ability to predict volatility. This suggests that incorporating simplistic functions for memory certainly alters the accuracy of the model; however, a quick fix to the model, such as incorporating a simple summation function, cannot substantially enhance the predictive ability of the model.

**Table 7.1: Number of Days of Accurate Prediction for Modified Memory-Based Models**

<table>
<thead>
<tr>
<th>Change</th>
<th>Original Model</th>
<th>Decay Function</th>
<th>Four Day Average</th>
<th>Three Day Average</th>
<th>Four Day Sum</th>
<th>Three Day Sum</th>
<th>Two Day Sum</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>469</td>
<td>487</td>
<td>483</td>
<td>488</td>
<td>450</td>
<td>462</td>
<td>469</td>
<td></td>
</tr>
<tr>
<td>Increase</td>
<td>252</td>
<td>260</td>
<td>248</td>
<td>258</td>
<td>237</td>
<td>239</td>
<td>246</td>
<td></td>
</tr>
<tr>
<td>Decrease</td>
<td>217</td>
<td>227</td>
<td>235</td>
<td>230</td>
<td>213</td>
<td>223</td>
<td>223</td>
<td></td>
</tr>
<tr>
<td>Stability</td>
<td>221</td>
<td>22</td>
<td>108</td>
<td>94</td>
<td>214</td>
<td>212</td>
<td>202</td>
<td></td>
</tr>
</tbody>
</table>

**On-Line Model**

As mentioned above, the on-line model also makes specific assumptions about the role of memory for campaign information in candidate evaluation. The on-line model contends that descriptive campaign information is discarded once the affective value of that information has been extracted. While the on-line model is not specific about the way that the campaign information is discarded, Lodge et al (1995) argue that the information can be assumed to decay at a normal rate. However, there is no discussion as to why the on-line tally itself remains intact and does not also decay at a normal rate. Each affective reaction is stored in the on-line tally and the on-line tally does not decay overtime. What this assumption does is allow for substantial stability in the direction of support. This assumption makes it difficult for the model to switch direction after the on-line tally becomes entrenched (i.e. at the end of the campaign season). As a result, the model mispredicts volatility to a greater extent than the memory-based model and it
mispredicts towards the end of the campaign season to a greater extent than earlier in the campaign season.

In the formalization of the model, the on-line tally is assumed to be a continuous accumulation of affective reactions about political candidates. This accumulation of affective reactions does not recede overtime, but is recalled intact when an evaluation of the candidate is required, even if that evaluation is asked months after the information is received. What if instead we assume that the value of the tally also declines overtime? That is, when new information is added to the tally at time $t$, the value of the original tally (formed at $t-1$) is only worth a percentage of what it was worth at $t-1$. To incorporate this notion into the formalized model, all we need to do is add a parameter, $\phi$, representing the rate at which the original tally formed in $t-1$ decays (Equation 7.7). I consider a number of different decay rates—five percent, ten percent, twenty percent, and thirty percent—the results of which are displayed in Table 7.2.

$$\text{UpdatedTally}_{t} = \phi \text{Tally}_{t-1} + \sum_{i=1}^{n} AffectResponse_{t,i}$$ \hspace{1cm} \text{Equation 7.7}

The results in Table 7.2 demonstrate that simply incorporating a tally that declines overtime eliminates the ability of the model to predict stability, but substantially increases the model's ability to predict volatile public opinion. Regardless of which decay rate is used, the modified tally more accurately predicts volatility in public opinion. Altering the formalization of the on-line tally to overcome the model's weakness serves only to mitigate the model's strength—accurately predicting stability.
Table 7.2: Number of Days of Accurate Prediction for Modified On-Line Models

<table>
<thead>
<tr>
<th></th>
<th>Original Model</th>
<th>5% Decay Rate</th>
<th>10% Decay Rate</th>
<th>20% Decay Rate</th>
<th>30% Decay Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>392</td>
<td>499</td>
<td>518</td>
<td>497</td>
<td>494</td>
</tr>
<tr>
<td>Increase</td>
<td>222</td>
<td>260</td>
<td>271</td>
<td>275</td>
<td>269</td>
</tr>
<tr>
<td>Decrease</td>
<td>170</td>
<td>239</td>
<td>247</td>
<td>222</td>
<td>225</td>
</tr>
<tr>
<td>Stability</td>
<td>584</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The results of modifying the models in an ad hoc fashion presented in Tables 7.1 and 7.2 suggest a number of important conclusions. First, the models can be modified to overcome the weaknesses of the original formalization of the models—the tendency of the on-line model to mispredict volatile public opinion and the tendency of the memory-based model to mispredict stability. Including simple ad hoc functions into the formalization improves the ability of these models to predict certain days; however, the second important point is that these simple functions also negate the original strengths of the models—the tendency of the on-line model to accurately predict stable public opinion and the tendency of the memory-based model to accurately predict volatility.

As a result, incorporating memory for campaign information into our current models of public opinion requires understanding the particular way that memory structures affect the availability of such information for use in evaluating political candidates. Not only does incorporating ad hoc memory functions fail to consider the advances psychologists have made in studying the structures of memory and the role of those structures in enhancing or inhibiting information recall, but it also does not take into account important conclusions from my own work—that is, variation in political awareness has real implications for recall of campaign information and candidate evaluation (Miller and Stevenson, 2006).
Focusing Explicitly on Memory for Campaign Information

The overall goal of this dissertation was to determine how well our current models of information processing could predict the course of public opinion over the course of a political campaign. I conclude this dissertation with the unfortunate finding that neither model can completely explain the course of public opinion across eight political campaigns.

This project serves as the first step in a research program designed to focus explicitly on the relationship between memory and individual variation in opinion. There are two overarching questions guiding this research program: how do the structures and processes of memory influence what information is available for use by individuals when they are faced with evaluating political candidates, and in what ways do certain individual-level characteristics, like political awareness, moderate this relationship? I believe these two questions must be answered before we can modify current public opinion models in any meaningful way to take explicit consideration of memory for campaign information. Luckily, my future research program will not be stabbing blindly at the relationship between memory for campaign information and candidate evaluation, psychologists have studied in detail the structures of memory and the particular ways these structures might inhibit or enhance recall of information.

In the previous section, I discuss the particular assumptions current models make about memory and the ability of individuals to recall campaign information. The notion that individuals cannot recall campaign information is based on work using the National Election Studies (NES). Both models use this empirical result—that individuals do not recall campaign information—to be a fundamental theoretical assumption about human
behavior—that is, that individuals cannot recall campaign information. This is done without any empirical support that individuals truly cannot recall campaign information outside the context of the NES. The problem with using the NES to gauge information recall is that the NES cannot determine whether failure to recall information is a sign of memory failure or a failure of information exposure. Without control over information exposure, the NES has no way to determine if recall failures stem from a lack of exposure to information or from failure to recall that information.

To overcome this lack of control, I am working on a project that examines information recall in an experimental setting (Miller and Stevenson, 2006). If we are interested in constructing a model to explain candidate evaluation over the course of a campaign, we must first understand how recall of campaign information works. Is it the case that individuals are unable to recall campaign information? If individuals are unable to recall campaign information, then our public opinion models should take explicit consideration of this finding. However, if individuals can recall substantial campaign information under certain conditions, then we should not ignore campaign information in formulating public opinion models. The results from this experiment suggest that individuals can recall campaign information when information is presented overtime and the ability to recall campaign information is a function of an individual’s level of political awareness.

The next step in this research program then is to turn to the well-developed theoretical and empirical findings in cognitive psychology and ask what might prevent or enhance memory for campaign information. In particular, I am interested in the research that psychologists have conducted on the notion of forgetting. Psychologists have
proposed two theories of forgetting: memory decay and interference. I am most
interested in which theory is most important for campaign information. Does campaign
information decay overtime—that is, do memories fade overtime? Or, is campaign
information not recalled because it has been interfered with—that is, are memories
replaced by other memories? If memories fade overtime, can we mitigate this decay? If
campaign information in general cannot be recalled because it has been forgotten, can
certain types of campaign information avoid such forgetting?

Importantly, my future research on memory does not end with a determination of the
reason why individuals cannot recall campaign information, and the specific type of
information that is most easily forgotten. Once I determine if forgetting plays a role in
the recall of campaign information, the next step is to return to the fundamental question
of how our models of public opinion might be modified to incorporate such findings. If I
find there are ways to prevent individuals from forgetting campaign information, can the
on-line model continue to argue that candidate evaluations are not related to recall of
campaign information or can the memory-based model continue to support the notion that
recently presented information is the most influential in candidate evaluation? The
answers to the above questions will guide my future research.

**Conclusion**

Information processing models are critical to examining the relationship between
campaign information and candidate evaluation. An important question to ask is whether
it is really important to know more about information processing than that individuals are
limited in their ability to process information. As Miller (1991) points out, the form in
which such information is stored is important as it helps distinguish which various
cognitions are activated when an individual is thinking about a candidate and employed in that individual's evaluation of the candidate. If our current models of candidate evaluation rely on assumptions about information processing that fail to accurately predict the course of public opinion during political campaigns, then it is critical that we identify the reasons why these models fail. This research project sought to determine if and how the models fail so that future research can focus on constructing public opinion models to overcome these failures.

While this project, and the research program that extends from it, ought to be of interest to public opinion scholars, the practical implications of this project are also significant. In the last two presidential campaigns, we have seen an unprecedented amount of television advertising and media coverage. In the 2000 campaign alone, over 200,000 television spots were run nationwide. The incredible amount of spending on campaign advertising and the desire by campaign managers and their candidates to get free advertising from the news media suggests that campaign managers believe voters use campaign information to make decisions about political candidates. The on-line and memory-based models assume that voters use such information at different points in time and the role of that information in guiding decision-making differs.

The on-line model suggests that the voter uses information the minute it is encountered—the affective value is extracted from the descriptive information and the information itself is forgotten. While the information decays at a normal rate, the tally itself remains intact. This suggests a number of important conclusions for campaign managers. The first is that the campaign manager should not be concerned with the timing of campaign messages. In fact, a smart campaign manager would be most
effective in running messages early in the campaign season. Doing this would build up an on-line tally for the candidate before the opposition could advertise negative information about the candidate. The on-line model also suggests that only information that has an affective value should be publicized. That is, campaign managers might consider avoiding issue ads that do not have an emotional appeal.

In contrast, the memory-based model proposed by Zaller (1992, 1996) assumes information is stored in memory when an individual receives and accepts the information. When asked to make a decision, it is this information that is recalled. The particular information recalled is a function of which information or considerations are most salient at the time a decision is required. Evaluations of political candidates then depend on the extent to which the relative flow of campaign messages is favorable towards the candidate. In this model, the saliency of campaign messages is critical. Wise campaign managers would be encouraged to reserve considerable funds for the end of the campaign season to ensure that positive information about their candidate is the most salient consideration.

These propositions are overtly simplistic and tend to ignore an important component of information processing—memory—that ought to alter the suggestions we offer campaign managers interested in fashioning efficient political campaigns. Knowing the way in which information is forgotten overtime allows us to provide more than superficial advice. Once we understand the particular ways that memory for campaign information can be interfered with or enhanced, we can offer advice that is more mindful of the role of memory in public opinion formation and change.
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