RFS Advance Access published August 30, 2013

Asset Pricing in the Dark: The Cross-Section of OTC Stocks

Andrew Ang
Columbia University

Assaf A. Shtauber
Columbia University

Paul C. Tetlock
Columbia University

Over-the-counter (OTC) stocks are far less liquid, disclose less information, and exhibit lower institutional holdings than do listed stocks. We exploit these different market conditions to test theories of cross-sectional return premiums. Compared with premiums in listed markets, the OTC illiquidity premium is several times higher, the size, value, and volatility premiums are similar, and the momentum premium is three times lower. The OTC illiquidity, size, value, and volatility premiums are largest among stocks held predominantly by retail investors and those not disclosing financial information. Theories of differences in investors' opinions and limits on short sales help explain these return premiums. (*JEL* G02, G12, G14)

Although hundreds of studies have investigated expected return patterns in listed stocks that trade on the NYSE, AMEX, and NASDAQ, many U.S. stocks—roughly one-fifth of the number of stocks listed on the major exchanges—trade in over-the-counter (OTC) markets. The definition of an OTC stock is one that trades on either the OTC Bulletin Board (OTCBB) or OTC Link (formerly Pink Sheets, or PS) interdealer quotation system, where at least one licensed broker-dealer agrees to make a market in the stock. We examine market data for 6,668 OTC firms from 1977 through 2008. To our knowledge, this is the largest dataset of U.S. stock prices to be introduced to research since the Center for Research on Security Prices (CRSP) added data on NASDAQ stocks in 1984.

We thank Bill Aronin for providing MarketQA data. We appreciate helpful comments from Andrew Karolyi (editor), David Hirshleifer (executive editor), two anonymous referees, Randy Cohen, Kent Daniel, Larry Harris, Cam Harvey, Narasimhan Jegadeesh, Charles Jones, Tyler Shumway, Rossen Valkanov, and Adrien Verdelhan. We are also grateful to seminar participants at the Western Finance Association meetings and at the following universities: Arizona, Berkeley, Columbia, Michigan, North Carolina, Stanford, and Virginia. This work was supported by the Netspar (to A.A.). Send correspondence to Paul Tetlock, Uris Hall 811, Columbia Business School, New York, NY 10027, USA; telephone: (212) 854-1901. E-mail: paul.tetlock@columbia.edu.

doi:10.1093/rfs/hht053

The OTC and listed stock markets consist of many similar firms and market participants. More than 80% of OTC firms with market capitalizations above $1 million are traded in listed markets before, concurrently, or after their OTC trading activity. Most broker-dealers who act as market makers in OTC stocks are also market makers in listed markets. Moreover, many investors, including retail investors and hedge funds, actively trade both groups of stocks.

There are, however, three important differences between OTC and listed stocks. First, there is far lower liquidity in OTC markets than on the major exchanges. Second, whereas firms in listed stock markets must file regular financial disclosures, disclosure requirements for firms traded in OTC markets are minimal, if nonexistent, for most of our sample period.[1] Third, noninstitutional (i.e., retail) investors are the primary owners of most OTC stocks, whereas institutional investors hold significant stakes in nearly all stocks on listed exchanges, including small stocks. Possibly as a consequence of low ownership by institutions, the main lenders of shares, short selling of OTC stocks is difficult, expensive, and rare.

We exploit these features of OTC and listed stock markets to distinguish among numerous theories of return premiums. Differentiating theories whose predictions depend on stocks' information environments and investor clientele using only the listed markets is challenging because all listed stocks are subject to the same reporting requirements and nearly all are held by institutions.[2] We estimate return premiums both within and across OTC markets and listed markets, sorting stocks by the characteristics that distinguish the two markets. This combined cross-market and within-market identification strategy allows for powerful tests of competing theories because the data exhibit enormous heterogeneity along both dimensions.

In light of the large cross-market differences in liquidity, we devote special attention to measuring illiquidity premiums. We find that the return premium for illiquid stocks is much higher in OTC markets than in listed markets. One of our key liquidity measures is the proportion of nontrading days (*PNT*), where higher *PNT* indicates higher illiquidity, and we sort OTC stocks into *PNT* quintiles. When constructing listed return factors, we focus on *comparable*-listed stocks with market capitalizations similar to the typical OTC stock to control for differences in firm size. We first evaluate factors' precost returns. We find that an OTC PNT factor has an annual Sharpe ratio of 0.91, whereas the comparable-listed PNT factor has a Sharpe ratio of just 0.14.

Asset pricing theories based on transaction costs, such as Amihud and Mendelson (1986) and Constantinides (1986), do not explain the OTC

[1] After June 2000, firms listed on the OTCBB, but not the PS, must have at least 100 shareholders, file annual reports, hold annual shareholder meetings, and meet other governance requirements (see Bushee and Leuz 2005).

[2] Researchers can also use international data, e.g., Bekaert, Harvey, and Lundbland (2007), or different asset classes, e.g., Karolyi and Sanders (1998), to study determinants of return premiums. International studies are hampered by different treatments of creditor rights and securities not having the same claims to cash flows across countries.

illiquidity premium. These theories predict that stocks exhibit precost risk-adjusted returns that are positive and increase with bid-ask spreads to compensate rational investors for their expected trading costs. Empirically, the most liquid OTC stocks exhibit negative risk-adjusted monthly precost returns of –4.0%, implying that their postcost returns are even more negative. In addition, the typical OTC investor incurs trading costs of less than 50 basis points per month, suggesting that the magnitudes of trading costs are too small to explain our findings. Data errors or microstructure biases in OTC stocks also do not explain the OTC illiquidity premium. Such errors and biases should be smaller in the most liquid stocks and actually would bias the returns of OTC stocks upward, implying their returns after adjusting for illiquidity effects and data errors should be even more negative.

The strongly negative returns of liquid OTC stocks are consistent with the idea that limits to arbitrage allow the OTC illiquidity premium to remain so high during our thirty-two-year sample. Given the difficulty in short selling even liquid OTC stocks, an arbitrageur could be unable to attain the high Sharpe ratio of the OTC illiquidity premium. We also provide evidence that trading costs, although relatively insignificant for the typical OTC investor who trades very infrequently, could severely limit the effectiveness of short-horizon arbitrage in OTC stocks.

Next, we test whether the well-known return premiums for stocks with low market capitalizations ("size"), high ratios of book equity to market equity ("value" or B/M), low idiosyncratic volatility ("volatility"), and high past returns ("momentum") generalize to OTC markets.[3] Interestingly, the return premiums for size, value, and volatility are similarly large in OTC stocks and comparable-listed stocks. In contrast, the return premium for momentum is considerably smaller and less robust in OTC markets than in listed markets.[4] Most of the OTC return premiums above are driven by the negative returns on the short legs of the long-short portfolios, again consistent with theories in which limits to short selling affect prices.

We find that traditional factor models—using factors constructed from listed returns—do not account for the large illiquidity, size, value, and volatility return premiums in OTC markets. We also show that the correlations between OTC return factors and their listed counterparts are typically well below 0.5. The correlation between the OTC illiquidity factor and Pastor and Stambaugh's (2003) listed illiquidity factor is close to zero. These facts show that the OTC factor structure differs significantly from the factor structure of listed stocks, presenting a challenge for explanations of return premiums based on economy-wide risk factors.

---

[3] Studies of listed stocks by Banz (1981), Fama and French (1992), Ang et al. (2006), and Jegadeesh and Titman (1993) provide early evidence of the size, value, volatility, and momentum premiums, respectively.

[4] Momentum is often thought to be pervasive in that it occurs in many different countries and asset classes (see, for example, Asness, Moskowitz, and Pedersen 2013).

We examine in our final tests whether theories based on behavioral biases and limits to arbitrage can explain OTC and listed return premiums. Models analyzing the impact of differences in opinion and limits on short sales could apply to both OTC and listed markets. In Appendix A, we present a model of OTC stock pricing inspired by the theories of Miller (1977), Duffie, Garleanu, and Pedersen (2002), and Scheinkman and Xiong (2003). The key mechanism is that costs of short selling discourage the participation of investors with the most pessimistic views of a stock, which causes overpricing followed by negative risk-adjusted returns. In the model, investors' overconfidence in their preferred valuation signals causes disagreement. Disclosure of financial information reduces differences in opinion by resolving uncertainty, over which investors can disagree.

The model predicts that differences in opinion and overpricing are associated with high values of four stock characteristics: trading volume, return volatility, market capitalization, and market-to-book equity ratio (M/B). These relations are stronger for stocks with higher investor overconfidence and those with fewer disclosures. The model's first four predictions are consistent with the evidence that OTC stocks with high volume, volatility, size, and M/B exhibit negative abnormal returns. Importantly, we also find evidence consistent with both sets of the model's predicted interaction effects. Motivated by Barber and Odean's (2000) evidence that retail investors are overconfident, we use a stock's institutional ownership as an inverse measure of investor overconfidence. We show that the return premiums for *PNT*, volume, volatility, value, and size are 1.0% to 4.4% per month larger in OTC stocks that are not held by institutions. We then measure OTC firms' disclosure of book equity data, which is basic financial information relevant for valuation. Empirically, OTC return premiums based on three proxies for disagreement—*PNT*, volume, and volatility—are 1.4% to 1.6% per month larger among stocks with undisclosed book equity.

Our cross-market findings are also consistent with the idea that our model of overpricing applies more to OTC markets than listed markets. Our evidence indicates that short selling is more difficult in OTC markets; the lower disclosure and higher proportion of retail clientele in OTC markets suggest investor disagreement could be greater. The fact that the OTC illiquidity premium exceeds the listed premium is consistent with this notion. Moreover, we find that the return on the entire OTC market is actually significantly negative at –0.8% per month, implying widespread overpricing of OTC stocks. This negative return is driven by the OTC stocks with the most trading activity, over which investors likely disagree most.

Although our model of overpricing provides a plausible account of many return premiums, it does not make clear predictions for the momentum premium. We investigate momentum further and find evidence that is most consistent with Hong and Stein's (1999) model based on the gradual diffusion of information across investors. The lack of momentum for most OTC stocks is consistent with the idea that investors do not attend closely to most OTC firms' fundamentals, perhaps because these firms lack credibility. We also find that momentum is strongest among OTC stocks that disclose basic financial information and among the largest OTC firms, which presumably have more credibility. Furthermore, momentum among large OTC firms does not exhibit any reversal over five years, consistent with Hong and Stein's (1999) model but difficult to reconcile with some alternative models of momentum.

1. Related Studies of OTC Stocks

Only a few studies investigate stock pricing in OTC markets.[5] Studies by Luft, Levine, and Larson (2001) and Eraker and Ready (2011) find that the average OTC market return is negative during sample periods spanning 1995 to 2008. Although we use the OTC market return as a factor in some of our tests, we focus on the cross-section of OTC returns.[6] In many cases, the differences among OTC stocks' returns are much larger than the (negative) OTC market premium and are not explained by exposures to the OTC market factor.

Studies of OTC firms' liquidity and disclosure are also relevant. Three studies examine how liquidity changes for stocks that move from listed markets to the OTC markets. Sanger and Peterson (1990) show that quoted bid-ask spreads triple for 57 firms that are delisted and then trade in OTC markets from 1971 to 1985. Harris, Panchapagesan, and Werner (2008) show that volume falls by two-thirds, quoted bid-ask spreads double, and effective spreads triple for 1,098 firms that are delisted from NASDAQ in 1999 to 2002 and subsequently trade on OTC markets. Macey, O'Hara, and Pompilio (2008) also find higher spreads for most of the 58 NYSE stocks that move to OTC markets in 2002. These studies suggest that the shift in trading to OTC venues actually causes stocks to become less liquid.

Leuz, Triantis, and Wang (2008) investigate a firm's decision to "go dark," which means a firm ceases to report to the SEC while continuing to trade publicly in OTC markets. They find that 480 firms go dark between 1998 and 2004 and experience negative average abnormal returns of –10% upon announcement. We analyze the returns of all OTC firms, including those that have gone dark (a minority), those that have never reported to the SEC, and those that currently report to the SEC. OTC firms' past disclosure policies and financial reports are available to investors and thus should be reflected in stock prices insofar as they affect investors' valuations.

---

5 Bollen and Christie (2009) examine various aspects of OTC stock microstructure but do not investigate cross-sectional return premiums.

6 Luft and Levine (2004) also explore how OTC stocks' returns are related to their size and liquidity, but they do not perform formal statistical tests, presumably because their sample spans only the five years from 1996 to 2000.

2. OTC Market Data

2.1 Institutional details

Our data consist of U.S. common stocks traded in the OTCBB and PS markets from 1977 through 2008. We obtain these data through MarketQA, a Thomson Reuters data analytics platform. The OTC markets are regulated by the Financial Industry Regulatory Authority (FINRA), formerly the National Association of Securities Dealers (NASD), and the SEC to enhance market transparency, fairness, and integrity. For most of our sample, the defining requirement of an OTC stock is that at least one FINRA (formerly NASD) member is willing to act as a market maker for the stock.

As of June 2010, over 211 FINRA firms were market makers in OTC stocks, facilitating daily trading activity of \$395 million (\$100 billion annualized). The most active firms, e.g., Archipelago Trading Services and Knight Equity Markets, are also market makers in stocks listed on the NASDAQ and are SEC-registered broker-dealers. FINRA requires market makers to trade at their publicly displayed quotations.

Prior to 2000, the key formal disclosure requirement for firms traded on the OTCBB and PS was Section 12(g) of the Exchange Act. This provision applies only to OTC firms with more than 500 shareholders of record and \$10 million in assets. Yet the vast majority of beneficial owners of OTC firms are not shareholders of record as their shares are held in "street name" through their brokers. So even large OTC firms can circumvent this disclosure requirement.

FINRA and SEC regulation of OTC markets, however, has increased substantially since 2000. After June 2000, firms quoted on the OTCBB must have at least 100 shareholders, file annual reports, hold annual shareholder meetings, and meet other governance requirements (Bushee and Leuz 2005). However, these disclosure requirements do not apply to PS firms, and they did not apply to OTCBB firms for most of our sample period.

We later provide evidence that the majority of investors in the firms traded exclusively on OTC markets are individuals rather than institutions. Individual investors can buy and sell OTCBB and PS stocks through most full-service and discount brokers, such as E-Trade, Fidelity, and Schwab. However, short selling OTC stocks is difficult for investors, especially individuals. We collect short-selling data for a sample of 50 OTC stocks and 50 similarly sized listed stocks in June 2012.[7] A retail customer of Fidelity could buy all 100 of these stocks, but the broker would allow short selling in only one of the OTC stocks and eight of the listed stocks. Despite the constraints on individuals, for the 50 listed stocks, short interest as a percentage of floating shares averages 4.1% and exceeds 0.1% for all 50. In contrast, for the 50 OTC stocks, short interest averages just 0.5% and is lower than 0.1% for 28 of the stocks—though it is positive for all but seven stocks. We infer that it is hard for individual investors

[7] These data are available upon request.

to short most small stocks; nearly all investors have difficulty shorting OTC stocks. Thus, the OTC market is a natural place to test theories of limits on short sales.

2.2 OTCBB and PS data

We examine the universe of firms incorporated in the U.S. with common stocks that are traded in OTC markets from 1977 through 2008. Our analysis uses only OTC firms without stocks that have been listed on the NYSE, NASDAQ, or AMEX exchanges within the last three months. We purposely exclude listed firms to ensure our sample firms are distinct from those listed on the traditional venues. MarketQA provides daily trading volume, market capitalization, and closing, bid, and ask prices for these firms.

To ensure adequate data quality, we further restrict the sample to firms that meet each of the following requirements in the previous month. Firms must have

- nonmissing data on stock price, market capitalization, and returns,
- a stock price that exceeds \$1,
- market capitalization that exceeds \$1 million in 2008 dollars,
- at least one nonzero daily return, and
- positive trading volume—imposed only after 1995 when volume data are reliable.[8]

The above price restriction follows Ince and Porter (2006), who find that errors in computed returns are more likely to occur for firms with prices of less than \$1.[9] The market capitalization restriction is designed to eliminate thinly traded and economically unimportant firms that would otherwise dominate equal-weighted portfolios. The nonzero return and positive volume restrictions exclude thinly traded firms that suffer from bid-ask bounce and nonsynchronous trading issues.[10] Our final OTC sample includes an average of 486 firms per month.

2.3 Comparison to listed stocks

We compare our sample of OTC stocks to common stocks listed on the NYSE, NASDAQ, or AMEX exchanges using CRSP data. We define three groups of stocks: active, eligible, and comparable. *Active* stocks have at least one nonzero daily return in the past year. *Eligible* stocks meet our data requirements in

[8] Prior to 1995, some OTC firms' volume data are recorded as missing when they are actually zero and vice versa. We set all missing volume to zero prior to 1995 because we find that such firms have low volume when volume data become available. Our results are virtually unchanged if we instead treat these firms' volume data as missing.

[9] In untabulated results, we find that using a minimum price of \$0.10 results in similar OTC return premiums.

[10] These filters also minimize the impact of market manipulation on our results. Aggarwal and Wu (2006), Böhme and Holz (2006), and Frieder and Zittrain (2007) show that market manipulation can affect OTC stocks.

Table 1
Summary statistics for the OTC and listed samples in July 1997

	OTC	Comparable listed	Eligible listed
Total market capitalization (billions)	21.3	15.1	9,592
Median market capitalization (millions)	12.9	12.9	36
Mean market capitalization (millions)	35.5	12.7	1,346
Trading volume (annualized billions)	8.2	15.2	11,472
Median trading volume (annualized millions)	2.3	6.1	101
Mean trading volume (annualized millions)	13.7	12.8	1,608
Number of firms	600	1,190	7,127

We report statistics for size, volume, and the number of firms in the OTC, comparable-listed, and eligible-listed samples in July 1997, a typical month in terms of our OTC sample size. We construct the comparable-listed sample to have the same median size as the OTC sample. The eligible-listed sample consists of all listed stocks that satisfy the same data requirements as the OTC stocks in our sample, as described in Section 2.2.

Section 2.2. *Comparable* stocks in the listed sample consist of the $2N$ eligible-listed firms with the lowest market capitalizations, where N is the number of listed firms with a market capitalization below the median market capitalization in OTC markets in each month. These listed firms are comparable to OTC firms in terms of size.

Table 1 provides a snapshot of summary statistics for the OTC, comparable-listed, and eligible-listed samples in July 1997, a typical month of OTC market activity. In this month, the median market capitalization of an OTC stock is \$12.9 million, as compared with \$36 million for the eligible-listed sample. The difference in total market capitalization is much larger (\$21.3 billion vs. \$9.59 trillion) because the largest listed firms are enormous and because there are twelve times fewer OTC stocks (600 OTC stocks vs. 7,127 listed stocks). The annualized median OTC trading volume is only 2.2% of the median eligible-listed trading volume (\$2.3 million vs. \$101 million, respectively).[11] The aggregate annualized transactions in OTC stocks exceed \$8.2 billion, whereas trades in eligible-listed stocks exceed \$11.4 trillion.

By design, the OTC sample is more similar to the comparable-listed sample described in the second column of Table 1. In particular, the median size is identical in the two samples (\$12.9 million). Although median sizes match perfectly, the mean size in the OTC markets is larger (\$35.5 million) than that of the comparable-listed sample (\$12.7 million) because some OTC firms are quite large, as discussed below.[12] In July 1997, the mean of OTC trading volume at \$13.7 million is very similar to that of the comparable-listed sample at \$12.8 million. Although mean volumes match well, the median OTC volume is smaller than that of the comparable-listed sample (\$2.3 million vs. \$6.1 million, respectively), which is not surprising given the thinner OTC market. In summary, the comparable-listed sample is a benchmark

[11] Listed trading volume statistics do not adjust for possible double-counting of NASDAQ interdealer trades.

[12] The average fraction of shares floating is reasonably similar for smaller manually collected samples of 50 OTC firms (53% floating) and 50 similarly sized listed firms (35% floating) in June of 2012.

group that is close in terms of size and trading characteristics to the OTC firms.

Averaging across all months in our sample, the number of firms is 5,228 in the listed sample and is 5,708 in the active-listed universe. The averages are 486 in our OTC sample and 3,357 in the active OTC universe. The OTC sample contains fewer firms than the active OTC universe, partly because 30% of OTC firms have a stock concurrently listed on the NASDAQ, making them ineligible for the sample.[13] When imposed individually, our sample filters for a nonzero daily return, minimum price of $1, nonmissing price, minimum market capitalization of $1 million, and nonmissing market capitalization eliminate 28%, 28%, 21%, 19%, and 16% of active OTC firms, respectively. Notably, none of these sample requirements has much impact on the listed sample, which contains 92% of the active firms in CRSP in an average month.

We now compare the size, volume, and number of firms in the OTC and eligible-listed samples over time. For this comparison, we transform the size and volume data to minimize the influence of outliers, which sometimes reflect data errors. In each month, we compute the difference in the cross-sectional average of the logarithms of size and ($1 plus) volume in the two samples. After taking the difference, we invert the log transform to obtain a ratio that can be interpreted as the OTC characteristic divided by the listed characteristic.

Figure 1 summarizes the size, trading volume, and number of firms in the OTC sample as a percentage of the corresponding amounts in the eligible-listed sample. The number of firms in the OTC sample averages 10% of the number in the listed sample, though this percentage increased to 24% by the end of 2008. The average firm size and trading volume in the OTC sample are an order of magnitude smaller than they are in the listed sample. The average OTC stock is 11% of the size of the average listed stock. The average OTC stock's volume is just 6% of that of the average listed stock. The relative size of OTC stocks has almost always been higher than their relative volume, consistent with lower liquidity in OTC markets. This gap between relative size and volume widens after 2000, as more illiquid firms are traded in OTC markets relative to listed markets.[14] The increase in the number of OTC firms in the late 1990s outpaces the concurrent rise in the number of listed firms. The relative increase in OTC firms after 2003 coincides with the passage of the Sarbanes-Oxley Act when many listed firms choose to "go dark."

Although the typical OTC firm is smaller than most listed firms, there are several large OTC firms that have market capitalizations similar to large listed

[13] In untabulated tests, we find that cross-listed OTC and NASDAQ stocks exhibit return premiums much like other listed stocks. The impact of NYSE versus NASDAQ listing choice has been studied in Baruch and Saar (2009) and others. International cross-listing effects have been studied by Baruch, Karolyi, and Lemmon (2007) and others.

[14] As explained in footnote 8, a structural break in OTC volume reporting causes the gap to appear to widen in July 1995. Average OTC volume would be lower prior to July 1995 if volume data on all OTC firms were available.

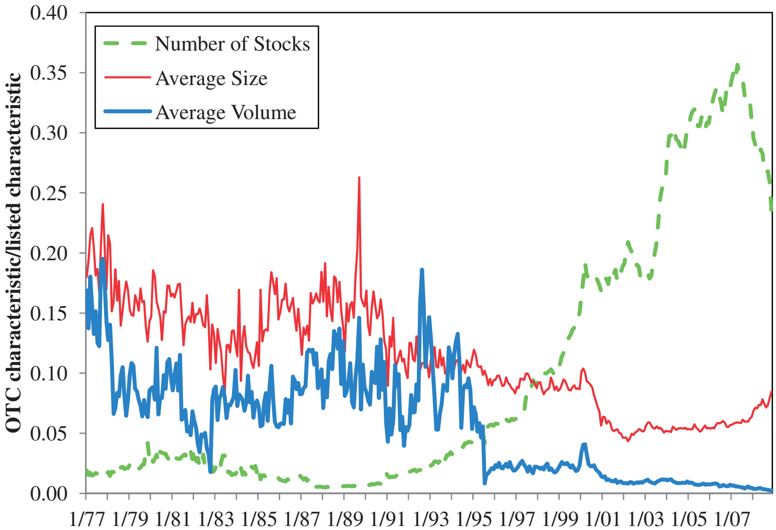

Figure 1
OTC sample characteristics as a percentage of listed sample characteristics
For each month, we plot the average size, average trading volume, and number of stocks in the OTC sample as a percentage of the corresponding statistics in the eligible-listed sample. To minimize the influence of outliers and possible data errors, we transform the size and volume data for this comparison. In each month, we compute the difference in the cross-sectional average of the logarithms of size and ($1 plus) volume in the two samples. We then invert the log transform to obtain a ratio that can be interpreted as the OTC characteristic divided by the listed characteristic. We exclude volume data from firms with zero monthly volume prior to July 1995, the date when volume data become reliable. The eligible-listed sample consists of the CRSP stocks that satisfy the same data requirements as the OTC sample described in Section 2.2.

firms. Table 2 lists the firm size and month in which the ten largest firms in our sample attain their peak size. These firms have market capitalizations measured in billions. The largest firm, Publix Supermarkets, reaches a market capitalization of $88 billion at the end of our sample in December 2008. It would rank 18th in size in the listed sample in that month, which exceeds the median of the top percentile. Several large companies, such as Delphi Corp., trade on PS after delisting from NYSE, NASDAQ, or AMEX. We inspect the entire time series of data for all 77 OTC firms with peak sizes exceeding $1 billion. We correct 19 errors arising from an incorrect number of shares outstanding. Such errors apply mainly to the largest of these 77 firms and do not affect the firms' returns. Still, these data errors suggest one should be careful when interpreting OTC size data and value-weighted portfolio returns.

In summary, the typical OTC stock is smaller, less liquid, and harder to short than the typical listed stock. However, the largest 10% of OTC stocks are comparable in size to the median-sized listed stock. The number of firms in our OTC sample is substantial, averaging almost 10% of all listed stocks and increasing dramatically after 2000. Thus, although the OTC market is much smaller than the market for listed stocks, the OTC universe is a powerful new venue to test the determinants of return premiums.

Table 2
The peak sizes of the largest ten OTC firms

Company name	Peak month	Trading venue	Peak size in billions	Size rank in listed sample	Size percentile in listed sample
PUBLIX SUPER MARKETS INC	Dec-08	OTCBB	88.5	18th	99.5%
DELPHI CORP	Mar-08	Pink Sheets	13.0	225th	94.8%
MCI INC	Jan-04	Pink Sheets	7.7	292nd	93.9%
MAXIM INTEGRATED PRODS INC	May-08	Pink Sheets	7.1	381st	91.2%
LEVEL 3 COMMUNICATIONS INC	Feb-98	OTCBB	6.6	297th	95.8%
NAVISTAR INTL CORP NEW	May-08	Pink Sheets	5.3	464th	89.3%
COMVERSE TECHNOLOGY INC	May-07	Pink Sheets	4.7	567th	87.6%
MERCURY INTERACTIVE CORP	Oct-06	Pink Sheets	4.6	515th	88.8%
ACTERNA CORP	Oct-00	OTCBB	3.0	623rd	89.8%
HEALTHSOUTH CORP	Dec-04	Pink Sheets	2.5	734th	84.4%

This table describes the ten largest OTC firms in our sample from 1977 to 2008. The first column shows the month in which each firm attains its peak size. The third column shows its size in that month. The two rightmost columns show each OTC firm's size rank and percentile within the eligible-listed sample. The eligible-listed sample consists of all listed stocks that satisfy the same data requirements as the OTC stocks in our sample, as described in Section 2.3.

3. Variable Definitions

This section summarizes the key variables used in our analyses. Our return predictability tests require estimates of stocks' monthly returns and betas. We also measure several firm characteristics known to predict returns in listed stocks, such as size, book-to-market equity, past returns, idiosyncratic volatility, and illiquidity.

We compute a stock's return as the monthly percentage change in MarketQA's "total return index" variable, a cumulative stock price that accounts for dividends and splits.[15] We assign a monthly index value based on the last available daily index value. The sample filters we use ensure that this value is available within the last month. We use two past return variables: past one-month returns (*Ret*[–1]), which capture short-term serial correlation, and past twelve-month returns (*Ret*[–12,–2]), not including the past month, which capture stock price momentum.

Idiosyncratic volatility is defined relative to Fama and French's (1993) three-factor model, as in Ang et al. (2006). To estimate a stock's volatility in month t, we use a time-series regression from month $t-2$ to $t-1$ of the stock's daily return on the daily market (MKT), size (SMB), and value (HML) factors, as defined in Fama and French (1993). The stock's idiosyncratic volatility (*Volatility*) in month t is the log of the standard deviation of the residuals from its time-series regression. We use the same regression procedure as described in Appendix B, except that we apply this to daily rather than monthly observations.

We use three measures of individual stock illiquidity in our analyses. The main illiquidity measure is the proportion of days with no trading volume (*PNT*)

15 Much like Ince and Porter (2006), we correct firms' returns in cases in which extremely improbable return reversals occur—e.g., a firm's stock price changes from $57.00 to $5.70 and back to $57.00. None of the main results depend on our correction procedure, which is available upon request.

in each month. The *PNT* variable measures an investor's ability to trade a stock at all, which is highly relevant in illiquid markets, such as the OTC market. It more directly measures a lack of trading than does Lesmond, Ogden, and Trzcinka's (1999) proportion of days with zero returns. The variable *Volume* is the log of one plus a stock's monthly dollar volume. The variable *Spread* is the difference between a stock's ask and bid quotes divided by the bid-ask midpoint from the last day when both quotes are available. These other two illiquidity measures capture the amount of trading and the cost of trading in a stock, respectively.

In our return predictability tests, we use data on firm disclosure, institutional holdings, size, and book-to-market ratios. Firm disclosure (*Disclose*) is a dummy variable that is equal to one if a firm's book equity data is available from Compustat, Reuters Fundamentals, or Audit Analytics. We define book equity data as available if it appears in a firm's annual report between 7 and 19 months before the date of our tests. Institutional holdings (*InstHold*) is a dummy variable that indicates whether a firm's stock appears as a holding of at least one institutional manager or mutual fund that filed Form 13F, N-CSR, or N-Q with the SEC in the past three months, as recorded by Thomson Reuters. Firm *Size* is the log of the most recently available market capitalization data from MarketQA. The book-to-market variable (B/M) is the log of the ratio of book-to-market equity. We winsorize all independent variables at the 5% level to minimize the influence of outliers.

We report summary statistics of returns and variables for OTC stocks and comparable-listed stocks in Table 3, Panels A and B, respectively. The mean monthly return of OTC stocks is slightly negative at –0.04%, compared with 0.66% for comparable-listed stocks, which is consistent with Luft, Levine, and Larson (2001) and Eraker and Ready (2011). The cross-section of monthly OTC returns is also significantly more disperse than listed stocks, with cross-sectional standard deviations of 28.08% and 19.46%, respectively. OTC stocks are substantially more volatile than comparable-listed stocks, with average monthly average volatilities of 6.56% and 4.29% for the OTC and listed samples, respectively. The size and book-to-market distributions of firms in the OTC and comparable-listed samples are similar.

However, the OTC and listed samples exhibit very different levels of disclosure, institutional ownership, and liquidity. The mean of the *Disclose* dummy for book equity data is 0.60 in the OTC sample and 0.83 in the comparable-listed sample, suggesting that 40% of OTC firms choose not to disclose accounting data, whereas only 17% of small listed firms omit this information.[16] Table 3 shows that institutions hold an average of 26% of OTC stocks versus 71% of comparable-listed stocks. This evidence suggests that the

[16] Some of the lack of book equity data reflects incomplete coverage in our data sources. In unreported analyses, we find that our three data sources have significantly overlapping coverage, but no single source subsumes the others.

Table 3
Cross-sectional summary statistics for key variables

Panel A: OTC stocks

	Monthly averages								Total months
Variable	Mean	SD	P5	P25	P50	P75	P95	Firms	
Return (%)	−0.04	28.08	−34.73	−9.95	−1.30	4.86	39.23	486	383
Disclosure	0.60	0.46	0.00	0.29	0.65	1.00	1.00	486	383
Size	2.35	1.30	0.19	1.36	2.32	3.28	4.72	486	383
B/M	1.09	2.17	0.06	0.30	0.69	1.28	3.28	231	383
Volatility	6.56	5.52	0.79	2.33	4.95	8.97	20.57	476	383
Volume	8.25	3.57	4.43	5.67	7.01	10.96	14.62	486	383
PNT	0.55	0.34	0.01	0.28	0.63	0.82	0.94	486	383
Spread	0.15	0.14	0.02	0.05	0.10	0.20	0.51	391	192
InstHold	0.26	0.41	0.00	0.00	0.00	0.47	1.00	477	344

Panel B: Comparable-listed sample

	Monthly averages								Total months
Variable	Mean	SD	P5	P25	P50	P75	P95	Firms	
Return (%)	0.66	19.46	−24.45	−8.99	−1.22	7.28	32.16	1,018	383
Disclosure	0.83	0.33	0.28	0.65	1.00	1.00	1.00	1,018	383
Size	2.21	0.53	1.08	1.85	2.32	2.66	2.89	1,018	383
B/M	1.29	1.64	0.18	0.54	0.96	1.57	3.26	789	383
Volatility	4.29	2.13	1.22	2.65	3.97	5.61	8.99	1,005	383
Volume	10.77	1.98	8.11	9.48	10.27	12.35	14.26	1,018	383
PNT	0.20	0.21	0.00	0.03	0.13	0.33	0.67	1,018	383
Spread	0.08	0.04	0.02	0.04	0.07	0.10	0.18	538	303
InstHold	0.71	0.39	0.08	0.51	0.82	0.99	1.00	890	344

(*continued*)

Table 3
Continued

Panel C: Cross-sectional correlations among OTC stocks

	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	*Size*	B/M	*Volatility*	*Ret[−1]*	*Ret[−12,−2]*	*PNT*	*Volume*	*Disclosure*	*InstHold*
β_{MKT}	1.00	−0.08	0.42	0.02	0.03	−0.09	0.05	−0.01	−0.02	−0.15	0.12	0.06	0.02
β_{SMB}	−0.08	1.00	0.13	−0.01	−0.04	−0.05	0.10	−0.01	0.01	−0.14	0.11	0.03	−0.03
β_{HML}	0.42	0.13	1.00	0.03	0.03	−0.04	−0.03	0.01	−0.04	−0.03	0.03	0.03	0.04
β_{UMD}	0.02	−0.01	0.03	1.00	0.06	−0.02	−0.03	−0.01	0.02	0.00	0.02	0.01	0.02
Size	0.03	−0.04	0.03	0.06	1.00	−0.19	−0.36	0.05	0.15	−0.17	0.36	0.06	0.27
B/M	−0.09	−0.05	−0.04	−0.02	−0.19	1.00	−0.03	−0.03	−0.13	0.22	−0.19	−0.22	−0.02
Volatility	0.05	0.10	−0.03	−0.03	−0.36	−0.03	1.00	0.02	−0.01	−0.06	−0.11	0.01	−0.19
Ret[−1]	−0.01	−0.01	0.01	−0.01	0.05	−0.03	0.02	1.00	−0.01	0.04	0.01	0.02	−0.01
Ret[−12,−2]	−0.02	0.01	−0.04	0.02	0.15	−0.13	−0.01	−0.01	1.00	0.00	0.05	0.04	0.00
PNT	−0.15	−0.14	−0.03	0.00	−0.17	0.22	−0.06	0.04	0.00	1.00	−0.84	−0.12	−0.06
Volume	0.12	0.11	0.03	0.02	0.36	−0.19	−0.11	0.01	0.05	−0.84	1.00	0.10	0.17
Disclosure	0.06	0.03	0.03	0.01	0.06	−0.22	0.01	0.02	0.04	−0.12	0.10	1.00	0.17
InstHold	0.02	−0.03	0.04	0.02	0.27	−0.02	−0.19	−0.01	0.00	−0.06	0.17	0.17	1.00

We summarize the distributions of monthly returns and the main firm characteristics for the OTC and comparable-listed samples in Panels A and B, respectively. We construct the comparable-listed sample to have the same median size as the OTC sample. Panel C contains average cross-sectional correlations between betas and characteristics among OTC sample firms. We compute all statistics separately for the cross-section of stocks in each month and then average across months. We measure firm characteristics, except for *PNT*, using logarithms. We winsorize all firm characteristics at the 5% level, but we do not winsorize returns. The first seven columns in Panels A and B report monthly averages of means, standard deviations, and various percentiles. The second to last column reports the average number of firms with nonmissing values of each variable in each month. The last column reports the total number of months in which there is any data for each variable.

investor clientele in OTC markets is mainly retail, whereas institutions play a bigger role in listed markets.

The average of log volume (*Volume*) is much smaller for OTC stocks (8.25) than for comparable-listed stocks (10.77). OTC stocks also trade much less frequently: the mean fraction of days with no trading in a month, *PNT*, is 0.55 for OTC stocks, compared with 0.20 for comparable-listed stocks. The 95th percentile *PNT* value is 0.94, implying that the least frequently traded OTC stocks trade just one day per month. Average OTC *Spreads* are quite high at 0.15 versus 0.08 for comparable-listed stocks. We explicitly account for the impact of bid-ask bounce bias in OTC stocks' average returns using the Asparouhova, Bessembinder, and Kalcheva (2010) method described below.

Panel C in Table 3 shows average cross-sectional correlations among OTC firms' characteristics and their betas on listed return factors. Nearly all of the pairwise correlations are much less than 0.5. The exception is the large negative correlation of –0.84 between *PNT* and *Volume*, which indicates that these two variables reflect a common source of OTC illiquidity.

4. Comparing the Cross-Sections of OTC and Listed Returns

Following researchers who study listed stocks, we construct calendar-time portfolios of OTC stocks ranked by characteristics to estimate the expected returns of OTC factors. We compare OTC factor returns to those in the comparable-listed and eligible-listed samples. Forming portfolios has the advantage that the means of the portfolios have economic interpretations as return premiums. These portfolio tests also do not require linearity assumptions imposed by regressions. The disadvantages of portfolios are that confounding effects can obfuscate return premiums based on univariate sorts and they lead to less powerful tests. Accordingly, we also present cross-sectional regressions below in which we jointly estimate return premiums. Our analysis focuses on portfolios ranked by two illiquidity measures, *PNT* and *Volume*. We also estimate the returns of factor portfolios ranked by size, value, volatility, and momentum.

To construct portfolios, we sort firms into quintiles at the end of each month based on the firm characteristic of interest, such as a firm's *PNT* value in that month. A long-only quintile portfolio return in month t is the weighted average of returns in month t of firms in the quintile, as ranked by their characteristics in month $t-1$ among sample firms. A long-short factor portfolio return is the difference between the returns of the top and bottom quintile portfolios. The portfolios use three sets of weights: equal-weighted (EW), value-weighted (VW), and weighted by the prior month's gross return (gross-return weighted or GRW). Asparouhova, Bessembinder, and Kalcheva (2010) show that the expected return of a GRW portfolio is the same as that of an EW portfolio, except that it corrects for the bid-ask bounce bias noted by Blume and Stambaugh

(1983).[17] A long-only portfolio's excess return is its monthly return minus the risk-free rate that prevails at the end of the prior month. Each factor portfolio's alpha is the intercept from a time-series regression of its monthly returns on various monthly factor returns. All standard errors are based on the robust estimator in Newey and West (1987).[18]

To measure factor loadings in portfolios that may be infrequently traded, we include six monthly lags of each factor and report the sum of the contemporaneous and six lagged coefficients as the factor loading.[19] We analyze five factors based on listed returns, including the MKT, SMB, HML, momentum (UMD), and illiquidity (ILQ) factors. We define UMD using Carhart's twelve-month momentum measure (1997) and ILQ using Pastor and Stambaugh's (2003) volume-induced reversal measure. We create a sixth factor equal to the value-weighted OTC market return minus the standard (thirty-day Treasury bill) risk-free rate, which we refer to as "OTC $\mathrm{Mkt}_{\mathrm{VW}}$." Our three return benchmarks are the OTC CAPM, Listed CAPM, and the Listed Five-Factor models. The OTC CAPM and Listed CAPM models include only the OTC market and listed market factors, respectively. The Listed Five-Factor model includes the MKT, SMB, HML, UMD, and ILQ factors.

We summarize the return premiums for each OTC factor in Table 4. Panel A shows the Sharpe ratios of each OTC and listed factor and their information ratios (alphas divided by idiosyncratic volatilities) relative to the factor model benchmarks. Panel B displays the average monthly returns and alphas of each OTC factor relative to the factor model benchmarks. Panel C shows the listed factor loadings of OTC factors. Panels D and E report the analyses of Panels B and C for comparable-listed stocks. The returns in Table 4 do not include trading costs, and we use them to test theories' predictions of precost returns.

Table 4 shows three interesting comparisons between factor premiums in OTC markets and those in comparable-listed markets: (1) the illiquidity return premium is much larger in OTC markets; (2) the size, value, and volatility premiums are similar in OTC and listed markets;[20] and (3) the momentum premium is much smaller in OTC markets.

---

17 In unreported tests, we simulate OTC stock returns in the presence of empirically realistic bid-ask bounce and nontrading, as well as persistent 50% errors in recorded prices that occur with 5% probability. For portfolios sorted by *PNT* values, we find that the bias in observed monthly GRW portfolio returns is always less than 0.85%, and adjusting for the bias would only strengthen our main results.

18 We follow Newey and West's (1994) recommendation to set the number of lags equal to the highest integer less than $4^*(T/100)^{(2/9)}$, where T is the number of periods in the sample. Applying this formula to our sample of $T = 383$ months results in a lag length of five months.

19 Our method is the monthly analog to the one proposed by Dimson (1979), who analyzes stocks that are infrequently traded at the daily frequency.

20 All OTC and listed value portfolios exclude firms with negative book equity.

Table 4
Time-series analysis of OTC and comparable-listed factor portfolios

Panel A: Evaluating OTC and comparable-listed factor returns

	Annualized Sharpe ratios (GRW returns)			Annualized information ratios (GRW returns)			
				Listed CAPM			5-factor model
Factor	OTC	Comparable listed	Eligible listed	OTC	Comparable listed	Eligible listed	OTC
PNT	0.91**	0.14	−0.01	1.24**	0.29	0.08	1.34**
	(0.20)	(0.19)	(0.17)	(0.19)	(0.19)	(0.24)	(0.32)
$PNT^{\ddagger}_{VW}$	0.66**	0.04	0.13	1.00**	0.21	0.32	1.06**
	(0.21)	(0.20)	(0.20)	(0.23)	(0.19)	(0.27)	(0.32)
Volume	−0.90**	0.07	0.15	−1.14**	0.16	0.30	−1.23**
	(0.20)	(0.18)	(0.18)	(0.20)	(0.19)	(0.24)	(0.35)
Size	−1.02**	−0.98**	0.04	−0.98**	−0.81**	0.20	−0.92**
	(0.21)	(0.20)	(0.19)	(0.19)	(0.19)	(0.21)	(0.28)
Value	0.82**	1.19**	0.53*	1.19**	1.22**	0.68**	1.00**
	(0.24)	(0.20)	(0.21)	(0.22)	(0.22)	(0.25)	(0.33)
Momentum	0.41**	1.56**	1.30**	0.54**	1.71**	1.35**	0.09
	(0.15)	(0.15)	(0.16)	(0.14)	(0.15)	(0.17)	(0.20)
Volatility	−0.55**	−0.75**	−0.64**	−0.79**	−1.08**	−1.01**	−0.50
	(0.21)	(0.20)	(0.21)	(0.19)	(0.19)	(0.20)	(0.28)
OTC $Mkt^{\ddagger}_{VW}$	−0.52*			−1.21**			−1.52**
	(0.23)			(0.19)			(0.26)

Panel B: Evaluating OTC factor returns

	Monthly returns		Alphas by Model (GRW returns)		
Factor	EW returns	GRW returns	OTC CAPM	Listed CAPM	Listed 5-factor
PNT	2.94**	2.92**	2.22**	3.70**	3.67**
	(0.58)	(0.63)	(0.54)	(0.57)	(0.86)
$PNT^{\ddagger}_{VW}$	1.68**	N/A	1.01*	2.19**	2.19**
	(0.53)		(0.42)	(0.49)	(0.66)
Volume	−3.16**	−2.77**	−2.22**	−3.36**	−3.44**
	(0.56)	(0.63)	(0.59)	(0.57)	(0.99)
Size	−3.45**	−3.07**	−3.14**	−2.95**	−2.81**
	(0.56)	(0.63)	(0.76)	(0.57)	(0.85)
Value	1.99**	2.08**	1.77**	2.88**	2.29**
	(0.54)	(0.60)	(0.55)	(0.52)	(0.76)
Momentum	0.49	1.39**	1.28*	1.84**	0.30
	(0.43)	(0.53)	(0.60)	(0.49)	(0.69)
Volatility	−0.85	−1.87**	−1.00	−2.63**	−1.59
	(0.62)	(0.72)	(0.71)	(0.62)	(0.90)
OTC $Mkt^{\ddagger}_{VW}$	−0.74*	N/A	N/A	−1.32**	−1.50**
	(0.33)			(0.21)	(0.26)

(continued)

Table 4
Continued

Panel C: Systematic variation in OTC factor returns

	Factor loadings							R^2 by model		
Factor	β_{OMKT}	$\beta_{\text{MKT CAPM}}$	$\beta_{\text{MKT 5F}}$	β_{SMB}	β_{HML}	β_{UMD}	β_{LIQ}	OTC CAPM	Listed CAPM	Listed 5-factor
PNT	−1.05**	−1.41**	−1.24**	−1.02*	0.89	−0.16	0.13	24.3%	15.3%	34.1%
	(0.25)	(0.36)	(0.36)	(0.43)	(0.57)	(0.42)	(0.39)			
PNT_{VW}	−0.90**	−1.06**	−0.88**	−0.91*	0.70	−0.03	−0.14	36.1%	27.1%	40.1%
	(0.20)	(0.25)	(0.30)	(0.40)	(0.41)	(0.31)	(0.36)			
Volume	0.86**	1.04**	0.97*	0.82	−0.75	0.16	−0.01	17.7%	11.5%	26.5%
	(0.25)	(0.36)	(0.41)	(0.47)	(0.66)	(0.45)	(0.41)			
Size	0.02	−0.36	−0.01	−1.01	0.16	−0.39	0.33	2.4%	2.6%	8.1%
	(0.31)	(0.40)	(0.50)	(0.61)	(0.67)	(0.56)	(0.51)			
Value	−0.71**	−1.19**	−0.85**	0.15	0.67	−0.54	1.00*	11.3%	9.6%	25.3%
	(0.22)	(0.28)	(0.30)	(0.39)	(0.41)	(0.43)	(0.47)			
Momentum	−0.34	−0.62	−0.22	−0.72	0.74	1.09**	0.47	3.0%	2.2%	12.0%
	(0.26)	(0.40)	(0.39)	(0.51)	(0.47)	(0.41)	(0.44)			
Volatility	1.07**	1.63**	0.87*	1.06*	−1.11	0.31	−1.38*	15.5%	8.6%	21.8%
	(0.27)	(0.40)	(0.37)	(0.42)	(0.65)	(0.50)	(0.56)			
OTC Mkt_{VW}	N/A	1.17**	1.15**	0.59**	0.00	−0.02	0.11	N/A	43.5%	57.3%
		(0.11)	(0.13)	(0.17)	(0.17)	(0.14)	(0.18)			

Panel D: Evaluating comparable-listed factor returns

	Monthly returns		Alphas by model (GRW returns)		
Factor	EW returns	GRW returns	OTC CAPM	Listed CAPM	Listed 5-factor
PNT	0.11	0.22	−0.01	0.40	0.07
	(0.30)	(0.30)	(0.29)	(0.26)	(0.28)
$\text{PNT}^{\ddagger}_{\text{VW}}$	0.06	N/A	−0.22	0.28	−0.14
	(0.31)		(0.29)	(0.25)	(0.28)
Volume	0.16	0.10	0.17	0.22	0.21
	(0.27)	(0.27)	(0.27)	(0.26)	(0.30)
Size	−1.01**	−0.98**	−1.21**	−0.79**	−0.43
	(0.19)	(0.20)	(0.24)	(0.19)	(0.25)
Value	1.39**	1.36**	1.36**	1.40**	1.40**
	(0.23)	(0.23)	(0.24)	(0.25)	(0.24)
Momentum	1.77**	2.10**	1.95**	2.23**	2.06**
	(0.21)	(0.21)	(0.20)	(0.19)	(0.28)
Volatility	−0.91*	−1.35**	−0.81*	−1.76**	−1.87**
	(0.36)	(0.36)	(0.37)	(0.30)	(0.28)

(*continued*)

Table 4
Continued

Panel E: Systematic variation in comparable-listed factor returns

	Factor loadings							R^2 by model		
Factor	β_{OMKT}	$\beta_{MKT\ CAPM}$	$\beta_{MKT\ 5F}$	β_{SMB}	β_{HML}	β_{UMD}	β_{LIQ}	OTC CAPM	Listed CAPM	Listed 5-factor
PNT	−0.28*	−0.41**	−0.20	−0.66**	0.76**	0.17	−0.05	32.9%	26.5%	56.7%
	(0.14)	(0.14)	(0.16)	(0.20)	(0.19)	(0.18)	(0.14)			
PNT_{VW}	−0.32**	−0.51**	−0.31	−0.57**	0.72**	0.29	−0.09	37.4%	31.7%	60.2%
	(0.12)	(0.14)	(0.16)	(0.21)	(0.19)	(0.17)	(0.15)			
Volume	0.01	−0.10	−0.18	0.39	−0.46*	0.10	0.01	32.6%	26.6%	58.0%
	(0.13)	(0.14)	(0.15)	(0.21)	(0.19)	(0.16)	(0.14)			
Size	−0.32**	−0.36**	−0.31*	−0.35	0.04	−0.19	−0.28	7.9%	8.0%	21.0%
	(0.10)	(0.11)	(0.14)	(0.26)	(0.22)	(0.22)	(0.15)			
Value	0.01	−0.05	0.14	−0.37**	0.49**	−0.38**	0.29	5.9%	3.4%	40.2%
	(0.09)	(0.14)	(0.12)	(0.13)	(0.15)	(0.13)	(0.15)			
Momentum	−0.20*	−0.29*	−0.29	−0.23	−0.07	0.34*	−0.10	6.4%	9.1%	35.0%
	(0.09)	(0.12)	(0.16)	(0.17)	(0.17)	(0.16)	(0.14)			
Volatility	0.69**	0.87**	0.63**	1.21**	−0.44	0.12	−0.03	34.6%	22.2%	54.9%
	(0.17)	(0.16)	(0.19)	(0.29)	(0.28)	(0.25)	(0.21)			

This table summarizes the returns and risk of long-short factor portfolios constructed using data on OTC stocks and comparable-listed stocks from 1977 through 2008. We construct the comparable-listed sample to have the same median size as the OTC sample. To construct each factor, we sort firms in each sample into quintiles at the end of each month based on the firm characteristics in the Factor column. Each factor's return for month t is the difference between the weighted returns of firms in the top and bottom quintiles, as ranked in month $t-1$. We use equal weights (EW), a firm's prior month gross returns (GRW), or its prior month size (VW) when computing quintile portfolio returns. The PNT_{VW} and OTC Mkt_{VW} portfolios are marked with ‡ to indicate that they are always value-weighted while all other returns are weighted as indicated in the table.

We estimate time-series regressions of the monthly factor returns on various contemporaneous listed return factors and six lags of these factors to account for nonsynchronous trading. Each factor loading is the sum of the estimated coefficients on the contemporaneous factor and its six lags. The regressors in these time-series regressions are the OTC market (OTC CAPM model), the listed MKT (Listed CAPM model), or the listed MKT, SMB, HML, UMD, and ILQ (Listed 5-Factor model) return factors. The last three columns in Panel B report the intercepts from these three regressions for each factor, whereas the first two columns show the average factor returns. Panel C shows the factor loadings from each regression, along with the R^2 statistics. Panels D and E report the analogous statistics for the comparable-listed sample. Panel A shows the ratio of the intercepts in Panels B and D to the volatilities of the factors, where all ratios have been annualized by multiplying by the square root of 12. See the text for further details and definitions. We denote statistical significance at the 5% and 1% levels using * and **, respectively. These statistical tests employ Newey and West (1987) standard errors with the number of lags based on the formula from Newey and West (1994).

4.1 Liquidity premiums

The first four rows of Table 4, Panel A, report the illiquidity premiums. The raw Sharpe ratios of the OTC illiquidity factors based on *PNT* and *Volume* are both large at 0.91 and –0.90, respectively. Both *PNT*, which captures whether investors trade, and *Volume*, which quantifies how much they trade, appear to be relevant aspects of liquidity for OTC stocks. The average returns of the value-weighted *PNT* factor (PNT_{VW}) are also highly positive and significant. They are lower returns than are the GRW returns, partly because size-based weightings place the lowest weights on the least liquid stocks, which have the highest returns.[21]

In contrast to the large OTC premiums based on the *PNT* and *Volume* measures of illiquidity, the listed premiums based on these measures are tiny and insignificant. For comparable- and eligible-listed stocks, the Sharpe ratios and information ratios based on either liquidity measure are 0.30 or lower and are statistically insignificant. Our analysis of illiquidity premiums complements the results from numerous studies of listed U.S. and international stocks, including Amihud and Mendelson (1986), Lee and Swaminathan (2000), Pastor and Stambaugh (2003), Bekaert, Harvey, and Lundbland (2007), and Hasbrouck (2009). These studies show that the least liquid listed stocks have higher returns than do the most liquid listed stocks, though the magnitude of the listed illiquidity premium depends on the liquidity measure and time horizon. In particular, listed illiquidity premiums constructed by sorting on price impact rather than volume measures could differ from those examined here.

Neither the Listed CAPM nor the Listed Five-Factor model, which includes the illiquidity (ILQ) factor of Pastor and Stambaugh (2003), can explain the OTC *PNT* and *Volume* illiquidity premiums. In fact, the OTC *PNT* factor's information ratio of 1.34 with respect to the Listed Five-Factor model is larger than its Sharpe ratio of 0.91. The OTC illiquidity premiums become larger after controlling for listed risk factors, mainly because the OTC illiquidity factors are negatively correlated with the listed market and SMB factors. Panel C of Table 4 shows that the OTC *PNT* factor has negative market and SMB betas of –1.24 and –1.02, respectively, and an insignificant ILQ beta. The very negative beta on the market and SMB factors and the insignificant ILQ beta pose a serious challenge for theories in which the OTC illiquidity premium represents compensation for bearing systematic risk as measured by listed factors.

Next, we test whether asset pricing theories that emphasize transaction costs, such as Amihud and Mendelson (1986) and Constantinides (1986), can account for the OTC illiquidity premium. In such theories, prices adjust until investors' postcost risk-adjusted expected returns are equal across assets and equal to the risk-free rate, assuming one can costlessly trade the risk-free asset. These

[21] In general, we do not focus on the value-weighted returns of OTC portfolios because these results are sensitive to interactions between the large OTC size premium and the other factor premiums. Panel C of Table 8 in the following section reports how each return premium varies with firm size.

conditions imply that all risky portfolios' precost alphas should be positive and equal to the cost of trading risky assets, where cost is bid-ask spread times the average investor's turnover. We test this hypothesis in Table 5 for OTC and listed portfolios sorted by illiquidity measures. In each month, we either sort stocks into *PNT* deciles (Panel A) or into ten bid-ask spread ranges (Panel B), using increments of 2.5% from 0% to 25%. Because these finely partitioned sorts result in portfolios with fewer than ten firms in the early years when liquidity data are limited, Table 5 only includes data from August 1995 through December 2008.

The results in Table 5 are inconsistent with several implications of trading cost theories. First and foremost, the precost CAPM alphas of the OTC stocks in all but one of the bottom four (eight) deciles (ranges) of *PNT* (Spread) are significantly negative, implying that their postcost alphas must be even more negative. The OTC stocks with the lowest *PNT* values have especially negative precost alphas of –3.98% per month, whereas the comparable-listed stocks with the lowest *PNT* values have roughly zero precost alphas of –0.06%. Both groups of low *PNT* stocks have similar turnover, and the OTC stocks actually have higher bid-ask spreads (6.3% versus 4.6%). Thus, a transaction cost theory would predict that the OTC stocks should have higher returns, rather than returns that are 3.92% lower; it would not predict negative risk-adjusted returns for any group of stocks.

Table 5
Testing transaction cost theories of the illiquidity premium

Panel A: Sorts by PNT

	CAPM alphas (GRW)			Mean *PNT*		Mean *Spread*		Mean *Turnover*		Trading costs	
PNT decile	OTC	Comp. listed	Difference	OTC	Comp. listed	OTC	Comp. listed	OTC	Comp. listed	OTC	Comp. listed
1 liquid	−3.98**	−0.06	−3.92**	0.000	0.000	6.3%	4.6%	20.7%	18.7%	1.30%	0.85%
	(0.95)	(0.55)	(0.67)								
2	−3.40**	−0.02	−3.39**	0.051	0.048	9.8%	5.6%	9.5%	8.2%	0.93%	0.46%
	(0.86)	(0.48)	(0.89)								
3	−2.12	0.11	−2.23	0.113	0.092	11.2%	5.8%	7.5%	5.8%	0.84%	0.34%
	(1.09)	(0.57)	(1.23)								
4	−1.93**	−0.19	−1.74**	0.198	0.137	12.7%	6.3%	5.6%	4.5%	0.71%	0.29%
	(0.56)	(0.44)	(0.59)								
5	−1.24	0.27	−1.52	0.301	0.183	14.2%	6.5%	3.5%	3.6%	0.50%	0.24%
	(0.79)	(0.43)	(0.84)								
6	−0.55	0.13	−0.68	0.410	0.231	15.4%	6.6%	2.8%	3.1%	0.43%	0.21%
	(0.58)	(0.44)	(0.66)								
7	0.22	0.74	−0.52	0.519	0.285	15.9%	7.0%	1.8%	2.7%	0.29%	0.19%
	(0.69)	(0.56)	(0.90)								
8	0.88	0.31	0.57	0.629	0.352	18.5%	7.3%	1.4%	2.5%	0.26%	0.18%
	(1.28)	(0.42)	(1.30)								
9	0.47	0.18	0.29	0.757	0.464	22.2%	7.9%	0.9%	1.9%	0.19%	0.15%
	(0.62)	(0.32)	(0.67)								
10 illiquid	1.36	−0.17	1.52**	0.898	0.661	30.9%	8.8%	0.5%	1.0%	0.14%	0.09%
	(0.70)	(0.34)	(0.58)								
Monotonicity	3.75**	0.20	3.55**								
	(0.76)	(0.38)	(0.76)								

(*continued*)

Table 5
Continued

Panel B: Sorts into bid-ask spread ranges

	CAPM alphas (GRW)			Mean *PNT*		Mean *Spread*		Mean *Turnover*		Trading costs	
Spread range	OTC	Comp. listed	Difference	OTC	Comp. listed	OTC	Comp. listed	OTC	Comp. listed	OTC	Comp. listed
(0.000,0.025]	−1.25	0.48	−1.73*	0.215	0.137	1.5%	1.5%	14.7%	18.2%	0.21%	0.28%
	(0.68)	(0.39)	(0.68)								
(0.025,0.050]	−1.52**	0.59	−2.12**	0.297	0.178	3.7%	3.6%	10.5%	8.5%	0.39%	0.31%
	(0.52)	(0.46)	(0.50)								
(0.050,0.075]	−1.62*	0.14	−1.76**	0.336	0.214	6.2%	6.1%	7.8%	5.8%	0.48%	0.36%
	(0.75)	(0.43)	(0.66)								
(0.075,0.100]	−2.30**	−0.88	−1.43**	0.353	0.242	8.7%	8.6%	6.7%	5.1%	0.58%	0.44%
	(0.51)	(0.54)	(0.52)								
(0.100,0.125]	−2.27**	−0.15	−2.11**	0.369	0.278	11.2%	11.1%	6.3%	3.9%	0.71%	0.44%
	(0.64)	(0.61)	(0.73)								
(0.125,0.150]	−2.21**	−0.64	−1.58	0.388	0.297	13.7%	13.6%	5.3%	3.6%	0.72%	0.50%
	(0.77)	(0.76)	(0.96)								
(0.150,0.175]	−1.57*	0.25	−1.82	0.417	0.311	16.2%	16.1%	4.5%	4.0%	0.73%	0.65%
	(0.77)	(0.93)	(1.19)								
(0.175,0.200]	−2.47**	−0.68	−1.79*	0.434	0.333	18.6%	18.6%	4.7%	3.4%	0.88%	0.63%
	(0.75)	(0.73)	(0.90)								
(0.200,0.225]	−0.36	−1.93	1.57	0.456	0.387	21.4%	21.2%	3.4%	3.1%	0.73%	0.65%
	(1.23)	(1.15)	(2.29)								
(0.225,0.250]	−0.28	−1.51	1.22	0.483	0.398	24.0%	23.8%	2.6%	2.9%	0.62%	0.69%
	(1.10)	(1.31)	(2.23)								
Monotonicity	0.54	−1.73*	2.27**								
	(0.54)	(0.66)	(1.00)								
Concavity	−2.63**	−0.38**	−2.25**								
	(0.98)	(0.93)	(1.61)								

This table reports the risk-adjusted returns and summary statistics for portfolios sorted by two illiquidity measures, *PNT* in Panel A and *Spread* in Panel B. In Panel A, we rank firms based on their *PNT* values in each month and divide them into decile portfolios. In Panel B, we divide firms into portfolios containing firms with the *Spread* ranges noted in the first column of Panel B. We require at least five firms in each portfolio in each month. We include data from August 1995 through December 2008 when volume and bid-ask data are widely available. A decile portfolio return for month t is based on month $t-1$ sorting. We compute returns corrected for bid-ask bounce by weighing each firm's return by its prior month's gross return.

The first two columns in both panels report CAPM alphas for portfolios composed of OTC stocks and of stocks included in the comparable-size-listed sample, as described in Section 2.3. These alphas are the intercepts from time-series regressions of monthly portfolio returns on the listed MKT factor, including six lags to account for nonsynchronous trading. Columns 8 and 9 in both panels report mean *Turnover* values for each portfolio, whereas Columns 10 and 11 report mean monthly trading costs. *Turnover* is defined as monthly volume divided by end-of-month market capitalization. Trading costs are defined as *Spread***Turnover*.

We denote statistical significance at the 5% and 1% levels using * and **, respectively. These statistical tests employ Newey and West (1987) standard errors with the number of lags based on the formula from Newey and West (1994).

Moreover, the magnitudes of trading costs incurred by OTC investors are small relative to the precost return premiums in Table 4. In Constantinides' (1986) model, an asset's illiquidity premium is equal to the representative investor's one-way trading cost, which is the asset's turnover multiplied by half of its bid-ask spread. The last two columns in Table 5 report twice this amount and show that the round-trip costs range from 0.14% for the highest *PNT* stocks to 1.30% for the lowest *PNT* stocks. These magnitudes are much smaller than the top minus bottom decile *PNT* premium of 5.34% $(1.36-(-3.98))$. Furthermore, because equilibrium trading costs actually decrease with *PNT*, subtracting trading costs from returns would only increase the magnitude of the *PNT* premium. Unreported tests show the same point applies to the *Volume* premium and five of the other six premiums reported in Table 4. OTC investors incur higher trading costs in low *PNT* and high *Volume* OTC stocks because they trade these stocks more by definition, which more than offsets the lower average spreads associated with these stocks. This is an important difference between liquidity measures based on volume versus price impact, such as bid-ask spread. Although OTC investors trade low *Spread* stocks more often, they incur lower costs in such stocks (see Panel B) because of their low spreads.

We also test the unique predictions of Amihud and Mendelson's (1986) model, which assumes heterogeneous investors with exogenously specified horizons. This theory predicts that the risk-adjusted returns of portfolios sorted by bid-ask spreads will be increasing and weakly concave. Intuitively, the marginal compensation for illiquidity diminishes with bid-ask spreads because investors with longer horizons choose to hold illiquid stocks in equilibrium, and they require less additional compensation per unit increase in spread than short-horizon investors. We formally test for monotonicity and concavity by constructing long-short portfolios based on the ten spread-sorted portfolios in Panel B. The monotonicity portfolio puts increasing weights of (–5, –4, –3, –2, –1, 1, 2, 3, 4, 5) / 15 on the ten spread portfolios, whereas the concavity portfolio applies initially increasing and then decreasing weights of (–2, –1, 0, 1, 2, 2, 1, 0, –1, –2) / 3. The concavity portfolio represents the difference between two long-short illiquidity factors formed within spread ranges of [0%, 12.5%] and [12.5%, 25%]. Its expected return is zero if the return-spread relation is linear, positive if it is concave, and negative if it is convex.

The results from the monotonicity and concavity tests are ostensibly inconsistent with the implications of trading cost theories. The monthly alpha of the monotonicity portfolio based on spread sorts is only slightly positive (0.54%) and is statistically insignificant. The monthly alpha of a monotonicity portfolio formed from *PNT* sorts in Panel A is significantly higher at 3.75%. Furthermore, the concavity portfolio based on spread sorts exhibits a significantly negative alpha of 2.63% per month, implying that the spread-return relation is actually convex, not concave.

The results in Table 5 are also inconsistent with the hypothesis that data errors and microstructure biases, such as bid-ask bounce, explain the OTC illiquidity premium. Both panels demonstrate that the negative alphas of liquid OTC stocks are the primary driving force behind the observed illiquidity premium. These negative alphas are unlikely to be spurious because errors and microstructure biases are smaller among liquid stocks and typically produce an upward bias, implying that the liquid OTC stocks' true alphas could be even more negative.

In unreported tests, we investigate whether the OTC illiquidity premium is driven by survivorship bias. As we show in Table 7 below, the annual return of a *PNT* factor portfolio with a twelve-month holding period is 32.9%

(12 * 2.74%). For the top and bottom *PNT* decile portfolios, twelve-month returns are missing for 15.5% and 16.5% of firms during the postformation period. The similarity in these twelve-month disappearance rates suggests that survivorship bias does not explain the OTC illiquidity premium. Furthermore, the annual return of the twelve-month *PNT* factor portfolio of 32.9% is twice as high as the 16% disappearance rates above. Thus, even an enormous return differential of –50% between the disappearing high and low *PNT* firms would explain only one quarter (–50% * 16% / 32.9% = 24.3%) of the OTC illiquidity premium.

4.2 Size and value premiums

Table 4 shows that the size, value, and volatility premiums found in listed markets also exist in OTC markets and have similar magnitudes. Panel A indicates that the annual Sharpe ratios of the GRW size and value factors in the OTC market are –1.02 and 0.82, respectively, as compared with –0.98 and 1.19 in the comparable-listed sample. This evidence demonstrates that the size and value premiums are robust to the differences across OTC and listed markets.

Whereas the magnitudes of these premiums are similar, neither the listed size nor the listed value factor explain much of the variation in the OTC size and value factors. In Panel B, the monthly alpha of the OTC size factor is –2.81% after controlling for its loading on the listed size factor and the other four listed factors. These listed factors explain just 8.1% of the variance in the OTC size factor, as reported in the R^2 columns in Panel C. Even after controlling for the five listed factors, the monthly alpha of the OTC value factor is still 2.29%. Although the loading on the listed value (HML) factor is positive, all five listed factors explain just 25.3% of the variance in the OTC value factor. Hence, there are independent size and value factors in the OTC market that are not captured by listed factors.

4.3 Volatility premium

Panel A in Table 4 shows that OTC stocks with high volatility have lower average returns than those with low volatility. The Sharpe ratio of the OTC volatility factor at –0.55 is close to the corresponding listed Sharpe ratios at –0.75 and –0.64. Panel B shows that the alpha of the OTC volatility factor with respect to the listed CAPM is significantly negative at –2.63% per month. At first glance, OTC stocks with high idiosyncratic volatility seem to exhibit low returns just like listed stocks with high idiosyncratic volatility.

Interestingly, the OTC volatility factor's negative alpha is much smaller in the OTC CAPM regression. The OTC market itself has an overall negative return: Panel A of Table 4 reports that the Sharpe ratio of the OTC market is –0.52. The fact that there is no idiosyncratic volatility effect in OTC markets after controlling for the OTC market factor implies that a single root cause could explain both the low return of the OTC market and the low returns of highly volatile OTC stocks. Panel C shows that the OTC market beta of the long-short OTC volatility factor is 1.07 and that exposure to the OTC market explains 15.5% of the variance in the volatility factor. Panel C of Table 4 also indicates that the OTC volatility factor has a negative loading of –1.38 on the listed illiquidity factor, implying that the volatility effect in OTC stocks is related to the modest illiquidity premium in listed stocks.

4.4 Momentum

The third key result is that the return premium for momentum in OTC markets is surprisingly small. Whereas the Sharpe ratio of 1.56 for listed momentum is the largest among all the comparable-listed premiums in Table 4, Panel A, the Sharpe ratio of 0.41 for OTC momentum is the smallest of the OTC premiums. Panel E in Table 4 shows that the OTC and listed momentum factors are significantly positively correlated.[22] This explains why the information ratio of the OTC momentum factor against the Listed Five-Factor model, which includes listed momentum, is close to zero at 0.09.

The OTC momentum premium shown in Table 4 is much smaller than the momentum premium in listed stocks reported in Jegadeesh and Titman (1993) and the high Sharpe ratio of 1.30 for momentum in the eligible listed universe. The average OTC momentum premium has the same sign as the listed premium, but the magnitude of the OTC premium is at least three times smaller, depending on the exact specification. This evidence contrasts with the robust evidence that illiquidity, size, value, and volatility premiums exist in the OTC markets. Only the OTC illiquidity premium is significantly larger than its listed counterpart.

4.5 OTC market returns

The last rows in Panels A to C of Table 4 report time-series regressions that use the excess return on the value-weighted OTC market as the dependent variable. The alpha of the OTC market is negative, regardless of which listed factor model is used (also see Eraker and Ready 2011). In addition, the listed CAPM explains only 43.5% of the variation in the OTC market, whereas the five-factor model explains 57.3% and leaves 42.7% unexplained. This is broadly consistent with the inability of the other systematic listed factors to explain much of the variation in the OTC size, value, momentum, illiquidity, and volatility factors.

Motivated by the differences in volatility and liquidity between OTC and listed stocks in Table 3, we explore the empirical relationship between the OTC market premium and the OTC volatility and illiquidity premiums. In an untabulated regression, we find that the OTC market has highly significant loadings on the OTC volatility and *PNT* factors with t-statistics of 3.85 and –5.98, respectively. Moreover, after controlling for these two factors, the OTC market's alpha changes from –0.74% to 0.01% (i.e., near zero). This regression

[22] Like the listed momentum factor, the OTC momentum factor exhibits statistically and economically significantly lower returns in January: its January Sharpe ratio is –0.89 versus a non-January Sharpe ratio of 0.54.

Table 6
Cross-sectional regressions of monthly returns on firm characteristics

	OTC sample			Comparable-listed sample			Eligible-listed sample		
	1	2	3	1	2	3	1	2	3
β_{MKT}	−0.228**		−0.140*	−0.233**		−0.057	−0.282**		−0.069
	(0.063)		(0.054)	(0.072)		(0.059)	(0.086)		(0.059)
β_{SMB}	−0.160**		−0.063*	−0.128**		−0.014	−0.199**		−0.047
	(0.034)		(0.031)	(0.038)		(0.032)	(0.052)		(0.031)
β_{HML}	0.141**		0.091*	0.061		0.012	0.198**		0.054
	(0.044)		(0.042)	(0.039)		(0.028)	(0.062)		(0.034)
β_{UMD}	−0.065		−0.060	0.007		−0.005	0.047		0.028
	(0.044)		(0.041)	(0.027)		(0.026)	(0.029)		(0.023)
Size		−0.692**	−0.688**		−0.607**	−0.625**		−0.134**	−0.142**
		(0.141)	(0.124)		(0.097)	(0.095)		(0.038)	(0.038)
B/M		0.380**	0.316**		0.659**	0.631**		0.522**	0.475**
		(0.119)	(0.117)		(0.104)	(0.102)		(0.083)	(0.074)
Volatility		−0.247**	−0.245**		−0.356**	−0.347**		−0.436**	−0.414**
		(0.034)	(0.033)		(0.043)	(0.038)		(0.060)	(0.046)
Ret[−1]		−0.038**	−0.038**		−0.064**	−0.065**		−0.043**	−0.046**
		(0.007)	(0.007)		(0.006)	(0.006)		(0.005)	(0.005)
Ret[−12,−2]		0.008**	0.008**		0.018**	0.019**		0.013**	0.014**
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
PNT		4.302**	4.053**		−0.364	−0.475		0.050	−0.086
		(0.642)	(0.639)		(0.334)	(0.301)		(0.373)	(0.306)
Average R^2	6.8%	10.6%	15.0%	1.6%	3.7%	4.7%	2.6%	4.8%	5.8%
Avg. stocks	454	441	439	919	905	905	4,809	4,762	4,762

This table displays corrected estimates of cross-sectional regressions of monthly stock returns on several firm characteristics and factor loadings. We estimate monthly cross-sectional weighted least squares regressions as in Asparouhova, Bessembinder, and Kalcheva (2010), using each stock's gross return in the previous month as the weighting. The table reports average coefficients that weigh each monthly coefficient by the inverse of its squared standard error as in Ferson and Harvey (1999). We compute Newey and West (1987) standard errors with five lags based on the formula from Newey and West (1994). The R^2 in the bottom row is the average from the monthly regressions. We denote statistical significance at the 5% and 1% levels using * and **, respectively.

establishes strong links between the OTC volatility and illiquidity premiums and the negative OTC market premium.

4.6 Multivariate cross-sectional regressions

We also estimate return premiums using monthly multivariate linear regressions that simultaneously control for firms' betas and characteristics. In Table 6, we report Fama and MacBeth (1973) return predictability coefficients; Newey and West (1987) standard errors are reported in parentheses. The point estimate is the weighted-average of monthly coefficients, where each coefficient's weight is the inverse of its squared monthly standard error as in Ferson and Harvey (1999). As before, we use GRW returns to correct for bid-ask bounce bias. We group regressors into firms' betas on the MKT, SMB, HML, and UMD factors and firms' characteristics based on size, book-to-market equity, volatility, past returns, and illiquidity.[23] Regressions 1, 2, and 3 include only betas, only characteristics, and both betas and characteristics, respectively. In Appendix

[23] Regression specifications 1 and 2 also include an unreported dummy variable for firms with missing or negative book equity to keep these firms in the sample without affecting the coefficient on book-to-market equity.

B, we explain how we estimate firms' betas and adjust them to account for nonsynchronous trading. The three sets of columns in Table 6 represent estimates of return premiums in the OTC, comparable-listed, and eligible-listed samples.

There are two main findings from Table 6. First, firms' betas do not strongly predict returns in any of the three samples, especially in regression 3, which includes both firms' betas and characteristics. This echoes Daniel and Titman's (1997) findings in listed stock markets. Although using estimated betas as regressors induces attenuation bias in the coefficients on betas, this bias cannot explain why half of the beta coefficients are negative and statistically significant in regression 1. Furthermore, controlling for firms' betas has virtually no impact on the coefficients on firms' characteristics, which are nearly identical in regressions 2 and 3. The weak predictability from betas indicates that most of the predictive power in the cross-section comes from characteristics and supports our use of characteristics in constructing portfolios.

Second, with few exceptions, a joint estimation of return premiums on firms' betas and characteristics results in premiums that are quite similar to those found using portfolio methods. For example, the *PNT* coefficient in the OTC sample in regression 3 is 4.053, which implies a 3.36% per month ($4.053 \cdot (0.08\text{–}0.91)$) difference in returns between firms ranked at the medians of the top and bottom quintiles of *PNT* (0.08 and 0.91, respectively). This magnitude closely matches the top-to-bottom quintile difference in the GRW returns of *PNT* portfolios of 2.92% per month in Table 4, Panel B. The same qualitative result applies to the other return premiums. These findings in Table 6 show that none of the return premiums that are estimated using univariate portfolio sorts in Table 4 is due to the correlations among firm characteristics. This makes sense in light of the low cross-correlations among the variables reported in Table 3, Panel C. Consequently, we focus on portfolio tests in the rest of the paper.

5. Testing Theories of Limited Arbitrage and Behavioral Biases

We exploit the differences between the OTC and listed markets as well as within-market heterogeneity on several dimensions to test asset pricing theories based on limits to arbitrage and behavioral biases. Our main strategy is to contrast return premiums in subsamples of OTC and listed stocks, and we use additional tests to shed additional light on the momentum premium.

5.1 Trading costs as a limit to arbitrage

We first test whether trading costs limit the extent to which arbitrageurs can exploit the precost returns of OTC factors in Table 4. We estimate the postcost returns of an arbitrageur who takes positions in each of the OTC factors, assuming that the investor pays each stock's bid-ask spread in every round-trip trade. Studies such as Frazzini, Israel, and Moskowitz (2012) show that spread data overstate the trading costs incurred by arbitrageurs who use sophisticated

Table 7
Impact of trading costs and rebalancing frequency on arbitrageur returns

	Precost returns		Postcost returns		Breakeven spread		Breakeven frequency (Months)		
OTC factor	1 months	12 months	1 months	12 months	1 months	12 months	GRW	VW	LW
PNT	4.53%**	2.74%**	−8.94%**	0.87%	5.41%	17.04%	6	4	4
Volume	4.53%**	2.48%**	−14.02%**	0.05%	4.73%	14.12%	12	9	6
Size	4.59%**	1.44%*	−10.59%**	−0.96%	6.42%	9.25%	24+	9	10
Value	4.1%**	2.51%**	−5.81%**	0.64%	6.33%	16.19%	6	3	3
Momentum	1.96%**	0.87%	−15.17%**	−2.11%**	2.19%	4.41%	24+	24+	24+
Volatility	2.44%*	2.22%**	−15.11%**	−0.43%	2.69%	12.87%	17	24+	24+

This table evaluates the returns for an arbitrageur who pays stocks' bid-ask spreads on each round-trip trade, trying to implement the OTC factor returns. We compute summary statistics for long-short factor portfolios that are rebalanced at frequencies of one and twelve months, using the method in Jegadeesh and Titman (1993) in which up to $1/n$ of the firms in each portfolio change in each month, based on rankings of OTC firms' values of the characteristics listed in the first column in the prior month.

The first two columns report factor portfolios' average precost returns for 1– and 12-month rebalancing frequencies. Columns 3 and 4 report factor portfolios' average postcost returns at these frequencies. Estimated monthly costs are equal to average portfolio turnover multiplied by average bid-ask spreads. Columns 5 and 6 show the bid-ask spreads such that average postcost returns would be zero for the two rebalancing frequencies. In Columns 1 to 6, all stocks' returns are weighted by their prior month's gross return (GRW). Columns 7, 8, and 9 report rebalancing frequencies at which, using actual bid-ask spreads, average postcost returns are closest to zero for three portfolio weighing methods: GRW (as used in Columns 1–6), value-weighted (VW) returns, and liquidity-weighted (LW) returns, which are weighted by the inverse of stocks' bid-ask spreads. These statistics are based on 192 months of data from January 1993 through December 2008. We denote statistical significance at the 5% and 1% levels using * and **, respectively. These statistical tests employ Newey and West (1987) standard errors with five lags based on the formula from Newey and West (1994).

strategies to minimize costs. Our postcost return calculation is more relevant for the average investor in OTC markets.

We compute postcost returns at rebalancing frequencies between 1 and 24 months to evaluate how arbitrageurs' profitability depends on their portfolio turnover. We rebalance portfolios at n-month frequencies, using the Jegadeesh and Titman (1993) method in which $1/n$ of the firms in each portfolio can change in each month based on rankings of firms' characteristics in the prior month. As before, we focus on portfolios with GRW weights, which remain gross-return weighted in the absence of rebalancing. We also analyze VW and liquidity-weighted (LW) portfolios to assess whether arbitrageurs lower their trading costs by concentrating on large and liquid stocks. The LW weights are inversely proportional to stocks' bid-ask spreads.[24]

Table 7 reports precost and postcost returns of GRW portfolios and breakeven rebalancing frequencies and spreads for the postcost factor portfolios. The breakeven frequency (spread) is the rebalancing frequency (bid-ask spread) at which the postcost return of the factor portfolio is closest to 0%. Table 7 reports the precost returns, postcost returns, and breakeven spreads of the GRW OTC factors with rebalancing frequencies of 1 and 12 months. We complement the table with Figure 2, Panels A and B, which show the GRW OTC factors' precost

24 Because limited spread data are available, we compute postcost returns only in the second half of the sample (1993 to 2008) and estimate costs based on average portfolio turnover multiplied by average bid-ask spreads.

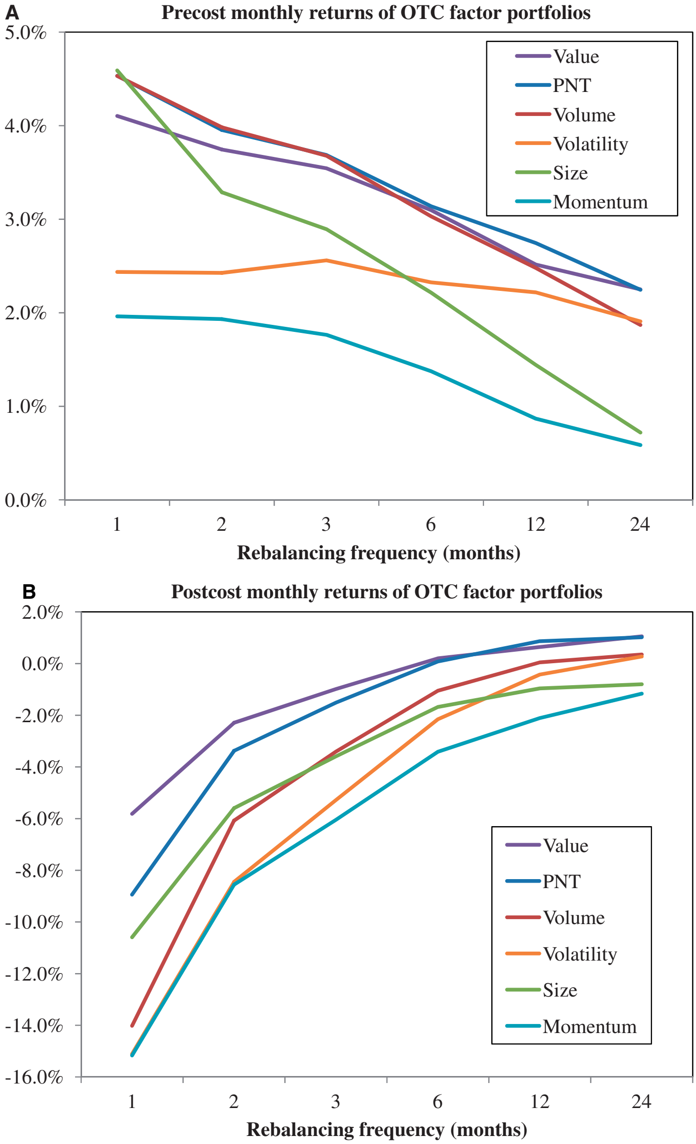

Figure 2
Impact of trading costs and rebalancing frequency on arbitrageur returns
We plot the average monthly returns of long-short OTC factor portfolios that are rebalanced at various frequencies using the method in Jegadeesh and Titman (1993) in which up to $1/n$ of the firms in each portfolio change in each month based on rankings of OTC firms' characteristics in the prior month. In both figures, rebalancing frequencies are indicated on the x-axis and stocks' returns are weighted by their prior month's gross return (GRW). In Panel A, we plot average pretrading cost returns. In Panel B, we plot average posttrading cost returns for an arbitrageur who pays stocks' bid-ask spreads on each round-trip trade. Estimated monthly costs are equal to average portfolio turnover multiplied by average bid-ask spreads. Figures are based on 192 months of data from January 1993 through December 2008.

returns and postcost returns at rebalancing frequencies ranging from 1 to 24 months.

The main finding in Table 7 is that the postcost returns for arbitrageurs who try to exploit the OTC factors are much lower than the factors' precost returns. Even at the annual rebalancing frequency, the postcost GRW returns of all six OTC factors are less than 1% per month and are not statistically significantly greater than 0%—in contrast to the precost returns that are as high as 2.74% per month and almost always statistically significant. Only the *PNT*, *Volume*, and *Value* factors exhibit positive postcost GRW returns at the annual frequency, which is why the GRW breakeven horizons of these factors are less than one year. If an arbitrageur uses VW or LW strategies, the breakeven horizons decline for these three factors and the breakeven horizon for the *Size* factor decreases to less than one year. However, one cannot profitably exploit the OTC *Momentum* and *Volatility* factors with a one-year rebalancing frequency, regardless of which weighting scheme one uses.

Figure 2, Panels A and B, show that precost GRW factor returns monotonically decrease with frequency, presumably because the information used to form the portfolios gradually becomes outdated at longer frequencies. Despite this effect, the postcost factor returns steadily increase with frequency because the longer frequency portfolios have much lower trading costs. At the twenty-four-month frequency, the postcost returns of the *PNT* and *Value* factors exceed 1% per month, but only the *Value* factor return is statistically significant at the 5% level.

The breakeven spread columns in Table 7 indicate that effective bid-ask spreads must be quite high—the average across the six factors is 12.3%—to deter arbitrage at the one-year rebalancing frequency. However, because the median OTC spread in Table 3, Panel 2, is 10%, it seems that OTC trading costs are indeed high enough to limit the effectiveness of arbitrage, especially when one also considers the limits noted earlier on short selling in OTC markets. Such limits help explain why these large OTC return premiums persist, but one needs a model of investor behavior—such as the one provided in Appendix A—to understand why premiums arise in the first place. We now turn to tests that allow us to distinguish among theories of limited arbitrage.

5.2 Evidence from double sorts

We measure return premiums within each market in subsamples of stocks sorted by characteristics that distinguish OTC and listed markets: institutional holdings, disclosure, and size. We select these three characteristics to construct powerful tests of competing theories of return premiums. We form double-sorted portfolios by ranking stocks based on a distinguishing characteristic in month $t-1$ and sorting them into portfolios with sufficiently many stocks. In these initial sorts, we use two portfolios when sorting on the two binary variables (*InstHold* and *Disclose*) and three portfolios when sorting on size. Within each of these portfolios, such as stocks not held by institutions, we sort stocks into terciles based on the characteristics, such as liquidity, used in constructing factors. Holding each distinguishing characteristic (e.g., institutional holdings) constant, we measure return premiums (e.g., illiquidity) as the difference between returns in month *t* of stocks in the top and bottom terciles from the second sort. Our method also allows us to test whether the distinguishing characteristic is priced within each tercile from the second sort.

Table 8 shows the excess returns from these double-sorted portfolios. Panel A shows that the return premiums for illiquidity (both *PNT* and *Volume*) and size are much larger within OTC stocks that are not held by institutions. Panel B indicates that both illiquidity premiums and the volatility premium are roughly twice as large among OTC stocks that do not disclose book equity. Panel C shows that the OTC illiquidity premium is larger among small stocks, whereas the OTC momentum premium is four times larger among big stocks. Twelve of the 13 statistically significant differences in return premiums in Table 8

Table 8
Double-sorted portfolios

Panel A: Double-sorted portfolios: Initial sort based on institutional holdings

	Held stocks monthly returns			Nonheld stocks monthly returns			Premium difference (%)
	Top tercile	Bottom tercile	Premium	Top tercile	Bottom tercile	Premium	
OTC stocks							
PNT	0.21	−1.44	1.65	1.11	−4.12	5.23**	−3.58**
Size	−0.31	0.40	−0.71	−2.13	1.74	−3.87**	3.16**
Volume	−0.80	0.51	−1.30	−3.97	1.72	−5.70**	4.39**
Value	1.18	−1.36	2.54**	1.10	−2.56	3.66**	−1.12
Momentum	0.77	−1.20	1.97**	−0.28	−2.46	2.18**	−0.21
Volatility	−0.76	0.52	−1.28	−2.01	0.23	−2.24**	0.96
Comparable-listed stocks							
PNT	0.46	0.35	0.11	0.54	−0.28	0.82*	−0.71*
Size	0.17	0.90	−0.73**	−0.05	0.70	−0.75*	0.02
Volume	0.57	0.28	0.29	−0.18	0.53	−0.71	1.00**
Value	0.89	−0.03	0.92**	1.08	−0.76	1.84**	−0.92*
Momentum	1.23	−0.34	1.56**	1.08	−0.93	2.01**	−0.44
Volatility	−0.22	0.88	−1.10**	−0.67	0.98	−1.65**	0.55

Panel B: Double-sorted portfolios: Initial sort based on disclosure

	Disclosing stocks monthly returns			Nondisclosing stocks monthly returns			Premium difference (%)
	Top tercile	Bottom tercile	Premium	Top tercile	Bottom tercile	Premium	
OTC stocks							
PNT	0.89	−1.04	1.94**	0.75	−2.56	3.31**	−1.38*
Size	−0.22	1.16	−1.38**	−1.47	1.42	−2.89**	1.51
Volume	−0.62	1.02	−1.64**	−2.40	0.89	−3.28**	1.64*
Momentum	0.89	−0.66	1.55**	−0.04	−0.65	0.61	0.94
Volatility	−0.24	0.70	−0.94	−1.61	0.93	−2.54**	1.60*
Comparable-listed stocks							
PNT	0.69	0.36	0.33	0.41	−0.35	0.76	−0.43
Size	0.25	1.08	−0.83**	−0.03	0.41	−0.45	−0.38
Volume	0.40	0.55	−0.15	−0.15	0.35	−0.50	0.35
Momentum	1.45	−0.14	1.59**	1.27	−0.73	2.00**	−0.41
Volatility	−0.12	1.04	−1.16**	−0.90	0.89	−1.79**	0.63*

(*continued*)

Table 8
Continued

Panel C: Double-sorted portfolios: Initial sort based on size

	Big stocks monthly returns			Small stocks monthly returns			Premium difference (%)
	Top tercile	Bottom tercile	Premium	Top tercile	Bottom tercile	Premium	
OTC stocks							
PNT	0.12	−2.00	2.12*	2.31	−1.32	3.62**	−1.50
Volume	−1.47	−0.33	−1.14	−1.59	3.21	−4.80**	3.65**
Value	0.33	−2.72	3.05**	2.03	0.19	1.84	1.20
Momentum	−0.09	−1.86	1.78**	1.26	0.84	0.41	1.37
Volatility	−2.12	0.44	−2.55**	0.95	1.53	−0.58	−1.97
Comparable-listed stocks							
PNT	0.31	0.10	0.21	0.77	0.83	−0.06	0.27
Volume	0.41	0.11	0.29	1.02	0.61	0.42	−0.12
Value	0.50	−0.19	0.70**	1.46	0.54	0.92**	−0.23
Momentum	1.08	−0.73	1.81**	1.54	0.24	1.29**	0.51*
Volatility	−0.72	0.78	−1.50**	0.47	1.19	−0.72*	−0.78**

This table contains average monthly returns for double-sorted portfolios within OTC stocks and within stocks included in the comparable-listed sample, which consists of stocks that are comparable to stocks in the OTC sample in terms of size, as described in Section 2.3. We first rank stocks according to one characteristic of interest and sort them into portfolios. We then rank stocks within these portfolios according to other characteristics and again sort into portfolios. We sort stocks into terciles rather than quintiles to ensure that we have a sufficient number of stocks in each portfolio, and we require at least ten stocks in each tercile. Within each double-sorted tercile, we compute returns corrected for bid-ask bounce by weighing each stock's return by its prior month's gross return. We display returns for the top and bottom terciles (i.e., the extreme terciles) according to the second sort within the first-sort extreme terciles. For binary variables (*InstHold* and *Disclose)*, we sort stocks into two portfolios based on their values. Panel A reports the returns of double-sorted portfolios in which stocks were first sorted according to *InstHold*. Panel B reports returns of stocks that were first sorted according to *Disclose.* Panel C reports returns of stocks that were first sorted according to *Size.* We denote statistical significance at the 5% and 1% levels using * and **, respectively. These statistical tests employ Newey and West (1987) standard errors with five lags based on the formula from Newey and West (1994).

exhibit the same signs in the OTC and comparable-listed samples, though the magnitudes are often smaller in the listed sample. We now discuss the implications of these results and others for theories of return premiums.

5.3 Testing theories of investor disagreement and limits on short sales

We test the Miller (1977) hypothesis that investor disagreement combined with limits on short sales leads to overpricing and negative abnormal returns. As we show in Appendix A, this theory can help explain the illiquidity, size, volatility, and value premiums in OTC and listed markets because these characteristics are natural proxies for investor disagreement. In particular, both our OTC illiquidity measures are based on trading volume, which is directly linked to investor disagreement as formalized in Propositions 1 and 2 in Appendix A.

There are several additional testable implications of this theory. If retail (institutional) investors are more (less) likely to disagree, stocks not held by institutions should exhibit higher return premiums based on proxies for disagreement. A complementary story is that a lack of institutional ownership could be a proxy for limits on short sales, as suggested by Nagel (2005); such limits are positively associated with overpricing in Miller's (1977) theory. Consistent with both interpretations, Panel A in Table 8 shows that the return premiums for illiquidity (both *PNT* and *Volume* measures), volatility, value, and size are 0.96% to 4.39% per month larger in OTC stocks that are not held by institutions. The differences in the illiquidity and size premiums are especially large and statistically significant. Hinting at a role for limits on short sales, the premiums among nonheld stocks arise mainly from the negative returns of stocks with high liquidity, size, volatility, and valuation. There are also significant differences in the illiquidity (*PNT* and *Volume*) premiums between stocks held and not held by institutions in the comparable-listed sample, suggesting similar mechanisms operate in listed markets.

In the model in Appendix A, the impact of differences in opinion is especially strong among OTC stocks that do not disclose basic financial information. Investors are likely to hold widely divergent views about the financial condition of firms without disclosures, implying overpricing of such firms' stocks will be more severe. Consistent with this idea, Panel B in Table 8 shows that the return premiums based on four proxies for disagreement—*PNT*, volume, volatility, and size—are 1.38% to 1.64% per month larger among OTC stocks that do not disclose book equity. Three of the four differences in premiums are significant at the 5% level. The difference in size premiums is significant only at the 10% level.

We further test disagreement theories by analyzing whether disclosure itself can predict returns. If the disclosure of financial information helps to resolve investor disagreement, as predicted by the model in Appendix A, disclosing firms will earn higher returns than nondisclosing firms.[25] We look for a disclosure premium within firms in the top terciles of liquidity and volatility, where disagreement could significantly affect investors' valuations. Panel B of Table 8 shows that disclosing firms do exhibit higher returns than do nondisclosing firms, especially among liquid and volatile firms. The disclosure premium is 1.52% [= –1.04 – (–2.56)], 1.78%, and 1.37% per month, respectively, when evaluated within the *PNT*, volume, and volatility terciles, representing the most liquid and volatile firms. All three premiums are statistically significant, economically large, and in line with the theory in Appendix A.

Furthermore, the negative market returns on OTC stocks are consistent with the overpricing argument. Investor disagreement can cause overpricing of the entire market when there are market-wide limits on short sales (e.g., Jarrow 1980). Because few OTC stocks can be shorted and there is no tradable index of OTC stocks that can be shorted, limits on short sales plausibly apply to the OTC market as a whole. Thus, disagreement combined with limits on short sales could explain the negative returns of the OTC market. It could also help explain the strong empirical links between the OTC market premium and the

---

25 Hirshleifer and Teoh (2003) develop a theory of attention that makes a similar prediction. Firms can choose whether to disclose financial information to investors with limited attention. In equilibrium, firms do not disclose if they have negative news, knowing that investors fail to take this self-selection into account. This theory predicts that investors overprice firms that do not disclose, implying that these firms have lower returns than disclosing firms.

OTC premiums for illiquidity and volatility, which could all stem from the same underlying investor disagreement.

Lastly, Miller's (1977) theory could help explain why the coefficients on market beta are negative and statistically significant in predicting returns in Table 6. He argues that "the riskiest stocks are also those about which there is the greatest divergence of opinion." If so, in the presence of limits on short sales, stocks with the highest systematic risk (i.e., beta) could become so overpriced that they exhibit lower future returns than do stocks with low risk.

5.4 Testing theories of momentum

Firms traded in OTC markets disclose much less information than do those in listed markets, and retail investors dominate in OTC markets. We now test whether theories that emphasize the roles of the information environment and retail versus institutional trader behavior can explain the relatively small OTC momentum premium. This section presents evidence that is most consistent with Hong and Stein's (1999) model of momentum based on the gradual diffusion of information.

Two elements in Hong and Stein's (1999) model are necessary for momentum. First, there must be a group of "newswatcher" investors who only attend to firms' fundamentals and disregard stock price movements. Such newswatchers may not follow many OTC firms. Greenstone, Oyer, and Vissing-Jorgensen (2006) argue that investors view information disclosed by most OTC firms as being less credible than is information from listed firms. In contrast, OTC firms' stock prices are reliable, verifiable, and widely available. If OTC stocks lack newswatchers, they would not exhibit momentum. This argument is consistent with the evidence in Tables 4 and 6 that shows OTC momentum is on average lower than is listed momentum.

The second key element in Hong and Stein's (1999) model is the gradual transmission of information across newswatchers. The model predicts that momentum is stronger and longer-lasting when information transmission is slower. Because fewer investors hold and discuss OTC stocks, information transmission is likely to be slower in OTC stocks than it is in listed stocks. Under this reasoning, momentum should be strong and long-lasting among OTC stocks that newswatchers might follow, such as large OTC firms and those that disclose key financial information. Consistent with this prediction, Panels B and C of Table 8 show that momentum is two to four times higher among OTC stocks that newswatchers might follow. Specifically, momentum is 1.78% and 1.55% per month and highly statistically significant among the largest OTC firms and those that disclose book equity, respectively, whereas it is only 0.41% and 0.61% and insignificant among the smallest OTC firms and those that do not disclose book equity.

Next, we examine the time horizon of momentum in OTC markets. We construct long-short momentum portfolios at various horizons using Jegadeesh and Titman's (1993) method, similar to the rebalanced portfolios examined in

Table 9
Long-term returns of momentum portfolios

	OTC stocks		Comparable-listed stocks		Eligible-listed stocks	
Horizon in months	GRW returns	VW returns	GRW returns	VW returns	GRW returns	VW returns
[1,1]	1.39**	3.15**	2.10**	1.97**	1.68**	1.29**
[1,12]	−0.08	1.57**	0.58**	0.75**	0.44*	0.47
[13,24]	−0.75	0.71	−0.12	−0.03	−0.21	−0.23
[25,36]	−0.07	0.37	0.13	0.24	−0.17	−0.11
[37,48]	−0.66	0.37	0.05	0.05	0.10	0.08
[49,60]	−0.99	0.42	−0.08	0.18	−0.29**	−0.20
[13,60]	−0.56	0.45	0.02	0.12	−0.13	−0.10

This table contains average returns for long-short momentum portfolios constructed at various time horizons using the method described in Jegadeesh and Titman (1993). We first form top and bottom quintile portfolios for each month $t-1$ based on stocks' momentum, defined as the return from month $t-12$ to month $t-2$. Returns within each extreme quintile portfolio are either weighted by the prior month's gross returns ("GRW returns") or are value weighted ("VW returns"). Then to measure momentum returns n years after portfolio formation in each month t, we equally weight the twelve monthly returns of the extreme quintile portfolios formed in months t – n*12 to t – n*12 – 11. The top minus bottom quintile portfolio return is the momentum premium at the n-year horizon. We compute returns for portfolios within our three samples: OTC stocks, stocks included in the comparable-listed sample, which consists of stocks that are comparable to stocks in the OTC sample in terms of size, as described in Section 2.3, and stocks included in the eligible-listed sample, which consists of all listed stocks that satisfy the same data requirements as the OTC stocks in our sample, as described in Section 2.2. We denote statistical significance at the 5% and 1% levels using * and **, respectively. These statistical tests employ Newey and West (1987) standard errors with five lags based on the formula from Newey and West (1994).

Table 7.[26] Table 9 reports the momentum portfolios' GRW and VW returns at horizons of up to five years. There is no momentum (–0.08% per month) at the one-year horizon in OTC markets, using the GRW method. There is, however, significant one-year momentum (1.57% per month) in the VW OTC portfolios, but this places extremely large weights on a few big OTC firms.

Analysis of the long-term returns of momentum portfolios in OTC and listed markets helps us differentiate theories of momentum. In the models of Hong and Stein (1999) and Barberis, Sheifer, and Vishny (1998), momentum originates from investors' underreaction to tangible firm-specific information, such as news about firm earnings, and thus momentum need not reverse.[27] In contrast, in Daniel, Hirshleifer, and Subrahmanyam's (1998) theory, momentum arises from "continuing overreaction" to intangible information, implying that momentum eventually reverses. Table 9 shows that VW momentum portfolios in OTC markets exhibit positive but statistically insignificant returns of 0.45% per month in years two through five after portfolio formation. In addition, momentum in listed markets exhibits limited reversal in the eligible sample

---

26 This procedure entails two steps. First, we form top and bottom quintile portfolios based on stocks' *Ret*[–12,–2] as of month $t-k$. Second, to measure returns n years after portfolio formation in each month t, we apply GRW weights to the 12 monthly returns of the extreme quintile portfolios formed in months $t-n$*12 to $t-n$*12–11. The average difference in the extreme quintile portfolios' returns is the momentum premium at the n-year horizon.

27 Because we lack earnings data for OTC firms, we cannot test several predictions of Barberis, Sheifer, and Vishny's (1998) model, which is based on a representative investor's underreaction and overreaction to sequences of news. However, Loh and Warachka (2012) argue that listed stock price reactions to sequences of earnings surprises are inconsistent with this model.

and no reversal in the comparable-size sample in years two through five.[28] The observed lack of reversal lends support to the two underreaction theories of momentum: Hong and Stein (1999) and Barberis, Sheifer, and Vishny (1998).

An alternative explanation for the weak GRW momentum premium in OTC markets is the small role of institutional investors in OTC markets. In listed stock markets, institutions herd (e.g., Nofsinger and Sias 1999; Sias 2004) and institutions follow momentum strategies (e.g., Badrinath and Wahal 2002; Griffin, Harris, and Topaloglu 2003). Gutierrez and Pirinsky (2007) and Vayanos and Woolley (2013) argue that momentum in listed markets arises partly because of agency issues in delegated institutional money managers. Our cross-market evidence is broadly consistent with this view. Table 4 shows that momentum is three times higher among comparable-listed stocks, which are far more likely to be held by institutions (see Table 3).

However, the evidence within the OTC market is ostensibly inconsistent with the theory that institutions per se cause momentum. Panel A in Table 8 shows that OTC stocks experience nearly identical momentum (1.97% versus 2.18% per month) whether or not they are held by institutions. Nevertheless, the types of institutions likely differ across OTC and listed markets. Large asset managers that are subject to the delegated agency problems described by Vayanos and Woolley (2013) play important roles in listed markets. Table 3 shows that few large institutions invest in OTC stocks. However, small hedge funds without reporting obligations could significantly affect OTC market prices. These smaller institutions may not be subject to the same agency issues as the largest institutions. Future theories on institutional investors and momentum should account for the different roles played by these various types of investors.

6. Concluding Discussion

Whereas many cross-sectional return premiums in listed markets, such as size, value, and volatility, generalize to OTC markets, other return premiums are strikingly different. The premium for illiquidity in OTC markets is several times larger than it is in listed markets. The pronounced momentum effect in listed markets is economically small in OTC markets. Listed return factors cannot explain the majority of the variation in OTC return factors.

Variation in the illiquidity, size, value, and volatility premiums within OTC markets is consistent with theories in which disagreement and limits on short sales cause temporary overpricing. Variation in the momentum premium within OTC markets is most consistent with Hong and Stein's (1999) theory based on the gradual diffusion of information. We test and find only limited support for several alternative explanations of these premiums, including theories based on exposures to systematic factor risk and those based on transaction costs.

[28] Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) show that momentum in listed stocks partially reverses in their samples.

The return premiums in OTC markets offer insights into the future of listed markets. For example, the finding that size, value, and volatility premiums exist in OTC markets provides new evidence that these premiums are robust to differences in market structure and liquidity and therefore could persist in the future. The finding that the most actively traded OTC stocks appear to be overpriced could also have an important counterpart in listed markets: Ofek and Richardson (2003), Baker and Stein (2004), and others show that apparent speculative bubbles are often associated with high trading volume. Our evidence suggests that such bubbles are magnified when investors must price assets in the dark, and thus improved financial disclosures could mitigate future bubbles.

Appendix

A. Model of OTC Stock Pricing

Our stylized model of OTC stock prices features costly short selling and differences in investors' opinions. We analyze the price of a single equity-financed firm in three periods: 0, 1, and 2. At date 0, the firm has assets in place normalized to \$1. At date 2, the firm liquidates all assets and pays all cash flows. The share price of the stock (p) endogenously adjusts to clear the market. We normalize the supply of stock to one and the return on the risk-free asset to zero.

We assume that short-selling costs are related to the cost of locating shares to borrow. Short sellers borrow shares from share lenders, such as brokers or custodians, who incur deadweight quadratic costs of finding shares $(c/2)(\text{shares lent})^2$, where $c>0$. Share lenders pass these costs on to short sellers who can borrow shares and pay total dollar fees of $(c/2)(\text{shares short})^2$. Based on this total fee, the average borrowing fee per share is $f = f(\text{shares short}) = (c/2)(\text{shares short})$. This lending fee ($f$) is akin to a negative rebate rate earned on collateral posted to borrow shares. We assume share owners do not receive payment when share lenders lend their shares.

There are two types of risk-neutral overconfident investors and N investors of each type. Each investor owns $1/(2N)$ of the firm's shares at date 0. At date 1, investors observe two public signals, s_A and s_B, about the firm's date 2 earnings (π_2). Earnings satisfy $\pi_2 = s_A + s_B + u_1 + u_2$, where s_A, s_B, u_1, and u_2 are independently uniformly distributed from $[-\sigma, +\sigma]$ and $\sigma \geq 0$ is a measure of fundamental volatility. Stockholders receive $1+\pi_2$ at date 2.

The two types of investors differ in which signal they believe more, where the parameter $\eta \in [0, 1]$ represents agents' overconfidence in their preferred signal. Specifically, the investors mistakenly perceive the u_t components of earnings to be correlated with their preferred signals. Type $X \in \{A, B\}$ believes that these components of earnings satisfy $u_t = \eta s_X + (1-\eta^2)^{1/2} v_t$, where $t=1$ or 2, and the v_t are uniformly distributed from $[-\sigma, +\sigma]$ and independent of each other, s_A, and s_B. Both types' beliefs are correct if and only if $\eta = 0$.

We consider two variants of the model: one in which the firm publicly discloses financial information ($e_1 = s_A + s_B + u_1$) about date 2 earnings at date 1 and one without such disclosure. We denote the date 1 earnings beliefs of investor type $X \in \{A, B\}$ by E_X. Based on only the two signals, the rational expectation of the firm's date 2 earnings is $s_A + s_B$. At date 1, investors' earnings expectations in the cases with and without financial disclosure are given by

$$\text{no disclosure: } E_A = (1+2\eta)s_A + s_B \quad \text{and} \quad E_B = (1+2\eta)s_B + s_A, \tag{A1}$$

$$\text{disclosure: } E_A = (1+\eta)s_A + s_B + u_1 \quad \text{and} \quad E_B = (1+\eta)s_B + s_A + u_1. \tag{A2}$$

Define the difference in opinion between investors to be $DO = |E_A - E_B|$. From the above expressions, financial disclosure decreases difference in opinion as follows:

$$\text{no disclosure: } DO = 2\eta|s_A - s_B|, \tag{A3}$$

$$\text{disclosure: } DO = \eta|s_A - s_B|. \tag{A4}$$

For simplicity, we analyze the model's symmetric rational expectations equilibrium in which each investor takes the market price as given, and investors within each type use the same strategies. Type $X \in \{A, B\}$ chooses q_X at date 1 to maximize expected profit, implying

$$q_X \in \text{argmax} \left\{ q_X(1 + E_X - p_1) - I(q_X < 0)(c/2)q_X^2 \right\} \tag{A5}$$

where I( ) is an indicator function. The more optimistic type, for which $E_X = \max(E_A, E_B)$, chooses a long position, has a linear profit function, and buys stock until the price satisfies

$$1 + \max(E_A, E_B) - p_1 = 0. \tag{A6}$$

This condition implies the stock price reflects only the beliefs of the optimistic investors:

$$p_1 = 1 + \max(E_A, E_B) = 1 + (E_A + E_B)/2 + DO/2. \tag{A7}$$

Because prices reflect optimistic investors' beliefs, the pessimistic investor type chooses to short the stock and has a quadratic profit function. The pessimistic type's demand satisfies

$$\min(q_{A,}q_B) = (1 + \min(E_A, E_B) - p_1)/c = -DO/c < 0 \ \text{ if } \ \eta > 0. \tag{A8}$$

The second-order condition for pessimistic investors is satisfied because their expected profit is quadratic in q_X and $-c < 0$. Optimistic investors are also maximizing because their expected profit is zero for all $q_X > 0$. Market clearing $[N(q_A + q_B) = 1]$ implies optimists' demand is

$$\max(q_{A,}q_B) = 1/N + DO/c \ \text{ if } \ \eta > 0. \tag{A9}$$

The resulting average stock lending/borrowing fee per share is

$$f = (c/2)|\min(q_A, q_B)| = DO/2. \tag{A10}$$

In expectation, the equilibrium price at date 1 (p_1) exceeds the efficient price (p_{1e}) that would prevail if there were no overconfidence. The efficient price is

$$\text{no disclosure: } p_{1e} = 1 + s_A + s_B, \tag{A11}$$

$$\text{disclosure: } p_{1e} = 1 + s_A + s_B + u_1. \tag{A12}$$

We define overpricing (Ovp) as the equilibrium price minus the efficient price ($p_1 - p_{1e}$):

$$\text{no disclosure: } Ovp_1 = 2\eta\max(s_A, s_B), \tag{A13}$$

$$\text{disclosure: } Ovp_1 = \eta\max(s_A, s_B). \tag{A14}$$

At date 0, before the signals are known, expected overpricing is

$$\mathrm{E}[Ovp_1] = \mathrm{E}[DO]/2 > 0 \ \text{ if } \ \eta > 0. \tag{A15}$$

At date 0, all investors anticipate the date 1 equilibrium, so the price is

$$p_0 = 1 + \mathrm{E}[DO]/2 > 1 \ \text{ if } \ \eta > 0. \tag{A16}$$

The date 0 price is higher than its efficient value of one because expected overpricing is positive due to expected differences in opinion. As a consequence of overpricing, at date 0 the stock's expected return $\mathrm{E}[r]$ from date 1 to date 2 is negative and given by

$$\mathrm{E}[r] = \mathrm{E}[p_2 - p_1] = -\mathrm{E}[DO]/2 < 0 \ \text{ if } \ \eta > 0. \tag{A17}$$

Expected return decreases with expected difference in opinion, which arises from overconfidence. The overconfidence bias causes the stock's expected return to be lower than the risk-free rate of zero even though investors are risk neutral.

Equilibrium trading volume from date 0 to date 1 is

$$Volume = |N\max(q_A, q_B) - 1/2| = 1/2 + (N/c)DO \quad \text{if} \quad \eta > 0, \tag{A18}$$

where 1/2 is the initial share endowment of type A investors. Expected trading volume is thus

$$\mathrm{E}[Volume] = 1/2 + (N/c)\mathrm{E}[DO] \quad \text{if} \quad \eta > 0. \tag{A19}$$

Return volatility at date 1 is the standard deviation of the change in price:

$$\sqrt{\mathrm{Var}(p_1 - p_0)} = (1/2)\sqrt{\mathrm{Var}[E_A + E_B + DO]} = (1/2)\sqrt{\mathrm{Var}[E_A + E_B] + (1/2)\mathrm{E}[DO]^2}, \tag{A20}$$

where the second equality is based on the properties of the two uniformly distributed signals.

In summary, ex ante overpricing increases with expected difference in opinion, consistent with Miller (1977) and related theories. The equilibrium relies on the assumptions that the cost of short selling is positive ($c > 0$) and convex and that investors are overconfident ($\eta > 0$). Firm disclosure of financial information reduces differences in investors' opinions.

We now establish seven model predictions based on the above equilibrium.

Proposition 1. If $\eta > 0$, expected return is negative and decreases with expected difference in opinion. If $\eta = 0$, expected return is zero, and an equilibrium with no trading exists.

Proof. If $\eta > 0$, expected return is –E[DO]/2, so it decreases with E[DO]. If $\eta = 0$, then $DO =$ 0 regardless of disclosure; all traders believe firm value is $1 + E_A = 1 + E_B$, so this must be the equilibrium date 1 price. In this case, the price $p_1 = 1 + E(\pi_2)$ is efficient and equal to E(p_2), implying that expected return is the risk-free rate of zero. At the price p_1, all traders are content to hold their initial endowments, implying an equilibrium with no trading exists. ■

Proposition 2. If $\eta > 0$, expected trading volume increases with expected DO and is thus negatively related to expected return.

Proof. If $\eta > 0$, E[$Volume$] = 1/2 + (N/c)E[DO], which increases with DO. By substituting E[r] = –E[DO]/2, we obtain E[$Volume$] = 1/2 – ($2N/c$)E[r], which shows the negative relation. ■

Proposition 3. If $\eta > 0$, an increase in σ leads to an increase in expected DO, a decrease in expected return, and an increase in return volatility.

Proof. E[DO] is proportional to η E[$|s_A - s_B|$] = (2/3) $\eta\sigma$, where the equality is based on the expectation of a random variable with a uniform difference distribution [$(2/3)\sigma$]. Thus, E[DO] increases proportionally with σ. Because expected return is –E[DO]/2, it decreases proportionally with σ. Return volatility is proportional to σ because both the E[DO]^2 term and the Var[$E_A + E_B$] in the return variance expression in Equation (A20) are proportional to σ^2, and volatility is the square root of variance. ■

Proposition 4. If $\eta > 0$, market equity (M) and the ratio of market-to-book equity (M/B) increase with expected DO, and thus size and M/B are negatively related to expected return.

Proof. Because the firm's book value is one, its M = M/B = p_0 = 1 = E[DO]/2. Thus, M/B and M depend linearly on E[DO], which is negatively related to expected return. ■

Proposition 5. The average stock lending fee per share (f) increases with expected DO and is negatively related to expected return.

Proof. From Equation (A10), the average lending fee is $f = DO/2$, which increases proportionally with *DO*. Expected return decreases with E[*DO*] and thus with the lending fee. ■

Proposition 6. An increase in overconfidence (η) increases expected *DO* and decreases expected return. In addition, higher η amplifies each of the effects in Propositions 1 to 5.

Proof. Regardless of disclosure, expected *DO* is proportional to $\eta \mathrm{E}[|s_A - s_B|]$, which increases with η. Expected return is –E[*DO*]/2, which must decrease with η. Because the effects in Propositions 1 to 5 all rely on the expression for expected *DO* and this expression increases with η, an increase in η amplifies each of these effects. ■

Proposition 7. Expected difference in opinion is higher and expected return is lower with no firm disclosure; a lack of disclosure amplifies the effects in Propositions 1 to 5.

Proof. From Equations (A3) and (A4), nondisclosure increases *DO* by $= \eta |s_A - s_B|$ and increases E[*DO*] by $\eta \mathrm{E}[|s_A - s_B|]$. Because Propositions 1 to 5 rely on the expression for expected *DO*, which decreases with disclosure, a lack of disclosure amplifies these effects. ■

The model delivers several intuitive results. Proposition 1 shows that difference in opinion (*DO*) decreases expected return if agents are overconfident ($\eta > 0$). If agents are not overconfident, the model predicts no trading and no overpricing because agents agree on the firm's value. Thus, Proposition 1 formally justifies our *PNT* (nontrading) proxy for no *DO* and its positive relation with expected return. Proposition 2 extends this idea to trading volume. An increase in expected *DO* increases expected shorting demand from the pessimistic investor type, generating high trading volume. Because agents trade more when they disagree more and disagreement causes overpricing, stocks with high volume tend to be more overpriced.

Propositions 3 and 4 show that expected differences in opinion are also positively related to return volatility, firm size, and firms' ratios of market-to-book equity. Intuitively, an increase in the firm's fundamental volatility (σ) increases return volatility and expected *DO* because the public signals that generate disagreement are more volatile. In addition, an increase in expected *DO* increases overpricing and thus the firm's market capitalization, justifying size as a proxy for *DO*. Similarly, an increase in expected *DO* produces a higher stock price, holding book value constant, thereby raising the firm's M/B ratio, which justifies M/B as a proxy for *DO*. In this stylized model, size and M/B are the same because book value is normalized to one. Allowing firms' book values (B) to differ would generate cross-sectional variation in M/B ratios and overpricing even among firms with identical size (M).

Proposition 5 shows that markets with higher lending fees, such as OTC markets, will exhibit larger overpricing. This proposition is consistent with studies such as D'Avolio (2002) that interpret lending fees as arising from differences in investors' opinions.

Proposition 6 shows that an increase in investors' overconfidence (η) increases *DO* because disagreement results from placing excessive weight on different public signals. This overconfidence channel justifies *DO* proxies based on retail trading if retail traders are especially prone to overconfidence. In addition, Proposition 6 implies that stocks held primarily by retail investors are more subject to the overpricing effects stated in Propositions 1 to 5. This motivates our double-sorting methodology in which the initial sort is based on the presence of institutional (nonretail) investors.

Proposition 7 shows that a lack of firm disclosure increases differences in opinion because investors agree on how to interpret basic financial disclosures made by the firm. As a result, nondisclosure is associated with higher overpricing. Intuitively, lack of disclosure increases the uncertainty over which investors can disagree, thereby increasing expected overpricing. Furthermore, nondisclosure amplifies the overpricing effects in Propositions 1 to 5, motivating our double sorts using disclosure.

Appendix B. Estimating Betas and Accounting for Nonsynchronous Trading

To estimate a stock's betas in month t on return factors, we use a time-series regression of the stock's monthly return on the monthly return factors from month $t-24$ to month $t-1$. In cases in which a stock is not traded for one month or longer, we cumulate monthly factors during the entire nontrading period to align the stock and factor returns. We compute stocks' betas on the MKT, SMB, and HML factors using the three-factor Fama and French (1993) regression. Using regressions of returns on MKT, SMB, and HML, in addition to the respective factor, we compute betas with respect to the UMD momentum factor constructed by Kenneth French and originally used by Carhart (1997) and Pastor and Stambaugh's (2003) illiquidity factor (ILQ). We require at least ten observations in each regression.

Because many OTC stocks do not trade every day, we correct stocks' raw betas for nonsynchronous trading by extending the method used in Lo and MacKinlay (1990). Suppose that the unobservable "true" return process for stock i is

$$R_{it}=\alpha_i+F_t\beta_i+\varepsilon_{it}, \tag{B1}$$

where F_t is a $1\times m$ vector of factor returns. The econometrician only observes prices and returns in periods in which trading occurs. We denote the probability that stock i does not trade by p_i and assume that this probability is constant across periods. If a security does not trade for several periods, the observed return when it eventually does trade is the sum of all unobserved true returns per period. Formally, we define a variable $X_{it}(k)$ as follows:

$$X_{it}(k)=\begin{cases} 1 & \text{if stock } i \text{ traded in period } t \text{ but did not trade in all } k \text{ period prior to } t\\ 0 & \text{otherwise.}\end{cases} \tag{B2}$$

This definition implies that $X_{it}(k)=1$ with probability $(1-p_i)p_i^k$. Now we can write the observed return process (R_{it}^o) as

$$R_{it}^o=\sum_{k=0}^{\infty}X_{it}(k)R_{it-k}. \tag{B3}$$

We assume that factor returns (F_t) are independent and identically distributed over time with $E(F_t)=\mu_F$ and

$$Var(F_t)=\Sigma_f=\begin{pmatrix} \sigma_1^2 & . & . & . & \sigma_{1m}\\ . & . & & & .\\ . & & . & & .\\ . & & & . & .\\ \sigma_{m1} & . & . & . & \sigma_m^2 \end{pmatrix}. \tag{B4}$$

We estimate regressions of observed monthly returns on observed monthly factors. The observed beta vectors that we estimate are

$$\beta_i^o=\left[E\left(F_t^{o'}F_t^o\right)-E\left(F_t^{o'}\right)E\left(F_t^o\right)\right]^{-1}\left[E\left(F_t^{o'}R_{it}^o\right)-E\left(F_t^{o'}\right)E\left(R_{it}^o\right)\right]. \tag{B5}$$

Simplifying and rearranging Equation (B5) yields a relation between stock i's true beta and its observed beta and alpha:

$$\beta_i=\beta_i^o-\frac{2p_i}{1-p_i}\alpha_i^o\left[1-\frac{2p_i}{1-p_i}\mu_f\left(\Sigma_f+\frac{2p_i}{1-p_i}\mu_f^{'}\mu_f\right)^{-1}\mu_f^{'}\right]^{-1}\left(\Sigma_f+\frac{2p_i}{1-p_i}\mu_f^{'}\mu_f\right)^{-1}\mu_f^{'}. \tag{B6}$$

When F_t is a scalar, such as an intercept in a factor regression, this formula simplifies to

$$\beta_i=\beta_i^o-\frac{2p_i}{1-p_i}\alpha_i^o\frac{\mu_F}{\sigma_F^2}. \tag{B7}$$

We estimate the parameters needed to compute β_i as follows. First, we estimate the observed betas and alphas (β_i^o and α_i^o) for each firm in each month with regressions based on the twenty-four previous months. Second, we estimate the factor means and covariances (μ_F and Σ_f) during the same twenty-four months. Third, we estimate the probability of a stock not trading p_i, using the proportion of months in which the stock did not trade during the regression period. We then substitute these parameter estimates into Equation (B7) to estimate stock i's true beta.

References

Aggarwal, R. K., and G. Wu. 2006. Stock market manipulations: Theory and evidence. *Journal of Business* 79:1915–53.

Amihud, Y., and H. Mendelson. 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17:223–49.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61:259–99.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *Journal of Finance* 68:929–85.

Asparouhova, E., H. Bessembinder, and I. Kalcheva. 2010. Liquidity biases in asset pricing tests. *Journal of Financial Economics* 96:215–37.

Badrinath, S. G., and S. Wahal. 2002. Momentum trading by institutions. *Journal of Finance* 57:2449–78.

Baker, M. P., and J. C. Stein. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7:271–99.

Banz, R. W. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9:3–18.

Barber, B. M., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55:773–806.

Barberis, N., A. Sheifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49:307–43.

Baruch, S., G. A. Karolyi, and M. L. Lemmon. 2007. Multimarket trading and liquidity: Theory and evidence. *Journal of Finance* 62:2169–200.

Baruch, S., and G. Saar. 2009. Asset returns and the listing choice of firms. *Review of Financial Studies* 22:2239–74.

Bekaert, G., C. Harvey, and C. Lundbland. 2007. Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies* 20:1783–831.

Blume, M. E., and R. F. Stambaugh. 1983. Biases in computed returns: An application to the size effect. *Journal of Financial Economics* 12:387–404.

Böhme, R., and T. Holz. 2006. The effect of stock spam on financial markets. Working Paper, Technische Universität Dresden.

Bollen, N. P. B., and W. G. Christie. 2009. Market microstructure of the Pink Sheets. *Journal of Banking and Finance* 33:1326–39.

Bushee, B. J., and C. Leuz. 2005. Economic consequences of SEC disclosure regulation: Evidence from the OTC Bulletin Board. *Journal of Accounting and Economics* 39:233–64.

Carhart, M. M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Constantinides, G. M. 1986. Capital market equilibrium with transaction costs. *Journal of Political Economy* 94:842–62.

D'Avolio, G. M. The market for borrowing stock. *Journal of Financial Economics* 66:271–306.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53:1839–85.

Daniel, K., and S. Titman. 1997. Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance* 52:1–33.

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7:197–226.

Duffie, D., N. Garleanu, and L. H. Pedersen. 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics* 66:307–39.

Eraker, B., and M. J. Ready. 2011. Over the counter stock markets. Working Paper, University of Wisconsin, Madison.

Fama, E. F., and K. R. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47:427–65.

———. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81:607–36.

Ferson, W. E., and C. R. Harvey. 1999. Conditioning variables and the cross section of stock returns. *Journal of Finance* 54:1325–1360.

Frazzini, A., R. Israel, and T. J. Moskowitz. 2012. Trading costs of asset pricing anomalies. Working Paper, University of Chicago.

Frieder, L., and J. Zittrain. 2007. Spam works: Evidence from stock touts and corresponding market activity. *Hastings Communications and Entertainment Law Journal* 30:479–520.

Greenstone, M., P. Oyer, and A. Vissing-Jorgensen. 2006. Mandated disclosure, stock returns, and the 1964 Securities Acts Amendments. *Quarterly Journal of Economics* 121:399–460.

Griffin, J. M., J. H. Harris, and S. Topaloglu. 2003. The dynamics of institutional and individual trading. *Journal of Finance* 58:2285–320.

Gutierrez, R. C., and C. Pirinsky. 2007. Momentum, reversal, and the trading behaviors of institutions. *Journal of Financial Markets* 10:48–75.

Harris, J. H., V. Panchapagesan, and I. M. Werner. 2008. Off but not gone: A study of NASDAQ delistings. Working Paper, Ohio State University.

Hasbrouck, J. 2009. Trading costs and returns for U.S. equities: Estimating effective costs from daily data. *Journal of Finance* 64:1445–77.

Hirshleifer, D., and S. H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36:337–86.

Hong, H., and J. C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54:2143–84.

Ince, O. S., and R. B. Porter. 2006. Individual equity return data from Thomson Datastream: Handle with care. *Journal of Financial Research* 29:463–79.

Jarrow, R. 1980. Heterogeneous expectations, restrictions on short sales, and equilibrium asset prices. *Journal of Finance* 35:1105–13.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48:65–91.

———. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance* 56:699–720.

Karolyi, G. A., and A. B. Sanders. 1998. The variation of economic risk premiums in real estate returns. *Journal of Real Estate Finance and Economics* 17:245–62.

Lee, C. M. C., and B. Swaminathan. 2000. Price momentum and trading volume. *Journal of Finance* 55:2017–69.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12:1113–41.

Leuz, C., A. Triantis, and T. Y. Wang. 2008. Why do firms go dark? Causes and economic consequences of voluntary SEC deregistrations. *Journal of Accounting and Economics* 45:181–208.

Lo, A. W., and A. C. MacKinlay. 1990. An econometric analysis of nonsynchronous trading. *Journal of Econometrics* 45:181–211.

Loh, R. K., and M. Warachka. 2012. Streaks in earnings surprises and the cross-section of stock returns. *Management Science* 58:1305–21.

Luft, C., L. M. Levine, and S. Larson. 2001. Over the Counter Bulletin Board Exchange: Market structure, risk, and return. *Journal of Alternative Investments* Fall:33–42.

Luft, C., and L. M. Levine. 2004. Over the Counter Bulletin Board Exchange: The impact of liquidity and size to return, volatility, and bid/ask spread. *Journal of Alternative Investments* Winter:95–106.

Macey, J. R., M. O'Hara, and D. Pompilio. 2008. Down and out in the stock market: The law and economics of the delisting process. *Journal of Law and Economics* 51:683–713.

Miller, E. M. 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32:1151–68.

Nagel, S. 2005. Short sales, institutional investors and the cross section of stock returns. *Journal of Financial Economics* 78:277–309.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

———. 1994. Automatic lag selection in covariance matrix estimation. *Review of Economic Studies* 61:631–53.

Nofsinger, J. R., and R. W. Sias. 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54:2263–95.

Ofek, E., and M. Richardson. 2003. DotCom mania: The rise and fall of Internet stock prices. *Journal of Finance* 58:1113–38.

Pastor, L., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–58.

Sanger, G. C., and J. D. Peterson. 1990. An empirical analysis of common stock delistings. *Journal of Financial and Quantitative Analysis* 25:261–72.

Scheinkman, J. A., and W. Xiong. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111:1183–220.

Sias, R. W. 2004. Institutional herding. *Review of Financial Studies* 17:165–206.

Vayanos, D., and P. Woolley. 2013. An institutional theory of momentum and reversal. *Review of Financial Studies* 26:1087–145.