RICE UNIVERSITY

Essays on Asset Pricing

by

Ruomeng Liu

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE
Doctor of Philosophy

APPROVED, THESIS COMMITTEE:

Kerry Back, Chair
J. Howard Creekmore Professor of Finance
and Professor of Economics

Yuhang Xing
Associate Professor of Finance

Alexander Butler
Professor of Finance

Ted P. Loch-Tenvezelides
Professor of Economics

Houston, Texas
July, 2018
ABSTRACT

Essays on Asset Pricing

by

Ruomeng Liu

This dissertation studies asset pricing from three perspectives.

The first chapter takes the view of a long-run buy-and-hold investor, and offers an explanation to prominent cross-sectional return anomalies. A commonality shared by these anomalies is that their returns are negatively correlated with the market. I show that this negative covariance implicitly embeds the mispricing of the CAPM beta – the first and one of the most robust asset pricing puzzles – in these cross-sectional anomalies. Taking into account the exposure to the beta mispricing either attenuates or eliminates the economic and statistical significance of risk-adjusted returns to a large set of asset pricing puzzles.

Given the presence of well-documented cross-sectional return anomalies, the second chapter examines whether and how institutional investors trade to profit, and thereby to mitigate these anomalies. Consistent with the literature, I find that institutions in aggregate do not trade to take advantage of most of these cross-sectional return predictabilities. However, I present evidence that institutions in fact correctly trade to capture the beta risk-premium when and only when it is present in the market.
Findings support the view that institutions are the more rational set of investors that seem to capture and correct mispricing caused by opportunistic noise trading.

The third chapter takes a closer look at one particular type of asset markets – the over-the-counter (OTC) markets, and analyzes how trade disclosure impacts market participants’ optimal game-strategic behaviors. My co-authors and I show that mandatory trade disclosure makes a market intermediary engage in costly signaling, which reduces transaction prices for investors and equivalently rent per transaction for the intermediary. Investors as a result benefit, and are more likely to trade. The intermediary, however, could benefit too if the increase in trading volume is sufficient to offset the reduction in rent per transaction.
I would like to thank my parents for their unconditional support and encouragement over the years.

I am honored to have as my advisor Dr. Kerry Back. He kindly showed me the way into the profession, and put no constraint on the path of my academic endeavor. His patience, insights, and guidance shaped my perspective on conducting scholarly work.

I would also like to express my gratitude to Dr. Alexander Butler and Dr. Yuhang Xing, for asking hard questions, and providing invaluable advice both within and outside the Ph.D. program.
# Contents

Abstract i  
Acknowledgments iii  

1 Asset Pricing Anomalies and the Low-risk Puzzle 1  

1.1 Literature 5  
1.2 Motivation 8  
1.2.1 The Beta Anomaly 8  
1.2.2 Hypothesis Development 9  
1.3 Data and Empirical Measures 11  
1.3.1 Return and Accounting Data 11  
1.3.2 Beta Estimates 12  
1.3.3 Anomalies and Long-short Strategies 13  
1.4 Empirical Results: Examining Cross-sectional Anomalies After Mitigating the Beta Imbalance 16  
1.4.1 Mitigating Exposure to the Beta Anomaly: Weighting by Beta Ranks 16  
1.4.2 Balancing Portfolio Betas: Removing Low (High) Beta Stocks in the Short (Long) Leg Portfolio 20  
1.4.3 Falsification Tests 22
1.4.4 The Low-risk Puzzle as Explanation ............................. 23
1.5 On Other Cross-sectional Anomalies ................................. 25
1.6 On the Methodology to Mitigate Exposure to Beta Anomaly ..... 27
1.6.1 Alternatives ......................................................... 27
1.6.2 Limitations of using ranked betas as weights and eliminating
portfolio holdings ....................................................... 29
1.7 Conclusion ............................................................... 32

2 Institutional Investors and the Beta Risk Premium 46
2.1 Related Literature ....................................................... 49
2.2 Data ................................................................. 51
  2.2.1 Stock Return Data ................................................. 51
  2.2.2 Investor Sentiment ................................................. 51
  2.2.3 Institutional Trades Data ......................................... 52
2.3 Empirical Measures .................................................... 55
  2.3.1 Investor Buying Intensity ........................................ 55
  2.3.2 Individual Stock Beta Estimates and Beta-sorted Portfolios .. 57
2.4 Institutions and the Risk-return Relation ............................. 58
  2.4.1 Trading Pattern Conditional on Investor Sentiment ............ 58
  2.4.2 Difference-in-difference Estimates .............................. 61
2.5 Conclusion ............................................................... 62

3 Signaling in OTC Markets 71
3.1 Introduction and Literature ............................................. 71
3.2 Model and First Best ............................................. 80
3.3 The Transparent Market ........................................ 85
3.4 The Opaque Market ............................................. 93
3.5 A Uniform/Normal Model ....................................... 95
3.6 Conclusion ....................................................... 100

Bibliography .......................................................... 106

Appendices .............................................................. 115

A Anomaly Variable Descriptions ................................... 115
   A List of Anomalies ................................................. 115

B Proofs ..................................................................... 120
   A Proofs .............................................................. 120
   B Uniqueness of Equilibrium ...................................... 128
   C Calculations in the Uniform/Normal Model ................ 134
— Chapter 1 —

Asset Pricing Anomalies and the Low-risk Puzzle

Defying both theory and intuition, low beta assets have consistently outperformed high beta assets, both over time and across various asset markets (Frazzini and Pedersen, 2014). This observation has come to be known as the beta anomaly. In this paper, I present evidence that the beta anomaly is embedded in a broad set of cross-sectional asset pricing puzzles. I document that anomaly portfolio returns share a striking and peculiar pattern: returns are positive and peak in market downfalls, but are negative when the market rises. I verify that this negative covariance is empirically equivalent to the long portfolios holding stocks with lower betas relative to the short portfolios, and that the strategy of buying low beta stocks and shorting high beta stocks produces a significant monthly alpha, with a point estimate of 51 basis points and a $t$-statistic of 3.09. Mitigating the exposure to the beta anomaly either attenuates or eliminates the economic and statistical significance of the risk-adjusted returns to numerous cross-sectional anomalies.

This paper analyzes a set of ten asset pricing puzzles representative of different types of cross-sectional return predictors documented in the literature. The sample includes anomalies that are operation-based (total accruals, return on assets, profitability, investment growth), return-based (momentum), risk-based (O-score, default probability, return volatility, idiosyncratic volatility), as well as issuance-related (composite equity
issues). It is remarkable that portfolios formed on such a wide range of characteristics all have returns that are negatively correlated with the market. The observed negative covariance has two immediate implications. First, to the extent that these anomaly portfolios hold “quality” stocks (profitable, high past return, mature, low probability of failure, etc.), the fact that they pay off in bad states of the world is consistent with flight to quality in market downturns. The negative covariance between “quality” stocks and the market points to the beta anomaly as an explanation for why “quality” stocks have high average returns (Asness, Frazzini, and Pedersen, 2014). Second, the shared negative covariance with the market is suggestive of the data mining concern in the empirical asset pricing literature (see for instance Harvey, Liu, and Zhu, 2016, Chordia, Goyal, and Saretto, 2017). Somehow the search for cross-sectional return patterns has led to different dimensions to slice the data, many of which implicitly take advantage of the beta anomaly.

To show that the beta anomaly subsumes the risk-adjusted returns of the cross-sectional anomalies, I mitigate the long-short portfolios’ exposure to the beta anomaly in two complementary ways. First, I consider an alternative weighting scheme when aggregating returns to the portfolio level: I weight stocks in long legs using the ascending decile ranking of their pre-formation betas, and weight stocks in short legs using the descending decile beta rankings. This way of constructing portfolios keeps the original portfolio constituents while putting more weight on high beta stocks in the long leg, and more weight on low beta stocks in the short leg, relative to value-weighted portfolios. The second approach complements the first by keeping the value-weighting scheme from the original portfolio construction, but removing
stocks with low betas in the long leg, and stocks with high betas in the short leg. Together these two approaches allow me to separate the effect of beta exposure from the effect of the anomaly characteristics on the long-short portfolios’ alphas. Both modified portfolio construction methods reduce or remove the exposure to the beta anomaly, and lead to reduced CAPM alphas for the anomaly trading strategies. In terms of economic magnitude, the reduction in trading profitability ranges from 27% up to a reversed sign. The $t$-statistics of the CAPM alpha estimates all drop below 3, the significance threshold suggested by Harvey, Liu, and Zhu (2016) to account for data mining concerns. The results hold after ensuring that the resulting anomaly portfolios are ex post market neutral, in different time periods, and are robust to alternative beta measures. Falsification tests show that reductions of such magnitude are difficult to replicate through random adjustments to the anomaly portfolios.

There are two alternative ways to control the extent to which the long-short portfolios are susceptible to the beta anomaly. However, neither is effective for the purpose of this paper. The first alternative approach is a regression specification where the return to the beta-sorted portfolio is added to the CAPM as an explanatory variable. I show that this regression specification suffers from multicollinearity: by construction, the beta-sorted portfolio is highly negatively correlated with the market excess return. I verify this negative correlation in my sample and find a correlation coefficient of -0.77. Therefore it should not be expected that adding the beta anomaly return to the CAPM significantly improves the explanatory power of the CAPM. Moreover, the regression specification implies that returns to the beta-sorted portfolio proxy for a systematic risk factor, while this paper analyzes individual stock betas as
characteristics. The second approach is to form anomaly portfolios from independent double-sorts on beta and an anomaly characteristic. However, this method does not effectively adjust the ex-post beta estimates of the long-short portfolios: within each beta quintile, the variation in betas between extreme anomaly quintiles is comparable in magnitude to that from the univariate sort on the anomaly characteristic alone.

The CAPM beta is one of many common measures of risk. The literature (see for instance Ang, Hodrick, Xing, and Zhang, 2006, Baker, Bradley, and Wurgler, 2011) has identified a number of alternative risk measures that are also negatively related to expected returns in the cross-section. I analyze return volatility as a model-free alternative measure of risk. I find a positive average cross-sectional correlation between beta and return volatility of about 0.32. I show that over the sample period, the anomaly long portfolios have lower realized return volatility relative to the short portfolios. Moreover, removing the return volatility anomaly imbalance in the long-short strategies has similar effects as mitigating the long-short portfolios’ beta anomaly exposure. This is suggestive evidence that more general than the beta anomaly, the low-risk puzzle adds to the cross-sectional return anomalies.

The paper proceeds as follows. The next section discusses the relevant literature. Section 1.2 motivates the hypothesis that the beta anomaly is embedded in many cross-sectional asset pricing puzzles. Section 1.3 discusses the data and the empirical measures used in the paper. Section 1.4 presents the main empirical findings. Section 1.5 discusses a set of anomalies not covered in the paper. Section 1.6 discusses alternative ways to mitigate the long-short portfolios’ exposure to the beta anomaly, and limitations of the methods applied in this paper. Section 3.6 concludes.
1.1 Literature

The beta anomaly has been documented as early as Black, Jensen, and Scholes (1972): high (low) beta stocks tend to have low (high) risk-adjusted returns under the CAPM, resulting in a security market line flatter than predicted by the CAPM. The beta anomaly since then has been extended in a number of ways to the more general low-risk puzzle. Ang, Hodrick, Xing, and Zhang (2006) consider alternative measures of risk, and find that return volatility and idiosyncratic volatility are negatively correlated with expected returns in the cross-section. Bali, Cakici, and Whitelaw (2011) find that investors have preferences for the risky lottery-like assets by documenting a negative relation between a stock’s recent maximum daily return and expected returns. Asness, Frazzini, and Pedersen (2014) show that “quality” stocks offer high average returns relative to “junks”. More recently, Kapadia, Ostdiek, Weston, and Zekhnini (2015) extend the literature by showing that stocks that are predicted to hedge market downturns out-of-sample significantly outperform those that do not.

The literature proposes several explanations for the beta anomaly, most of which rely on some type of investor preference for risk. Such preferences could arise due to behavioral reasons (Karceski, 2002, Baker, Bradley, and Wurgler, 2011, ?, Hong and Sraer, 2016), or due to institutional constraints (Frazzini and Pedersen, 2014). Independent from the investor preference argument, Cederburg and O’Doherty (2016) find no consistently significant alpha from the beta-sorted portfolio after accounting for the time-variation in beta under a conditional CAPM framework. In contrast, I study the asset pricing anomalies in an unconditional model. This paper does not
take a stance on the source of the beta anomaly. Rather, I verify its empirical validity in an unconditional setting, and show that the beta anomaly is embedded in the other cross-sectional anomalies. Therefore, to the extent the beta anomaly is explained in the literature, my results suggest that we have explanations for a wide range of other anomalies as well.

In a related paper, Novy-Marx (2014) attributes the abnormal performance of the defensive minus aggressive (DMA) strategy to small, growth, and unprofitable stocks, and argues that the converse does not hold. The converse is studied by analyzing alphas from time-series regressions of anomaly portfolio returns on a model where the DMA return is added to the market excess return. While I am silent on the source of the beta anomaly, I find a correlation coefficient of -0.77 between the return to the beta-sorted portfolio and the market. Therefore in the context of my paper, it might not be surprising that adding the beta anomaly return to the market model does not significantly improve its performance explaining anomaly returns. Moreover, the regression specification implies that the DMA portfolio return proxies for a systematic risk factor, while I study stock betas as characteristics.

This paper relates to the literature connecting the cross-sectional anomalies with mispricing and limits to arbitrage. Market-wide sentiment causes mispricing (Baker and Wurgler, 2006, Stambaugh, Yu, and Yuan, 2012, Stambaugh and Yuan, 2016), which in combination with some form of limits to arbitrage (for example high short-selling fees in Drechsler and Drechsler, 2014), lead to the observed cross-sectional anomalies. Two papers in this literature relate most closely to my work. Stambaugh, Yu, and Yuan (2015) explains the idiosyncratic volatility (IVOL) puzzle
with mispricing by arguing that arbitrage asymmetry makes overpricing more difficult to correct compared to underpricing, rendering the negative IVOL-return relation among overpriced stocks more prevalent. Liu, Stambaugh, and Yuan (2016) explain the beta anomaly by showing that it exists through positive cross-sectional correlation with IVOL. Together the above two papers suggest mispricing with arbitrage asymmetry should be the cause of the low-risk puzzle. The result in this paper that the low-risk puzzle is embedded in other anomalies is consistent with the mispricing explanation of the anomalies. My work adds to the literature by presenting direct evidence that the low-risk puzzle is a channel through which mispricing contributes to the anomalies.

Given the plethora of the cross-sectional asset pricing puzzles (Harvey, Liu, and Zhu, 2016, McLean and Pontiff, 2016), Cochrane (2011) calls for consolidation. A burgeoning literature in the intersection of asset pricing and econometrics aims at reducing the set of cross-sectional anomalies, or “risk factors.” This literature employs machine-learning techniques to evaluate the explanatory power of new factors in addition to existing ones (Feng, Giglio, and Xiu, 2017, Freyberger, Neuhierl, and Weber, 2017, Kozak, Nagel, and Santosh, 2017). My paper adds to this literature by taking an empirically-motivated approach, and shedding light on a viable dimension along which the space of cross-sectional anomalies could be reduced.


1.2 Motivation

1.2.1 The Beta Anomaly

Black, Jensen, and Scholes (1972) make the observation that the CAPM alphas “are consistently negative for the high-risk portfolios ($\beta > 1$) and consistently positive for the low-risk portfolios ($\beta < 1$). Thus the high-risk securities earned less on average ... than the amount predicted by the traditional form of the asset pricing model. At the same time, the low-risk securities earned more than the amount predicted by the model.”

Figure 1 presents a visual illustration of the beta anomaly. CRSP stocks in each month are sorted into quintiles based on their trailing 12-month beta estimated using daily returns. The plots show the cumulative returns from a $1$ investment in 1927 in each of the two extreme quintiles.

[Insert figure 1 here]

Returns in the plots are not adjusted for inflation, and do not take into account transaction costs. The inflation adjustment would be the same for both portfolios. Transaction costs, if anything, should only be higher for the top quintile, resulting in an even lower cost-adjusted cumulative return. What matters here is the contrast in cumulative returns. A $1$ invested in the low beta portfolio in 1927 increased to $135.16$ in 2016, whereas $1$ invested in the high beta portfolio only increased in nominal terms to $16.73$ in the same time period. Such a sharp contrast is

---

1See Black, Jensen, and Scholes (1972) table 2.
inconsistent with either theory or intuition: investors holding high beta assets do not get compensated in expected returns commensurate with the risk they bear.

1.2.2 Hypothesis Development

Table 1 reports the long-short anomaly portfolio returns conditional on the market excess return.

[Insert table 1 here]

The monotonically increasing pattern of the market excess return from the worst to the best months is perfectly reversed for all the anomaly portfolios. For all ten of the tabulated anomaly portfolios, the best performing months are in fact the months in which the market performs the worst, whereas their best performing months are the ones in which the market rises the most. Take the composite equity issues portfolio for example. The average return in months with extreme market downfalls is almost 3% higher than that in months with the highest market increases. Furthermore, the decreasing trend in each row going from the left to the right indicates that on average, the higher the overall market return is in a given month, the worse are returns to anomaly portfolios, suggesting a negative covariance between returns to the anomaly portfolios and the contemporaneous market excess return. The same pattern holds under daily returns: the anomaly portfolios perform the best in the 20% of trading days when the market falls the most, and perform the worst when the market rises the most. Results from table 1 are robust to the exclusion of the great depression, the dot-com bubble, and the housing crisis periods.
Conventionally, the anomaly portfolio return is taken as the return to the long leg minus the return to the short leg, where the long and short portfolios have the same weight. A long-short portfolio having a negative beta is equivalent to the condition that the long portfolio has a lower beta relative to the short portfolio

\[ \beta_{LS} \equiv \beta_L - \beta_S < 0 \iff \beta_L < \beta_S. \]

\( \beta_L < \beta_S \) then is equivalent to the condition that on average, the long portfolios hold stocks of lower betas compared to the stocks in the short portfolio

\[ \beta_L < \beta_S \iff \sum_{i \in L} \omega_i \cdot \beta_i - \sum_{j \in S} \omega_j \cdot \beta_j < 0, \tag{1.1} \]

where \( i \) denotes a stock in the long portfolio, \( j \) denotes a stock in the short portfolio, and \( \omega_k \) denotes the weight a stock carries when returns are aggregated to the portfolio level. To the extent the beta anomaly holds in the data, it is most likely that the same stocks that are heavily-weighted in the long-leg should have lower alpha compared to the heavily-weighted stocks in the short-leg. Taking the difference between the long and short portfolio returns then results in a positive alpha for the anomaly portfolio\(^2\).

---

\(^2\)This argument relies on the function that maps a stock’s beta to its alpha being “regular.” A class of functions that are sufficient for this argument are those that are monotonically decreasing and affine. For example, suppose \( f : \beta \to \alpha \) satisfies

\[ f' < 0, \quad f(\sum_i k_i \cdot x_i) = \sum_i k_i \cdot f(x_i), \]

for \( \sum_i k_i = 1 \) and \( x_i \in \mathbb{R} \). Then we have that

\[ \alpha_i \equiv \sum_{i \in L} \omega_i \cdot f(\beta_i) = f(\sum_{i \in L} \omega_i \cdot \beta_i) > f(\sum_{j \in S} \omega_j \cdot \beta_j) = \sum_{j \in S} \omega_j \cdot f(\beta_j) \equiv \alpha_j, \]
Hence the long-short portfolio has a source of positive alpha that is independent of the intended anomaly characteristic.

1.3 Data and Empirical Measures

1.3.1 Return and Accounting Data

The sample of stocks comes from the Center or Research in Security Prices (CRSP) and Compustat. The stock return data cover the period from 1927 to 2016. The accounting data cover the period from 1963 to 2016. The sample of stocks consists of common stocks (shrcd 10 and 11) that are listed on NYSE, AMEX, or NASDAQ (exchcd 1, 2, 3). I require that a Compustat firm must have non-negative total assets to be included in the sample. I carry a firm’s accounting data forward up to the earliest occurrence of any of the following three conditions. First, the next financial statement is available. Second, the firm is delisted. Third, 24 months have passed in between the firm’s two consecutive financial statement releases. Returns are adjusted for delisting bias wherever applicable.

Because market betas are of primary interest in this study, the 2% of stocks with extreme beta estimates each month are excluded from the sample (1% on each end) in an attempt to reduce the impact of outliers. The sample includes all stocks surviving the restrictions outlined above. Robustness tests are done with microcap stocks excluded from the sample. All main results remain. The proxy for the market

where the inequality in the middle follows from condition (1.1).
return is the CRSP value-weighted index. The proxy for the risk-free rate is the one month T-bill rate, obtained from Ken French’s data library.

### 1.3.2 Beta Estimates

At the beginning of every month I estimate a stock’s CAPM $\beta$ using its daily excess returns (gross return minus one-month T-bill rate) in the past 12 months, with a minimum of 150 observations of non-missing returns required. To limit the impact of non-synchronous trading, I estimate a stock’s $\beta$ using the sum of coefficients method following Dimson (1979). The rolling window regression specification is

$$
    r_{i,t} = \alpha_i + \sum_{l=0}^{5} \beta_{i,t-l}R_{m,t-l} + \epsilon_{i,t},
$$

where $r_{i,t}$ denotes the excess return on stock $i$ on day $t$, and $R_{m,t}$ denotes the market excess return on day $t$.

The stock’s beta estimate for month $t$ is then calculated as

$$
    \hat{\beta}_{i,t} = \sum_{l=0}^{5} \beta_{i,t-l}.
$$

As an alternative way to measure betas, I use rolling windows of monthly returns in the past five years requiring at least 24 non-missing return observations, and estimate the specification

$$
    r_{i,t} = \alpha_i + \beta_{i,t}R_{m,t} + \beta_{i,t-1}R_{m,t-1} + \epsilon_{i,t},
$$
where $r_{i,t}$ denotes the excess return on stock $i$ in month $t$, and $R_{m,t}$ denotes the market excess return in month $t$.

The stock’s beta estimate for month $t$ is then calculated as

$$
\hat{\beta}_{i,t} = \beta_{i,t} + \beta_{i,t-1}.
$$

All analyses in this paper use betas estimates from daily returns. However, results remain qualitatively similar across both beta estimation methods.

1.3.3 Anomalies and Long-short Strategies

I focus on ten asset pricing anomalies that are based on both accounting data and past stock return information. The list is taken from the union of the sets of anomalies studied by Stambaugh, Yu, and Yuan (2012) and Fama and French (2016), and is representative of the different types of cross-sectional return puzzles documented in the literature. Specifically, I consider anomalies on profitability (Novy-Marx, 2013, Fama and French, 2016), momentum (Jegadeesh and Titman, 1993), composite equity issues (Daniel and Titman, 2006), financial distress (Ohlson, 1980), default probability Campbell, Hilscher, and Szilagyi (2008), total accruals (Sloan, 1996), investment growth rate (Xing, 2008), return on assets (Chen, Novy-Marx, and Zhang, 2011, Fama and French, 2006), return volatility and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006). I follow the construction outlined in Fama and French (2016) wherever possible, and then that in Stambaugh, Yu, and Yuan (2012). A detailed description and the calculations of the anomalies are in A. Absent from
the Stambaugh et al. (2012) and Fama and French (2016) list are the net operating assets, the asset growth, and the net stock issues anomalies. I address these omitted anomalies as well as the size and value effects in section 1.5.

I consider the monthly-rebalanced long-short trading strategies. For all accounting-based anomalies, stocks in each month are sorted into quintiles by the most recently available accounting variable. All accounting data are assumed to be available four months after the end of the fiscal period. For momentum, I require a one-month gap between the six-month window in which momentum is measured and the month in which the momentum measure becomes available. I measure return volatility using the standard deviation of the stock’s daily excess return in the past 60 days. For idiosyncratic volatility, I use the standard deviation of the CAPM residuals estimated using daily returns in the past 60 days. The long-short portfolio return is defined as the difference in the value-weighted returns between the extreme quintiles. Thus all anomalies are traded using zero-cost long-short portfolios. I require each extreme quintile portfolio to have at least 50 stocks in any given month to be included in the sample. The summary statistics are presented in table 2.

[Insert table 2 here]

The parameter $\gamma$ presented in panel B of table 2 is estimated in

$$R_{i,t} = \alpha_i + \gamma_i \cdot R_{b,t} + \epsilon_{i,t},$$

where $R_{i,t}$ denotes the return to a zero-cost portfolio $i$ in month $t$, and $R_{b,t}$ denotes the month $t$ return to the beta-sorted portfolio. Thus $\gamma$ captures the sensitivity of the
anomaly portfolio returns to the return of trading on the beta anomaly. All portfolios in the table have returns that are positively related to $R_{b,t}$, although the magnitude of the covariance varies. The return volatility, idiosyncratic volatility and default probability portfolios show the highest sensitivity, while the investment growth and total accruals portfolios show the lowest.

Note that the starting years for the time-series of the anomaly portfolios vary. The sample period for each portfolio is set based on two constraints. The first is data availability: variables that require only CRSP data to compute have data available as early as 1927, while variables that require Compustat data only go back to 1963. The second constraint is that I require both the long and short leg portfolios to hold at least 50 stocks each month. The row minimum holdings in panel A of table 2 shows that this constraint appears to be binding for the total accruals, return volatility, idiosyncratic volatility, and default probability portfolios. Note this constraint leads to different starting years for total accruals (1968) and default probability (1973) portfolios relative to other accounting-based anomalies.

The bottom panel presents the realized (post-formation) beta estimates for each anomaly. The realized estimates are obtained from the whole-sample estimation of the CAPM model using the time-series of portfolio returns, as in

$$\hat{\beta}_a = \hat{\beta}_L - \hat{\beta}_S,$$

where $\hat{\beta}_L (\hat{\beta}_S)$ is estimated from projecting the time-series of long (short) leg portfolio returns on the time-series of market excess returns in the entire sample.
Because non-synchronous trading is less of a concern for portfolios of stocks, the realized portfolio betas are estimated in the CAPM without lagged market excess returns. For all anomalies, the long leg portfolios exhibit lower beta estimates relative to their short legs. In most cases, long legs show beta estimates below 1. The two exceptions are the investment growth and total accruals portfolios, which show beta estimates of 1.19 and 1.13 in their long legs, respectively. However, in all cases short leg portfolios exhibit beta estimates above 1.25. Due to the high beta estimates from long legs, the investment growth and total accruals exhibit the lowest variation in realized betas between the extreme quintiles. In comparison, the volatility-related and default probability anomaly portfolios show that greatest variation in realized betas between the extreme quintiles. The strong beta imbalance in the volatility-related anomaly portfolio is consistent with the observation in Liu, Stambaugh, and Yuan (2016) that beta is positively related to IVOL in the cross-section.

1.4 Empirical Results: Examining Cross-sectional Anomalies After Mitigating the Beta Imbalance

1.4.1 Mitigating Exposure to the Beta Anomaly: Weighting by Beta Ranks

I mitigate the long-short portfolio’s exposure to the beta anomaly in two complementary ways.

First, instead of value-weighting, I weight stocks in each portfolio by their ranked betas. Specifically, in each month stocks in the sample are ranked into deciles based
on their pre-formation beta estimates in an ascending order. Stocks in the long portfolios are weighted by decile ranking of their betas, so that the high-beta stocks get higher weights in the long-leg portfolios relative to the value-weighted portfolios. For example, in any given anomaly’s long leg portfolio, stock \( i \) would have weight \( w_i \)

\[
w_i = \frac{R_i}{\sum_j R_j},
\]

where \( R_i \in \{1, ..., 10\} \) denotes the ascending decile ranking of stock \( i \)’s beta estimate so that \( R_i \geq R_k \) for \( \beta_i \geq \beta_k \), and \( j \) denotes a stock in the long leg, so the denominator is the sum of all long leg stocks’ beta decile rankings. Symmetrically, stocks in the short leg portfolios are weighted by the descending decile ranking of their pre-formation betas, so that the low-beta stocks get higher weights in the short-leg portfolios relative to the value-weighted portfolios. Stock \( i \) in a short leg portfolio carries weight \( w_i \)

\[
w_i = \frac{DR_i}{\sum_j DR_j},
\]

where \( DR_i \in \{1, ..., 10\} \) denotes the descending decile ranking of stock \( i \)’s beta estimate so that \( DR_i \leq DR_k \) for \( \beta_i \geq \beta_k \), and the summation in the denominator runs over all stocks in the short leg.

This approach of balancing beta has two advantages. The first is that it preserves the original long-short portfolio constituents, so that the overall portfolio still has a long position on the set of stocks with the desirable anomaly characteristics, and a short position on the set of stocks with undesirable characteristic measures. It
only modifies the weights that each stock carries when returns are aggregated to the portfolio level. The second advantage is that it only considers the information in the relative ranking of betas in each cross-section, rather than relying on the specific values of the beta estimates, which can be rather noisy and have extreme values.

I obtain the CAPM estimates for both the value-weighted, and the beta rank-weighted long-short portfolios. The results are presented in table 3. The top row in each panel presents the whole-sample CAPM estimates for the value-weighted long-short anomaly portfolios, hence the subscript $vw$. The second row in each panel presents the whole-sample CAPM estimates for the beta rank-weighted portfolios, hence the subscript $br$.

[Insert table 3 here.]

In panel A, the first row indicates that the CAPM beta estimates are negative for all value-weighted anomaly portfolios, with those for the volatility-related anomalies being of the highest magnitude. The negative betas are consistent with the negative return covariance documented in table 1. By construction, weighting stocks by their beta ranks, however, effectively increases the beta estimates for all anomaly portfolios, as shown in the second row in panel A. Note that despite the increase, the post-formation beta estimates for a number of anomaly portfolios, in particular the return volatility and idiosyncratic volatility portfolios remain negative. Note also that weighting by ranked betas leads to positive ex post beta estimates in some cases. I address the concern of “over-correction” in section 1.6.
The first row in panel B shows that, not surprisingly, all value-weighted portfolios produce both economically and statistically significant alpha estimates. Using ranked betas as weights for individual stocks reduces both the economic and statistical significance of the alpha estimates. In terms of the economic magnitude, the reduction in trading profitability ranges from 27% for the total accruals portfolio, to 100% for the return on assets portfolio. The reduction in statistical significance also shows variation. The alpha estimate for the momentum portfolio remains significant at 1% level despite a 50% reduction in magnitude. The p-values for alpha estimates for the investment growth and total accruals portfolios remain above 5%, whereas alpha estimates for all other anomaly portfolios are no longer significant at the 5% level.

Panel C presents results on annualized portfolio information ratios, which are defined as

\[ IR = \sqrt{12} \cdot \frac{\alpha}{RMSE}, \]

where \( \alpha \) denotes the whole-sample portfolio alpha estimate, and \( RMSE \) denotes the regression root mean-square error. The factor \( \sqrt{12} \) serves to annualize the information ratio. \( IR \) can be interpreted as the portfolio Sharpe ratio after hedging out the market risk, and is a commonly-used metric to measure portfolio performance\(^3\). It rewards value-added \( (\alpha) \) on top of the benchmark returns, and punishes high tracking error, or equivalently, residual risk.

For all anomaly portfolios, the information ratio estimates tell a similar story: increasing the beta loadings of the long-leg portfolio and decreasing that of the short-

\(^3\) For more details see Goodwin (1998).
leg portfolio significantly reduces the trading profitability of the anomaly portfolios. The magnitude of the reduction in $IR$ is comparable to that in alphas for each of the anomaly. This means weighting stocks by their ranked betas results in similar portfolio residual volatility relative to value-weighting\(^4\).

Taken together, table 3 presents evidence indicating that portfolios, which trade in the direction suggested by the documented cross-sectional anomalies but also in a way that mitigates the negative beta exposure, exhibit risk-adjusted returns of both lower economic and statistical significance.

### 1.4.2 Balancing Portfolio Betas: Removing Low (High) Beta Stocks in the Short (Long) Leg Portfolio

The second approach also starts with an independent double-sort each month on the pre-ranking betas and the anomaly characteristic into quintiles. Long-short portfolios are still taken as the extreme quintiles based on the anomaly characteristic sort. In the long (short) leg, stocks whose betas are ranked in the bottom (top) 40\% in the cross-section are removed, so that the long (short) leg essentially holds stocks that are both predicted to have high (low) returns by the anomaly characteristic and

\(^4\)To see this, note $IR = \alpha/RMSE$. So the change $(IR_{br} - IR_{vw})/IR_{vw}$ simplifies to

$$\frac{RMSE_{vw} \cdot \alpha_{br}}{RMSE_{br} \cdot \alpha_{vw}} - 1,$$

which differs from the change in alpha

$$\frac{\alpha_{br}}{\alpha_{vw}} - 1$$

only by the multiplicative fraction $RMSE_{vw}/RMSE_{br}$. Therefore similar changes in alphas and $IR$'s necessarily means that $RMSE_{vw}/RMSE_{br}$ is close to 1.
have high (low) betas. The choice of 40% is made so that most anomaly portfolios have a positive ex post beta estimate that is close to zero. To complement the beta rank-weighting method, in this elimination approach stocks remain weighted by their one-month lagged market capitalization, the same as in the original anomaly portfolio construction. The whole-sample CAPM estimates are presented in table 4. The top row in each panel presents estimates for the original value-weighted portfolios, hence the subscript \( vw \). The second row in each panel presents the whole-sample CAPM estimates for anomaly portfolios after eliminating the low (high) beta stocks in the long (short) leg, hence the subscript \( el \).

[Insert table 4 here.]

As in table 3, panel A presents the beta estimate before and after eliminating stocks in each leg. As intended, removing stocks with low (high) beta in the long (short) portfolios results in an increase in the beta estimates. Similar to the results in table 3, however, the beta estimate for the return volatility portfolio remains negative even after the elimination. I address the concern of “over-compensating” the long-short portfolios’ negative beta imbalance in section 1.6.

Panel B presents the alpha estimates. Again across the ten anomalies analyzed in the paper, there is consistent reduction in both the economic and statistical significance of the alpha estimates. The reduction in economic magnitude ranges from 36% for the return on asset portfolio, to 80% in the composite equity issues. The \( t \)-statistics for the alphas after elimination become under 2.58 for all but the momentum portfolio, and seven out of ten alpha estimates have \( t \)-statistics below
1.96. After elimination, the momentum and default probability portfolios show the highest alpha estimate, with the momentum portfolio’s alpha showing the largest $t$-statistic.

The information ratio estimates show reductions of very similar magnitudes compared to the reductions in alphas, suggesting significant reductions in the anomaly portfolios’ benchmark-adjusted performance. This again means that the anomaly portfolios formed after elimination has similar residual risk relative to the original portfolios.

1.4.3 Falsification Tests

To test whether the presented reductions in the anomaly portfolio performance are due to chance, I perform falsification tests of both methods of balancing the long-short portfolio betas.

For the beta rank weighting method, I randomly assign stocks in the long and short portfolios into deciles each month. I then use the decile rankings as weights when aggregating individual stock returns to the portfolio level in the long-leg, and use the descending decile rankings (computed as 11 - groups numbers) as weights in the short-leg. This process is repeated 500 times$^5$. The distributions of the alpha estimates after random weighting are summarized in figure 2.

[Insert figure 2 here.]

$^5$The number of runs is limited only by the computing time this procedure requires.
In each subplot, the 500 alpha estimates are put into 100 bins, denoted by the green bars. The red vertical lines denote alpha estimates from portfolios using beta ranks as individual stock weights. For each anomaly, the test result indicates that none of the simulated portfolios produces an alpha estimate as small as the one from beta rank-weighted portfolios.

For the elimination method, I randomly eliminate 40% of the long and short portfolio holdings each month, and then compute the unconditional alpha for the new long-short portfolios. This process is also repeated 500 times. The distributions of alpha estimates after random elimination are summarized in figure 3.

[Insert figure 3 here.]

The results indicate that almost no simulation run produces alpha estimate as small as the one from eliminating low (high) beta stocks from the long (short) portfolios. Only the total accruals anomaly has a few out of 500 estimates falling to the left of the alpha estimate after inflating long-short portfolio betas as intended.

Taken together, the falsification tests suggest that it is difficult to replicate reductions in portfolio performance of comparable magnitude to the ones presented in the previous section. Similar results would be difficult, if not impossible, to reproduce.

1.4.4 The Low-risk Puzzle as Explanation

The average cross-sectional correlation between beta and return volatility is about 32% in the sample period from 1927 to 2016. In light of this positive cross-sectional correlation, I test the hypothesis that the results of this study are more general than
the beta anomaly: the low-risk puzzle is behind the high risk-adjusted returns to the cross-sectional anomalies examined in this study. In table 5, I tabulate the realized return volatility for anomaly long and short portfolios.

[Insert table 5 here.]

In the sample period from 1927 to 2016, long leg portfolios for all anomalies exhibit lower realized return volatility relative to short legs. The difference is statistically significant. The Bartlett tests reject the null hypothesis that the long and short portfolios for each anomaly have equal variances with low p-values.

I then repeat the tests from the previous section, but replace beta with return volatility. The results are presented in table 6.

[Insert table 6 here.]

Note in table 6 the volatility-related anomaly portfolios are excluded. This is because under the elimination method, given the strong cross-sectional correlation between idiosyncratic volatility and return volatility, removing stocks with low (high) return volatility would almost empty the long (short) portfolio formed on idiosyncratic volatility.

Panel A shows that increasing weights on high return volatility stocks in the long leg and low return volatility stocks in the short leg has a similar effect on portfolio betas as does the attempt to balance beta directly. Results in panel B show that eliminating low (high) return volatility stocks in the long (short) portfolios leads to reductions in the magnitude of the alpha estimates that range from 50% to 100%. The
anomaly portfolio showing the largest alpha estimate and statistical significance is still the momentum portfolio. Panel C shows an comparable reduction in information ratio across all anomaly portfolios as well, indicating similar portfolio residual risk levels in addition to reduced alphas after elimination.

The method of weighting stocks by return volatility (descending) ranks in the long (short) portfolios also leads to decreases in both the alpha and information ratio estimates. Reductions in magnitude range from about 30% to 100%. The alpha estimates for the return on assets, O score, and profitability portfolios are no longer significant at the 5% level. However, despite a 43% reduction in magnitudes, the momentum portfolio still shows a $t$-statistic above 3 and the largest alpha point estimate.

Overall adjusting return volatilities in the anomaly long-short portfolios leads to reductions in the anomaly portfolios’ trading profitability. Under both methods, the momentum portfolio appears to have consistent and strong benchmark-adjusted performance, measured in terms of both alpha and information ratio.

### 1.5 On Other Cross-sectional Anomalies

The list of all anomalies examined also includes size (Banz, 1981), value (Fama and French, 1992), net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004), and asset growth (Cooper, Gulen, and Schill, 2008, Hou, Xue, and Zhang, 2015). This section addresses these anomalies.
The long-short portfolios formed on size, value, and net operating assets are not negatively correlated with the contemporaneous market excess return. The size anomaly, when value-weighted, has returns that are positively related to the market, suggesting that the long portfolio has on average a higher beta relative to the short portfolio. This is consistent with the observation in Fama and French (1992) that on average beta and size are negatively correlated in the cross-section. In addition, the value-weighted size portfolio does not produce significant alphas in the sample period of 1927 to 2016. On the value effect, I find that when book-to-market equity ratio is computed using the most recently available market value of equity, the monthly BM-sorted portfolio is roughly market-neutral. The CAPM-adjusted return to the BM-sorted portfolio has a statistical significance below 5% level.

In the case of the portfolio sorted on net operating assets, there is no clear relation between its time-series of returns and the market excess return, and not surprisingly, no significant difference between its long and short portfolio betas. The asset growth portfolio (also interpreted as investment-to-assets, as in Hou, Xue, and Zhang, 2015) and net stock issues on the other hand, has returns that are negatively correlated with the market excess return. However, mitigating long-short portfolios’ beta imbalance has negligible effect on their risk-adjusted returns and information ratios. These findings suggest that portfolios formed on sorts of net operating assets, asset growth, and net stock issues have more substantial returns that are beyond and not attributable to the beta anomaly relative to the other cross-sectional anomalies.
1.6 On the Methodology to Mitigate Exposure to Beta Anomaly

In this section I discuss two alternative ways to mitigate the long-short portfolios’ exposure to the beta anomaly, and the limitations of the methods applied in this paper.

1.6.1 Alternatives

The first alternative is the regression specification where return to the long-short portfolio formed on sorts of stocks’ pre-formation betas, in similar spirit to the ‘betting against beta’ factor in Frazzini and Pedersen (2014), is added to the CAPM, as in

\[ R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \gamma_i \cdot R_{b,t} + \epsilon_{i,t}. \]  

(1.2)

In specification (1.2) \( R_{b,t} \) denotes the return to the portfolio formed on sorts of pre-formation betas. There are two reasons why this specification might not be appropriate for the purpose of this study. The first reason is that specification 1.2 necessitates the interpretation that \( R_{b,t} \) proxies for a systematic risk factor. However, this paper considers betas as characteristics, and looks to adjust long and short anomaly portfolios in order to mitigate their imbalance in this characteristic. Specification 1.2 is not well-suited for adjustment in characteristics.

The second reason is that this regression specification suffers from multicollinearity. Intuitively, the market excess return \( R_{m,t} \) and the beta portfolio return \( R_{b,t} \) should be negatively correlated. This is because the portfolio that buys low beta stocks and sells high beta stocks has returns that, by design, negatively covary with the market.
In the sample period from January 1927 to December 2016, the time-series of \( R_{m,t} \) and \( R_{b,t} \) have a correlation coefficient of \(-0.77\). Projecting \( R_{b,t} \) on \( R_{m,t} \) produces a regression coefficient of \(-1.08\) with a \( t \)-statistic of \(-18.26\). Together the correlation coefficient and the regression coefficient estimate suggest that \( R_{m,t} \) and \( R_{b,t} \) are highly negatively correlated, making interpreting the coefficient estimates \( \gamma_i \) in 1.2 difficult. Moreover, the high correlation makes the \( R_{b,t} \) have limited marginal explanatory power beyond that of \( R_{m,t} \) in the CAPM.

The second alternative way to mitigate the beta anomaly exposure is an independent double-sort, which is a common approach to control for one characteristic while studying the effect of another (Fama and French, 1993, 2006, 2016). However, independent double-sorts on pre-formation betas and an anomaly characteristic do not effectively mitigate the exposure to beta anomaly. To construct table 7, in each month stocks are sorted into quintiles independently by an anomaly characteristic and pre-formation betas. The intersections form 25 portfolios for each anomaly. The table reports the difference in post-formation betas between extreme anomaly quintile portfolios within each beta quintile. The row ‘all’ presents the difference in post-formation betas between extreme anomaly quintiles unconditional on the pre-formation betas.

[Insert table 7 here]

It is evident in table 7 that within each beta quintile, the extreme return volatility portfolios still exhibit significant variation in beta estimates. Take return volatility (VOL) for example. In each of the five beta quintiles, the magnitude of the variation
in betas between extreme return volatility quintiles is more than half of that from the univariate sort. Similar lack of sufficient reductions in beta variation across extreme quintiles is observed among the other anomaly variables. The investment growth (IG) anomaly seems to be the only exception: the long-short portfolios formed among low beta stocks exhibit balance in betas.

1.6.2 Limitations of using ranked betas as weights and eliminating portfolio holdings

Both the beta rank-weighting and the elimination methods effectively remove or mitigate the anomaly portfolios’ exposure to the beta anomaly. However, there are cases where these two methods result in “over-compensation” for the long-short portfolios’ imbalance in beta. For example in table 4, all but the volatility-related portfolios have positive realized betas after low (high) betas are removed from the long (short) portfolios. One way to address the concern of over-correcting the beta imbalance in the anomaly portfolios is to apply leverage to the long and short leg portfolios, after ensuring that the long leg holds more high beta stocks and the short leg holds more low beta stocks, as in

\[ R_{i,t} = x_{L,t} \cdot R_{L,t} - x_{S,t} \cdot R_{S,t}, \]  

(1.3)

where,

\[ x_{L,t} = \frac{2 \cdot \beta_{S,t} + 0.15}{\beta_{L,t} + \beta_{S,t}}, \quad x_{S,t} = \frac{2 \cdot \beta_{L,t} - 0.15}{\beta_{L,t} + \beta_{S,t}}. \]
In (1.3) $\beta_{L,t}$ and $\beta_{S,t}$ are the weighted average beta of the long and short portfolios, and $R_{L,t}$ and $R_{S,t}$ are the excess returns to the long and short leg portfolios, respectively.

[Insert table 8 here]

The parameter 0.15 in the coefficients $x_{L,t}$ and $x_{S,t}$ is set to address the downward bias in the realized long-short portfolio beta: based on table 8, extreme betas exhibit tendency to revert to the cross-sectional mean of roughly 1, leading to an overall negative realized anomaly portfolio beta. Therefore I pick $0.15 > 0$ such that the realized portfolio betas are close to zero. The results are not sensitive to the specific choice of this parameter, provided it is chosen to mitigate the slight downward bias of the realized portfolio beta. Trimming the sample by betas at 1% level in each month serves to mitigate the impact of outliers. In addition, in all empirical implementations of the coefficients estimated as in equation 1.3, I shrink the individual stocks’ raw beta estimates toward the cross-sectional mean of 1, as in

$$\beta_{i,t} = 0.61 \cdot \hat{\beta}_{i,t} + 0.39 \cdot 1,$$

---

6Leveraging the long and short portfolios to ensure that the overall portfolio is ex post beta-neutral is borrowed from Frazzini and Pedersen (2014). The coefficients $x_{L,t}$ and $x_{S,t}$ together solve the system of two equations

$$\begin{cases} x_{L,t} + x_{S,t} = 2, \\ \beta_{L,t} \cdot x_{L,t} - \beta_{S,t} \cdot x_{S,t} = 0.15 \end{cases}$$

The first equation ensures that the new strategy has in total $2$ invested in the long and short legs in total, the same as in the original construction, so that the comparison before and after applying leverage is meaningful. The second equation ensures that the ex ante long-short portfolio beta is 0.15.
where $\hat{\beta}_{i,t}$ is the raw estimate, and the parameter 0.61 and 0.39=1-0.61 are taken from Frazzini and Pedersen (2014). The average coefficient estimates $x_L$ and $x_S$ are presented in table 9.

[Insert table 9 here]

By construction, the two coefficient estimates in table 9 together serve two purposes. First, for each anomaly portfolio, the sum of $x_L$ and $x_S$ is 2, meaning the trading strategy always has $2 invested so that the comparing alphas before and after applying leverage is meaningful. Second, the coefficients are chosen so that the ex ante portfolio betas are 0.15 in order to account for the post-formation downward drift in the portfolio betas. The results after applying leverage to the anomaly long-short portfolios are presented in table 10.

[Insert table 10 here]

Panel A shows that leveraging seems to have mitigated the ranked-weighted and elimination methods’ positive impact on the realized portfolio betas. Panel B in table 10 suggests that applying leverage to obtain ex ante beta-neutral portfolios leads to little change in the alpha estimates from those obtained from anomaly portfolios without leverage. The investment growth and total accruals portfolios show an increase in the statistical significance in their alpha estimates relative to ones obtained before applying leverage.

Panel C reports mostly consistent reductions in the information ratio estimates across the anomaly portfolios under both methods, except for total accruals. For the
total accruals portfolio, the beta rank-weighting method after applying leverage leads to a decrease of only 5% in the information ratio estimate. Given the reduction in the alpha estimate of about 29%, the smaller decrease in IR suggests that leveraging significantly reduces the residual volatility of the total accruals portfolio.

1.7 Conclusion

Returns to long-short portfolios formed on a broad set of cross-sectional puzzles are negatively correlated with the contemporaneous market excess return. This negative covariance implies that the anomaly portfolios hold low beta assets and sell high beta assets, thus taking advantage of the well-documented beta anomaly. Mitigating the long-short portfolios’ imbalance in beta either attenuates or eliminates the risk-adjusted returns to the asset pricing puzzles, and leads to worse anomaly portfolio performance as measured by information ratios.

This paper suggests a new direction towards understanding the cross-section of expected returns. Results shed light on a viable way of consolidating a large set of documented anomalies, thereby reducing the number of cross-sectional puzzles in the literature. To the extent the beta anomaly can be explained by investor preferences or trading constraints, this paper suggests possible extensions of the same explanations to the other cross-sectional puzzles. At the same time, the negative covariance between the long-short portfolios and the market excess return presents a challenge to the risk-based interpretation of these cross-sectional anomalies.
Tables and Figures

Table 1: Anomaly portfolio returns conditional on market excess returns

Each column reports the average gross returns of the corresponding portfolios (row title) in months in which the market excess return falls into the corresponding quintile. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month stocks are sorted into quintiles based on their anomaly characteristics, where extreme quintiles make up the long-short portfolios. Monthly returns are reported in percents. Reported in square brackets are the t-statistics.

<table>
<thead>
<tr>
<th></th>
<th>Bottom 20%</th>
<th>20% to 40%</th>
<th>40% to 60%</th>
<th>60% to 80%</th>
<th>Top 20%</th>
<th>Hi-Lo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Excess Return (MKTRF)</td>
<td>-6.517</td>
<td>-1.396</td>
<td>0.979</td>
<td>3.122</td>
<td>7.188</td>
<td>13.846</td>
</tr>
<tr>
<td>Composite Equity Issues (CEI)</td>
<td>1.429</td>
<td>0.704</td>
<td>0.148</td>
<td>-0.089</td>
<td>-1.361</td>
<td>-2.844</td>
</tr>
<tr>
<td>Default Probability (DP)</td>
<td>5.525</td>
<td>1.441</td>
<td>0.428</td>
<td>-1.321</td>
<td>-3.937</td>
<td>-9.388</td>
</tr>
<tr>
<td>Investment Growth (IG)</td>
<td>1.085</td>
<td>0.565</td>
<td>0.39</td>
<td>0.053</td>
<td>-0.061</td>
<td>-1.114</td>
</tr>
<tr>
<td>Idiosyncratic Volatility (IVOL)</td>
<td>5.15</td>
<td>1.58</td>
<td>0.534</td>
<td>-1.646</td>
<td>-3.291</td>
<td>-8.361</td>
</tr>
<tr>
<td>Momentum (MOM)</td>
<td>1.959</td>
<td>1.094</td>
<td>1.42</td>
<td>0.714</td>
<td>-2.418</td>
<td>-4.296</td>
</tr>
<tr>
<td>O Score (O-SCORE)</td>
<td>3.38</td>
<td>1.129</td>
<td>-0.049</td>
<td>-1.139</td>
<td>-1.556</td>
<td>-4.903</td>
</tr>
<tr>
<td>Profitability (PROF)</td>
<td>2.9</td>
<td>1.302</td>
<td>0.173</td>
<td>-1.1</td>
<td>-1.438</td>
<td>-4.232</td>
</tr>
<tr>
<td>Return on Assets (ROA)</td>
<td>3.189</td>
<td>1.227</td>
<td>-0.101</td>
<td>-1.23</td>
<td>-1.657</td>
<td>-4.743</td>
</tr>
<tr>
<td>Total Accruals (TAC)</td>
<td>1.327</td>
<td>0.828</td>
<td>0.331</td>
<td>-0.099</td>
<td>-0.377</td>
<td>-1.689</td>
</tr>
<tr>
<td>Return Volatility (VOL)</td>
<td>6.466</td>
<td>1.844</td>
<td>0.435</td>
<td>-1.95</td>
<td>-4.53</td>
<td>-10.928</td>
</tr>
</tbody>
</table>

\( t \geq 2.58 \iff p \leq 1\%, \ t \geq 1.96 \iff p \leq 5\%, \ t \geq 1.64 \iff p \leq 10\% \)
Table 2: Summary Statistics

Reported in this table are the summary statistics of the long-short anomaly portfolios. Monthly returns are reported as percents. Return volatility is the standard deviation of the time-series of portfolio returns. Mean (min, max) holdings is the average (minimum, maximum) number of stocks in a quintile in a month. $\gamma$ is estimated in the specification $R_{i,t} = \alpha_i + \gamma_i \cdot R_{b,t} + \epsilon_{i,t}$, where $R_{i,t}$ denotes the return to a zero-cost portfolio $i$ in month $t$, and $R_{b,t}$ denotes the return in month $t$ to the beta-sorted portfolio. The $t$-statistics are computed using the Newey and West (1987) standard errors with a six-month lag.

<table>
<thead>
<tr>
<th>Panel A: Summary</th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly return</td>
<td>0.55</td>
<td>0.181</td>
<td>0.333</td>
<td>0.395</td>
<td>0.415</td>
<td>0.417</td>
<td>0.426</td>
<td>0.456</td>
<td>0.465</td>
<td>0.492</td>
</tr>
<tr>
<td>Return volatility</td>
<td>0.066</td>
<td>0.04</td>
<td>0.048</td>
<td>0.049</td>
<td>0.044</td>
<td>0.027</td>
<td>0.031</td>
<td>0.078</td>
<td>0.075</td>
<td>0.066</td>
</tr>
<tr>
<td>Mean holdings</td>
<td>588.02</td>
<td>561.07</td>
<td>762.7</td>
<td>648.75</td>
<td>772.13</td>
<td>682.0</td>
<td>674.77</td>
<td>582.42</td>
<td>584.3</td>
<td>674.41</td>
</tr>
<tr>
<td>Min holdings</td>
<td>64</td>
<td>94</td>
<td>116</td>
<td>90</td>
<td>110</td>
<td>88</td>
<td>52</td>
<td>52</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>Max holdings</td>
<td>1393</td>
<td>1303</td>
<td>1321</td>
<td>1090</td>
<td>1334</td>
<td>1132</td>
<td>1074</td>
<td>1394</td>
<td>1395</td>
<td>1103</td>
</tr>
</tbody>
</table>

| Panel B: Covariance with returns to beta anomaly |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| $\gamma$| 0.367  | 0.191  | 0.364  | 0.363  | 0.353  | 0.088  | 0.059  | 0.716  | 0.582  | 0.507  |
| $t$      | [4.88] | [2.85] | [9.72] | [10.74]| [9.0]  | [2.93] | [2.25] | [13.89]| [10.87]| [7.98] |

| Panel C: Difference in realized betas |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Long     | 0.976  | 0.976  | 1.004  | 0.97   | 0.973  | 1.185  | 1.131  | 0.757  | 0.852  | 0.889  |
| $t$      | [20.03]| [32.01]| [61.72]| [70.15]| [65.56]| [52.29]| [35.02]| [59.87]| [93.02]| [38.62]|
| Short    | 1.419  | 1.263  | 1.416  | 1.4    | 1.343  | 1.278  | 1.274  | 1.484  | 1.392  | 1.639  |
| $t$      | [24.31]| [21.71]| [24.96]| [25.61]| [29.02]| [41.0] | [44.38]| [24.14]| [23.38]| [20.97]|
| Diff     | -0.443 | -0.286 | -0.412 | -0.43  | -0.37  | -0.093 | -0.144 | -0.727 | -0.54  | -0.75  |
Table 3: CAPM estimates for beta-rank weighted long-short anomaly portfolios

Reported in this table are the whole-sample CAPM estimates of long-short portfolios on cross-sectional anomalies and the corresponding t-statistics. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month, value-weighted anomaly portfolios are formed from univariate sorts into quintiles of all NYSE, AMEX and NASDAQ stocks. The monthly anomaly portfolio returns are defined as the difference between value-weighted average returns of extreme quintiles. $\alpha_{v\text{w}}$ ($\beta_{v\text{w}}$) is the CAPM alpha (beta) estimate of the value-weighted long-short portfolios. $\alpha_{br}$ ($\beta_{br}$) is the CAPM alpha estimate of the beta rank-weighted long-short portfolios. $\Delta_\alpha$ ($\Delta_\beta$) is the difference between $\alpha_{v\text{w}}$ ($\beta_{v\text{w}}$) and $\alpha_{br}$ ($\beta_{br}$). The t-statistics are computed using Newey and West (1987) standard errors with a three-month lag.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{v\text{w}}$</td>
<td>-0.443</td>
<td>-0.286</td>
<td>-0.412</td>
<td>-0.43</td>
<td>-0.37</td>
<td>-0.093</td>
<td>-0.144</td>
<td>-0.727</td>
<td>-0.54</td>
<td>-0.75</td>
</tr>
<tr>
<td>$\beta_{br}$</td>
<td>-0.131</td>
<td>0.034</td>
<td>0.113</td>
<td>0.133</td>
<td>0.162</td>
<td>0.267</td>
<td>0.291</td>
<td>-0.595</td>
<td>-0.436</td>
<td>-0.141</td>
</tr>
<tr>
<td>$\alpha_{v\text{w}}$</td>
<td>0.838</td>
<td>0.366</td>
<td>0.547</td>
<td>0.619</td>
<td>0.607</td>
<td>0.466</td>
<td>0.5</td>
<td>0.928</td>
<td>0.815</td>
<td>0.938</td>
</tr>
<tr>
<td>$\alpha_{br}$</td>
<td>0.416</td>
<td>0.11</td>
<td>-0.045</td>
<td>0.095</td>
<td>0.089</td>
<td>0.289</td>
<td>0.366</td>
<td>0.295</td>
<td>0.184</td>
<td>0.349</td>
</tr>
<tr>
<td>$\Delta_\alpha$</td>
<td>-50.4%</td>
<td>-69.9%</td>
<td>-108.2%</td>
<td>-84.7%</td>
<td>-85.3%</td>
<td>-38.0%</td>
<td>-26.8%</td>
<td>-68.2%</td>
<td>-77.4%</td>
<td>-62.8%</td>
</tr>
<tr>
<td>$\Delta_\beta$</td>
<td>-50.4%</td>
<td>-69.9%</td>
<td>-108.2%</td>
<td>-84.7%</td>
<td>-85.3%</td>
<td>-38.0%</td>
<td>-26.8%</td>
<td>-68.2%</td>
<td>-77.4%</td>
<td>-62.8%</td>
</tr>
</tbody>
</table>

Panel C: Information ratios

| IR_{v\text{w}} | 0.474 | 0.341 | 0.43 | 0.475 | 0.51 | 0.602 | 0.566 | 0.473 | 0.412 | 0.576 |
| $\Delta_\text{IR}_{v\text{w}}$ | -49.8% | -66.3% | -108.1% | -83.8% | -84.1% | -31.1% | -22.3% | -68.9% | -77.9% | -62.8% |
Table 4: CAPM estimates for long-short anomaly portfolios after elimination

Reported in this table are the whole-sample CAPM estimates of long-short portfolios on cross-sectional anomalies and the corresponding t-statistics. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month, value-weighted anomaly portfolios are formed from univariate sorts into quintiles of all NYSE, AMEX and NASDAQ stocks. The monthly anomaly portfolio returns are defined as the difference between value-weighted average returns of extreme quintiles. $\alpha_{vw}$ ($\beta_{vw}$) is the CAPM alpha (beta) estimate of the value-weighted long-short portfolios. $\alpha_{el}$ ($\beta_{el}$) is the CAPM alpha estimate of the long-short portfolios after eliminating low beta stocks in the long-legs, and high beta stocks in the short-leg. $\Delta_{\alpha}$ ($\Delta_{\beta}$) is the difference between $\alpha_{vw}$ ($\beta_{vw}$) and $\alpha_{el}$ ($\beta_{el}$). The t-statistics are computed using Newey and West (1987) standard errors with a three-month lag.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{vw}$</td>
<td>-0.443</td>
<td>-0.286</td>
<td>-0.412</td>
<td>-0.43</td>
<td>-0.37</td>
<td>-0.093</td>
<td>-0.144</td>
<td>-0.727</td>
<td>-0.54</td>
<td>-0.75</td>
</tr>
<tr>
<td>$\beta_{el}$</td>
<td>0.075</td>
<td>0.214</td>
<td>0.14</td>
<td>0.109</td>
<td>0.184</td>
<td>0.388</td>
<td>0.297</td>
<td>-0.166</td>
<td>0.005</td>
<td>-0.114</td>
</tr>
<tr>
<td>t</td>
<td>[1.11]</td>
<td>[2.857]</td>
<td>[2.707]</td>
<td>[1.886]</td>
<td>[3.882]</td>
<td>[6.41]</td>
<td>[3.842]</td>
<td>[-2.882]</td>
<td>[0.08]</td>
<td>[-1.281]</td>
</tr>
<tr>
<td>$\alpha_{vw}$</td>
<td>0.838</td>
<td>0.366</td>
<td>0.547</td>
<td>0.619</td>
<td>0.607</td>
<td>0.466</td>
<td>0.5</td>
<td>0.928</td>
<td>0.815</td>
<td>0.938</td>
</tr>
<tr>
<td>t</td>
<td>[4.83]</td>
<td>[3.01]</td>
<td>[2.81]</td>
<td>[3.2]</td>
<td>[3.12]</td>
<td>[4.17]</td>
<td>[3.51]</td>
<td>[4.02]</td>
<td>[3.6]</td>
<td>[3.35]</td>
</tr>
<tr>
<td>$\alpha_{el}$</td>
<td>0.477</td>
<td>0.072</td>
<td>0.352</td>
<td>0.381</td>
<td>0.297</td>
<td>0.096</td>
<td>0.17</td>
<td>0.47</td>
<td>0.372</td>
<td>0.487</td>
</tr>
<tr>
<td>t</td>
<td>[2.665]</td>
<td>[0.548]</td>
<td>[2.07]</td>
<td>[1.93]</td>
<td>[1.804]</td>
<td>[0.677]</td>
<td>[0.871]</td>
<td>[2.082]</td>
<td>[1.735]</td>
<td>[1.742]</td>
</tr>
<tr>
<td>$\Delta_{\alpha}$</td>
<td>-43.1%</td>
<td>-80.3%</td>
<td>-35.6%</td>
<td>-38.4%</td>
<td>-51.1%</td>
<td>-79.4%</td>
<td>-66.0%</td>
<td>-49.4%</td>
<td>-54.4%</td>
<td>-48.1%</td>
</tr>
</tbody>
</table>

Panel B: $\alpha$ estimates

<table>
<thead>
<tr>
<th></th>
<th>IR$_{vw}$</th>
<th>0.474</th>
<th>0.341</th>
<th>0.43</th>
<th>0.475</th>
<th>0.51</th>
<th>0.602</th>
<th>0.566</th>
<th>0.473</th>
<th>0.412</th>
<th>0.576</th>
</tr>
</thead>
<tbody>
<tr>
<td>t</td>
<td>[4.497]</td>
<td>[3.233]</td>
<td>[3.16]</td>
<td>[3.487]</td>
<td>[3.744]</td>
<td>[4.424]</td>
<td>[3.95]</td>
<td>[4.49]</td>
<td>[3.898]</td>
<td>[3.754]</td>
<td></td>
</tr>
<tr>
<td>IR$_{el}$</td>
<td>0.287</td>
<td>0.06</td>
<td>0.279</td>
<td>0.301</td>
<td>0.283</td>
<td>0.095</td>
<td>0.14</td>
<td>0.249</td>
<td>0.196</td>
<td>0.317</td>
<td></td>
</tr>
<tr>
<td>t</td>
<td>[2.719]</td>
<td>[0.569]</td>
<td>[2.049]</td>
<td>[2.21]</td>
<td>[2.079]</td>
<td>[0.701]</td>
<td>[0.973]</td>
<td>[2.273]</td>
<td>[1.852]</td>
<td>[2.062]</td>
<td></td>
</tr>
<tr>
<td>$\Delta_{ir}$</td>
<td>-39.5%</td>
<td>-82.4%</td>
<td>-35.1%</td>
<td>-36.6%</td>
<td>-44.5%</td>
<td>-84.2%</td>
<td>-75.3%</td>
<td>-47.4%</td>
<td>-52.4%</td>
<td>-45.0%</td>
<td></td>
</tr>
</tbody>
</table>
Table 5: Realized return volatility for anomaly long and short portfolios

Reported in this table are the realized return volatility estimates of anomaly long (Long Vol) and short (Short Vol) portfolios. Return volatility is measured as the standard deviation of monthly returns. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. The row $p$-value reports the $p$-value from the Bartlett’s test of the null hypothesis that the long and short portfolio variances are the same.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Vol</td>
<td>0.059</td>
<td>0.056</td>
<td>0.046</td>
<td>0.044</td>
<td>0.044</td>
<td>0.057</td>
<td>0.056</td>
<td>0.043</td>
<td>0.047</td>
<td>0.042</td>
</tr>
<tr>
<td>Short Vol</td>
<td>0.087</td>
<td>0.073</td>
<td>0.075</td>
<td>0.075</td>
<td>0.069</td>
<td>0.061</td>
<td>0.063</td>
<td>0.1</td>
<td>0.097</td>
<td>0.087</td>
</tr>
<tr>
<td>Diff</td>
<td>-0.028</td>
<td>-0.017</td>
<td>-0.029</td>
<td>-0.031</td>
<td>-0.025</td>
<td>-0.004</td>
<td>-0.007</td>
<td>-0.057</td>
<td>-0.05</td>
<td>-0.045</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.01167</td>
<td>0.00019</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

The long and short portfolio variances are the same.
Table 6: CAPM estimates for long-short anomaly portfolios after mitigating exposure to return volatility

Reported in this table are the whole-sample CAPM estimates of long-short portfolios on cross-sectional anomalies and the corresponding t-statistics. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month, value-weighted anomaly portfolios are formed from univariate sorts into quintiles of all NYSE, AMEX and NASDAQ stocks. The monthly anomaly portfolio returns are defined as the difference between value-weighted average returns of extreme quintiles. The subscript vw denotes the CAPM estimates of the value-weighted long-short portfolios. The subscript el denotes the estimates of the long-short portfolios after eliminating low return volatility stocks in the long-legs, and high return volatility stocks in the short-leg. The subscript rank denotes the estimates of the return volatility rank-weighted long-short portfolios. $\Delta_{el}$ ($\Delta_{rank}$) is the difference between the estimate of the original vw portfolio and the el (rank) portfolio. The t-statistics are computed using Newey and West (1987) standard errors with a three-month lag.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: $\beta$ estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{vw}$</td>
<td>-0.443</td>
<td>-0.286</td>
<td>-0.412</td>
<td>-0.43</td>
<td>-0.37</td>
<td>-0.093</td>
<td>-0.144</td>
<td>-0.75</td>
</tr>
<tr>
<td>$\beta_{el}$</td>
<td>-0.089</td>
<td>0.122</td>
<td>0.211</td>
<td>0.253</td>
<td>0.279</td>
<td>0.343</td>
<td>0.368</td>
<td>0.025</td>
</tr>
<tr>
<td>$t$</td>
<td>[-0.686]</td>
<td>[1.232]</td>
<td>[4.185]</td>
<td>[5.124]</td>
<td>[5.935]</td>
<td>[7.414]</td>
<td>[5.916]</td>
<td>[0.296]</td>
</tr>
<tr>
<td>$\beta_{rank}$</td>
<td>-0.218</td>
<td>-0.045</td>
<td>0.072</td>
<td>0.103</td>
<td>0.121</td>
<td>0.161</td>
<td>0.193</td>
<td>-0.246</td>
</tr>
<tr>
<td>$t$</td>
<td>[-2.365]</td>
<td>[-0.761]</td>
<td>[1.413]</td>
<td>[2.849]</td>
<td>[2.581]</td>
<td>[4.676]</td>
<td>[4.124]</td>
<td>[-2.945]</td>
</tr>
<tr>
<td><strong>Panel B: $\alpha$ estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{vw}$</td>
<td>0.838</td>
<td>0.366</td>
<td>0.547</td>
<td>0.619</td>
<td>0.607</td>
<td>0.466</td>
<td>0.5</td>
<td>0.938</td>
</tr>
<tr>
<td>$t$</td>
<td>4.83</td>
<td>3.01</td>
<td>2.81</td>
<td>3.2</td>
<td>3.12</td>
<td>4.17</td>
<td>3.51</td>
<td>3.35</td>
</tr>
<tr>
<td>$\alpha_{el}$</td>
<td>0.399</td>
<td>0.036</td>
<td>0.081</td>
<td>-0.111</td>
<td>0.046</td>
<td>0.01</td>
<td>0.069</td>
<td>0.077</td>
</tr>
<tr>
<td>$t$</td>
<td>2.102</td>
<td>0.32</td>
<td>0.424</td>
<td>-0.61</td>
<td>0.278</td>
<td>0.065</td>
<td>0.362</td>
<td>0.278</td>
</tr>
<tr>
<td>$\Delta_{el}$</td>
<td>-52.4%</td>
<td>-90.2%</td>
<td>-85.2%</td>
<td>-117.9%</td>
<td>-92.4%</td>
<td>-97.9%</td>
<td>-86.2%</td>
<td>-91.8%</td>
</tr>
<tr>
<td>$\alpha_{rank}$</td>
<td>0.474</td>
<td>0.194</td>
<td>-0.054</td>
<td>0.08</td>
<td>0.077</td>
<td>0.286</td>
<td>0.353</td>
<td>0.478</td>
</tr>
<tr>
<td>$t$</td>
<td>3.124</td>
<td>2.163</td>
<td>-0.31</td>
<td>0.507</td>
<td>0.562</td>
<td>2.021</td>
<td>2.071</td>
<td>2.359</td>
</tr>
<tr>
<td>$\Delta_{rank}$</td>
<td>-43.4%</td>
<td>-47.0%</td>
<td>-109.9%</td>
<td>-87.1%</td>
<td>-87.3%</td>
<td>-38.6%</td>
<td>-29.4%</td>
<td>-49.0%</td>
</tr>
<tr>
<td><strong>Panel B: Information ratios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$IR_{vw}$</td>
<td>0.474</td>
<td>0.341</td>
<td>0.43</td>
<td>0.475</td>
<td>0.51</td>
<td>0.602</td>
<td>0.566</td>
<td>0.576</td>
</tr>
<tr>
<td>$IR_{el}$</td>
<td>0.213</td>
<td>0.028</td>
<td>0.065</td>
<td>-0.092</td>
<td>0.043</td>
<td>0.009</td>
<td>0.054</td>
<td>0.046</td>
</tr>
<tr>
<td>$t$</td>
<td>2.069</td>
<td>0.267</td>
<td>0.478</td>
<td>-0.678</td>
<td>0.314</td>
<td>0.065</td>
<td>0.381</td>
<td>0.295</td>
</tr>
<tr>
<td>$\Delta_{el}$</td>
<td>-55.1%</td>
<td>-91.8%</td>
<td>-84.9%</td>
<td>-119.4%</td>
<td>-91.6%</td>
<td>-98.5%</td>
<td>-90.5%</td>
<td>-92.0%</td>
</tr>
<tr>
<td>$IR_{rank}$</td>
<td>0.297</td>
<td>0.215</td>
<td>-0.051</td>
<td>0.082</td>
<td>0.093</td>
<td>0.312</td>
<td>0.348</td>
<td>0.314</td>
</tr>
<tr>
<td>$t$</td>
<td>2.819</td>
<td>2.035</td>
<td>-0.373</td>
<td>0.606</td>
<td>0.683</td>
<td>2.295</td>
<td>2.43</td>
<td>2.047</td>
</tr>
<tr>
<td>$\Delta_{rank}$</td>
<td>-37.3%</td>
<td>-37.0%</td>
<td>-111.9%</td>
<td>-82.7%</td>
<td>-81.8%</td>
<td>-48.2%</td>
<td>-38.5%</td>
<td>-45.5%</td>
</tr>
</tbody>
</table>
Table 7: Post-formation beta estimates for the long-short anomaly portfolios within beta quintiles

Each month stocks are sorted into quintiles independently by an anomaly characteristic and pre-formation betas. The intersections form 25 portfolios. The table reports the difference in post-formation betas between extreme anomaly quintile portfolios within each beta quintile. The row ‘all’ presents the difference in post-formation betas between extreme anomaly quintiles unconditional on the pre-formation betas.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beta1</td>
<td>-0.353</td>
<td>0.2</td>
<td>-0.139</td>
<td>0.215</td>
<td>-0.103</td>
<td>-0.009</td>
<td>0.103</td>
<td>0.497</td>
<td>0.473</td>
<td>0.485</td>
</tr>
<tr>
<td>Beta2</td>
<td>-0.309</td>
<td>0.1</td>
<td>-0.166</td>
<td>0.191</td>
<td>-0.146</td>
<td>0.019</td>
<td>0.124</td>
<td>0.589</td>
<td>0.5</td>
<td>0.343</td>
</tr>
<tr>
<td>Beta3</td>
<td>-0.23</td>
<td>0.176</td>
<td>-0.147</td>
<td>0.214</td>
<td>-0.117</td>
<td>-0.003</td>
<td>0.056</td>
<td>0.435</td>
<td>0.309</td>
<td>0.368</td>
</tr>
<tr>
<td>Beta4</td>
<td>-0.272</td>
<td>0.076</td>
<td>-0.112</td>
<td>0.207</td>
<td>-0.064</td>
<td>0.063</td>
<td>0.071</td>
<td>0.512</td>
<td>0.256</td>
<td>0.373</td>
</tr>
<tr>
<td>Beta5</td>
<td>-0.334</td>
<td>0.292</td>
<td>-0.175</td>
<td>0.296</td>
<td>-0.186</td>
<td>0.06</td>
<td>0.061</td>
<td>0.63</td>
<td>0.269</td>
<td>0.367</td>
</tr>
<tr>
<td>All</td>
<td>-0.443</td>
<td>0.287</td>
<td>-0.308</td>
<td>0.368</td>
<td>-0.299</td>
<td>0.086</td>
<td>0.118</td>
<td>0.727</td>
<td>0.542</td>
<td>0.63</td>
</tr>
</tbody>
</table>
Table 8: Conditional change in beta in month \( t + 1 \)

The sample period is 1927 to 2016. In each month, all NYSE, AMEX and NASDAQ stocks are sorted into deciles according to their pre-formation betas, estimated using trailing 12-month daily returns. The row \( \beta \) denotes the average beta estimate in the corresponding decile. Row \( \Delta_\beta \) denotes the average change in the pre-formation betas in the following month.

<table>
<thead>
<tr>
<th></th>
<th>BETA1</th>
<th>BETA2</th>
<th>BETA3</th>
<th>BETA4</th>
<th>BETA5</th>
<th>BETA6</th>
<th>BETA7</th>
<th>BETA8</th>
<th>BETA9</th>
<th>BETA10</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>.251</td>
<td>.564</td>
<td>.700</td>
<td>.812</td>
<td>.920</td>
<td>1.03</td>
<td>1.152</td>
<td>1.30</td>
<td>1.507</td>
<td>1.993</td>
</tr>
<tr>
<td>( \Delta_\beta )</td>
<td>0.046</td>
<td>0.019</td>
<td>0.012</td>
<td>0.008</td>
<td>0.004</td>
<td>0.000</td>
<td>-0.006</td>
<td>-0.013</td>
<td>-0.022</td>
<td>-0.055</td>
</tr>
<tr>
<td>( t(\Delta_\beta) )</td>
<td>112.9</td>
<td>73.42</td>
<td>49.66</td>
<td>32.34</td>
<td>14.5</td>
<td>-2.65</td>
<td>-20.85</td>
<td>-42.44</td>
<td>-67.01</td>
<td>-116.29</td>
</tr>
</tbody>
</table>
Table 9: CAPM estimates for beta-neutral long-short anomaly portfolios after mitigating beta anomaly exposure

The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month, anomaly portfolios are formed from univariate sorts into quintiles of all NYSE, AMEX and NASDAQ stocks. The monthly anomaly portfolio returns are defined as the difference between average returns of extreme quintiles. \(x_L\) and \(x_S\) denote the time-series averages of the coefficients obtained by solving equation 1.3 at the beginning of each month when constructing long-short portfolios.

<table>
<thead>
<tr>
<th></th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Average leverage coefficients under elimination method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(x_L)</td>
<td>0.873</td>
<td>0.892</td>
<td>0.883</td>
<td>0.857</td>
<td>0.89</td>
<td>0.867</td>
<td>0.883</td>
<td>0.907</td>
<td>0.889</td>
<td>0.894</td>
</tr>
<tr>
<td>(x_S)</td>
<td>1.127</td>
<td>1.108</td>
<td>1.117</td>
<td>1.143</td>
<td>1.11</td>
<td>1.133</td>
<td>1.117</td>
<td>1.093</td>
<td>1.111</td>
<td>1.106</td>
</tr>
<tr>
<td>Panel B: Average leverage coefficients under rank-weighting method</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(x_L)</td>
<td>0.867</td>
<td>0.902</td>
<td>0.837</td>
<td>0.83</td>
<td>0.834</td>
<td>0.847</td>
<td>0.846</td>
<td>1.038</td>
<td>0.999</td>
<td>0.874</td>
</tr>
<tr>
<td>(x_S)</td>
<td>1.133</td>
<td>1.098</td>
<td>1.163</td>
<td>1.17</td>
<td>1.166</td>
<td>1.153</td>
<td>1.154</td>
<td>0.962</td>
<td>1.001</td>
<td>1.126</td>
</tr>
</tbody>
</table>
Table 10: CAPM estimates for beta-neutral long-short anomaly portfolios after eliminating beta anomaly exposure

Reported in this table are the whole-sample CAPM estimates of long-short portfolios on cross-sectional anomalies and the corresponding t-statistics. The sample period is 1927 to 2016 for all portfolios whose calculations only require CRSP data (MOM, CEI, VOL, IVOL), 1963 to 2016 for most accounting-based portfolios (ROA, O-SCORE, PROF, IG), 1968 to 2016 for TAC, and 1973 to 2016 for DP. In each month, value-weighted anomaly portfolios are formed from univariate sorts into quintiles of all NYSE, AMEX and NASDAQ stocks. The monthly anomaly portfolio returns are defined as the difference between value-weighted average returns of extreme quintiles. The subscript vw denotes the CAPM estimates of the value-weighted long-short portfolios. The subscript el denotes the estimates of the long-short portfolios after eliminating low beta stocks in the long-legs, and high beta stocks in the short-leg. The subscript rank denotes the estimates of the beta rank-weighted long-short portfolios. $\Delta_{el}$ ($\Delta_{rank}$) is the difference between the estimate of the original vw portfolio and the el (rank) portfolio. The t-statistics are computed using Newey and West (1987) standard errors with a six-month lag.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>MOM</th>
<th>CEI</th>
<th>ROA</th>
<th>O-SCORE</th>
<th>PROF</th>
<th>IG</th>
<th>TAC</th>
<th>VOL</th>
<th>IVOL</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: $\beta$ estimates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{vw}$</td>
<td>-0.443</td>
<td>-0.286</td>
<td>-0.412</td>
<td>-0.43</td>
<td>-0.37</td>
<td>-0.093</td>
<td>-0.144</td>
<td>-0.727</td>
<td>-0.54</td>
<td>-0.75</td>
</tr>
<tr>
<td>$\beta_{el}$</td>
<td>-0.127</td>
<td>-0.011</td>
<td>-0.113</td>
<td>-0.183</td>
<td>-0.048</td>
<td>0.105</td>
<td>0.02</td>
<td>-0.343</td>
<td>-0.24</td>
<td>-0.335</td>
</tr>
<tr>
<td>$\beta_{rank}$</td>
<td>-0.237</td>
<td>-0.113</td>
<td>-0.219</td>
<td>-0.213</td>
<td>-0.166</td>
<td>-0.011</td>
<td>-0.016</td>
<td>-0.453</td>
<td>-0.418</td>
<td>-0.351</td>
</tr>
<tr>
<td>Panel B: $\alpha$ estimates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{vw}$</td>
<td>0.838</td>
<td>0.366</td>
<td>0.547</td>
<td>0.619</td>
<td>0.607</td>
<td>0.466</td>
<td>0.5</td>
<td>0.928</td>
<td>0.815</td>
<td>0.938</td>
</tr>
<tr>
<td>$t$</td>
<td>[4.83]</td>
<td>[3.01]</td>
<td>[2.81]</td>
<td>[3.2]</td>
<td>[3.12]</td>
<td>[4.17]</td>
<td>[3.51]</td>
<td>[4.02]</td>
<td>[3.6]</td>
<td>[3.35]</td>
</tr>
<tr>
<td>$\alpha_{el}$</td>
<td>0.501</td>
<td>0.076</td>
<td>0.449</td>
<td>0.486</td>
<td>0.364</td>
<td>0.111</td>
<td>0.276</td>
<td>0.414</td>
<td>0.363</td>
<td>0.589</td>
</tr>
<tr>
<td>$t$</td>
<td>[2.844]</td>
<td>[0.671]</td>
<td>[2.364]</td>
<td>[2.243]</td>
<td>[2.038]</td>
<td>[0.747]</td>
<td>[1.566]</td>
<td>[1.65]</td>
<td>[1.535]</td>
<td>[2.031]</td>
</tr>
<tr>
<td>$\Delta_{el}$</td>
<td>-40.2%</td>
<td>-79.2%</td>
<td>-17.9%</td>
<td>-21.5%</td>
<td>-40.6%</td>
<td>-76.2%</td>
<td>-44.8%</td>
<td>-55.4%</td>
<td>-55.5%</td>
<td>-37.2%</td>
</tr>
<tr>
<td>$\alpha_{rank}$</td>
<td>0.31</td>
<td>0.032</td>
<td>-0.048</td>
<td>0.086</td>
<td>0.012</td>
<td>0.235</td>
<td>0.357</td>
<td>0.26</td>
<td>0.154</td>
<td>0.255</td>
</tr>
<tr>
<td>$t$</td>
<td>[2.0]</td>
<td>[0.31]</td>
<td>[-0.194]</td>
<td>[0.352]</td>
<td>[0.058]</td>
<td>[2.475]</td>
<td>[2.736]</td>
<td>[1.285]</td>
<td>[0.735]</td>
<td>[0.984]</td>
</tr>
<tr>
<td>$\Delta_{rank}$</td>
<td>-63.0%</td>
<td>-91.3%</td>
<td>-108.8%</td>
<td>-86.1%</td>
<td>-98.0%</td>
<td>-49.6%</td>
<td>-28.6%</td>
<td>-72.0%</td>
<td>-81.1%</td>
<td>-72.8%</td>
</tr>
<tr>
<td>Panel C: Information ratios</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$IR_{vw}$</td>
<td>0.474</td>
<td>0.341</td>
<td>0.43</td>
<td>0.475</td>
<td>0.51</td>
<td>0.602</td>
<td>0.566</td>
<td>0.473</td>
<td>0.412</td>
<td>0.576</td>
</tr>
<tr>
<td>$t$</td>
<td>[4.497]</td>
<td>[3.233]</td>
<td>[3.16]</td>
<td>[3.487]</td>
<td>[3.744]</td>
<td>[4.424]</td>
<td>[3.95]</td>
<td>[4.49]</td>
<td>[3.898]</td>
<td>[3.754]</td>
</tr>
<tr>
<td>$IR_{el}$</td>
<td>0.311</td>
<td>0.068</td>
<td>0.322</td>
<td>0.344</td>
<td>0.322</td>
<td>0.117</td>
<td>0.247</td>
<td>0.199</td>
<td>0.171</td>
<td>0.367</td>
</tr>
<tr>
<td>$t$</td>
<td>[2.948]</td>
<td>[0.64]</td>
<td>[2.364]</td>
<td>[2.531]</td>
<td>[2.367]</td>
<td>[0.863]</td>
<td>[1.725]</td>
<td>[1.816]</td>
<td>[1.62]</td>
<td>[2.39]</td>
</tr>
<tr>
<td>$\Delta_{el}$</td>
<td>-34.4%</td>
<td>-80.1%</td>
<td>-25.1%</td>
<td>-27.6%</td>
<td>-36.9%</td>
<td>-80.6%</td>
<td>-56.4%</td>
<td>-57.9%</td>
<td>-58.5%</td>
<td>-36.3%</td>
</tr>
<tr>
<td>$IR_{rank}$</td>
<td>0.196</td>
<td>0.035</td>
<td>-0.031</td>
<td>0.056</td>
<td>0.009</td>
<td>0.421</td>
<td>0.537</td>
<td>0.141</td>
<td>0.079</td>
<td>0.15</td>
</tr>
<tr>
<td>$t$</td>
<td>[1.86]</td>
<td>[0.332]</td>
<td>[-0.226]</td>
<td>[0.411]</td>
<td>[0.068]</td>
<td>[3.097]</td>
<td>[3.751]</td>
<td>[1.333]</td>
<td>[0.744]</td>
<td>[0.976]</td>
</tr>
<tr>
<td>$\Delta_{rank}$</td>
<td>-58.6%</td>
<td>-89.7%</td>
<td>-107.2%</td>
<td>-88.2%</td>
<td>-98.2%</td>
<td>-30.1%</td>
<td>-5.1%</td>
<td>-70.2%</td>
<td>-80.8%</td>
<td>-74.0%</td>
</tr>
</tbody>
</table>
Figure 1: Return from Trading on Beta  This figure plots returns to monthly-rebalanced value-weighted portfolios sorted on individual stock betas, from 1927 to 2016. Each month stocks are sorted into quintiles based on their betas estimated using the trailing 12 months of daily returns. The green plot denotes the cumulative returns to the portfolio that holds stocks of betas in the bottom quintile each month, hence the label long. The red plot denotes the cumulative returns to the portfolio that holds stocks with betas in the top quintile each month, hence the label short.
Figure 2: **Falsification test on the beta-rank weighting method**  The falsification test randomly assigns stocks into deciles each month. Stocks in long legs are weighted by their decile numbers, and stocks in short legs are weighted by descending decile numbers. The anomaly portfolio returns are then taken as the difference between decile number-weighted returns from extreme quintiles from sorts on anomaly characteristics. The histograms plot the distributions of anomaly portfolios’ CAPM alphas after random weight assignments, from 500 runs. The red vertical lines indicate CAPM alpha estimates from anomaly portfolios after weighting stocks by ascending beta ranks in long legs and by descending beta ranks in short legs.
Figure 3: Falsification test on the elimination method  

The falsification test assigns stocks in the long and short portfolios, independently, into 10 groups. In both long and short leg portfolios, stocks from 4 random groups are eliminated from the process of constructing extreme anomaly quintile portfolios. The anomaly portfolio returns are then taken as the difference between value-weighted returns from the remaining stocks in extreme quintiles from sorts on anomaly characteristics. The histograms plot the distributions of anomaly portfolios’ CAPM alpha estimates after this elimination, repeated 500 times. The red vertical lines indicate CAPM alpha estimates from the anomaly portfolios using the beta ranks as weights in the long-legs, and the descending beta ranks as weights in the short-legs.
Institutional Investors and the Beta Risk Premium

Violations of the capital asset pricing model (the CAPM of Sharpe, 1964, Lintner, 1975) have led to the discovery of a long list of cross-sectional return predictors. Despite concerns over their discovery process (e.g. Harvey, Liu, and Zhu, 2016), many of these anomalies prove to be robust and survive the test of time. However, institutional investors, who are generally regarded as the more sophisticated set of market participants, in aggregate do not appear to take advantage of the well-documented cross-sectional return predictability (Edelen, Ince, and Kadlec, 2016).

In this paper, I complement previous studies by showing that instead of trading violations of the CAPM, institutions in fact seem to recognize mispricing caused by noise trading, and consistently adjust their trading pattern to capture the beta risk premium as predicted by the CAPM during subdued levels of noise in markets.

In an efficient market, investors get compensated for bearing systematic risks. Yet it is hard to find support for a positive risk-return relation in the data when systematic risk is measured by the market beta. Black, Jensen, and Scholes (1972) document that low (high) beta stocks tend to have higher (lower) risk-adjusted returns relative to what is predicted by the CAPM, rendering the security market line flat as opposed to upward sloping on average. Since then more and more portfolios have been shown
to have returns that cannot be explained by the CAPM (e.g. Harvey, Liu, and Zhu, 2016, McLean and Pontiff, 2016). The literature put forth numerous explanations for the CAPM’s failure. Particularly relevant to this paper is Antoniou, Doukas, and Subrahmanyam (2015), who find positive and significant beta risk premium in the data when noise traders are out of the market. Specifically, unsophisticated investors are attracted to high beta assets in periods of high market sentiment, making such stocks overpriced and thus have low expected returns. These investors are sidelined in pessimistic times, however, and the risk-return relation as predicted by the CAPM gets to be restored. Unconditional on market sentiment, the two forces off-set and the result is the observed beta anomaly, or the flat security market line.

To the extent noise trading comes from the set of irrational investors, Friedman (1953) argues that rational investors would trade against the irrational ones and thereby mitigate or eliminate mispricing. Building on Antoniou, Doukas, and Subrahmanyam (2015) and Friedman (1953), I examine how a representative sample of institutional investors trade the prevailing market sentiment in relation to beta-mispricing. I show that in pessimistic times, institutional investors exhibit stronger tendency to buy high beta stocks relative to low beta stocks, taking advantage of the positive risk-return relation. Back-of-envelope calculations show that in a month with pessimistic investor sentiment, an average institution in this sample executes about 4,000 more buy trades for stocks in high beta decile, and commits roughly $800 million more buying high beta stocks, all relative low beta stocks. In optimistic times, institutions’ tendency to buy either the set of high or low beta stocks does not differ to quite the same extent, suggesting that institutions in aggregate do not view
the CAPM beta as a source of positive risk premium in such times. Results remain consistent across three different measures of investor buying intensity.

In Friedman (1953)’s framework, findings from this paper support the view that institutions are the more sophisticated and rational set of investors in the market, and that their trades take into account the existence and impact of noise traders. It is reasonable, however, to ask why rational investors do not drive out noise traders to the extent that the positive risk-return relation is valid in the data on a consistent basis. This could be a consequence of two types of arbitrage risk. First, noise trading may drive prices further from fundamentals, which may force early liquidation by arbitrageurs (*noise trader risk*, see DeLong, Shleifer, Summers, and Waldmann, 1988, De Long, Shleifer, Summers, and Waldmann, 1990). Alternatively, institutions may not be certainty as to when other rational investors would step in and correct the flat security market line (*syncronization risk*, see Abreu and Brunnermeier, 2002).

I verify that the security market line has a negative slope in optimistic months. The profitable trading strategy under the presence of the negative beta risk premium is to “bet against beta” (Frazzini and Pedersen, 2014). However, data show that overall institutions in the sample merely adjust to trade high and low beta stocks at a comparable level of buying intensity, as opposed to heavily favoring low beta stocks over the others. Baker, Bradley, and Wurgler (2011) propose an explanation based on benchmarking as limit to arbitrage: fund managers are expected to maximize information ratios with respect to some benchmark. The need to minimize tracking error in fact gives incentive to underweight, as opposed to overweight the low beta stocks whose expected return is “not high enough”, and vice versa for the high beta
stocks whose expected return is “not low enough”. Thus managers facing benchmark constraints are discouraged to bet against beta.

2.1 Related Literature

This paper adds to the debate on whether professional investors possess stock-pricking skills. This literature has reached mixed conclusions. Several studies find positive answers (e.g. Kacperczyk, Sialm, and Zheng, 2005, Alexander, Cici, and Gibson, 2006). In particular Chen, Jegadeesh, and Wermers (2000) documents that stocks which institutions recently bought tend to outperform the ones that institutions recently sold, suggesting trades, as opposed to existing positions, reveal that fund managers have value-adding skills picking stocks. However, Edelen, Ince, and Kadlec (2016) do not find skills in terms of how institutions trade known cross-sectional return predictability: 13-F filing institutions do not seem to trade in directions suggested by several prominent cross-sectional stock return anomalies\textsuperscript{1}. This result is surprising because institutions are oftentimes assumed to be the more sophisticated set of investors, and intuition would thus suggest that they take advantage of known sources of our performance. My findings support the former side of this debate by showing that institutions, as the more rational group of investors, trade correctly mispricing induced by noise traders.

In a related paper, Huang, Lou, and Polk (2016) show that trading activity profiting off of the beta anomaly generates “booms and busts” of payoffs to the

\textsuperscript{1}I verify this result with trade-by-trade data used in this paper in unreported analysis.
betting against beta strategy. The authors use return correlations amongst stocks in the same beta-sorted portfolios as a measure of beta-arbitrage activity. I instead directly examine the executed trades by a sample of institutional investors, and find that they do not sufficiently trade against beta in times when it should be profitable to do so.

Given the result from Chen et al. (2000) that institutional buys outperform institutional sells, it is natural to ask about the source of this outperformance. Although Edelen et al. (2016) show that the outperformance does not seem to come from trading asset pricing anomalies, the literature points out several other viable avenues, for example the positive abnormal ex-dividend returns (Henry and Koski, 2017), contrarian trading strategies (Jame, 2017), and just being able to “identify above-average firms” (Gibson, Safieddine, and Sonti, 2004). My paper adds yet another source of this outperformance by showing that institutions seem to identify and trade correctly the most fundamental and yet seemingly elusive positive risk-return relation as predicted by the CAPM.

The CAPM-predicted risk-return relation is elusive because it has been documented that it does not in general hold in the data (Black et al., 1972). There have been several explanations to the CAPM’s failure, many of which rely on some type of investor preference for risk. Such preferences could arise due to behavioral reasons (Karceski, 2002, Baker, Bradley, and Wurgler, 2011, Bali, Brown, Murray, and Tang, 2017, Hong and Sraer, 2016), or due to institutional constraints (Frazzini and Pedersen, 2014). Particularly important to this paper is Antoniou, Doukas, and Subrahmanyam (2015), who show that the beta anomaly is in fact driven by the noise traders mispricing the
high beta stocks in optimistic times, and that beta commands a positive risk premium when investor sentiment is pessimistic, times when noise traders tend to be sidelined. I verify this result, and building on Antoniou et al. (2015), I find that institutions actively trade to take advantage of the presence of noise traders, consistent with Friedman (1953).

2.2 Data

2.2.1 Stock Return Data

The sample of stocks comes from the Center or Research in Security Prices (CRSP) monthly stock file, in the time period from 2000 to 2010. This time window is constrained by the availability of institutional trades data. I keep common shares (shrcd 10 and 11) that are listed on NYSE, AMEX, or NASDAQ (exchcd 1, 2, 3). Returns are adjusted delsiting for bias wherever applicable.

2.2.2 Investor Sentiment

The investor sentiment is proxied using the monthly sentiment index from Baker and Wurgler (2006), which has been extensively used in the literature, including Antoniou, Doukas, and Subrahmanyam (2015). The index synthesizes information from six proxies for the investors’ propensity to speculate, after the proxies are purged of the effect of economic fundamentals. Readers are directed to Baker and Wurgler (2006) for a detailed description of the sentiment index construction. Figure 1 plots the time-series of the index in the sample period January 2000 to December 2010.
Following the literature Baker and Wurgler (e.g. 2006), Stambaugh et al. (e.g. 2012), in all analyses in the paper, I consider a month to be in optimistic state if the investor sentiment index level in that month is above its time-series mean of 0. A month is said to be in pessimistic state if the investor sentiment index level is below 0. In the sample period of 2000 to 2010, there are in total 54 months in pessimistic state, and 78 months in optimistic state. Note from figure 1 that the sentiment index shows significant autocorrelation. A time-series regression shows an AR(1) coefficient on the lagged sentiment level of 0.98.

2.2.3 Institutional Trades Data

The institutional trades data are provided by ANcerno Ltd. (formerly the Abel Noser Corporation)\(^2\). ANcerno provides trading cost analysis to its clients (identified by variable \textit{clientcode}), which in the dataset are classified under three categories (identified by variable \textit{clienttype}): plan sponsors, money managers, and brokers. I consider only plan sponsors and money managers in this paper. The data are available from 2000 to 2010, and that is the sample period in this study.

Each stock in the ANcerno dataset is identified by the fields \textit{symbol} (stock ticker) and \textit{CUSIP}, and transactions are identified by date. For individual stock return information and anomaly characteristics, I match the ANcerno dataset with CRSP

\(^2\)For a much more detailed description of the ANcerno data and an up-to-date list of published and forthcoming papers that have used this dataset, see Hu, Jo, Wang, and Xie (2018). For a list of working papers using the ANcerno data, see \url{http://ganghu.org/an/AN_WP.htm}.
using ticker and transaction time: I require that the field symbol matches the field tic from the CRSP menames file, and that the transaction time falls in between the time interval in which this symbol is a valid match with a permno from CRSP (using the menames file).

Using trade-by-trade data circumvents the need to rely on changes in quarterly holdings from 13-F filing to infer actual trades. This offers two advantages. First, it allows trade analysis at monthly frequency. Using monthly as opposed to quarterly or annual trade data not only permits a more precise measure of the actual institutional trades, but also captures shifts in market sentiment (Baker and Wurgler, 2006) as well as the changes in individual stock betas at the frequency in agreement with previous studies. Second, using actual trades with trade volume frees the analysis from quarter- and year-end window-dressing concerns, which confounds the inference of trades from changes in quarterly holdings.

The sample of institutional investors covered by the ANcerno database has been shown to be representative of the universe of institutional investors. Hu, Jo, Wang, and Xie (2018) states that it has been widely quoted that the trading activities on ANcerno accounts for 8% of the dollar value of CRSP trading volume, and 10% of all institutional trading volume. In the Internet appendix to Puckett and Yan (2011), a comparison between a subsample of 64 random ANcerno institutions and

---


13F institutions in general indicates that the stocks held and traded by both sets of investors are similar. The only dimension along which the two sets seem to differ is size. It is reported in Puckett and Yan (2011) that “ANcerno institutions are larger than the average 13F institution with respect to the number of different stock holdings (603 vs. 264), total net assets ($22.04 billion vs. $4.34 billion), and dollar value of trades ($1,285 million vs. $842 million).”

Presented in table 1 is a summary of the ANcerno institutions’ trading patterns by year.

[Insert table 1 here]

In all years but year 2008 (279), there are over 300 distinct institutions in the sample. Over time, an institution does more trades in a month, as is evident by the increasing trend in both the mean and medians in the second column. The number of trades an institution does on average increases by more than 5 times from 1,174 at the beginning of the sample period 2000 to 6,195 in 2010. Accompanying this increase in number of trades is however a decrease in average (and median) trade size, meaning that institutions came to trade in smaller chunks, but in more trades. The last column indicates an increasing trend in the number of stocks an institution trades in a month, suggesting an increase in the breadth of institutions’ portfolio holdings and diversification over time.

Note in all years for all three measures of trading patterns, the median values (in square brackets) are smaller than the means. This suggests that the distribution of ANcerno institutions’ size is right-skewed, and hints at the presence of large
institutions that trade commits disproportionately more trades, trade in large dollar amounts, and trades more stocks than the rest.

2.3 Empirical Measures

2.3.1 Investor Buying Intensity

To quantify investor buying intensity for each stock in each month, I consider three measures. They all are defined as percentages of some variation of buy trades over total trades.

1. Fraction of net buyers.

2. Fraction of trades that are buys.

3. Fraction of dollar trading volume that are buys.

In the first measure, a net buyer of a stock is defined as an investor whose trades in a month in the stock net out a positive change in dollar amount invested in the stock. For each stock in each month, the fraction is then defined as the number of net buyers over the total number of investors who traded the stock at one point or another during the month. The second measure I consider is the fraction of buy trades. It is calculated simply as the percentage of executed buys over the total number of executed trades in a month. Barber, Odean, and Zhu (2009) also use the proportion of trades that are purchases as proxy for retail investors’ buying intensity in individual stocks. The third measure for buying intensity for a stock is how much of the total dollar trading volume in a month is accounted for by the purchasing
trades. It is computed as the percentage of total dollar trading volume in a stock in a month across all investors that comes from buy trades.

The three measures all have their pros and cons. All three are constructed to be positively related to investors’ buying intensity. However, the percentage of total dollar trading volume accounted for by purchases tends to be dominated by the presence of institutions with large dollar trading volumes. While large institutions are important, their trading patterns do not necessarily represent the general behavior of all institutions. The fraction of net buyers considers all institutions evenly, but it is not perfect either. It is possible there are cases where an investor’s trades in a month amount to a positive (negative) sum, but the stock price declines (rises) sufficiently so that the investor’s net change in position in the stock ends up being negative (positive).

Because these are all relative measures defined with respect to a sum, thinly traded stocks could have extreme buying intensity measures (either 0 or 1) and thus heavily distort results. To mitigate the impact of thinly traded stocks while retaining most of the stock-month observations, in every month I only keep in the sample stocks that are traded by two or more distinct institutions. Note the requirement of two or more institutions mechanically adds the restriction that each stock be traded twice at the minimum. I repeat the main analyses in the paper for all three proxies for investor buying intensity. Table 2 presents a summary of the three measures. The table indicates that the time-series properties of all three measures do not differ much between the low and high beta portfolios.
2.3.2 Individual Stock Beta Estimates and Beta-sorted Portfolios

At the beginning of every month I estimate a stock’s CAPM $\beta$ using its daily excess returns (gross return minus one-month T-bill rate) in the past 12 months, with a minimum of 150 observations of non-missing returns required. To limit the impact of non-synchronous trading, I estimate a stock’s $\beta$ using the sum of coefficients method following Dimson (1979). The rolling window regression specification is

$$r_{i,t} = \alpha_i + \sum_{l=0}^{5} \beta_{i,t-l} R_{m,t-l} + \epsilon_{i,t},$$

where $r_{i,t}$ denotes the excess return on stock $i$ on day $t$, and $R_{m,t}$ denotes the market excess return on day $t$.

The stock’s beta estimate for month $t$ is then calculated as

$$\hat{\beta}_{i,t} = \sum_{l=0}^{5} \beta_{i,t-l}.$$

I conduct main analyses in the paper at the portfolio level. At the beginning of each month, all stocks are sorted into deciles based on their trailing 12-month beta estimates, as calculated above. I then consider stocks in decile 1 the low beta stocks, and those in decile 10 high beta stocks. The point of interest is how institutions trade low and high beta stocks depending on prevailing investor sentiment in the month.
2.4 Institutions and the Risk-return Relation

2.4.1 Trading Pattern Conditional on Investor Sentiment

The security market line is flat unconditionally (Black et al., 1972). However, Antoniou, Doukas, and Subrahmanyam (2015) find the lack of beta risk premium a consequence of the noise traders overpricing the high beta stocks when optimistic. The risk-return trade-off as predicted by the CAPM in fact holds valid when the general sentiment is pessimistic in the market, as the opportunistic noise traders tend to be sidelined in such times, allowing assets to be priced by the more rational investors. Given these observations, a sophisticated and rational investor has incentive to buy more high beta assets relative to low beta assets in pessimistic times, and thus take advantage of the positive risk-return relation. In times when market sentiment is optimistic, noise trading distorts the security market line, a sophisticated investor should then not view beta as a source of risk that is fairly compensated by the market, and therefore should be expected to exhibit no trading preferences over beta. This result is replicated and summarized in figure 2.

[Insert figure 2 here]

The test assets are the ten beta-sorted decile portfolios. The left subplot uses the subsample of all pessimistic months. The time-series average returns of the ten portfolios line up almost perfectly with the fitted security market line, consistent with Antoniou et al. (2015). The right subplot uses the subsample of pessimistic months. In comparison, the fitted security market line becomes downward sloping, which is
clearly inconsistent with beta commanding a positive risk premium. I next test to see whether and how institutions trade differently the low and high beta stocks in different sentiment states of the world. Results are first presented in plots in figure 3.

Each plot in figure 3 depicts how an institutional buying intensity measure varies across ten beta-sorted portfolios in each of the optimistic (dotted green line) and pessimistic (solid blue line) states. Perhaps the most glaring characteristic shared by all subplots is that the dotted green line is almost always above the solid blue line, meaning that unconditional on beta, institutions in general are more likely to buy when trading in high sentiment times. This observation suggests that to some extent, institutional investors are affected by the general sentiment in markets.

Moreover, consistent across all three buying intensity measures, institutions exhibit a higher tendency to buy high beta stocks relative to low beta stocks when investor sentiment is low. This finding supports the view that institutions trade to take advantage of the positive risk premium in pessimistic state (Antoniou et al., 2015). In optimistic state, however, the average buying intensity measures no longer seem to be positively related to beta. Institutions overall exhibit similar levels of buying intensity for low and high beta stocks. This observation shows that when noise trading is prevalent, institutions in aggregate do not view beta as a source of risk that markets fairly compensates for holding.

In table 3 is a summary of the difference in means tests on how institutions trade betas differently in high and low investor sentiment states.
Consistent with the plots, column *Pessimistic* in table 3 indicates that institutions have significantly lower interest in buying low beta stocks in pessimistic times under all three buying intensity measures. To make concrete the magnitude of the difference, we note that as of June 2006 (mid point in the sample period), there were about 660 stocks in each of the ten beta-sorted decile portfolios, and a stock saw about 155 trades on average. Thus on average an increase of 3.88% in the fraction of buy trades per stock means about $3970^5$ more buy trades for the high beta decile portfolio. Similarly, at the same point in time (June 2006), a stock on average saw $54$ million in dollar trading volume by ANcerno institutions. Therefore a 2.27% increase in fraction of buy dollar volume means that ANcerno institutions in total spend $809$ million$^6$ more buying high beta stocks relative to low beta stocks in pessimistic times.

However, when investor sentiment is high (column *Optimistic*), institutions overall do not seem to show difference in buying intensity for low and high beta stocks. Using all three buy intensity measures, however, we do see the row *H-L* showing negative signs, meaning institutions exhibit a slightly higher tendency to buy low beta stocks relative to high beta stocks. Nonetheless, neither the economic magnitude nor statistical significance warrants further inference.

Another interesting finding from table 3 is that for all institutions, on average, buying intensity for high beta stocks remains somewhat constant across the two investor sentiment states, and that the difference between the buying intensity for

---

$^5660 \cdot 3.88\% \cdot 155 \approx 3970.$

$^6660 \cdot 2.27\% \cdot 54 \approx 809.$
low beta stocks in the two sentiment states comes mainly from the lower demand for low beta stocks in pessimistic states, relative to the demand in optimistic states. This is consistent with the institutions deeming low beta stocks more attractive when investor sentiment is high relative to times when the general sentiment is pessimistic.

2.4.2 Difference-in-difference Estimates

I run the following difference-in-difference specification on the stock-by-month panel dataset to estimate how much the institutions’ preferences over high and low beta stocks differ in optimistic and pessimistic times. It is useful to think of the high and low beta stocks as two groups of samples, and think of a high sentiment state as treatment. The difference-in-difference tests show how a shift in investor sentiment impacts institutions’ buying intensity for high and low beta stocks differently.

\[
\text{Buying Intensity}_{i,t} = k_0 + k_1 \cdot \text{High } \beta + k_2 \cdot \text{High Sent} + k_3 \cdot \text{High } \beta \cdot \text{High Sent} + \epsilon_{i,t}. \tag{2.1}
\]

In specification (2.1), High $\beta$ is an indicator variable that takes value 1 if stock $i$ is in the high beta portfolio in month $t$. High Sent is an indicator variable that takes value 1 if the sentiment index in month $t$ is above its time-series average of 0. $k_0$ represents the baseline buying intensity estimate for low beta stocks in a pessimistic month. $k_1$ estimates the difference in buying intensity for high and low beta stocks in a pessimistic month. $k_2$ estimates the difference in buying intensity for low beta stocks in an optimistic and that in a pessimistic month. $k_3$, the coefficient on the
interaction term, estimates how much the difference in institutions’ buying intensity for high and low beta stocks in a optimistic month differs from the difference in buying intensity for high and low beta stocks in a pessimistic month on average. The results are summarized in table 4.

[Insert table 4 here]

The top panel in table 4 estimates specification (2.1) for all institutions in the sample. The first row shows that high beta stocks on average higher buying intensity in pessimistic times. The magnitude ranges from 2.1% to 3.8% on average. The second row in each panel indicates that low beta stocks in general see higher buying intensity in optimistic relative to pessimistic times. These estimates agree with those in table 3. The coefficient on the interaction term suggests that on average, an average institution’s differential buying intensity for high (High Beta) relative to low beta stocks is 2.5% to 4.3% lower in optimistic times (High Sent) compared to that in pessimistic times, depending on the measure for buying intensity, and this difference is statistically significant. This result supports the finding that institutions favor high relative over low beta stocks in pessimistic times to a greater extent compared to that in optimistic times.

2.5 Conclusion

Contrary to the view that institutional investors play a causal role in security mispricing (Edelen et al., 2016), I find evidence that institutions actively adjust their trading pattern in relation to beta-mispricing that arises due to noise trading.
In times of pessimistic investor sentiment, institutions favor high beta stocks over low beta stocks in their trades, taking advantage of the fact that the beta risk premium is positive in such times (Antoniou et al., 2015). In times of optimistic investor sentiment, noise trading distorts the risk-return relation. Institutions overall exhibit similar levels of buying intensity for both high and low beta stocks in such times, taking the view that beta is a risk that markets do not compensate for holding.
Tables and Figures

**Table 1: Institutional Trade Data Summary**

The column *distinct institutions* denotes the count of distinct institutional investors in the dataset in the corresponding year. *Number of trades* denotes the **monthly** average number of trades an institution completes. *Trade size* is the average dollar amount (in thousands) of a trade in a year, across all institutions. *Number of stocks* refers to the average number of distinct stocks in which an institution does one or more trades in a month in the corresponding year. Reported in square brackets in the last three columns are medians taken across the monthly averages for all institutions in the corresponding year.

<table>
<thead>
<tr>
<th>Year</th>
<th>Distinct institutions</th>
<th>Number of trades</th>
<th>Trade size</th>
<th>Number of stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>364</td>
<td>1,173.61 [359.57]</td>
<td>613.88 [68.44]</td>
<td>217.68 [120.96]</td>
</tr>
<tr>
<td>2002</td>
<td>398</td>
<td>1,578.05 [382.21]</td>
<td>404.69 [42.24]</td>
<td>234.12 [130.92]</td>
</tr>
<tr>
<td>2003</td>
<td>332</td>
<td>1,904.49 [372.97]</td>
<td>351.38 [34.72]</td>
<td>254.62 [133.0 ]</td>
</tr>
<tr>
<td>2004</td>
<td>344</td>
<td>2,417.56 [381.83]</td>
<td>442.81 [35.38]</td>
<td>292.07 [150.82]</td>
</tr>
<tr>
<td>2005</td>
<td>324</td>
<td>2,123.18 [475.67]</td>
<td>397.72 [33.03]</td>
<td>288.76 [153.79]</td>
</tr>
<tr>
<td>2006</td>
<td>336</td>
<td>2,829.81 [484.21]</td>
<td>359.72 [25.18]</td>
<td>329.3 [173.71]</td>
</tr>
<tr>
<td>2007</td>
<td>315</td>
<td>3,341.26 [568.75]</td>
<td>350.65 [17.03]</td>
<td>332.56 [188.67]</td>
</tr>
<tr>
<td>2008</td>
<td>279</td>
<td>4,258.5 [693.33]</td>
<td>298.89 [12.35]</td>
<td>370.61 [214.25]</td>
</tr>
<tr>
<td>2009</td>
<td>315</td>
<td>4,668.75 [734.67]</td>
<td>292.75 [8.69]</td>
<td>378.32 [207.42]</td>
</tr>
</tbody>
</table>
Table 2: Institutional Trade Data Summary

For each of the three buying intensity measures (column Fraction of), I first compute cross-sectional portfolio means in each month by averaging the corresponding measure over all constituent stocks. The columns report, from left to right, the time-series minimum, mean, median, maximum, and standard deviation of the corresponding measure for the low (top panel) and high (bottom panel) beta-sorted portfolios.

<table>
<thead>
<tr>
<th>Beta-sorted portfolio</th>
<th>Fraction of</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low beta portfolio</td>
<td>Net buyers</td>
<td>0.296</td>
<td>0.506</td>
<td>0.521</td>
<td>0.629</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>Buy trades</td>
<td>0.348</td>
<td>0.530</td>
<td>0.540</td>
<td>0.642</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>Buy dollar volume</td>
<td>0.332</td>
<td>0.511</td>
<td>0.511</td>
<td>0.640</td>
<td>0.055</td>
</tr>
<tr>
<td>High beta portfolio</td>
<td>Net buyers</td>
<td>0.359</td>
<td>0.514</td>
<td>0.512</td>
<td>0.614</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>Buy trades</td>
<td>0.389</td>
<td>0.548</td>
<td>0.551</td>
<td>0.638</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>Buy dollar volume</td>
<td>0.374</td>
<td>0.520</td>
<td>0.521</td>
<td>0.621</td>
<td>0.043</td>
</tr>
</tbody>
</table>
**Table 3: Buying Intensity Measures by Investor Sentiment and Beta**

This table tabulates the time-series averages of buying intensity measures for stocks in low and high beta portfolios, conditional on investor sentiment, for all institutions. The table is organized into three panels, each showing results using a different measure of institutional buying intensity (the left-most column *fraction of*). In each panel, the first two rows (beta portfolios 1.0 and 10.0) denote the low and high beta-sorted decile portfolios. The third row *H-L* denotes the difference between the high and low beta portfolios. The last row *t-stat* shows the *t*-statistic from a *t*-test of the null hypothesis that the buying intensity time-series for the high and low beta portfolios come from the same population. The column *H-L* denote the difference of each buying intensity measure between the optimistic and pessimistic states. The last column *t-stat* shows the *t*-statistic from a *t*-test of the null hypothesis that the buying intensity measures for each beta portfolios in the two sentiment states come from the same population.

<table>
<thead>
<tr>
<th>Fraction of Beta portfolio</th>
<th>Sentiment</th>
<th>Pessimistic</th>
<th>Optimistic</th>
<th>H-L</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net buyers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>48.91%</td>
<td>52.40%</td>
<td>3.49%</td>
<td>[8.93]</td>
<td></td>
</tr>
<tr>
<td>10.0</td>
<td>51.03%</td>
<td>51.78%</td>
<td>0.75%</td>
<td>[3.84]</td>
<td></td>
</tr>
<tr>
<td>H-L</td>
<td>2.12%</td>
<td>-0.62%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t-stat</td>
<td>[6.84]</td>
<td>[-2.47]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buy trades</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>51.09%</td>
<td>55.29%</td>
<td>4.20%</td>
<td>[10.3]</td>
<td></td>
</tr>
<tr>
<td>10.0</td>
<td>54.97%</td>
<td>54.88%</td>
<td>-0.09%</td>
<td>[-0.45]</td>
<td></td>
</tr>
<tr>
<td>H-L</td>
<td>3.88%</td>
<td>-0.42%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t-stat</td>
<td>[11.88]</td>
<td>[-1.55]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buy dollar volume</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>50.23%</td>
<td>52.12%</td>
<td>1.89%</td>
<td>[3.99]</td>
<td></td>
</tr>
<tr>
<td>10.0</td>
<td>52.49%</td>
<td>51.89%</td>
<td>-0.61%</td>
<td>[-2.35]</td>
<td></td>
</tr>
<tr>
<td>H-L</td>
<td>2.27%</td>
<td>-0.23%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t-stat</td>
<td>[5.66]</td>
<td>[-0.71]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Tabulated are the coefficient estimates for specification (2.1). The three columns represent three dependent variables. Only stocks in decile 1 (low beta) and 10 (high beta) are kept in the sample. High Beta is an indicator variable that takes value 1 if a stock is in decile 10. High Sent is an indicator variable that takes value 1 in a month with positive investor sentiment.

<table>
<thead>
<tr>
<th></th>
<th>Net buyers</th>
<th>Buy trades</th>
<th>Buy dollar volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Beta</td>
<td>0.0212</td>
<td>0.0388</td>
<td>0.0227</td>
</tr>
<tr>
<td></td>
<td>[5.89]</td>
<td>[10.39]</td>
<td>[5.23]</td>
</tr>
<tr>
<td>High Sent</td>
<td>0.0349</td>
<td>0.042</td>
<td>0.0189</td>
</tr>
<tr>
<td></td>
<td>[8.68]</td>
<td>[10.07]</td>
<td>[3.94]</td>
</tr>
<tr>
<td>High Beta×High Sent</td>
<td>-0.0274</td>
<td>-0.0429</td>
<td>-0.025</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.4891</td>
<td>0.5109</td>
<td>0.5023</td>
</tr>
<tr>
<td></td>
<td>[146.95]</td>
<td>[149.11]</td>
<td>[128.52]</td>
</tr>
</tbody>
</table>
Figure 1: Investor Sentiment Index  This figure plots the time-series of the monthly investor sentiment index (Baker and Wurgler, 2006) from January 2000 to December 2010.
Figure 2: Security Market Line Conditional on Investor Sentiment  The figures show the security market lines conditional on contemporaneous investor sentiment. The left subplot uses the subsample of months with investor sentiment below its time-series mean of 0. The right subplot uses the subsample of months with above-0 investor sentiment. A month is considered to be in optimistic state if the investor sentiment index level in that month is above its time-series mean of zero, and a month is said to be in pessimistic state otherwise. The scattered dots are ten beta-sorted portfolios, constructed by ranking individual stocks’ pre-formation beta into deciles at the beginning of each month.
Figure 3: Institutions’ Buying Intensity Conditional on Sentiment. A month is considered to be in optimistic state if the investor sentiment index level in that month is above its time-series mean of zero, and a month is said to be in pessimistic state otherwise. The x-axis denotes ten beta-sorted portfolios, constructed by ranking individual stocks’ pre-formation beta estimates into deciles at the beginning of each month. I calculate each buying intensity measure for all stocks in every month, and take the portfolio average across all constituent stocks as the portfolio measure. The y-axis denotes the time-series average of the corresponding measure for the beta-sorted portfolios.
Chapter 3

Signaling in OTC Markets: Benefits and Costs of Transparency

3.1 Introduction and Literature

Ex-post transparency has increased in securities markets over time but often over the objections of dealers. This was especially true during the implementation of the TRACE system for U.S. corporate bond reporting by the NASD.\(^1\) We investigate the benefits and costs of ex-post transparency for investors and dealers in a theoretical model of over-the-counter (OTC) markets. We consider a dealer who acquires and then disposes of inventory in a sequence of transactions. With ex-post transparency, the terms of the first trade may reveal private information of the dealer to the counterparty in the second transaction. This reduces the dealer’s ability to extract rents in the second transaction—the round-trip spread the dealer earns is reduced. Thus, we provide a rationale for dealer objections to ex-post transparency. However, we also show that ex-post transparency increases the volume of trade and increases allocative efficiency. Thus, investors benefit from transparency. In fact, it is even possible for dealers to benefit from transparency, depending on whether the larger

\(^1\)The TRACE system was implemented in 2002 by the NASD and expanded in stages through 2005. The reporting requirements are now imposed by FINRA. Bravo (2003), Laughlin (2005), Patterson and Zeng (2010), and Wigglesworth (2015) all provide reports of U.S. corporate bond dealers opposing trade disclosure. Similarly, Rothwell (2006) reports European bond dealers opposing disclosure, and Burne (2010) reports swap dealers opposing disclosure.
volume or the smaller spreads dominate. We determine the conditions under which one or the other is more important.

The mechanism that drives our results is costly signaling. Suppose that trade is initiated by a seller, and after acquiring inventory the dealer needs to find a buyer. We assume there are many investors in the dealer’s Rolodex who hold assets of the type being traded but have no special information about this particular asset. The dealer contacts one of them and quotes an ask price for the asset. In a transparent market, the price at which the dealer acquired the asset may signal private information possessed by the dealer to the buyer. We consider three types of markets: a hypothetical ("first best") market in which the dealer’s private information is directly observed by the buyer, a transparent market in which the price of the first transaction is observed by the buyer and hence may signal the dealer’s private information to the buyer, and an opaque market in which the buyer has no information other than the ask price quoted by the dealer for the second transaction. Our interest is in comparing the transparent and opaque markets. We show that in a separating equilibrium of the transparent market, dealers “overbid” for the asset in the first transaction to separate in the second transaction from other types of dealers with lower valuations. This overbidding is costly to dealers relative to the first-best world. However, overbidding also increases the likelihood of the dealer’s bid being accepted by the seller in the first transaction. Hence, costly signaling increases the volume of trade and increases gains from trade. In fact, realized gains from trade are higher in the separating equilibrium of the transparent market than they are either in the first-best world or in an opaque market.
On a per-trade basis, dealers always prefer opacity. The overbidding in the separating equilibrium of the transparent market causes spreads to be smaller in transparent than in opaque markets. However, the higher volume in transparent markets can sometimes offset the smaller spreads. Thus, dealers may earn higher profits in a transparent market than in an opaque market. Whether they prefer transparent or opaque markets depends on the magnitude of potential gains from trade relative to the extent of adverse selection. Dealers prefer opacity when potential gains from trade are large relative to adverse selection. The potential gains from trade depend on the private motives for trading of the customer who initiates the transactions. When the customer is highly motivated (or when adverse selection is low), trade is highly probable in both transparent and opaque markets. In that case, the increase in the volume of trade due to transparency is not large enough to overcome the lower spreads, and dealers prefer opacity. On the other hand, if potential gains from trade are low or adverse selection is high, then dealers benefit from transparency. The opposition to transparency cited in footnote 1 and the empirical evidence that bond dealers lost revenues when TRACE was introduced (Bessembinder, Maxwell, and Venkataraman, 2006, Edwards, Harris, and Piwowar, 2007) indicate that potential gains from trade were large in those markets relative to adverse selection.

We assume that a market is opaque unless disclosure is mandatory, because voluntary disclosure is not credible. If it were credible—that is, if there were some mechanism that would sufficiently punish any false disclosures—then the usual unraveling argument implies that there would be full and truthful disclosure in
equilibrium (Grossman, 1981, Milgrom, 1981). However, absent mandatory disclosure, it seems unlikely that false disclosures of trade terms could be detected and punished. Bravo (2003) quotes a commentator from a fixed income research service (cited in Bessembinder and Maxwell, 2008) stating that “before TRACE, it wouldn’t be unheard of for a trader to use the fact that there was no way of verifying the information that he gave about where a bond was trading to his advantage.”

In our model, there is only a single quantity traded, and we study price disclosure. In reality, disclosure involves both quantity and price. We show that dealers dislike price disclosure when gains from trade are large or adverse selection is low. Dealers may also dislike quantity disclosure. However, price disclosure seems to be important both in our model and in reality. Laughlin (2005) quotes a high-yield bond trader (cited in Bessembinder and Maxwell, 2008) describing the pre-TRACE corporate bond market as “customers felt like they never really knew where a dealer was buying or selling, and they were scared that dealers were working for too much margin. ... Many investors now think the real benefit of TRACE lies in knowing that they are not being raked over coals.”

We assume that the investor who is motivated to trade contacts only a single dealer, and the dealer has all of the bargaining power in the transaction. In particular, we assume the dealer makes a take-it-or-leave-it offer. Take-it-or-leave-it offers are indeed common in OTC markets. According to Duffie (2012), “An OTC trade negotiation is typically initiated when an investor contacts a dealer and asks for terms of trade ... A dealer making two-sided markets typically provides a take-it-or-leave-it pair of prices, a bid and an offer, to a customer.” In actual markets, there are of
course multiple dealers and a customer can reject an offer from one dealer and seek a better offer from another. However, if search is costly, then the outcome is the same as if there were only one dealer. With costly search, the Diamond paradox (Diamond, 1971) states that each dealer will behave as a monopolist, because the trader’s only alternative to trading with the dealer with whom he is currently in contact is to incur the search cost and then contact another dealer who in equilibrium also behaves as a monopolist. What a trader cannot do in an OTC market is to solicit quotes from multiple dealers and then select the best one; that is, he cannot induce dealers to engage in Bertrand competition. According to Bessembinder and Maxwell (2008), “Dealer quotations in corporate bonds are not disseminated broadly or continuously. Quotations are generally available only to institutional traders, mainly in response to phone requests . . . Telephone quotations indicate a firm price but are only good ‘as long as the breath is warm,’ which limits one’s ability to obtain multiple quotations before committing to trade.” Bessembinder and Maxwell (2008) go on to point out that even in OTC markets with electronic messaging systems, “price quotations mainly serve as an indication of the desire to trade, not a firm obligation on price and quantity.” In fact, whether competition is sequential or simultaneous would seem to be the key distinction between OTC markets and exchanges. Even if search is costless, sequential competition is not the same as simultaneous competition. Zhu (2012) shows in a theoretical model of informed dealers that a trader who turns down a dealer’s quote and then returns to that dealer after seeking other quotes will be disadvantaged, because the dealer can infer that other dealers have offered worse quotes and hence must have worse signals. This implies that the dealer will offer
worse terms when contacted a second time. Thus, costless sequential search is not equivalent to generating multiple quotes and choosing the best one; that is, it is not equivalent to running an auction among dealers.

We also assume the dealer makes a take-it-or-leave-it offer in the second transaction that serves to offload the dealer’s inventory. This assumption is motivated by the prevalence of take-it-or-leave-it offers in actual OTC markets. However, we could dispense with the assumption in the second transaction and assume that the dealer instead runs an auction among possible traders. Given our assumption that the traders in the second transaction are uninformed about the asset quality, this auction will be a Bertrand game in which the traders compete away all rents. The resulting transaction price will be exactly the price at which the asset trades in our model with take-it-or-leave-it dealer quotes.

For some assets, interdealer markets are important. They provide an alternative way for dealers to offload inventory rather than trading with a second customer. Costly signaling should also be important in the presence of an interdealer market if the original dealer has information not possessed by other dealers.

Signaling by intermediaries is a relevant question due to the importance and the distinct nature of OTC markets, but we are not aware of any other paper that studies it. There is a literature studying the role of signaling in dynamic asset markets (see Kremer and Skrzypacz, 2007, Daley and Green, 2012, Fuchs and Skrzypacz, 2013, Kurlat, 2013, Guerrieri and Shimer, 2014, Fuchs, Öry, and Skrzypacz, 2015, and references therein). However, the market design question related to the effect of transparency on welfare is absent from this literature with the exception of Fuchs,
Öry, and Skrzypacz (2015). They study a seller’s ability to signal a high asset value by rejecting offers and show that transparency, in the form of disclosing all price offers, reduces the probability of trading. We reach the opposite conclusion because, consistent with actual disclosure requirements, we study disclosure of transaction prices instead of disclosure of rejected offers.

There is a literature focused on the welfare effects of transparency in OTC markets. The paper closest to ours is Naik, Neuberger, and Viswanathan (1999). Like us, they study a dealer who first trades with an informed customer and then offloads the inventory in a second transaction. They conclude that transparency can reduce the welfare of investors depending on how much the dealer learns about the asset value in making the first transaction. A key difference between their paper and ours is that they assume dealers are competitive and do not earn any rents, in either a transparent or opaque market. Thus, dealers should be indifferent about transparency under their assumptions. This runs counter to the evidence cited in footnote 1 about dealers opposing disclosure and to the empirical evidence that bond dealers did lose revenues following the introduction of TRACE (Bessembinder et al., 2006, Edwards et al., 2007). Bessembinder and Maxwell (2008) provide interesting anecdotal evidence that dealers suffered from the introduction of TRACE. A second difference between our paper and Naik, Neuberger, and Viswanathan (1999) is that the dealer in their model is initially uninformed, so the key mechanism we study—quoting excessively favorable prices in the first transaction to separate from dealers with worse signals—does not arise in their model.
Other papers that study the welfare implications of various forms of transparency in OTC markets include Cujean and Praz (2015). They show that better information about counterparties’ liquidity needs improves aggregate welfare through improved allocative efficiency in an interdealer market. Dealers are absent in their model; thus, they do not address the effects of transparency on dealers’ welfare. Bhattacharya (2016) assumes that dealers compete in an auction to trade with a customer and may run an auction after the transaction to trade among themselves. He is not able to solve for the equilibrium of his dynamic model explicitly, but he is able to compare some features of equilibrium strategies with and without transparency. Duffie, Dworczak, and Zhu (2014) show that the publication of benchmark prices in OTC markets improves market efficiency while reducing per-trade profitability for the dealers. They find that the net effect is often an increase in aggregate welfare, because the publication of benchmarks reduces the information advantage of dealers over customers. Asriyan, Fuchs, and Green (2015) examine the spillover effects of transparency when investors in distinct markets can observe trades in correlated assets.

Most models of securities dealers (for example, Glosten and Milgrom, 1985, Kyle, 1985) assume dealers are uninformed. There are some exceptions, but the exceptions do not study signaling by informed dealers. Glode and Opp (2016) study intermediation between an uninformed seller and an informed buyer via a chain of increasingly informed dealers. They assume that the less informed party makes the offer in each bilateral trade, so there is no possibility of signaling. Endogenous
signaling does not arise in Duffie, Dworczak, and Zhu (2014) because the market is assumed to be opaque.

Our assumption that a dealer searches for a second counterparty to offload inventory is shared by Rubinstein and Wolinsky (1987) and Duffie, Gărleanu, and Pedersen (2005). However, in those papers, search is modeled by random matching, and all agents have identical information. The presence of dealers in those models reduces search time for customers who have private motives for trading, and some of the welfare gain is captured by dealers. In our model, search for the second counterparty is costless for the dealer.

Some of our model’s predictions are supported by empirical evidence. Edwards, Harris, and Piwowar (2007), Bessembinder, Maxwell, and Venkataraman (2006), Goldstein, Hotchkiss, and Sirri (2007), and Bessembinder and Maxwell (2008) all find that an increase in transparency leads to a decrease in transaction costs. This is consistent with our model’s prediction that the bid-ask spread is lower in a transparent market than in an opaque market. Regarding the impact of transparency on trading activities, Bessembinder and Maxwell (2008) conjecture that “TRACE likely increased traders’ willingness to submit electronic limit orders by allowing traders to choose limit prices with enhanced knowledge of market conditions.” This is consistent with our result that the probability of trade is higher in transparent markets. However, the empirical evidence on the impact of transparency on trading activity is mixed. Goldstein, Hotchkiss, and Sirri (2007) find from an experiment conducted by the NASD in 2003 that transparency led to no significant change in trading volume of BBB corporate bonds. Asquith, Covert, and Pathak (2013) document a significant decrease

### 3.2 Model and First Best

We assume that the party that initiates the sequence of transactions (the first counterparty) has some private benefit or cost that motivates him to trade; however, he also exploits his private information when trading. Dealers are less informed about the asset value than the first counterparty, and the least informed party is the customer approached by the dealer when the dealer seeks to trade out of the position established in the first transaction. We assume that this second counterparty has the least information about the asset value, because we assume her interest in the asset is solely a function of being contacted by the dealer regarding it. As mentioned in the introduction, we assume this second counterparty is one of many investors who are known to the dealer to invest in assets of the same general type but who have no special information about the particular asset in question. In a transparent market, the second counterparty and the market at large are informed by the price at which the first transaction takes place.
For concreteness, we assume the first counterparty seeks to sell an asset. The case of a purchase by the first counterparty is symmetric.\textsuperscript{2} We call the first counterparty the seller, and we call the second counterparty the buyer. All parties are risk neutral.

We denote the seller’s value for the asset as $\hat{v} - \Delta$. Here, $\hat{v}$ is a common-value component and is the value to all other market participants (excluding dealers), and $\Delta > 0$ is a private-value component that could represent a liquidity shock to the seller (for example, it could represent the haircut if the asset has to be used as collateral to raise cash). We call $\Delta$ the seller’s discount. When trade occurs, $\Delta$ is the gain from trade. The dealer has a signal $\hat{s}$ about $\hat{v}$. We call $s$ the dealer’s type.

We call the price quoted to the seller the dealer’s bid and denote it by $B$, and we call the price quoted to the buyer the dealer’s ask and denote it by $A$. The dealer’s strategy consists of a bid function $B(\cdot)$ and an ask function $A(\cdot)$ specifying the bid and ask for each dealer type. The dealer quotes an ask price to the buyer only when the dealer’s bid has been accepted by the seller. We assume the dealer has a strong aversion to holding inventories, and we model that by taking the dealer’s value for the asset to be $-\infty$. In equilibrium, the dealer never ends up holding the asset, and we could replace $-\infty$ by any sufficiently low number. The dealer will choose to participate in the game only if the expected profit is nonnegative, so a requirement for equilibrium (an individual rationality constraint) is that each type of dealer earn nonnegative expected profit.

\textsuperscript{2}To be more precise, the case of a purchase is symmetric if the dealer can go short in the first transaction. In reality, a dealer may search for a second counterparty in order to buy the asset before executing a sale to the first counterparty, when the first counterparty wishes to buy an asset. In this case, the second counterparty is obviously not informed by the price of the “first” transaction, as we assume in our model.
The seller has a dominant strategy, which is to accept all bids above $\tilde{v} - \Delta$ and to reject all others. We assume the seller plays his dominant strategy, and we focus on the subgame between the dealer and the buyer. Note that we do not need to assume that the seller knows the dealer’s signal $\tilde{s}$, because the seller has a dominant strategy that does not depend on $\tilde{s}$.

**Assumption 1.** The seller’s discount $\Delta$ is common knowledge, but the realization of the common value component $\tilde{v}$ is known only to the seller. The value $\tilde{v}$ and the dealer’s signal $\tilde{s}$ are linked by $\tilde{v} = \tilde{s} + \tilde{\varepsilon}$, where $\tilde{s}$ and $\tilde{\varepsilon}$ are independently distributed. The support of $\tilde{s}$ is a finite interval $[s_L, s_H]$. The random variable $\tilde{\varepsilon}$ has a continuous density function, its support is the entire real line, and its mean is zero. The distribution function $F$ of $\tilde{\varepsilon}$ is such that $\log F$ is strictly concave, and

$$
\lim_{x \to -\infty} \frac{F(x)}{f(x)} = 0. \tag{3.1}
$$

An example that satisfies Assumption 1 is $\tilde{v} = \tilde{s} + \tilde{\varepsilon}$, where $\tilde{s}$ has finite support and $\tilde{\varepsilon}$ is normally distributed with mean zero. We study this example when we solve the model numerically. We do not assume normality now, because it provides no simplification. Assumption 1 states that the asset value equals the signal plus noise. Some readers may be more familiar with ‘truth plus noise’ signals of the form $\tilde{z} = \tilde{v} + \tilde{e}$, where $\tilde{v}$ and $\tilde{e}$ are independent. Given such a signal $\tilde{z}$, we can always define a new signal $\tilde{s} = \mathbb{E}[\tilde{v} | \tilde{z}]$ with residual $\tilde{\varepsilon} = \tilde{v} - \tilde{s}$. Then, $\tilde{v} = \tilde{s} + \tilde{\varepsilon}$ and the mean of $\tilde{\varepsilon}$ is zero, as we assume. Furthermore, $\tilde{\varepsilon}$ is mean-independent of $\tilde{s}$, so our assumption that the two are independent is only a mild regularity condition.
Log concavity is a common and important assumption in information economics (see, for example, Bagnoli and Bergstrom, 2005). The details of its application to our model are provided in the appendices, but we explain the essential idea here. The conditional probability that the seller will accept a bid of $B$, conditioning on the dealer’s type $s$, is the probability that $\bar{v} \equiv \bar{\xi} + s \leq B + \Delta$, which is $F(B + \Delta - s)$.

Consider two dealer types $s > s'$. Log concavity implies that the ratio

$$\frac{F(B + \Delta - s)}{F(B + \Delta - s')}$$

is increasing in $B$. Thus, increasing the bid increases the probability of trade at a higher rate for a dealer of a higher type. This makes it possible in the transparent market for dealers to separate from dealers with lower types by offering higher bids. It also makes pooling equilibria implausible in the transparent market, because higher types of dealers have a greater incentive to deviate from pooling behavior by offering higher bids (formally, pooling equilibria violate the D1 criterion).

To see that the ratio (3.2) is increasing in $B$, define

$$g(x) = \frac{F(x)}{f(x)}.$$ 

We make extensive use of this function throughout the paper. The log concavity assumption implies that $g$ is an increasing function [this follows from the fact that
\((\log F)^\prime = (f/F)\). The derivative of the log of the ratio (3.2) is

\[
\frac{1}{g(B + \Delta - s)} - \frac{1}{g(B + \Delta - s')}
\]

which is positive for \(s > s'\), because \(g\) is increasing; thus, the ratio (3.2) is increasing in \(B\).

It is also useful to define the following function:

\[
G(x) = E[\bar{\xi} \mid \bar{\xi} \leq x] = \frac{1}{F(x)} \int_{-\infty}^{x} \bar{\varepsilon} f(\bar{\varepsilon}) d\bar{\varepsilon}.
\] (3.4)

The log concavity assumption implies that \(G' < 1\) (Bagnoli and Bergstrom, 2005, Lemma 1). It is also worth noting that the definitions of \(g\) and \(G\) imply directly that

\[
g(x)G'(x) = x - G(x).
\] (3.5)

Of course, \(g\) is positive. Condition (3.1) implies that all positive numbers are in the range of \(g\), so \(g^{-1}(a)\) is well defined for all \(a > 0\).

If the buyer knew the dealer’s type \(s\) and knew that a transaction had occurred between the dealer and the seller at a bid of \(B\), then he would know both \(s\) and that \(\bar{\varepsilon} \leq B + \Delta\). In this circumstance, the buyer’s reservation price for the asset would be

\[
R(s, B) \overset{\text{def}}{=} E[\bar{\varepsilon} \mid \bar{\varepsilon} \leq B + \Delta, \bar{s} = s] = s + G(B + \Delta - s).
\] (3.6)
In the first-best world, the dealer of type \( s \) chooses her bid \( B \) to maximize

\[
[R(s, B) - B] \prob(\tilde{v} \leq B + \Delta | \tilde{s} = s) = [R(s, B) - B] F(B + \Delta - s).
\]  

(3.7)

All proofs are in A.

**Theorem 1.** Set \( \gamma = g^{-1}(\Delta) \). In the first-best world, there is a unique equilibrium. In equilibrium, the dealer of type \( s \) bids

\[
B^!(s) = s + \gamma - \Delta
\]  

(3.8)

and plays the ask

\[
A^!(s) = R(s, B^!(s)) = s + G(\gamma).
\]  

(3.9)

The conditional probability of trade, the bid-ask spread, and the dealer’s conditional expected profit are all independent of the dealer’s type. For each type of dealer, the conditional probability of trade is \( F(\gamma) \), the bid-ask spread is

\[
\Delta + G(\gamma) - \gamma = [1 - G'(\gamma)]g(\gamma) > 0,
\]  

(3.10)

and the conditional expected profit is \([1 - G'(\gamma)]g(\gamma)F(\gamma) > 0\).

### 3.3 The Transparent Market

In a transparent market, the buyer observes the bid and ask and forms beliefs about \( \tilde{v} \) and \( \tilde{s} \). We search for an equilibrium in which different dealer types make different
bids to the seller—that is, we search for an equilibrium that is separating in bids. The reason is as follows. First, if two different dealer types play the same bid $B$, then they must play the same ask in equilibrium, because the highest ask that is accepted by the buyer after observing an initial transaction at $B$ is optimal for both dealer types. Thus, pooling in bids implies pooling in asks. But, we can show that an equilibrium with pooling in bids violates the D1 criterion. The details are provided in B. Intuitively, higher dealer types have more incentive to deviate from a pooling equilibrium by playing a higher bid, because increasing the bid increases the probability of trade more for a dealer with a higher signal (the ratio (3.2) is increasing in $B$ when $s > s'$). Hence, the buyer should (under the D1 criterion) infer that a deviation to a higher bid is made by a dealer with a higher type, making that deviation profitable for the higher type. So, the D1 criterion rules out equilibria that are pooling in bids. The actual argument is only slightly more complicated than this: It relies on the fact that the marginal rate of substitution (B.14) is increasing in the dealer’s type, which is a consequence of log concavity.

When contacted by the dealer, the buyer knows that the dealer has acquired inventory in a prior transaction, so the buyer’s beliefs put probability 1 on the dealer’s bid having been accepted by the seller, which is the event $\tilde{v} \leq B(\tilde{s}) + \Delta$. In an equilibrium that is separating in bids, the buyer therefore knows the realization $s$ of $\tilde{s}$ and he knows that $\tilde{v}$ satisfies $\tilde{v} \leq B(s) + \Delta$ when he is contacted by the dealer, before the dealer quotes an ask. The highest ask price the buyer would pay given that information is the reservation price $R(s, B(s))$ defined in (3.14). Hence, we look for an equilibrium that is separating in bids and in which the ask price is $R(s, B(s))$. 
We discuss whether there could be other separating equilibria—in which the ask price is different from $R(s, B(s))$—at the end of this section. To derive the equilibrium, we first need a technical lemma.

**Lemma.** Set $x_L = g^{-1}(\Delta)$. There exists $x_H < \infty$ such that

$$s_L + \int_{x_L}^{x_H} \frac{g(a) - \Delta}{G(a) + \Delta - a} \, da = s_H. \tag{3.11}$$

For $x_L \leq x \leq x_H$, define

$$s(x) = s_L + \int_{x_L}^{x} \frac{g(a) - \Delta}{G(a) + \Delta - a} \, da. \tag{3.12}$$

The function $s(\cdot)$ is strictly increasing on $[x_L, x_H]$ with range $[s_L, s_H]$.

The next theorem describes the equilibrium. The formula (3.12) in Lemma 3.3 is important, because it implies that the inverse function appearing in Theorem 2 solves an ODE that is equivalent to the dealer’s first-order condition. We demonstrate this in the proof of Theorem 2, and we also show that, due to log concavity, the first-order condition is sufficient for the optimum. We obtained the formula (3.12) by integrating the inverse ODE. These steps—deriving an ODE from the first-order condition and then analyzing the inverse ODE—follow Mailath (1987).

**Theorem 2.** Let $x(\cdot)$ be the inverse of the function (3.12) with domain $[s_L, s_H]$. Then, $x(s_L) = x_L \equiv g^{-1}(\Delta)$. For each dealer type $s$, define

$$B^*(s) = s + x(s) - \Delta. \tag{3.13}$$
Consider the following beliefs for the buyer:

- If the dealer’s bid \( B \) is equal to \( B^*(s) \) for some \( s \in [s_L,s_H] \), then, for any ask \( A \), the buyer puts probability 1 on \( \tilde{s} = s \).

- If the dealer’s bid \( B \) is less than \( B^*(s_L) \) then, for any ask \( A \), the buyer puts probability 1 on \( \tilde{s} = s_L \).

- If the dealer’s bid \( B \) is greater than \( B^*(s_H) \) then, for any ask \( A \), the buyer puts probability 1 on \( \tilde{s} = s_H \).

And, consider the following strategy for the buyer: The buyer accepts the dealer’s ask \( A \) if and only if either

- the dealer’s bid \( B \) is equal to \( B^*(s) \) for some \( s \in [s_L,s_H] \) and \( A \leq R(s,B) \), or

- the dealer’s bid \( B \) is less than \( B^*(s_L) \) and \( A \leq R(s_L,B) \), or

- the dealer’s bid \( B \) is greater than \( B^*(s_H) \) and \( A \leq R(s_H,B) \).

The bid function \( B^* \) and ask function

\[
A^*(s) = R(s,B^*(s)) = s + G(x(s))
\]  

(3.14)

constitute a separating Bayesian-Nash equilibrium in conjunction with the buyer’s beliefs and strategy just described. In this equilibrium, the conditional probability of trade is \( F(x(s)) \), which is strictly increasing in \( s \). The bid-ask spread is \( \Delta + G(x(s)) \) –
$x(s)$, which is strictly decreasing in $s$, and the dealer’s conditional expected profit is

$$[1 - G'(x_L)]g(x_L)F(x_L) \exp \left( - \int_{s_L}^{s} \frac{1}{g(x(a))} \, da \right), \quad (3.15)$$

which is positive and strictly decreasing in $s$.

Given the strategy of the buyer specified in the theorem, the expected profit that can be achieved by a dealer of type $s$ who plays the bid $B$ and is believed to be of type $s'$ is

$$U(s, s', B) \overset{\text{def}}{=} [R(s', B) - B]F(B + \Delta - s)$$

$$= [s' + G(B + \Delta - s') - B]F(B + \Delta - s) . \quad (3.16)$$

In equilibrium, the dealer of type $s$ plays the bid $B^*(s)$ and is correctly perceived to be of type $s$, so she earns expected profit equal to $U(s, s, B^*(s))$. As is standard, the worst type of dealer plays the same strategy and earns the same expected profit as in the first-best world; that is, $B^*(s_L) = B^t(s_L)$. The incentive compatibility condition for separating equilibrium with bid function $B(\cdot)$ is that $s' = s$ solve $\max_{s'} U(s, s', B(s'))$ for each $s$. The first-order condition for this maximization problem produces an ODE. As stated before, the function (3.12) solves the inverse of this ODE subject to the boundary condition $B^*(s_L) = B^t(s_L)$.

If we substitute $x_L = g^{-1}(\Delta)$ for $x(s)$ in the bid function (3.13) and ask function (3.14) of the transparent market, then we recover the bid function and ask function in the first-best world. Because $x(s) > x_L$ for $s \neq s_L$, we see that the desire to separate
from lower types induces dealers to bid higher in the transparent market, and we see that dealers also quote higher asks in the transparent market. The higher asks are possible because the average quality of assets purchased by the dealer is higher, due to the higher bids. The bid-ask spread is lower in the transparent market than in the first-best world; that is,

$$\Delta + G(x(s)) - x(s) < \Delta + G(x_L) - x_L,$$

for $s \neq s_L$, because $G' < 1$. Furthermore, the expected profit is lower in the transparent market, because (3.15) shows that the expected profit is less than $[1 - G'(x_L)]g(x_L)F(x_L)$, which is the expected profit of each dealer type in the first-best world. Of course, the dealer’s profit cannot be higher in a separating equilibrium of the transparent market than when the dealer’s signal is publicly observable. This is the standard result that signaling is costly, relative to the first-best world.

**On Uniqueness of the Separating Equilibrium.** The issue we address here is whether there can be separating equilibria other than the one identified in Theorem 2. We show in B that the equilibrium in Theorem 2 is the unique equilibrium that is separating in bids in which the bid function $B(\cdot)$ is differentiable and the ask price is the buyer’s reservation price $R(s, B(s))$. Thus, the main question is whether the ask price in a separating equilibrium can be some function $\hat{A}(s) \neq R(s, B(s))$. Given a separating bid function $B(\cdot)$, the ask price cannot be higher than the buyer’s reservation price, because higher prices are rejected by the buyer. So, the question is whether it is possible that $\hat{A}(s) < R(s, B(s))$. Such an ask price would give rents to
the buyer, so an equivalent question is whether it is possible for the buyer to earn rents in a separating equilibrium.

There is an alternate version of our model in which the question is easy to answer. Suppose that, instead of quoting an ask price, the dealer auctions the asset to buyers. Because the buyers are uninformed, the auction would be a Bertrand game, and competition between the buyers would eliminate their rents and result in a transaction price $R(s, B(s))$. Thus, in the auction version of the model, there is a unique separating equilibrium in which the bid function is differentiable, and the equilibrium is the one displayed in Theorem 2.

In the model in which the dealer quotes an ask price to the buyer, the question is more complex, because the party taking the action (the dealer) is the informed party. Thus, the ask price can signal to the buyer—even when dealer types have already been separated by the bid. This issue is similar to the issue that arises when a seller of a good can signal via both advertising and price. Kihlstrom and Riordan (1984) assume that sellers of different quality goods that separate via advertising can price the good at the customer’s reservation price, given the customer’s awareness of quality achieved via advertising. In our context, this approach implies that the ask is set at the buyer’s reservation price, after the dealers have separated via their bids, that is, the ask price is $R(s, B(s))$, as in Theorem 2. On the other hand, Milgrom and Roberts (1986) assume that both advertising and price signal. In this ‘dual signals’ model, in our context, there are multiple separating equilibria. The reason is as follows. Even though $R(s, B(s))$ would be the buyer’s reservation price given knowledge that $\tilde{s} = s$ and $\tilde{v} \leq B(s) + \Delta$, it is possible that the buyer expects the dealer of type $s$ to quote
a different ask $\hat{A}(s) < R(s, B(s))$. Furthermore, it is possible that the buyer would, if quoted $R(s, B(s))$, make the (out-of-equilibrium) inference that the dealer’s type is $s' < s$ and hence would reject the ask $R(s, B(s))$. In this circumstance, it may be optimal for the dealer to quote $\hat{A}(s)$, producing an equilibrium with ask prices below $R(s, B(s))$. Equilibria of this sort do not seem to be ruled out by standard refinements, because all dealers have the same preferences regarding ask prices: their utility goes up one-for-one with the ask price up to the point that the ask is rejected by the buyer.

Despite the existence of the equilibria described in the preceding paragraph, we feel that the equilibrium in Theorem 2 is the natural focal point. First, it is optimal for the dealer, who is the party taking the actions (quoting the bid and ask) because it gives no rents to the buyer. Second, the other equilibria require a non-monotonicity of beliefs that seems unreasonable. In the scenario described in the preceding paragraph, the buyer thinks the dealer’s type is $s$ when he observes an ask of $\hat{A}(s)$, but he infers that the dealer’s type is $s' < s$ when he observes an ask of $R(s, B(s)) > \hat{A}(s)$. If we suppose more reasonably that either inferences are unchanged by asks or that inferences are monotone in asks, then the ask price must be $R(s, B(s))$ in any equilibrium that is separating in bids. We demonstrate this formally in B: We show that the equilibrium in Theorem 2 is the unique separating equilibrium in which the bid function is differentiable and in which the buyer’s inferences are weakly monotone in the ask price.
3.4 The Opaque Market

In an opaque market, the buyer does not observe the price of the transaction between the seller and the dealer. The buyer’s only information is that the transaction occurred. Let $B^{o}(\cdot)$ denote an equilibrium bid function in the opaque market. The buyer knows that $\tilde{v} \leq B^{o}(\tilde{s}) + \Delta$, but he knows neither $\tilde{v}$ nor $\tilde{s}$. The buyer’s reservation price given this information is

$$\bar{R} \overset{\text{def}}{=} \mathbb{E}[\tilde{v} \mid \tilde{v} \leq B^{o}(\tilde{s}) + \Delta].$$  \hspace{1cm} (3.18)

All dealer types must play the same ask in equilibrium, because all dealer types will play the highest ask the buyer will accept. Given a planned ask price of $A$, the dealer of type $s$ chooses a bid $B$ to maximize expected profit:

$$(A - B) \cdot \text{prob}(\tilde{v} \leq B + \Delta \mid \tilde{s} = s) = (A - B) \cdot F(B + \Delta - s).$$  \hspace{1cm} (3.19)

For all real $x$, define

$$h(x) = x + g(x),$$

where $g(x) = F(x)/f(x)$ as before. In the proof of the next theorem, we show that, given a planned ask price of $A$, the optimal bid is

$$B(s) = s - \Delta + h^{-1}(A + \Delta - s).$$  \hspace{1cm} (3.20)
Substituting this into (3.18), we see that the buyer’s reservation price in equilibrium is

\[
\bar{R} = E[\tilde{v} \mid \tilde{v} \leq \tilde{s} + h^{-1}(A + \Delta - \tilde{s})] = E[\tilde{s} + \tilde{\varepsilon} \mid \tilde{\varepsilon} \leq h^{-1}(A + \Delta - \tilde{s})]
= E[\tilde{s} + \tilde{\varepsilon} \mid \tilde{s} + h(\tilde{\varepsilon}) \leq A + \Delta]. \tag{3.21}
\]

It seems reasonable that the dealer should set the ask at the buyer’s reservation price. However, there is a uniqueness issue similar to that in the transparent market. Equilibria in which the ask is less than the buyer’s reservation price—so the buyer earns rents—can be sustained by off-equilibrium beliefs. Also as in the transparent market, such off-equilibrium beliefs cannot be monotone in the ask (higher asks must be viewed as coming from dealers with lower types). We show in B that the equilibrium ask must be equal to the buyer’s reservation price in any equilibrium in which the the buyer’s beliefs are weakly monotone in the ask price. An equilibrium of this sort is computed by setting \(A = \bar{R}\) and solving (3.21) for \(A\). We verify numerically in the next section that this equation has a solution (see Figure 1 in particular).

**Theorem 3.** Suppose \(A = A^0\) is a solution of the equation

\[
A = E[\tilde{s} + \tilde{\varepsilon} \mid \tilde{s} + h(\tilde{\varepsilon}) \leq A + \Delta]. \tag{3.22}
\]
Set \( y(s) = h^{-1}(A^o + \Delta - s) \). It is an equilibrium of the opaque market for all dealer types to quote the ask price \( A^o \) and for the dealer of type \( s \) to bid

\[
B^o(s) = s + y(s) - \Delta. 
\] (3.23)

In this equilibrium, the conditional probability of trade is \( F(y(s)) \), which is strictly decreasing in \( s \). The bid-ask spread is \( g(y(s)) \), which is strictly decreasing in \( s \). The dealer’s conditional expected profit is \( g(y(s))F(y(s)) \), which is positive and strictly decreasing in \( s \).

One difference between transparent and opaque markets is that the probability of trade is higher for higher \( s \) in a transparent market (because the equilibrium bid rises more than one-for-one with the dealer’s signal) but falls with \( s \) in an opaque market (because the equilibrium bid rises less than one-for-one with the dealer’s signal). Expected profit falls with \( s \) in both markets, but it falls faster in an opaque market, because both the probability of trade and the bid-ask spread are lower for higher \( s \) in an opaque market. This produces the very intuitive result that higher dealer types may ex post prefer transparency, because transparency allows them to signal their types. In the next section, we look at ex ante dealer profits in the two markets.

### 3.5 A Uniform/Normal Model

To assess the effects of transparency, relative to an opaque market, we need to calculate the integral in (3.12) and we need to compute the fixed point in (3.22)
numerically. Thus, we now impose some additional structure on the model. We assume the dealer’s signal is uniformly distributed on an interval $[s_L, s_H]$, and we assume $\tilde{v} = \tilde{s} + \tilde{\varepsilon}$, where $\tilde{\varepsilon}$ is normally distributed with mean zero and variance $\sigma^2$ (the normal distribution has all of the properties we have assumed for $\tilde{\varepsilon}$). From numerical analysis of this model, we reach the following conclusions: Transparency increases both bid and ask prices and therefore increases volume, but it reduces bid-ask spreads. The welfare of the seller is improved by the higher bid prices, and the buyer does not earn any rents in either market by assumption, so the aggregate welfare of investors is higher under transparency. Whether dealers gain or lose from transparency depends on whether the lower spreads or the higher volume is more important. We find that the lower spreads are more important if adverse selection is low or if the seller’s discount is high. In either situation, volume is high even in an opaque market, so the reduction of spreads is the more important phenomenon, and dealer profits fall when transparency is introduced.

In presenting the numerical results, we express the bid and ask prices and the seller’s discount $\Delta$ as percentages of the unconditional expected asset value, which is $(s_L + s_H)/2$. We also parameterize the adverse selection in terms of the total amount of private information (seller’s plus dealer’s) and the fraction of the total that is explained by the dealer’s information. The variance of the uniformly distributed $\tilde{s}$ is $(s_H - s_L)^2/12$, so the variance of $\tilde{v} = \tilde{s} + \tilde{\varepsilon}$ (the total amount of private information) is

$$\phi^2 = \frac{(s_H - s_L)^2}{12} + \sigma^2. \quad (3.24)$$
The fraction of the variance of $\tilde{v}$ that is explained by $\tilde{s}$ is $\rho^2$, where $\rho$ is the correlation of $\tilde{s}$ and $\tilde{v}$; that is,
\[
\rho \defeq \frac{s_H - s_L}{\phi \sqrt{12}}. \tag{3.25}
\]
We can exogenously specify the total amount of private information $\phi^2$ and the fraction $\rho^2$ that is explained by the dealer’s signal and then recover $s_H - s_L$ and $\sigma$ as $s_H - s_L = \rho \phi \sqrt{12}$ and $\sigma^2 = (1 - \rho^2)\phi^2$.

We have earlier presented analytic solutions for all quantities of interest other than the fixed point in (3.22) in the opaque market. Figure 1 illustrates the calculation of the fixed point. It shows that the equilibrium $A^o$ equals the unconditional expected asset value minus a discount for adverse selection. The discount for adverse selection is smaller when the seller’s discount $\Delta$ is larger and when the total amount of private information $\phi$ is smaller.

Figure 2 illustrates the equilibria in the three markets: transparent, opaque, and first-best. The figure illustrates the general properties established in the theorems. The bid price is increasing in the dealer’s signal in all three markets. The ask price is increasing in the signal in the transparent market and in the first-best world but is independent of the signal in the opaque market. In the first-best world, the bid-ask spread, the conditional probability of trade, and the conditional expected profit are all independent of the dealer’s signal. In both the transparent and the opaque market, the bid-ask spread and the dealer’s expected profit are decreasing in her signal. However, the conditional probability of trade is increasing in the dealer’s
signal in the transparent market and decreasing in the dealer’s signal in the opaque market.

Figure 2 illustrates the relationship between the transparent market and the first-best market that is discussed in Section 3.3. Bid prices are higher in the transparent market, because the dealer bids higher to separate from dealers with lower signals. The ask price is also higher but does not rise as much as the bid, so the bid-ask spread is lower in the transparent market. Due to the higher bid price, the probability of trade is higher in the transparent market, but, from the dealer’s point of view, it does not rise enough to offset the lower bid-ask spread, so the dealer’s expected profit is lower in the transparent market.

All of the properties of Figure 2 discussed to this point were established analytically in earlier sections. Figure 2 provides new insights about the relationship between the transparent and opaque markets, the central issue with which this paper is concerned. For the particular parameter values used in Figure 2, we see that the bid price in the opaque market is uniformly lower than in the transparent market; hence, the probability of trade is uniformly lower in the opaque market. This means that the aggregate realized gains from trade are lower in the opaque market. Despite the lower bid price, the bid-ask spread is uniformly higher in the opaque market than in the transparent market. Whether the dealer gains or loses from transparency depends on whether the beneficial effect of transparency on the spread offsets the detrimental effect of transparency on volume. We see from the bottom panel that the former effect dominates when the dealer’s signal is low, and the latter effect dominates when the dealer’s signal is high. This is intuitive. In an opaque market, the ask price is
independent of the dealer’s signal. When the dealer has a low signal, she can expect the seller to accept a low bid, producing a relatively high likelihood of trade with a high spread. Hence opacity is desirable for the dealer conditional on the signal being low. Conversely, when the dealer has a high signal, she knows she has to bid high to buy the asset, producing a low spread, which diminishes the incentive to bid high, resulting in both a low probability of trade and a low spread, both of which contribute to a low expected profit. Thus, ex post, the dealer prefers opacity when her signal is low and prefers transparency when her signal is high. We examine the dealer’s ex ante preferences regarding transparency in Figures 3 and 4.

Figure 3 shows that the effect of transparency on the bid-ask spread and the probability of trade that is indicated in Figure 2 is robust when we vary one parameter at a time. For various values of the seller’s discount, the total amount of private information, and the fraction of private information that is explained by the dealer’s signal, we see in the left column that transparency increases the probability of trade, and we see in the middle column that transparency reduces the bid-ask spread. Both effects cause investors to benefit from transparency. Whether dealers prefer transparency or opacity depends on which of the two effects dominate. When potential gains from trade are large or when the dealer has little private information, trade is likely in either an opaque or transparent market (see the top two panels in the left column of Figure 3). In this circumstance, the beneficial effect of transparency on volume is relatively small and is offset by the detrimental effect on the bid-ask spread from the point of view of dealers. This is shown in the top two panels in the right column of Figure 3. The top right panel in Figure 3 shows that transparency is
beneficial to dealers when the potential gains from trade are small and detrimental when potential gains from trade are large. The middle right panel shows that transparency is beneficial to dealers when the dealer has a lot of private information and detrimental when private information is small. The bottom panel in Figure 3 shows that the fraction of the variance of $\tilde{v}$ that is explained by the dealer’s signal seems to have little effect on the relative performance of the two markets. We study the other two parameters ($\Delta$ and $\phi$) further in Figure 4.

Figure 4 provides more insight into the effect of transparency on dealer profits by varying $\Delta$ and $\phi$ simultaneously. For all values of $\phi$, the dealer prefers transparency when the seller’s discount $\Delta$ is small and prefers opacity when the seller’s discount is large. Conversely, for all values of $\Delta$, the dealer prefers opacity when $\phi$ is small and prefers transparency when $\phi$ is large. These results are consistent with the intuition described earlier: When either adverse selection is low or the seller’s private motive for trade is large, then trade is very likely in either market, so the lower spreads induced by transparency are more important than the increase in volume due to transparency, and dealer profits fall when transparency is introduced.

### 3.6 Conclusion

When markets are ex-post transparent and dealers have information not possessed by the second counterparty in a round-trip transaction, they engage in costly signaling, offering unduly favorable prices in the first transaction to signal to the second counterparty. This costly signaling increases volume, liquidity, and market efficiency.
From the perspective of dealers, the lower spreads and higher volume are partially offsetting factors. Which is more important depends on the magnitude of potential gains from trade and the extent of adverse selection. Dealers prefer opacity when potential gains from trade are high relative to adverse selection. Given the frequent opposition of dealers to transparency, we conclude that this condition characterizes many OTC markets.
Figure 1: Equilibrium Ask in the Opaque Market  The solid blue curves depict the function of $A$ that is on the right-hand side of (3.22), with $A$ expressed as a percent of the mean asset value $(s_L + s_H)/2$. The equilibrium ask is at the intersection with the $45^\circ$ line. In the top left panel, the standard deviation of $\tilde{v}$ is 5% of the mean asset value, the seller’s discount is 5% of the mean asset value, and 25% of the variance of $\tilde{v}$ is explained by the dealer’s signal. The parameters in the top right panel are the same except the seller’s discount is 10% of the mean asset value. The parameters in the bottom left panel are the same as in the top left panel except the standard deviation of the asset value is 10% of its mean. The parameters in the bottom right panel are the same as in the top left panel except that 75% of the variance of $\tilde{v}$ is explained by the dealer’s signal.
Figure 2: Equilibria in the Three Markets  The separating equilibrium of the transparent market, the equilibrium of the opaque market, and the equilibrium in the first-best world are presented. All variables other than the probability of trade (which is in percent) are expressed as a percent of the mean asset value \((s_L + s_H)/2\). In this example, the seller’s discount \(\Delta\) is 5% of the mean asset value, the standard deviation \(\phi\) of \(\tilde{v}\) is 5% of the mean asset value, and 50% of the variance of \(\tilde{v}\) is explained by the dealer’s signal.
Figure 3: Comparative Statics  The separating equilibrium of the transparent market and the equilibrium of the opaque market are compared for various parameter values. Except for the probability of trade and the fraction $\rho^2$ of the variance of $\tilde{v}$ that is explained by the dealer’s signal (which are in percent), all variables are expressed as a percent of the mean asset value $(s_L + s_H)/2$. The base parameters are that the seller’s discount $\Delta$ is 5% of the mean asset value, the standard deviation $\phi$ of $\tilde{v}$ is 5% of the mean asset value, and 25% of the variance of $\tilde{v}$ is explained by the dealer’s signal. Each row shows the effects of varying a single parameter, relative to the base case.
Figure 4: Comparative Statics of Dealer Profits  Expected dealer profits are calculated in the separating equilibrium of the transparent market and in the equilibrium of the opaque market. All variables are expressed as a percent of the mean asset value \( \frac{s_L + s_H}{2} \). In each case, 50% of the variance of \( \tilde{v} \) is explained by the dealer’s signal. The standard deviation of \( \tilde{v} \) (denoted by \( \phi \)) and the seller’s discount (denoted by \( \Delta \)) are as shown.
Bibliography


Asness, Clifford S, Andrea Frazzini, and Lasse Heje Pedersen, 2014, Quality minus junk, Available at SSRN 2312432.

Asquith, Paul, Thom Covert, and Parag Pathak, 2013, The effects of mandatory transparency in financial market design: Evidence from the corporate bond market, Available at SSRN 2320623.

Asriyan, Vladimir, William Fuchs, and Brett S Green, 2015, Information spillovers in asset markets with correlated values, Available at SSRN 2565944.


Bhattacharya, Ayan, 2016, Can transparency hurt investors in over-the-counter markets?, Available at SSRN 2746910 .


Cujean, Julien, and Rémy Praz, 2015, Asymmetric information and inventory concerns in over-the-counter markets, Available at SSRN 2464399.


Duffie, Darrell, Piotr Dworczak, and Haoxiang Zhu, 2014, Benchmarks in search markets, Available at SSRN 2515582.


Feng, Guanhao, Stefano Giglio, and Dacheng Xiu, 2017, Taming the factor zoo, Available at SSRN 2934020.


Friedman, Milton, 1953, The case for flexible exchange rates.

Fuchs, William, Aniko Öry, and Andrzej Skrzypacz, 2015, Transparency and distressed sales under asymmetric information, Available at SSRN 2563007.

Fuchs, William, and Andrzej Skrzypacz, 2013, Costs and benefits of dynamic trading in a lemons market, Available at SSRN 2320179.


Harvey, Campbell R, Yan Liu, and Heqing Zhu, 2016, ... and the cross-section of expected returns, The Review of Financial Studies 29, 5–68.


Hu, Gang, Koren Jo, Yi Alex Wang, and Jing Xie, 2018, Institutional trading and abel noser data, Available at SSRN 3090150.

Huang, Shiyang, Dong Lou, and Christopher Polk, 2016, The booms and busts of beta arbitrage, Available at SSRN 2843570.


Kapadia, Nishad, Barbara Ostdiek, James Weston, and Morad Zekhnini, 2015, Safe minus risky: Do investors pay a premium for stocks that hedge stock market downturns?, Available at SSRN 2627848.


Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2017, Shrinking the cross section, Available at SSRN 2945663.


Laughlin, Kate, 2005, Three years on, the TRACE impact for bond traders, technology can now trump analysis, The Investment Dealers’ Digest. July 04, 2005.


Liu, Jianan, Robert F Stambaugh, and Yu Yuan, 2016, Absolving beta of volatility’s effects, Available at SSRN 2834365.


O’Neal, Edward, 2001, Window dressing and equity mutual funds, Available at SSRN 275031.


A List of Anomalies

This appendix details the list of anomalies studied in chapter 1.

<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Construction</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composite Equity Issues (CEI)</td>
<td>CEI is calculated as the total change in the market capitalization of the firm in the past 12 months minus the cumulative stock return in the past 12 months. Buy bottom quintile. Sell Top quintile.</td>
<td>Daniel and Titman (2006)</td>
</tr>
<tr>
<td>Return on Assets (ROA)</td>
<td>ROA is calculated as the income before extraordinary items divided by lagged total assets. Buy top quintile. Sell bottom quintile.</td>
<td>Fama and French (2006), Chen, Novy-Marx, and Zhang (2011)</td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
<td>Reference</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Profitability (PROF)</td>
<td>PROF is calculated as sales minus cost of goods sold minus selling, general and administrative expenses minus total interest and related expense, all divided by book value of equity. Buy top quintile. Sell bottom quintile.</td>
<td>?</td>
</tr>
<tr>
<td>Investment Growth Rate (IGR)</td>
<td>IGR is calculated as the annual growth rate of the total capital expenditures. Buy bottom quintile. Sell top quintile.</td>
<td>Xing (2008)</td>
</tr>
<tr>
<td>Momentum (MOM)</td>
<td>MOM is calculated as the cumulative stock return in the past 6 months, with a one-month gap between the end of measurement period and the portfolio formation date. Buy top quintile. Sell bottom quintile.</td>
<td>Jegadeesh and Titman (1993)</td>
</tr>
<tr>
<td>Return Volatility (VOL)</td>
<td>VOL is calculated as the standard deviation of the daily gross stock return in the past 12 months, with a one-month gap between the end of measurement period and the portfolio formation date. Buy top quintile. Sell bottom quintile.</td>
<td>Ang, Hodrick, Xing, and Zhang (2006)</td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
<td>Reference</td>
</tr>
<tr>
<td>------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>Total Accruals (TAC)</td>
<td>See below for details. Buy bottom quintile. Sell top quintile.</td>
<td>(Sloan, 1996)</td>
</tr>
<tr>
<td>Idiosyncratic Volatility (IVOL)</td>
<td>IVOL is calculated as the root mean square error from the regression of the stock’s daily return in the past 12 months onto the market excess return in the same time period, with a one-month gap between the end of measurement period and the portfolio formation date. Buy bottom quintile. Sell top quintile.</td>
<td>Ang, Hodrick, Xing, and Zhang (2006)</td>
</tr>
</tbody>
</table>
\[ TAC = [DIF(\text{ACT}) - DIF(\text{CHE}) - (DIF(\text{LCT}) - DIF(\text{DLC})) - \\
\quad DIF(\text{TXP})) - \frac{DP}{(\text{AT} + \text{AT}_{t-1})/2}], \]

where \( \text{ACT} = \) total current assets; \( \text{AT} = \) total assets; \( \text{DLC} = \) total debt in current liabilities; \( \text{LCT} = \) total current liabilities; \( \text{CHE} = \) cash and short-term investments; \( \text{TXP} = \) income taxes payable; \( \text{DP} = \) depreciation and amortization.

\[ \text{OSCORE} = -1.32 - 0.407 \cdot \log \text{AT} + 6.03 \cdot \frac{(\text{DLC} + \text{DLTT})}{\text{AT}} - 1.43 \cdot \frac{(\text{ACT} - \text{LCT})}{\text{AT}} + 0.076 \cdot \frac{\text{LCT}}{\text{ACT}} - 1.72 \cdot \text{ONEEG} - 2.37 \cdot \frac{\text{NI}}{\text{AT}} - 1.83 \cdot \frac{\text{PI}}{\text{LT}} + 0.285 \cdot \text{INTWO} - 0.521 \cdot \frac{\text{NI}_t - \text{NI}_{t-1}}{|\text{NI}| + |\text{NI}_{t-1}|}, \]

where \( \text{AT} = \) total assets; \( \text{DLC} = \) total debt in current liabilities; \( \text{DLTT} = \) total long-term debt; \( \text{ACT} = \) total current assets; \( \text{LCT} = \) total current liabilities; \( \text{NI} = \) net income; \( \text{PI} = \) pretax income; \( \text{LT} = \) total liabilities; \( \text{ONEEG} = \) an indicator function that equals 1 if total liabilities (LT) > total assets (AT); \( \text{INTWO} = \) an indicator function that equals 1 if the net income (NI) in year \( t - 1 \) and year \( t - 2 \) are both negative.

\[ \text{DP} = -9.16 - 20.26 \cdot \text{NIMTAAVG} + 1.42 \cdot \text{TLMTA} - 7.13 \cdot \text{EXRTEAVG} + 1.41 \cdot \text{SIGMA} - 0.045 \cdot \text{RELSIZE} - 2.13 \cdot \text{CASHMTA} + 0.075 \cdot \text{MB} - 0.058 \cdot \text{PRICE}, \]
where

\[ NIMTAAVG_t = \frac{1 - \phi^3}{1 - \phi^{12}} \cdot \sum_{i=0}^{9} \phi^i \cdot NIMTA_{t-i,t-i-2}; \]

\[ EXRETAVG_t = \frac{1 - \phi}{1 - \phi^{12}} \cdot \sum_{i=0}^{11} \phi^i \cdot EXRET_{t-i}; \]

\[ \phi = 2^{-1/3}; \quad NIMTA = NIQ/(ME + LTQ); \quad NIQ \text{ is the quarterly net income; } ME \]

is the firm’s market capitalization; \( LTQ \) is the quarterly total liabilities; \( EXRET = \log R_i - \log R_{S&P500} \); \( R_i \) is the firm’s stock return in a month, and \( R_{S&P500} \) is the return to the S&P500 index in the same month; \( TLMTA = LTQ/(ME + LTQ) \); \( SIGMA \) is the annualized standard deviation of the stock’s daily return in the most recent 3 months; \( RELSIZE = \log(ME/USDVAL_{t-1}); \) \( USDVAL_{t-1} \) is the market cap of the S&P500 index in the previous month; \( CASHMTA = CHEQ/(ME + LTQ); \) \( CHEQ \) is the quarterly cash and cash equivalents; \( MB = ME/ADJBEQ; \) \( ADJBEQ \) is the adjusted book equity, obtained by increasing the Compustat book equity value (\( BEQ \)) by 10% of the difference between market equity and book equity; \( PRICE \) is the lagged stock price.
Appendix B — Proofs

A Proofs

Recall the definitions of $g$ and $G$ in (3.3) and (3.4). As pointed out in (3.5), the definitions imply directly that $g(x)G'(x) = x - G(x)$. Recall also that strict log concavity of $F$ implies $g' > 0$ and $G' < 1$.

Proof of Theorem 1. The dealer’s expected profit (3.7) is equal to

$$[s + G(B + \Delta - s) - B] F(B + \Delta - s).$$

For simplicity, set $x = B + \Delta - s$, so we can write the expected profit as

$$[G(x) + \Delta - x] F(x).$$

Maximizing in $x$ is equivalent to maximizing in $B$. The claim in (3.8) is that the optimal $x$ is $g^{-1}(\Delta)$. The derivative of expected profit with respect to $x$ is

$$[G'(x) - 1] F(x) + [G(x) + \Delta - x] f(x).$$

To prove the claim about the optimum, it suffices to show that this derivative is positive for $x < g^{-1}(\Delta)$ and negative for $x > g^{-1}(\Delta)$. Making the substitution $g(x)G'(x) = x - G(x)$,
we see that the derivative equals

\[ [G'(x) - 1]g(x)f(x) + [G(x) + \Delta - x]f(x) = [\Delta - g(x)]f(x). \]

By the monotonicity of \( g \), \( \Delta - g(x) \) is positive for \( x < g^{-1}(\Delta) \) and negative for \( x > g^{-1}(\Delta) \). This completes the proof that (3.8) is the unique optimal bid.

The probability of trade for a dealer of type \( s \) is \( F(B^\dagger(s) + \Delta - s) \). From (3.8), the probability of trade is \( F(g^{-1}(\Delta)) \) for all \( s \). The equilibrium ask price for a dealer of type \( s \) is

\[ R(s, B^\dagger(s)) = s + G(B^\dagger(s) + \Delta - s) = s + G(g^{-1}(\Delta)). \]

Therefore, the equilibrium bid-ask spread for a dealer of type \( s \) is

\[ R(s, B^\dagger(s)) - B^\dagger(s) = G(g^{-1}(\Delta)) + \Delta - g^{-1}(\Delta). \]

Substitute \( x - G(x) = g(x)G'(x) \) for \( x = \gamma = g^{-1}(\Delta) \) to obtain the formula in the theorem. The bid-ask spread is positive, because \( G' < 1 \). The expected profit is the bid-ask spread multiplied by the probability of trade. \( \square \)

*Proof of Lemma 3.3.* We first need to show that there exists \( x_H \) satisfying (3.11). Note that because \( G'(x) = [x - G(x)]/g(x) \) and \( G' < 1 \) (due to log concavity), we have \( G(x_L) + g(x_L) > x_L \). Furthermore, by definition, \( g(x_L) = \Delta \). Hence, \( G(x) + \Delta - x > 0 \) at \( x = x_L \). Define

\[ x_H^* = \inf\{a > x_L \mid G(a) + \Delta - a \leq 0\}. \]

The function \( G(a) + \Delta - a \) is monotone decreasing \( (G' < 1) \), so it is positive below \( x_H^* \) and negative above. Furthermore, \( g(a) - \Delta > 0 \) for \( a > x_L \) due to the definition \( x_L = g^{-1}(\Delta) \).
and the monotonicity of \( g \). Thus, the integrand in (3.11) is positive for \( x \) between \( x_L \) and \( x^*_H \). Our goal is to show that

\[
\int_{x_L}^{x^*_H} \frac{g(a) - \Delta}{G(a) + \Delta - a} \, da = \infty.
\]

Therefore, there exists some \( x_H \in (x_L, x^*_H) \) such that (3.11) holds.

From the definition of \( x^*_H \), \( \Delta = x^*_H - G(x^*_H) \). Substitute this and \( g(x_L) = \Delta \) and change variables to \( z = x^*_H - a \) to obtain

\[
\int_{x_L}^{x^*_H} \frac{g(a) - \Delta}{G(a) + \Delta - a} \, da = \int_{0}^{x^*_H - x_L} \frac{g(x_H^* - z) - g(x_L)}{z + G(x_H^* - z) - G(x_H^*)} \, dz. \tag{B.1}
\]

Consider any \( x \) between \( 0 \) and \( x^*_H - x_L \). The integral (B.1) is at least as large as the integral of the same integrand from 0 to \( x \). Between 0 and \( x \), the numerator of the integrand is at least as large as \( g(x_H^* - x) - g(x_L) > 0 \). Also, \( G(x_H^* - z) - G(x_H^*) < 0 \), so the denominator, while positive, is smaller than \( z \). Therefore, the integral is at least as large as

\[
[g(x_H^* - x) - g(x_L)] \int_0^x \frac{1}{z} \, dz = \infty.
\]

This completes the proof that there exists some \( x_H \in (x_L, x^*_H) \) such that (3.11) holds. We have already observe that the integrand in (3.12) is positive for \( a \) between \( x_L \) and \( x^*_H \). This implies that \( s \) defined in (3.12) is strictly monotone.

\[ \square \]

**Proof of Theorem 2.** Clearly, the buyer’s strategy is optimal given the beliefs, and the beliefs are consistent with Bayes’ rule. We need to show that the dealer’s strategy is optimal.
The dealer’s strategy that we claim is an equilibrium strategy is $B^*(s) = x(s) - \Delta + s$, where $x(\cdot)$ is the inverse of (3.12). For convenience, we drop the * on $B^*$. From the condition $x(s_L) = x_L = g^{-1}(\Delta)$, we have $B(s_L) = g^{-1}(\Delta) - \Delta + s_L = B^1(s_L)$. Both here and in the first best world, the ask prices are $R(s, B(s))$, so Hence, Theorem 1 shows that

$$U(s_L, s_L, B(s_L)) = [1 - G'(x_L)]g(x_L)F(x_L) > 0. \quad (B.2)$$

Consider a dealer of type $s$. To show that $B(s)$ is the optimal bid, given the buyer’s strategy, we need to show that

$$U(s, s, B(s)) \geq U(s, s', B(s')) \quad (B.3)$$
$$U(s, s, B(s)) \geq U(s, s_L, B) \quad (B.4)$$
$$U(s, s, B(s)) \geq U(s, s_H, B) \quad (B.5)$$

Condition (B.3) states that $s' = s$ solves the maximization problem $\max_{s'} U(s, s', B(s'))$.

Using subscripts to denote partial derivatives, we have

$$\frac{d}{ds'} U(s, s', B(s')) = U_2(s, s', B(s')) + U_3(s, s', B(s')) \frac{dB(s')}{ds'}. \quad (B.6)$$

The first-order condition for $s' = s$ to be maximal is that

$$U_2(s, s, B(s)) + U_3(s, s, B(s)) \frac{dB(s)}{ds} = 0. \quad (B.7)$$

The first-order condition is sufficient for optimality—that is, for (B.3)—if the derivative (B.6) is nonnegative for $s' < s$ and nonpositive for $s' > s$. 
From (3.17), we have

\[ U_2(s, s', B) = [1 - G'(B + \Delta - s')] \cdot F(B + \Delta - s) \]
\[ U_3(s, s', B) = [G'(B + \Delta - s') - 1] \cdot F(B + \Delta - s) \]
\[ + [s' + G(B + \Delta - s') - B] \cdot f(B + \Delta - s) \]

After substituting these, substituting \( x(s) = B(s) + \Delta - s \), dividing by \( f(x(s)) \), and substituting \( g = F/f \) and \( g'G = x - G \), the first-order condition (B.7) becomes

\[ G(x(s)) + g(x(s)) - x(s) + [\Delta - g(x(s))]{dB(s) \over ds} = 0. \quad (B.8) \]

This holds for all \( s \in (s_L, s_H) \), because

\[ B'(s) = x'(s) + 1 = \frac{1}{s'(x(s))} + 1 = \frac{G(x(s)) + g(x(s)) - x(s)}{g(x(s)) - \Delta}. \]

Note also that \( U_2 > 0 \) because \( G' < 1 \). Therefore, by Theorem 6 of Mailath and von Thadden (2013), the derivative (B.6) is nonnegative for \( s' < s \) and nonpositive for \( s' > s \) if

\[ \frac{U_3(s, s', B(s'))}{U_2(s, s', B(s'))} \]

is an increasing function of \( s \) for each \( s' \). Making the same substitutions we used to derive (B.8), we can calculate the ratio (B.9) as

\[ -1 + \frac{G(x(s')) + \Delta - x(s')}{[1 - G'(x(s'))]g(B(s') + \Delta - s)} \]. \quad (B.10)
We need to show that the ratio in (B.10) is increasing in \( s \). The denominator is positive and decreasing in \( s \), because \( G' < 1 \) and \( g \) is strictly increasing. Note that the formula (3.17) for \( U \) gives us

\[
U(s', s', B(s')) = [G(x(s')) + \Delta - x(s')]F(x(s')) ,
\]

so the sign of the numerator in (B.10) is the same as the sign of \( U(s', s', B(s')) \). The formula (3.15) shows that \( U(s, s, B(s)) > 0 \) for all \( s \), so we can complete the proof of (B.3) by verifying (3.15).

The first-order condition (B.7) implies that

\[
\frac{d}{ds} U(s, s, B(s)) = U_1(s, s, B(s)) .
\]

Furthermore,

\[
U_1(s, s, B(s)) = -[G(x(s)) + \Delta - x(s)]f(x(s)) = -\frac{U(s, s, B(s))}{g(x(s))} .
\]

Hence, \( dU/U = -1/g \), which implies

\[
U(s, s, B(s)) = U(s_L, s_L, B_L) \exp \left( -\int_{s_L}^{s} \frac{1}{g(x(a))} da \right) .
\]

Substituting (B.2) yields (3.15).

Now, we have completed the proof of (B.3). We still need to establish (B.4) and (B.5). First, consider any bid \( B < B(s_L) \). The dealer's expected profit at that bid is

\[
U(s, s_L, B) = U(s_L, s_L, B) \cdot \frac{F(B + \Delta - s)}{F(B + \Delta - s_L)} .
\]
If \( U(s_L, s_L, B) \leq 0 \), then \( U(s, s_L, B) \leq 0 < U(s, s, B(s)) \), and we are done. So, assume \( U(s_L, s_L, B) > 0 \). The first factor on the right-hand side of (B.11) is maximized at \( B(s_L) > B \). The second factor is also larger at \( B(s_L) \) than at \( B < B(s_L) \), because, as explained in Section 3.2, it is increasing in \( B \) for \( s \geq s_L \). Hence,

\[
U(s, s_L, B) \leq U(s, s_L, B(s_L)) \leq U(s, s, B(s)),
\]

using the incentive compatibility condition (B.3) for the second inequality.

The proof of (B.5) is symmetric. The dealer’s expected profit at a bid \( B > B(s_H) \) is

\[
U(s, s_H, B) = U(s_H, s_H, B) \cdot \frac{F(B + \Delta - s)}{F(B + \Delta - s_H)}.
\]

(B.12)

As in the previous case, we can assume \( U(s_H, s_H, B) > 0 \). The first factor in (B.12) is maximized at \( B(s_H) < B \), and the second factor is a decreasing function of \( B \) (because \( s \leq s_H \), so

\[
U(s, s_H, B) \leq U(s, s_H, B(s_H)) \leq U(s, s, B(s)).
\]

From \( x'(s) > 0 \), we obtain \( B'(s) > 1 \). The bid-ask spread is

\[
s + G(x(s)) - B(s) = G(x(s)) + \Delta - x(s),
\]

which is strictly decreasing in \( s \) because \( x \) is strictly increasing in \( s \) and \( G' < 1 \). The probability of trade is \( F(x(s)) \), which is strictly decreasing in \( s \) because \( x \) is strictly increasing in \( s \) and \( F \) is monotone. \( \square \)
Proof of Theorem 3. With some simple algebra, we can write the derivative with respect to $B$ of the objective function in (3.19) as

$$f(B + \Delta - s) \left[ A + \Delta - s - h(B + \Delta - s) \right]. \quad \text{(B.13)}$$

This has a unique critical point given by (3.23). Furthermore, the monotonicity of $h$ (which it inherits from $g$) implies that the derivative (B.13) is positive to the left of the critical point and negative to the right, so the critical point is the unique maximum. It follows that a solution of (3.22) is an equilibrium ask.

Trade occurs if and only if $\bar{v} - \Delta \leq B^o(\bar{s}) = \bar{s} + y(\bar{s}) - \Delta$, so trade occurs if and only if $\bar{\varepsilon} \leq y(s)$, which occurs with probability $F(y(s))$. We can write (3.23) as

$$h(B^o(s) + \Delta - s) = A^o + \Delta - s.$$ 

Since $h(x) = x + g(x)$, this implies

$$B^o(s) + \Delta - s + g(B^o(s) + \Delta - s) = A^o + \Delta - s,$$

which yields a bid-ask spread of

$$A^o - B^o(s) = g(B^o(s) + \Delta - s) = g(y(s)).$$

It follows that the conditional expected profit of the dealer is $g(y(s))F(y(s))$. The monotonicity conditions stated in the theorem all follow from monotonicity of $g$ and $F$ and the fact that $y(s)$ is decreasing in $s$. \qed
B Uniqueness of Equilibrium

This appendix verifies four claims made in the text.

(I) The D1 criterion rules out pooling equilibria in the transparent market.

(II) There is only one separating equilibrium in the transparent market in which the ask
price is \( A(s) = R(s, B(s)) \) and the bid function is differentiable. That equilibrium is
given in Theorem 2.

(III) In any separating equilibrium in the transparent market in which the buyer’s beliefs
are weakly monotone in the ask price, the ask price must be \( A(s) = R(s, B(s)) \).
Hence, there is only one equilibrium that satisfies the D1 criterion and for which the
bid function is differentiable and the buyer’s beliefs are weakly monotone in the ask
price. That equilibrium is given in Theorem 2.

(IV) In any equilibrium in the opaque market in which the buyer’s beliefs are weakly
monotone in the ask price, the ask price must be \( A = \bar{R} \); that is, the equilibrium ask
must be a fixed point of (3.22).

(I) Ramey (1996) shows that the D1 criterion rules out pooling equilibria when a single-
crossing property holds. To match our model to Ramey’s notation, define

\[
V(s, A, B) = (A - B) F(B + \Delta - s) .
\]

This is the expected profit of a dealer of type \( s \) who plays the bid \( B \) and ask \( A \), when the ask
is accepted. In our model, the dealer sets the ask \( A \) at the buyer’s reservation price, given
the buyer’s perception of the dealer’s type. The reservation price is higher if the perceived
dealer type is higher. In Ramey’s setup, the bid \( B \) is chosen by the sender (the dealer) and
the ask \( A \) is selected by the receiver (the buyer) after observing the sender’s action, with higher asks being chosen by the receiver when the sender’s type is thought to be higher. Ramey shows that the D1 criterion rules out pooling equilibria if (i) higher actions \( A \) are better for the sender (dealer), (ii) the action \( A \) that would be chosen is increasing in the sender’s perceived type and (iii) the ratio

\[
\frac{V_3(s, A, B)}{V_2(s, A, B)}
\]

is increasing in the type \( s \) (this is the single-crossing property). In our model, \( V \) is increasing in \( A \) and

\[
\frac{V_3(s, A, B)}{V_2(s, A, B)} = -1 - \frac{B}{g(B + \Delta - s)}.
\]

This is increasing in \( s \) because \( g \) is an increasing function (due to log concavity). Hence, the D1 criterion rules out pooling equilibria in our model.

To discuss the other items, we need some additional notation. In any equilibrium, the buyer observes the bid and ask and forms beliefs about \( \tilde{v} \) and \( \tilde{s} \). The beliefs put probability 1 on the bid having been accepted, which is the event \( B(\tilde{s}) \geq \tilde{v} - \Delta \). Let \( \mu(\cdot \mid B, A) \) denote the buyer’s marginal distribution over \( \tilde{s} \) after observing a bid \( B \) and ask \( A \). The buyer’s joint distribution over \((\tilde{s}, \tilde{v})\) is determined by \( \mu(\cdot \mid B, A) \) and by the exogenously given conditional distribution of \( \tilde{v} \), conditioning on \( \tilde{s} \) and on the event \( B(\tilde{s}) \geq \tilde{v} - \Delta \). Assume that the map \( A \mapsto \mu(\cdot \mid B, A) \) is continuous in the topology of weak convergence of measures, for each \( B \).

The buyer’s reservation value after observing a bid \( B \) and ask \( A \) is

\[
\omega(B, A) \overset{\text{def}}{=} \int_{s_L}^{s_H} R(s, B) \mu(ds \mid B, A).
\]

(B.15)
Because \( R(\cdot, B) \) is nondecreasing, \( R(s_L, B) \leq \omega(B, A) \leq R(s_H, B) \) for all \( A \). It is optimal for the buyer to accept an ask \( A \) if and only if \( A \leq \omega(B, A) \). Define

\[
\mathcal{A}(B) = \{ A \in [R(s_L, B), R(s_H, B)] \mid A \leq \omega(B, A) \}.
\] (B.16)

and set

\[
\alpha(B) = \sup \mathcal{A}(B).
\] (B.17)

The continuity assumption in the previous paragraph implies that \( \omega \) depends continuously on \( A \); therefore, \( \mathcal{A}(B) \) is compact. Hence, \( \alpha(B) \in \mathcal{A}(B) \). The ask \( \alpha(B) \) is the maximum ask that will be accepted by the buyer after the dealer plays a bid \( B \).

(II) For the second item, observe first that the lowest type must play her first-best bid \( B^\dagger = g^{-1}(\Delta) - \Delta + s_L \) in any separating equilibrium. Suppose otherwise; that is, suppose the lowest type plays some bid \( \hat{B} \neq B^\dagger \) in a separating equilibrium. Because the equilibrium is separating, \( R(s_L, \hat{B}) \) is the buyer’s reservation value after observing the bid \( \hat{B} \). Hence, the ask \( \hat{A} \) played by the lowest type in the separating equilibrium must satisfy \( \hat{A} \leq R(s_L, \hat{B}) \). Therefore, the lowest type dealer’s expected profit is

\[
[\hat{A} - \hat{B}] \cdot F(\hat{B} + \Delta - s_L) \leq [R(s, \hat{B}) - \hat{B}] \cdot F(\hat{B} + \Delta - s_L).
\]

The definition of the first-best is that \( B^\dagger \) maximizes the expression on the right-hand side of this inequality. The optimum is unique (see the proof of Theorem 1), so

\[
[\hat{A} - \hat{B}] \cdot F(\hat{B} + \Delta - s_L) < [R(s, B^\dagger) - B^\dagger] \cdot F(B^\dagger + \Delta - s_L).
\]
Now, suppose the lowest type of dealer deviates from $\hat{B}$ to $B^\dagger$. Whatever inference the buyer makes after seeing the deviation, it cannot be worse than that the dealer is the lowest type. Therefore, the buyer’s reservation price $\alpha(B^\dagger)$ after seeing the deviation cannot be lower than $R(s, B^\dagger)$. Thus,

$$[\hat{A} - \hat{B}] \cdot F(\hat{B} + \Delta - s_L) < [\alpha(B^\dagger) - B^\dagger] \cdot F(B^\dagger + \Delta - s_L).$$

However, the right-hand side is the expected profit the lowest type of dealer can achieve after deviating to $B^\dagger$. The inequality shows that the deviation is profitable, contradicting the assumption that the lowest type plays any $\hat{B} \neq B^\dagger$ in a separating equilibrium.

The first-order condition for incentive compatibility is the differential equation (B.7). This must hold in any equilibrium in which the bid function is differentiable. Make the change of variables

$$x(s) = B(s) + \Delta - s.$$  \hspace{1cm} (B.18)

Using the fact that $G'(x) = [x - G(x)]/g(x)$, we can write the first-order condition (B.7) as

$$x'(s) = B'(s) - 1 = \frac{U_2(s, s, B(s))}{U_3(s, s, B(s))} - 1 = \frac{G(x(s)) + \Delta - x(s)}{g(x(s)) - \Delta}.$$  \hspace{1cm} (B.19)

The inverse to (B.19) is

$$s'(x) = \frac{g(x) - \Delta}{G(x) + \Delta - x}.$$  \hspace{1cm} (B.20)

The function (3.12) is the unique solution of (B.20) satisfying $s(x_L) = s_L$ (note that (B.20) is not actually an ODE, because $s$ does not appear on the right-hand side, so uniqueness follows from the fundamental theorem of calculus—that is, we can compute $s(\cdot)$ just by integrating (B.20)). Therefore, its inverse $x(\cdot)$ is the unique solution of (B.19) satisfying...
\( x(s_L) = x_L = g^{-1}(\Delta) \). Therefore, \( B(s) = x(s) - \Delta + s \) is the unique solution of the first-order condition (B.7) satisfying \( B(s_L) = g^{-1}(\Delta) - \Delta + s_L \).

**III** For the third item, assume that the buyer’s beliefs are monotone in the ask price in the sense that the buyer’s reservation price \( \omega(B, A) \) is weakly increasing in \( A \) for each \( B \). Whatever bid \( B \) any type of dealer plays in any equilibrium, the ask the dealer plays must be \( \alpha(B) \), because this is the largest ask the buyer will accept upon learning there was a transaction at the bid \( B \). Thus, for each dealer type \( s \), \( A(s) = \alpha(B(s)) \). We use monotonicity of beliefs to show that \( \alpha(B) = \omega(B, \alpha(B)) \). Thus, equilibrium asks must be \( A(s) = \omega(B(s), A(s)) \). In a separating equilibrium, the reservation price of the buyer is \( \omega(B(s), A(s)) = R(s, B(s)) \) by definition. Thus, equilibrium asks are \( A(s) = R(s, B(s)) \) as claimed. What remains is to show that \( \alpha(B) = \omega(B, \alpha(B)) \).

To see that \( \alpha(B) = \omega(B, \alpha(B)) \), note first that, because \( \alpha(B) \in A(B) \), \( \alpha(B) \leq \omega(B, \alpha(B)) \). Suppose \( \alpha(B) < \omega(B, \alpha(B)) \). Choose any real number \( a \) satisfying \( \alpha(B) < a < \omega(B, \alpha(B)) \). By monotonicity of beliefs, \( a < \omega(B, \alpha(B)) \leq \omega(B, a) \), so \( a \in A(B) \). But, then \( \alpha(B) < a \) contradicts the fact that \( \alpha(B) \) is the supremum of \( A(B) \). This contradiction implies \( \alpha(B) = \omega(B, \alpha(B)) \).

**IV** For the fourth item, let \( \hat{\mu}(\cdot \mid A) \) denote the buyer’s marginal distribution over \( \tilde{s} \) and \( B \) after observing an ask \( A \) and knowing that \( \tilde{v} \leq B(\tilde{s}) + \Delta \), but without observing \( \tilde{s} \) or \( B(\tilde{s}) \). The buyer’s reservation value after observing an ask \( A \) is

\[
\hat{\omega}(A) \stackrel{\text{def}}{=} \int_{[s_L, s_H] \times \mathbb{R}} R(s, B) \hat{\mu}(ds, dB \mid A).
\]  

(B.21)

It is optimal for the buyer to accept an ask \( A \) if and only if \( A \leq \hat{\omega}(A) \). For an equilibrium ask \( A^0 \), the Bayesian-Nash requirement for a pooling equilibrium specifies that \( \hat{\omega}(A^0) = \tilde{R} \).
defined in (3.18); that is, the beliefs $\bar{\mu}(\cdot \mid A^o)$ must conform to the given exogenous distribution of $\bar{s}$ and equilibrium play $B^o(s)$.

Define

$$\hat{A} = \{A \mid A \leq \hat{\omega}(A)\} \quad (B.22)$$

and $\hat{\alpha} = \sup \hat{A}$. As in part (III), the dealer must charge $\hat{\alpha}$ in equilibrium—that is, $A^o = \hat{\alpha}$.

Thus, $\hat{\omega}(\hat{\alpha}) = \tilde{R}$, and we obtain the desired conclusion $A^o = \tilde{R}$ once we establish that $\hat{\alpha} = \hat{\omega}(\hat{\alpha})$. This follows as in part (III) when $\hat{\omega}(\cdot)$ is a continuous monotone function.
C  Calculations in the Uniform/Normal Model

This appendix explains how to calculate the equilibria in the transparent and opaque markets in the uniform/normal model. Let \( N \) denote the standard normal distribution function, and let \( n \) denote the standard normal density function. Then, \( F(x) = N(x/\sigma) \) and \( f(x) = n(x/\sigma)/\sigma \). Hence, \( g(x) = \sigma\, n(x/\sigma)/n(x/\sigma) \). Also,

\[
G(x) = -\frac{\sigma\, n(x/\sigma)}{N(x/\sigma)} = -\frac{\sigma^2}{g(x)}.
\]

Therefore, equation (3.12) for the transparent market becomes

\[
s(x) = s_L + \int_{x_L}^{x} \frac{g(a)^2 - \Delta g(a)}{(\Delta - a)g(a) - \sigma^2} da. \quad (3.12')
\]

Now, consider the opaque market. Note that

\[
\bar{R} = \frac{E[\bar{v} 1_{\{\bar{v} \leq B(\bar{s}) + \Delta\}]]}{E[1_{\{\bar{v} \leq B(\bar{s}) + \Delta\}]}] = \frac{E[R(\bar{s}, B(\bar{s}))F(B(\bar{s}) + \Delta - \bar{s})]}{E[F(B(\bar{s}) + \Delta - \bar{s})]}.
\]

The first equality is the definition of the conditional expectation, and the second equality follows from the law of iterated expectations applied to the numerator and denominator separately. Here, we have

\[
R(s, B) = s + G(B + \Delta - s) = s - \frac{\sigma^2}{g(B + \Delta - s)}.
\]

Therefore,

\[
R(s, B)F(B + \Delta - s) = sF(B + \Delta - s) - \sigma^2 f(B + \Delta - s).
\]
Substitute this and (3.20) into the fixed point condition (3.22) to obtain

\[
A = \left( \int_{s_L}^{s_H} F(h^{-1}(A + \Delta - s)) \, ds \right)^{-1} \\
\quad \times \int_{s_L}^{s_H} \left[ sF(h^{-1}(A + \Delta - s)) - \sigma^2 f(h^{-1}(A + \Delta - s)) \right] \, ds.
\]

In the integrals, make the change of variable \( z = h^{-1}(A + \Delta - s) \). In this normal example, \( h'(x) = 2 + xg(x)/\sigma^2 \). Therefore, \( ds = -[2 + zg(z)/\sigma^2] \, dz \). We obtain

\[
A = \left( \int_{h^{-1}(A + \Delta - s_L)}^{h^{-1}(A + \Delta - s_H)} F(z) \left[ 2 + \frac{zg(z)}{\sigma^2} \right] \, dz \right)^{-1} \\
\quad \times \int_{h^{-1}(A + \Delta - s_L)}^{h^{-1}(A + \Delta - s_H)} \left[ [A + \Delta - z - g(z)] F(z) - \sigma^2 f(z) \right] \left[ 2 + \frac{zg(z)}{\sigma^2} \right] \, dz,
\]

where \( z_i = h^{-1}(A + \Delta - s_i) \) for \( i = L, H \) (note \( z_H < z_L \)). We solve this condition numerically to find the equilibrium ask (see Figure 1).