Asset Pricing in the Dark:

The Cross Section of OTC Stocks

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Andrew Ang, Assaf A. Shtauber, and Paul C. Tetlock*

Columbia University

Abstract

Compared to listed stocks, over-the-counter (OTC) stocks are far less liquid, disclose less information, and exhibit lower institutional holdings. We exploit these different market conditions to test theories of cross-sectional return premiums. Compared to return premiums in listed markets, the OTC premium for illiquid stocks is several times higher, the OTC premiums for size, value, and volatility are similar, and the OTC premium for momentum is three times lower. The OTC premiums for illiquidity, size, value, and volatility are largest among stocks that are held almost exclusively by retail investors and those that do not disclose financial information. Theories of differences in investors' opinions and short sales constraints help to explain these return premiums. Our momentum results are most consistent with Hong and Stein's (1999) theory based on the gradual diffusion of information.

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While 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 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.

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 either 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 non-existent, for most of our sample period.[2] Third, non-institutional (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 and rare.

[2] 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).

We exploit these features of OTC and listed stock markets to distinguish among myriad 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.[3] 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 non-trading 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' pre-cost returns. We find that an OTC illiquidity factor has an annual Sharpe ratio of 0.91, whereas the comparable listed illiquidity factor has a Sharpe ratio of just 0.14.

Our evidence is inconsistent with asset pricing theories based on transaction costs, such Amihud and Mendelson (1986) and Constantinides (1986). These theories predict that stocks exhibit *positive* pre-cost risk-adjusted returns that increase with bid-ask spreads to compensate rational investors for their expected trading costs. Empirically, the most liquid OTC stocks

[3] Researchers can also use international data, like Bekaert, Harvey, and Lundblad (2007) who estimate illiquidity premiums, or different asset classes like 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.

exhibit risk-adjusted monthly pre-cost returns of –4.0%, implying that their post-cost 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. These facts not only refute asset pricing theories emphasizing transaction costs, but they are also inconsistent with the hypothesis that data errors or microstructure biases in OTC stocks explain the OTC illiquidity premium. Such errors and biases should be smaller in the most liquid stocks and tend to 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 help explain why the OTC illiquidity premium remains so high during our 32-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, while 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.[4] Interestingly, the return premiums for size, value, and volatility are similarly large in OTC markets and comparable listed markets. In contrast, the return premium for momentum is considerably smaller and less robust in OTC markets than in listed markets.[5] Most of the OTC

[4] 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.
[5] Momentum is often thought of to be pervasive in that it occurs in many different countries and asset classes (see, for example, Asness, Moskowitz, and Pedersen (2012)).

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 the listed Pastor and Stambaugh's (2003) 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 common risk factors.

Our final tests examine whether theories based on limits to arbitrage can explain OTC and listed return premiums. Models analyzing the impact of differences in opinions and short sales constraints 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) and Scheinkman and Xiong (2003). The key mechanism is that, when investors' opinions diverge, short sales constraints restrict participation to investors with the most optimistic views of a stock. This 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 firm 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 sales constraints are tighter in OTC markets; and 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, which likely exhibit the highest investor disagreement.

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 the largest OTC firms, which presumably have more credibility. Furthermore, momentum among large OTC firms does not exhibit any reversal over five years, which is consistent with Hong and Stein's (1999) model but is hard to reconcile with some alternative models of momentum.

I. Related Studies of OTC Stocks

Only a few studies investigate stock pricing in OTC markets.[6] Studies by Luft, Levine, and Larson (2001) and Eraker and Ready (2011) find that the average OTC market return is negative during their 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.[7] 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 moving 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 moving to OTC markets in 2002. These studies suggest that the shift in trading to OTC venues actually causes stocks to become less liquid.

[6] Bollen and Christie (2009) examine various aspects of OTC stock microstructure, but do not investigate cross-sectional return premiums.
[7] Luft and Levine (2004) also explore the 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.

A recent study by Leuz, Triantis, and Wang (2008) investigates 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 the 480 firms going dark between 1998 and 2004 experience negative average abnormal returns of –10% upon announcement. Our study analyzes the returns of all OTC firms, including those that have chosen to go dark (a minority), those that have never reported to the SEC, and those that currently report to the SEC. All 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.

II. OTC Market Data

A. Institutional Details

Our data consist of US common stocks traded in the OTCBB and PS markets from 1977 through 2008. We obtain these data through MarketQA, which is 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 must be 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, such as 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.

We later provide evidence suggesting 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, including Ameritrade, E-Trade, Fidelity, Schwab, and Scottrade. 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.[8] 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 to short most small stocks; and nearly all investors have difficulty shorting OTC stocks. Thus, the OTC market is a natural place to test theories of short sales constraints.

[8] These data are available upon request.

B. OTCBB and PS Data

We examine the universe of firms incorporated in the US 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 that we are analyzing a set of firms that is as orthogonal as possible to 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 meeting the following requirements in the previous month:

- Non-missing data on stock price, market capitalization, and returns
- Stock price exceeds $1
- Market capitalization exceeds $1 million in 2008 dollars
- At least one non-zero daily return
- Positive trading volume—imposed only after 1995 when volume data are reliable.[9]

The price restriction above follows Ince and Porter (2006), who find that errors in computed returns are more likely for firms with prices of less than $1.[10] The market capitalization restriction is designed to eliminate thinly traded and economically unimportant firms that would otherwise dominate equal-weighted portfolios. The non-zero return and positive volume restrictions exclude thinly traded firms that suffer from bid-ask bounce and nonsynchronous trading issues.[11] Our final OTC sample includes an average of 486 firms per month.

[9] Prior to 1995, some OTC firms' volume data is recorded as missing when it is 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 treat these firms' volume data as missing instead.
[10] In untabulated results, we find that using a minimum price of $0.10 results in similar OTC return premiums.
[11] 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.

C. 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 non-zero daily return in the past year. *Eligible* stocks meet our data requirements in Section II.B. *Comparable* stocks in the listed sample consist of the 2*N* 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 of 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 to $36 million for the eligible listed sample. The difference in total market capitalization is much larger ($21.3 billion versus $9.59 trillion) because the largest listed firms are enormous and because there are 12 times fewer OTC stocks (600 OTC stocks versus 7,127 listed stocks). The annualized median OTC trading volume is only 2.2% of the median eligible listed trading volume ($2.3 million versus $101 million, respectively).[12] The aggregate annualized transactions in OTC stocks exceed $8.2 billion, whereas trades in eligible listed stocks exceed $11.4 trillion.

[Insert Table 1 here.]

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

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

OTC firms are quite large, as discussed below.[13] 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 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.[14] When imposed individually, our sample filters for a non-zero daily return, minimum price of $1, non-missing price, minimum market capitalization of $1 million, and non-missing 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.

[13] The average fraction of shares floating is reasonably similar for the smaller samples of 50 OTC firms (53% floating) and 50 similarly-sized listed firms (35% floating) in June of 2012.
[14] 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.

Figure 1 summarizes the relative 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 stock in the listed sample. 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 now traded in OTC markets relative to listed markets.[15] 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 Sarbanes-Oxley Act when many listed firms to chose to "go dark."

[Insert Figure 1 here.]

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 firms. Table 2 lists the firm size and month in which the 10 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

[15] As explained in footnote 9, 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.

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 their returns. Still, these data errors suggest one should be careful when interpreting OTC size data and value-weighted portfolio returns.

[Insert Table 2 here.]

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, the OTC stock universe is a powerful new venue to test the determinants of return premiums.

III. 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, which is a cumulative stock price that accounts for dividends and splits.[16] We assign a monthly index value based on the last available daily index value. Our sample filters ensure that this value is available within the last month. Our tests use two past return variables:

[16] 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 our main results depend on our correction procedure, which is available upon request.

past one-month returns (*Ret*[-1]) which capture short-term serial correlation and past 12-month returns (*Ret*[-12,-2]), not including the past month, which capture stock price momentum.

Idiosyncratic volatility is defined relative to the Fama-French (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.

Our analyses use three measures of individual stock liquidity. The main illiquidity measure is the proportion of days with no trading volume (*PNT*) 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. This measure more directly measures a lack of trading than 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.

Our return predictability tests use data on firm disclosure, institutional holdings, size, and book-to-market ratios. Firm disclosure (*Disclose*) is a dummy variable that is one if a firm's book equity data is available from either Compustat, Reuters Fundamentals, or Audit Analytics. We define book equity data as available if it appears in a firm's annual report dated between 7 and 19 months ago. Institutional holdings (*InstHold*) is a dummy variable indicating 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, as computed by 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.

[Insert Table 3 here.]

Table 3 reports summary statistics of returns and variables for OTC stocks and comparable listed stocks in Panels A and B, respectively. The mean monthly return of OTC stocks is slightly negative at –0.04% compared to 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.[17] Table 3 shows that an average of 26% of OTC stocks are held by institutions (*InstHold*), as compared to 71% of comparable listed stocks. This suggests that the investor clientele in OTC markets is mainly retail, while institutions play a bigger role in listed markets.

[17] 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.

The average of log volume (*Volume*) is much smaller for OTC stocks (8.25) than for 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 to 0.20 for listed stocks. The 95th percentile *PNT* value is 0.94, implying 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 the 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.

IV. Comparing the Cross Sections of OTC and Listed Returns

Following researchers studying listed stocks, we construct calendar-time portfolios of OTC stocks ranked by various characteristics to estimate the expected returns of OTC factors. We compare OTC factor returns to those in the comparable listed sample and those in the eligible listed sample. Forming factors has the advantage that the means of the portfolios have direct economic interpretations as return premiums. The portfolio tests also do not require assumptions of linearity, which regressions impose. The disadvantage of portfolios is 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).[18] A long-only portfolio's excess return is its monthly return minus the monthly risk-free rate prevailing 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).[19]

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.[20] We analyze five factors based on listed returns, including the MKT, SMB, HML, momentum (UMD), and illiquidity (ILQ) factors. We define UMD using

[18] In unreported tests, we simulate OTC stock returns in the presence of empirically realistic bid-ask bounce and non-trading, 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.

[19] 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. For our sample of 383 months, applying this formula results in a lag length of 5 months.

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

Carhart's 12-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 (30-day Treasury Bill) risk-free rate, which we refer to as "OTC Mkt_{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 consists of 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 pre-cost returns.

[Insert Table 4 here.]

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;[21] and (3) the momentum premium is much smaller in OTC markets.

A. 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,

[21] All OTC and listed value portfolios exclude firms with negative book equity.

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 than the GRW returns partly because size-based weightings place the lowest weights on the least liquid stocks, which have the highest returns.[22]

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 US and international stocks, including Amihud and Mendelson (1986), Lee and Swaminathan (2000), Pastor and Stambaugh (2003), Bekaert, Harvey, and Lundblad (2007), and Hasbrouck (2009). These studies show that the least liquid listed stocks have higher returns than 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

[22] 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 A of Table 5 in the following section reports how each return premium varies with firm size.

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 factor risk as measured by listed common 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 magnitude of the OTC illiquidity premiums. In such theories, prices adjust until investors' *post*-cost risk-adjusted expected returns are equal across assets and equal to the risk-free rate, assuming one can costlessly trade the risk-free asset. This implies that all risky portfolios' *pre*-cost alphas should be positive by an amount reflecting the cost of trading risky assets, where cost is equal to 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 10 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 10 firms in the early years when liquidity data are limited, Table 5 only includes data from August 1995 through December 2008.

[Insert Table 5 here.]

The results in Table 5 are inconsistent with several implications of trading cost theories. First and foremost, the pre-cost CAPM alphas of the OTC stocks in all but one of the bottom four (eight) deciles of *PNT* (Spread) are significantly negative, implying that their post-cost alphas must be even more negative. The OTC stocks with the lowest *PNT* values have especially negative pre-cost alphas of –3.98% per month, whereas the comparable listed stocks with the lowest *PNT* values have roughly zero pre-cost 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; and it would not predict negative risk-adjusted returns for any group of stocks.

Moreover, the magnitudes of trading costs incurred by OTC investors are small relative to the pre-cost 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% (3.98 – (–1.36)). Furthermore, because equilibrium trading costs *decrease* with *PNT*, subtracting trading costs from returns would 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 differs from Constantinides' (1986) by assuming 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 10 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 10 spread portfolios, while 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 inconsistent with the implications of trading cost theories. The monthly alpha of the montonicity 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, meaning that the spread-return relation is actually convex, not concave.

Lastly, we note that the results in Table 5 are 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 may be even more negative.

B. 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 to –0.98 and 1.19 in the comparable listed sample. Thus, we infer that the size and value premiums are robust to the differences across OTC and listed markets.

While the magnitudes of the size and value premiums are similar to their counterparts in listed markets, neither the listed size nor the listed value factor explains 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 listed value (HML) factor is positive, all five listed factors explain just 25.3% of the variance in the OTC value factor. This indicates that there are independent size and value factors in the OTC market that are not captured by listed factors.

C. 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. Thus 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.

D. 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.[23] 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.

[23] 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.

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.

E. OTC Market Returns

The last rows in Panels A to C of Table 4 report time-series regressions using 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 (2010)). In addition, the listed CAPM explains only 43.5% of the variation in the OTC market, while 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 establishes strong links between the OTC volatility and illiquidity premiums and the negative OTC market premium.

F. Multivariate Cross-sectional Regressions

We also estimate return premiums using monthly multivariate linear regressions that allow us to simultaneously control for firms' betas and characteristics. Table 6 reports Fama and MacBeth (1973) return predictability coefficients, along with Newey and West (1987) standard errors 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 following Asparouhova, Bessembinder, and Kalcheva (2010) 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.[24] Regressions I, II, and III include only betas, only characteristics, and both betas and characteristics, respectively. In Appendix 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.

[Insert Table 6 here.]

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 III 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 an attenuation bias in the coefficients on betas, this bias cannot explain why half of the beta coefficients are negative and statistically significant in Regression I. Furthermore, controlling for firms' betas has virtually no impact on

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

the coefficients on firms' characteristics, which are nearly identical in Regressions II and III. 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, jointly estimating return premiums on firms' betas and characteristics results in premiums that are quite similar to those using portfolio methods. For example, the *PNT* coefficient in the OTC sample in Regression III is 4.053, which implies a 3.36% per month ($4.053 \cdot (0.08 - 0.91)$) 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.B. The same qualitative result applies to the other return premiums. These findings in Table 6 show that none of the return premiums 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.C. Consequently, we focus on portfolio tests in the rest of the paper.

V. Testing Theories of Limited Arbitrage

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. Our main strategy is to contrast return premiums in subsamples of OTC and listed stocks, and we use additional tests to shed further light on the momentum premium.

A. Trading Costs as a Limit to Arbitrage

We first test whether trading costs limit the extent to which arbitrageurs can exploit the pre-cost returns of OTC factors in Table 4. We estimate the post-cost 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 savvy arbitrageurs, who use sophisticated strategies to minimize costs. Our post-cost return calculation is more relevant for the average investor in OTC markets.

We compute post-cost 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. However, 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.[25] Table 7 reports the pre-cost and post-cost returns of GRW portfolios and the breakeven rebalancing frequencies and spreads for several post-cost factor portfolios. The breakeven frequency (spread) is the rebalancing frequency (bid-ask spread) at which the post-cost return of the factor portfolio is closest to 0%. For brevity, we report the pre-cost returns, post-cost returns, and breakeven spreads of the GRW OTC factors with rebalancing frequencies of 1 and 12 months.

[25] Because limited spread data are available, we compute post-cost 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.

[Insert Table 7 here.]

The main finding in Table 7 is that the post-cost returns for arbitrageurs trying to exploit the OTC factors are much lower than the factors' pre-cost returns. Even at the annual rebalancing frequency, the post-cost GRW returns of all six OTC factors are 0.87% per month or lower, which contrasts with the pre-cost returns that are as high as 2.74% per month. Only the *PNT*, *Volume*, and *Value* factors exhibit positive post-cost 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 strategies and the breakeven horizon for the *Size* factor decreases to less than one year. In contrast, one cannot profitably exploit the OTC *Momentum* and *Volatility* factors with a one-year rebalancing frequency, regardless of which weighting scheme one uses. Not surprisingly, the impact of trading costs is even greater at the one-month rebalancing frequency.

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%—in order to deter arbitrage at the one-year rebalancing frequency. However, because the median OTC spread in Table 3.B 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 on short selling in OTC markets noted earlier. Such limits help explain why these large OTC return premiums persist, but one needs a model of investor behavior—such as the one 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.

B. 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 first 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 shows that both return premiums for illiquidity and the premium for volatility are roughly twice as large among OTC stocks that do not disclose book equity. Panel C indicates that the OTC premium for illiquidity is larger among small stocks, while the OTC premium for momentum is four times larger among big stocks. Twelve of the 13 statistically significant differences in return premiums in Table 8 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.

[Insert Table 8 here.]

C. Testing Theories of Investor Disagreement and Short Sales Constraints

We test Miller's (1977) hypothesis that investor disagreement combined with short sales constraints 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 of 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 short sales constraints, as suggested by Nagel (2005), which are associated with larger 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 highly statistically significant. Hinting at a role for short sales constraints, the premiums among non-held stocks arise mainly from the extremely 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 could 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. The differences in all premiums except for size are significant at the 5% level. The difference in size premiums is significant at the 10% level.

We can 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 be less overpriced than non-disclosing firms and thus earn higher returns.[26] 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 non-disclosing 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.

[26] 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.

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 short sales constraints (*e.g.*, Jarrow (1980)). Because few OTC stocks can be shorted and there is no tradeable index of OTC stocks that can be shorted (or even purchased), short sales constraints plausibly apply to the OTC market as a whole. Thus, disagreement combined with short sales constraints could account for the overall negative returns of the OTC market. It could also help explain the strong empirical links between the OTC market premium and the OTC premiums for illiquidity and volatility, which could all stem from the same underlying cause—namely, 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 short sales constraints, stocks with the highest systematic risk (i.e., beta) could become so overpriced that they exhibit lower future returns than stocks with low risk.

D. Testing Theories of Momentum

Firms traded in OTC markets disclose much less information than those in listed markets, and retail investors dominate in OTC markets. This suggests that theories emphasizing how investors react to information and the role of institutions could 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 firms' stock price movements. Such newswatchers may not exist for many OTC firms. Greenstone, Oyer, and Vissing-Jorgensen (2006) argue that investors view financial information disclosed by most OTC firms as less credible than 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 5 showing that OTC momentum is on average lower than 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 in listed stocks. This reasoning suggests momentum should be quite strong and continue for a long time 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 shows that the momentum premium 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, while 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 investigate the time horizon of momentum in OTC markets. We construct long-short momentum portfolios at various time horizons using the Jegadeesh and Titman (1993) method, similar to the rebalanced portfolios examined in Table 8.[27] Table 9 reports the

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[27] This procedure entails two steps. First, we form top and bottom quintile portfolios based on stocks' momentum (*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 $t -$

momentum portfolios' GRW and VW returns at horizons up to five years. Notably, there is no momentum (–0.08% per month) at the one-year horizon in OTC markets using the GRW method (which corrects for bid-ask bounce). There is, however, significant one-year momentum (1.57% per month) in the VW OTC portfolios, but this places extremely large weights on big OTC firms.

[Insert Table 9 here.]

Analyzing the long-term returns of momentum portfolios in OTC and listed markets can help us differentiate theories of momentum. In the models of Hong and Stein (1999) and Barberis, Shleifer, 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.[28] 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 and no reversal in the comparable-size sample in years two through five.[29] The observed lack of reversal lends support to the two underreaction theories of momentum: Hong and Stein (1999) and Barberis, Shleifer, 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

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*n*12 – 11*. The average differences in the extreme quintile portfolios' returns is the momentum premium at the *n*-year horizon.

[28] Because we lack earnings data for OTC firms, we cannot test other key predictions of the Barberis, Shleifer, and Vishny (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.

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

(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 (2012) argue that momentum in listed markets partly arises because of agency issues in these 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, our within-market evidence 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 Wooley (2012) 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.

VI. Concluding Discussion

While 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 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 short sales constraints 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.

The return premiums that exist 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 potential bubbles.

Appendix A: Model of OTC Stock Pricing

Our stylized model of OTC stock prices features short sales constraints and differences in investors' opinions. We analyze the price of a single all-equity firm in three periods: 0, 1, and 2. The firm has assets in place with a value normalized to $1, and it will liquidate its assets and pay out all of its cash flows at date 2. We assume that short sellers pay a fee $f > 0$ per share borrowed, and stock lenders earn the same amount. There is also a deadweight quadratic cost of short selling representing the cost of locating shares to borrow $(c/2)(\text{shares short})^2$, where $c > 0$. The per-share price of the stock (p) endogenously adjusts to clear the market for stock. We normalize the supply of stock to one, and the rate of return on the risk-free asset to zero.

There are two types of risk-neutral overconfident investors. There are N investors of each type, and each investor is endowed with an equal amount of the firm's shares at date 0. At date 1, all investors observe two independent public signals, s_A and s_B, about the firm's date 2 earnings (π_2). True 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. The two investor types differ in which signal they believe more. Type A believes that signal A is correlated with the other components of earnings, so that $u_t = \eta\, s_A + \text{sqrt}(1 - \eta^2)v_t$, while type B believes that $u_t = \eta\, s_B + \text{sqrt}(1 - \eta^2)v_t$, where $\eta \in [0, 1]$ and $t = 1$ or 2. In fact, there is no correlation among the four earnings components—specifically, $u_t = v_t$, where the v_t are uniformly distributed from $[-\sigma, +\sigma]$ and independent of each other, s_A, and s_B. Thus, the extent to which the parameter η exceeds 0 represents agents' overconfidence in their preferred signal.

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 A (B) by E_A (E_B). Define the signed difference in opinion between investors as DO = $E_A - E_B$.

For simplicity, we analyze the model's symmetric rational expectations equilibrium in which each investor takes the market price as given (e.g., as N becomes large) and investors within each type use the same strategies. We solve the model in the limit as the share lending fee f approaches zero, but all the results generalize to the case in which f is large. We first note that the investors' belief biases are symmetric, which implies that their average belief $[(E_A + E_B) / 2]$ is the rational expectation of firm earnings. Without loss of generality, assume type A is more optimistic ($s_A \geq s_B$) at date 1, so that type A takes a long position in the stock in equilibrium. Type A chooses q_A at date 1 to maximize expected profit, implying

$$q_A \in \text{argmax } \{q_A * (1 + E_A - p_1) + \text{I}(q_A > 1/N)\, f q_A - \text{I}(q_A < 0)\, [f q_A + (c/2)\, q_A{}^2]\}, \qquad \text{(A1)}$$

where I( ) is an indicator function. The first-order conditions for the two types of investors are:

$$1 + E_A - p_1 + f = 0, \text{ when } q_A > 1/N; \text{ and} \qquad \text{(A2)}$$

$$1 + E_B - p_1 + f - c q_B = 0, \text{ when } q_B < 0. \qquad \text{(A3)}$$

FOC_A ensures that the optimistic investors buy until the price reflects their beliefs:

$$p_1 = 1 + E_A + f, \text{ when DO} > 0. \qquad \text{(A4)}$$

Note that prices reflect the beliefs of only the more optimistic investor A and the share lending fee. FOC_B determines the equilibrium trading volume between pessimists and optimists:

$$q_B = (1 + E_B + f - p_1)/c = -\text{DO}/c. \qquad \text{(A5)}$$

Market clearing $[N(q_A + q_B) = 1]$ implies

$$q_A = 1/N + \text{DO}/c. \qquad \text{(A6)}$$

Using symmetric logic, analogous results hold when investor type B is more optimistic.

The equilibrium price in Date 1 is inefficiently high (i.e., greater than the average trader's belief) only insofar as the two traders exhibit differences in opinion. We define overpricing as the difference between the equilibrium price and the efficient price, which on date 1 is:

$$\text{Overpricing}_1 = 1 + E_A + f - [1 + (E_A + E_B)/2] = \text{DO}/2 + f \text{ when DO} > 0. \qquad \text{(A7)}$$

Ex ante, we do not know which type is most optimistic, so $\text{Overpricing}_1 = |\text{DO}|/2 + f$.

At date 0, both types anticipate the date 1 equilibrium, so the price is

$$p_0 = 1 + \text{E}[|\text{DO}|]/2 + f \text{ when E}[|\text{DO}|] > 0. \qquad \text{(A8)}$$

Equilibrium trading volume from date 0 to date 1 is:

$$\text{Volume} = |Nq_A - 1/2| = 1/2 + |\text{DO}|/c, \text{ when } \eta > 0, \qquad \text{(A9)}$$

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

$$\text{E(Volume)} = 1/2 + \text{E}[|\text{DO}|]/c, \text{ when } \eta > 0. \qquad \text{(A10)}$$

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

$$\text{StdDev}(p_1 - p_0) = \text{StdDev}(|\text{DO}| - \text{E}[|\text{DO}|])/2 = \text{StdDev}(|\text{DO}|)/2. \qquad \text{(A11)}$$

Lastly, we note the following expressions for date 1 differences in investors' opinions in the cases with firm disclosure of financial information at date 1 and without such disclosure.

$$\text{No disclosure } [\pi_2 = s_A + s_B + u_1 + u_2]\text{: DO} = E_A - E_B = 2\eta(s_A - s_B). \qquad \text{(A12)}$$

$$\text{Disclosure } [\pi_2 = e_1 + u_2]\text{: DO} = E_A - E_B = \eta(s_A - s_B). \qquad \text{(A13)}$$

To summarize, the extent of ex-ante overpricing increases with difference in opinions, which is consistent with Miller (1977) and related theories. The equilibrium relies on the assumptions that short selling is costly ($c, f > 0$) and that investors are overconfident ($\eta > 0$). In addition, firm disclosure of financial information reduces differences in investors' opinions.

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

Proposition 1: When $\eta > 0$, expected overpricing increases with the expected difference in opinion. If $\eta = 0$, there is no difference in opinion, no trading, and the stock price is efficient.

Proof: When $\eta > 0$, expected overpricing is E[|DO|]/2 + f, so it increases with E[|DO|]. If $\eta = 0$, on date 1, then DO = 0 (regardless of disclosure) and both types of traders agree that the firm value is $1 + E_A = 1 + E_B$, so this must be the equilibrium price. At this price, no trader wishes to buy or sell his/her endowment, implying no trading. In addition, because both traders have rational beliefs and face no binding constraints, the equilibrium price must be efficient.

Proposition 2: When $\eta > 0$, expected trading volume increases with expected |DO| and is thus positively associated with expected overpricing.

Proof: When $\eta > 0$, E(volume) = 1/2 + E[|DO|]/c. Expected overpricing is E[|DO|]/2 + f. Thus, expected overpricing is [E(volume) – 1/2]c/2 + f.

Proposition 3: When $\eta > 0$, increases in σ lead to increases in expected |DO|, return volatility, and overpricing.

Proof: With no disclosure, E[|DO|] = 2η E[$|s_A - s_B|$] = $(4/3)\eta\sigma$, where the last equality is based on the expected value of a random variable with a uniform difference distribution [$(2/3)\sigma$]. With disclosure, E[|DO|] = η E[$|s_A - s_B|$] = $(2/3)\eta\sigma$. In both cases, E[|DO|] is proportional to σ. Because expected overpricing is E[|DO|]/2 + f, it follows that overpricing increases with σ. Lastly, return volatility is StdDev(|DO|)/2 = [sqrt(2)/4] E[|DO|], based on the moments of a random variable with a uniform difference distribution. Because return volatility is proportional to E[|DO], it is also proportional to σ in both disclosure regimes.

Proposition 4: When $\eta > 0$, market equity (M) and the ratio of market-to-book equity (M/B) increase with expected |DO| and thus size and M/B are positively related to overpricing.

Proof: Because the firm's book value is 1, its M = M/B = p_0 = 1 + E[|DO|]/2 + f. Thus, M/B and M depend linearly on E[|DO|] and M – 1 and M/B – 1 are both equal to ex ante overpricing.

Proposition 5: As overconfidence (η) increases, expected |DO| increases and so does overpricing. In addition, each of the results in Propositions 1 to 4 is stronger with higher η.

Proof: As noted earlier, E[|DO|] = (4/3)$\eta\sigma$ without disclosure and E[|DO|] = (2/3)$\eta\sigma$ with disclosure. Both expressions increase in η. Expected overpricing is E[|DO|]/2 + f, so this must also increase in η. Because Propositions 1 to 4 all rely on the expression for E[|DO|] and this expression increases in η, it follows that increases in η strengthen each of these results.

Proposition 6: Expected difference in opinion and thus overpricing is higher in the absence of firm disclosure; and a lack of disclosure strengthens the effects in Propositions 1 to 4.

Proof: As noted earlier, E[|DO|] = (4/3)$\eta\sigma$ without disclosure and E[|DO|] = (2/3)$\eta\sigma$ with disclosure. Thus, a lack of disclosure increases E[|DO|] by (2/3)$\eta\sigma > 0$. Because Propositions 1 to 4 all rely on the expression for E[|DO|] and this expression increases with a lack of disclosure, it follows that a lack of disclosure strengthens each of these results.

Now we briefly explain the intuition behind the model's key results. Proposition 1 shows that difference in opinion (DO) is positively related to overpricing in the model as long as agents are overconfident ($\eta > 0$). If agents are not overconfident, the model predicts zero trading activity and no overpricing because all agents agree on the firm's fundamental value. Thus, Proposition 1 formally justifies our *PNT* (non-trading) proxy for DO. Proposition 2 extends this idea to encompass the level of trading activity. An increase in expected DO increases expected shorting demand from the pessimistic investor type, which generates high trading volume. Because agents trade more when they disagree more and disagreement causes overpricing, stocks with high trading 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 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. Along the same lines, 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.

Proposition 5 shows that an increase in investors' overconfidence (η) increases expected DO because disagreement is higher for any given realization of the two public signals. This overconfidence channel provides a justification for DO proxies that are based on the presence of retail trading if one assumes that retail traders are more prone to overconfidence. In addition, one would expect that stocks held primarily by retail investors would be more subject to the overpricing effects in Propositions 1 to 4. This motivates our double-sorting methodology where the initial sort is based on the presence of institutional (non-retail) investors.

Proposition 6 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, non-disclosure is associated with higher overpricing. Intuitively, lack of disclosure increases the uncertainty over which investors can disagree, and with short-selling being costly, this translates to higher overpricing. Furthermore, non-disclosure amplifies the overpricing effects in Propositions 1 to 4, which motivates our double sorts using disclosure.

Lastly, overpricing increases with the share lending fee (*f*) whenever there is any investor disagreement, as shown in Equations (A7) and (A8). This implies markets with tighter short sales constraints, such as OTC markets, will exhibit larger overpricing.

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 non-trading 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. We compute betas with respect to the UMD momentum factor constructed by Kenneth French, which was originally used by Carhart (1997), and the illiquidity factor (ILQ) of Pastor and Stambaugh (2003) using regressions of returns on MKT, SMB and HML in addition to the respective factor. We require at least 10 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 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 when trading occurs. We denote the probability that stock *i* does not trade by p_i and assume 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:

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

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

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

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

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

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 obtain the parameters required for computing β_i as follows. First, we estimate the observed betas and alphas (β_i^o and α_i^o) for each firm for each month with regressions using the 24 previous months. Next, we estimate the factor means and covariances (μ_F and Σ_f) for each regression during the same 24 months. Lastly, 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.

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Table 1: Summary Statistics for the OTC and Listed Samples in July 1997

We report statistics for size, volume, and the number of firms in the OTC, comparable listed, and eligible listed samples in July of 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 II.B.

	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

Table 2: The Peak Sizes of the Largest 10 OTC Firms

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 II.C.

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	292th	93.9%
MAXIM INTEGRATED PRODS INC	May-08	Pink Sheets	7.1	381th	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	623th	89.8%
HEALTHSOUTH CORP	Dec-04	Pink Sheets	2.5	734th	84.4%

Table 3: Cross-Sectional Summary Statistics for Key Variables

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 below separately for the cross section of stocks in each month and then average across months. We measure all firm characteristics other than *PNT* using logarithms. We Winsorize all firm characteristics at the 5% level, but we do not Winsorize returns. The first seven columns report monthly averages of means, standard deviations, and various percentiles. The second to last column presents the average number of firms with non-missing values of each variable in each month. The last column presents the total number of months in which there is any data for each variable.

Panel A: OTC Stocks

	Monthly Averages								Total
Variable	Mean	SD	P5	P25	P50	P75	P95	Firms	Months
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
Variable	Mean	SD	P5	P25	P50	P75	P95	Firms	Months
Return (%)	0.66	19.46	-24.45	-8.99	-1.22	7.28	32.16	1018	383
Disclosure	0.83	0.33	0.28	0.65	1.00	1.00	1.00	1018	383
Size	2.21	0.53	1.08	1.85	2.32	2.66	2.89	1018	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	1005	383
Volume	10.77	1.98	8.11	9.48	10.27	12.35	14.26	1018	383
PNT	0.20	0.21	0.00	0.03	0.13	0.33	0.67	1018	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

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

Table 4: Time Series Analysis of OTC and Comparable Listed Factor Portfolios

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 either 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 ǂ 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 non-synchronous 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 either 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, while 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. Newey and West (1987) standard errors appear in parentheses. We denote statistical significance at the 5% and 1% levels using * and ** symbols, respectively.

Table 4 Continued

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_{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_{VW}	-0.52*			-1.21**			-1.52**
	(0.23)			(0.19)			(0.26)

Table 4 Continued

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_{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_{VW}	-0.74*	N/A	N/A	-1.32**	-1.5**
	(0.33)			(0.21)	(0.26)

Table 4 Continued

Panel C: Systematic Variation in OTC Return Factors

	Factor Loadings							R^2 by Model		
Factor	β_{OMKT}	β_{MKT_CAPM}	β_{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)			

Table 4 Continued

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)
PNT_{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)

Table 4 Continued

Panel E: Systematic Variation in Comparable Listed Return Factors

	Factor Loadings							R^2 by Model		
Factor	β_{OMKT}	β_{MKT_CAPM}	β_{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)			

Table 5: Testing Transaction Cost Theories of the Illiquidity Premium

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 5 firms in all portfolios 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 II.C. These alphas are the intercepts from time series regressions of monthly portfolio returns on the listed MKT factor, including six lags to account for non-synchronous trading. Columns 8 and 9 in both panels report mean *Turnover* values for each portfolio, while 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 ** symbols, respectively. These statistical tests employ Newey and West (1987) standard errors with four lags based on the formula from Newey and West (1994).

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)								

Panel B: Sorts into Bid-Ask Spread Ranges

Bid-Ask Spread Range	CAPM Alphas (GRW)			Mean *PNT*		Mean *Spread*		Mean *Turnover*		Trading Costs	
	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)								

Table 6: Cross-Sectional Regressions of Monthly Returns on Firm Characteristics

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 weight each monthly coefficient by the inverse of its squared standard errors 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 ** symbols, respectively.

	OTC Sample			Comparable Listed Sample			Eligible Listed Sample		
	I	II	III	I	II	III	I	II	III
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

Table 7: The Impact of Trading Costs on Arbitrageurs' Returns

This table evaluates the returns for an arbitrageur trying to implement the OTC factor returns who pays stocks' bid-ask spreads on each round-trip trade. We compute summary statistics for long-short factor portfolios that are rebalanced at frequencies of 1 and 12 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 pre-cost returns for 1- and 12-month rebalancing frequencies. Columns 3 and 4 report factor portfolios' average post-cost returns. Estimated 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 post-cost 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 post-cost returns would be 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.

	Pre-cost Returns		Post-cost Returns		Breakeven Spread		Breakeven Frequency		
OTC factor	1 month	12 months	1 month	12 months	1 month	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	4.10%	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+

Table 8: Double Sorted Portfolios

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 II.C. 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 require at least 10 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 returns. 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 where stocks are first sorted according to *InstHold*. Panel B reports returns where stocks are first sorted according to *Disclose.* Panel C reports returns where stocks are first sorted according to *Size.*

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

Panel A: Double Sorted Portfolios: Initial Sort Based on Institutional Holdings

	Held stocks monthly returns			Non-held stocks monthly returns			Premium
	Top tercile	Bottom tercile	Premium	Top tercile	Bottom tercile	Premium	Difference (%)
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			Non-disclosing 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*

Panel C: Double Sorted Portfolios: Initial Sort Based on Size

	Big stocks monthly returns			Small stocks monthly returns			Premium
	Top tercile	Bottom tercile	Premium	Top tercile	Bottom tercile	Premium	Difference (%)
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**

Table 9: Long–term Returns of Momentum Portfolios

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 value weighted ("VW returns"). Then, to measure momentum returns *n* years after portfolio formation in each month *t,* we equally weight the 12 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 3 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 II.C, 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 II.B. We denote statistical significance at the 5% and 1% levels using * and ** symbols, respectively. These statistical tests employ Newey and West (1987) standard errors with five lags based on the formula from Newey and West (1994).

	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

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. Then we 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, which is the date when volume data become reliable. The eligible listed sample consists of the CRSP stocks satisfying the same data requirements as the OTC sample described in Section II.B.

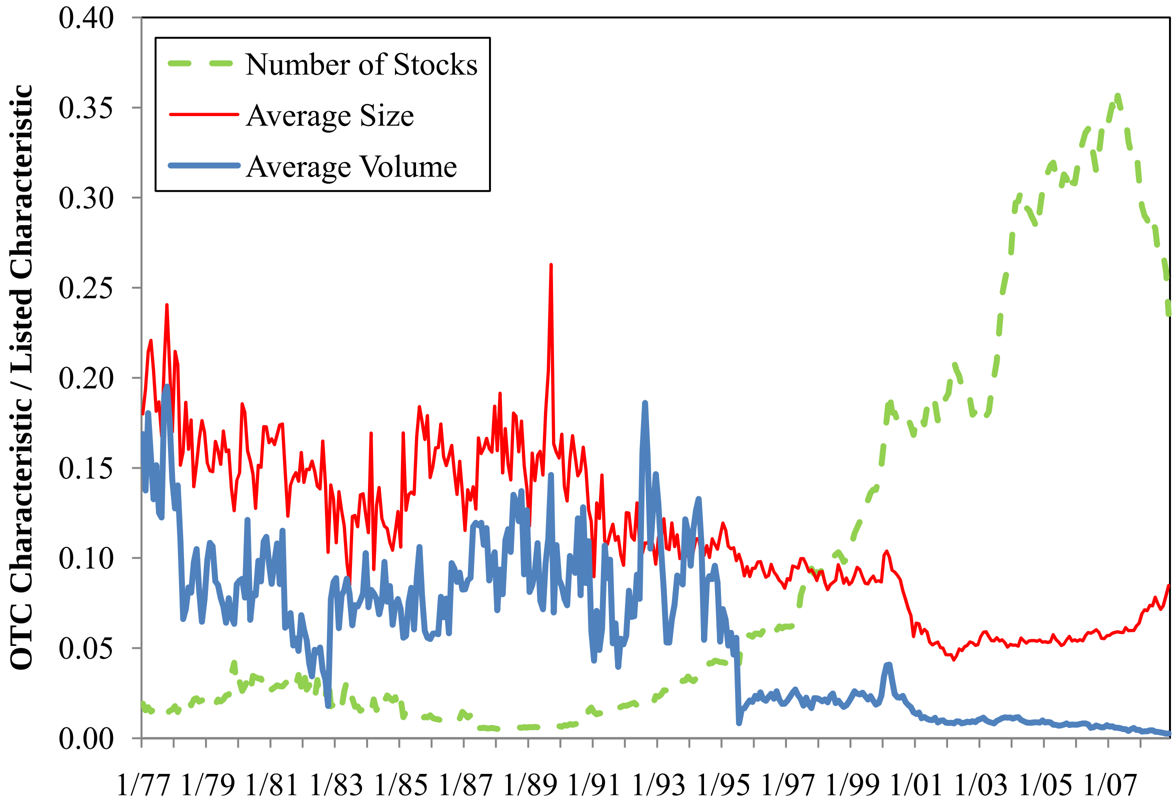

Figure 2: The Value of $1 Invested in Illiquidity Factors

We graph the cumulative returns for illiquidity factors in the OTC, comparable listed, and eligible listed samples. We use a logarithmic scale to represent the evolution of the value of a $1 investment from December 1976 to December 2008 for the illiquidity factors from each market. In all three markets, we sort stocks into quintiles according to their monthly *PNT* values, where *PNT* is the fraction of non-trading days in a month. Each *PNT* factor return is the difference between the gross-return-weighted returns of firms in the top and bottom *PNT* quintiles. We also plot the cumulative return of the value-weighted Pastor-Stambaugh illiquidity factor from the eligible listed sample. We assume that an investor begins with $1 long and $1 short and faces no margin or other funding requirements. To facilitate comparison, we scale the long-short portfolio positions in the OTC and eligible listed factors so that the volatility of these portfolios is equal to the volatility of the long-short portfolio based on the comparable listed factor. The comparable listed sample consists of stocks that are comparable to stocks in the OTC sample in terms of size, as described in Section II.C. The eligible listed sample consists of all listed stocks that satisfy the same data requirements as the OTC sample described in Section II.B.