# Disagreement and Liquidity

# Online Appendix

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# 1 Introduction

The main paper proposes three stylized facts about trading and liquidity in stock, option, and bond markets. This appendix describes the paper's empirical methodologies in more detail and reports stock results that are omitted in the main paper. It also reports additional stock market tests, including cross-sectional evidence and robustness checks across different types of stocks.

The three stylized facts are:

1. Trade and liquidity are positively correlated;

2. Asymmetric information increases trade and decreases liquidity; and

3. High past returns increase trade and liquidity.

# 2 Data and Methodology

I consider the trading and liquidity of New York Stock Exchange (NYSE) stocks between 1926 and 2011. I focus on the NYSE to control for differences in market structure and reporting across exchanges. Limiting attention to the NYSE also mitigates the impact of small stocks on my analysis. I also limit my analysis to stocks with share prices above $5 at the end of the previous month. If the model is true, its predictions should hold over time and across stocks so I utilize time series, cross sectional, panel, and event study methodologies. The biggest challenge facing this empirical work is that of the four relevant quantities (trading, liquidity, overconfidence, and asymmetric information), only trading is directly observable. To overcome this challenge, I consider multiple proxies for each unobserved quantity. Results are generally robust across proxies.

Table 1 and figure 1 summarize my primary data sources. Means represent equally weighted averages across stocks. Standard deviations are cross-sectional. Trading volume is the most straightforward data item because it is directly observable in CRSP monthly data from 1926 to 2011. To control for growth in share price and firm size, I use monthly turnover as my measure of trading. Average monthly turnover is 6.2% over the full sample with a standard deviation of 8.1%. On average, there are 1,100 observations per month. Turnover was relatively high (10%+) during the 1926 to 1935 period, dropped to the 2-5% range during the middle of the twentieth century, and has increased over the past three decades to a current level in excess of 20%. The time trend is clearest in figure 1, panel A. Table 1 shows that cross sectional standard deviations followed a similar trend.

Within the model, the relevant concept of illiquidity is the price impact caused by a buy or sell trade. While illiquidity is not directly observable, a large literature has identified different ways of estimating it. My first illiquidity measure is $illiq_{it} = \frac{|Return_{it}|}{\$Vol_{it}}$, proposed by Amihud (2002). *illiq* has the advantage of directly relating price changes to volume. It is also readily computable using daily return and volume data for the full 1926 to 2011 time series. Table 1 shows that equally-weighted average *illiq* has decreased dramatically over time from 134% per $100K of volume in the 1926 to 1945 period to 0.56% in the most recent period. Figure 1, panel B plots $\log(illiq)$ over time.

Bid-ask spread is another measure of illiquidity, and corresponds to asymmetric information price response in Glosten and Milgrom (1985). I consider three variations of bid-ask spread. *bidask* is a daily measure of a stock's final quoted bid-ask spread, scaled by its closing price. Quoted bid-ask spread (*qbidask*) is the transaction-level counterpart to *bidask*, using intraday trades and quotes instead of end-of-day data. Using TAQ data, I match trades to quotes prevailing two seconds earlier. *qbidask* is the equally weighted average across transactions of quoted bid-ask spread scaled by transaction price. Finally, I consider the effective bid-ask spread (*ebidask*) measure of Chordia, Roll, and Subrahmanyam (2000). I calculate *ebidask* by matching trades with prevailing quotes from two seconds earlier. *ebidask* is twice the deviation between price and the bid-ask midpoint, scaled by price. Effective bid-ask spread takes into account that many trades are executed within quoted spreads and that large trades can take place outside of the spread if they exceed quoted depth. The main assumption behind *ebidask* is that deviations in price from the bid-ask midpoint represent buying or selling pressure. Like *qbidask*, *ebidask* is an equally weighted average across all of a stock's transactions in a given day. Table 1 and panels C and D of figure 1 summarize and plot the bid-ask data. TAQ transaction data is available for *qbidask* and *ebidask* starting in 1993. Daily data on *bidask* is available from CRSP for this period and prior to 1942, but is missing in the interim period. In the overlapping post-1993 period, daily bid-ask spreads average 1.1%. Transaction data on quoted spreads record intraday spreads half as large. Effective spreads are smaller still at 0.4%. All three time series follow a similar pattern with significant decreases recently. The drop-off in daily bid-ask spreads has been particularly large. Where the series overlap, *illiq* and and the bid-ask spread time series follow a similar pattern.

For overconfidence proxies, I rely on the learning models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001). Self attribution bias causes investors to be particularly overconfident following high returns. Because investors hold the market on average, aggregate overconfidence should track market returns. Individual stock returns may also affect stock-level overconfidence. To the extent that investors specialize in certain industries or have industry-specific confidence levels, past industry returns will also affect stock-level overconfidence. Statman, Thorley, and Vorkink (2006) employ market and individual stock VAR analyses to show that aggregate turnover increases following high market returns and stock-level turnover increases following past market and stock-level returns. I extend Statman, Thorley, and Vorkink's market VAR to include measures of illiquidity as well as turnover. For stock-level analysis, I employ a panel VAR with stock-level turnover, stock-level illiquidity, stock-level returns, industry returns, and time and firm fixed effects. I also test the effects of stock-level returns by sorting stocks into cross-sectional momentum deciles. Stock-level return data comes from CRSP. Excess market return (CRSP value weight market return less the risk free rate) and industry return data is from Ken French's website. Return data is available starting in 1926. Industries are defined using Ken French's 10 industry groups and assigned based on Compustat (and where missing CRSP) SIC codes (available after 1950).[1]

I identify changes in asymmetric information in two ways. First, periods around earnings announcements are likely to have elevated asymmetric information. Prior to announcements private information can be in the form of leaks and insider trading. After announcements, investors process different pieces of information at different paces using different models, keeping private information high until the announcement is fully digested and reflected in prices. Public uncertainty is also high around earnings announcements because asset values are highly sensitive to the announcements. Second, I follow Sadka and Scherbina (2007) and use dispersion of analyst forecasts as a proxy for asymmetric information. Analyst dispersion may represent or cause public uncertainty. Dispersion could also stem from more private information. My specific measure of dispersion is the standard deviation across analysts of current year earnings forecasts scaled by the mean forecast. Stocks are included if they are covered by at least two analysts, have a non-zero mean earnings forecast, and

[1] I follow Ken French's methodology of updating industry definitions at the end of each June based on SIC codes from the end of the previous year.

have a December fiscal year end. The December fiscal year requirement ensures that all stocks have the same amount of time remaining in the current fiscal year. Monthly analyst forecasts, summarized in table 1, are available from I/B/E/S starting in 1976. Valid dispersion data is available for about 60% of the stocks in my other samples. Analyst dispersion has decreased over time from 20.6% in the 1976 to 1992 period to 13.8% in the 1993 to 2011 period.

All of the data items in table 1 and figure 1 show significant time trends and changing standard deviations, making direct regression analysis difficult. To correct for these trends, I use logs in all regressions. This makes deviations more comparable over time, but time trends still make the data non-stationary (for example, see the log($illiq$) time series in figure 1, panel A). In panel analysis, I avoid this problem by employing time and firm fixed effects. For market VAR analysis, I detrend the log time series using a Hodrick and Prescott (1997) filter.[2] The dashed lines in figure 1 plot the trends. Figure 2 shows the detrended time series.

## 3 Turnover and Liquidity

Before investigating overconfidence and asymmetric information, I first examine the reduced form relationship between turnover and liquidity. At the end of each month, I sort stocks into decile portfolios based on turnover in the past month. Table 2 shows the results. Turnover is persistent over the next month, and high turnover stocks are more liquid. Across all four measures, illiquidity monotonically decreases as turnover increases and differences between deciles 1 and 10 are highly significant.

One potential concern with the decile sort methodology is that lagged turnover is inevitably correlated with omitted stock characteristics. To control for omitted variables, I employ panel regressions with fixed effects for firms (to control for omitted firm characteristics), years (to control for time trends), and months (to control for seasonality). The resulting identification is based on changes to relative analyst dispersion over time for a given firm. Table 2 reports regression results with standard errors that are multidimensionally clustered by stock and time. The analyzed

[2]Following Statman, Thorley, and Vorkink (2006) and common practice, I use a penalty value of 14,400 for the filter. Also following Statman, Thorley, and Vorkink (2006), I employ a 2-sided filter. The 2-sided filter, which makes use of future data, would problematic if I was using it for forecasting purposes, but I am not. To verify that my results are unaffected by the use of future data, I replicated my market VAR with a 1-sided HP filter proposed by Stock and Watson (1999). Results (which are untabulated but are available on request) were unchanged.

variables are all logs so the coefficients can be interpreted as elasticities. Across all specifications, the panel regressions support the cross-sectional decile results. As lagged turnover increases within firms current turnover increases and all measures of illiquidity decrease. Turnover is highly persistent with a 69% coefficient estimate. For *illiq* the coefficient estimate is -56%. The bid-ask spread coefficients are in the range of -10% to -15%. All five coefficients are highly significant.

## 4 Overconfidence

I now turn to overconfidence and test the prediction that overconfidence increases trading and liquidity. Following Statman, Thorley, and Vorkink (2006), I use past returns as a proxy for overconfidence. Statman, Thorley, and Vorkink use a market VAR to show that turnover increases following high returns, consistent with the overconfidence story. My contribution is to test whether high returns also predict improved liquidity. My market VAR model is:

$$Y_t = \alpha + \sum_{k=1}^{2} A_k Y_{t-k} + e_t \tag{1}$$

where $Y_t$ is a $3 \times 1$ vector of detrended log turnover, detrended log illiquidity (*illiq*), and excess market returns. Using two lags is optimal according to the Bayesian information criteria. Table 4 shows parameter estimates and bootstrapped standard errors for the VAR. Starting with turnover in column 1, we can see that turnover is persistent. Its own first lag has a highly significant coefficient of 0.48. Lagged illiquidity also negatively forecasts turnover, though with borderline significance. Most interestingly, the last two lags of market returns both have significant positive coefficients (0.86 for the first lag and 0.39 for the second lag). Turning to *illiq* in column 2, the first lag of turnover predicts a decrease in illiquidity. This effect is partially offset in the following period. *illiq* itself is persistent, as demonstrated by the significant positive coefficients on its own lags. Lagged market return has a significant coefficient of -1.5, demonstrating that overconfidence (proxied by past returns) improves liquidity in addition to increasing trading. The market return coefficients in column 3 are not of direct interest to this paper, but the results are a little surprising. Past illiquidity and past returns both positively forecast future returns, which is at odds with the general unpredictability and slight negative autocorrelation of market returns in other studies. The bottom line from the market VAR results is that positive market returns forecast future increases in trading and decreases in illiquidity.

The VAR coefficients of table 4 can be better understood by plotting impulse response functions, which show how unexpected shocks to any of the variables affect future forecasts. Figure 3 plots the market VAR's impulse response functions. All shocks are one standard deviation in magnitude. The plot summarizes how the shocks affect forecasts 1-5 months in the future. Turnover and *illiq* are logs so their responses can be interpreted as percent changes. Solid lines represent the impulse response functions. Dashed lines are bootstrapped 95% confidence intervals. The first row of figure 3 shows responses to a one standard deviation shock to turnover. Turnover itself remains elevated for 2-3 months. *illiq* decreases by about 2% and then returns to normal. Returns are largely unaffected. Row 2 shows that *illiq* impulses are persistent and have a slight negative effect on turnover and positive effect on market returns. By contrast, the return impulse is barely persistent at all, but it significantly decreases illiquidity and increases turnover for about five months. The initial response is +5% for turnover and -8% for *illiq*. Assuming return shocks increase overconfidence, this is what proposition 1 predicts.

As a robustness check, I repeat the market VAR analysis of table 4 and figure 3 on bid-ask spreads, which are unfortunately only available in uninterrupted time series starting in 1993. Figure 4 shows impulse responses to one standard deviation return shocks for daily, quoted, and effective bid-ask spreads. Standard errors are larger, but the market return impulse significantly reduces all bid-ask spread forecasts, and the responses lasts a full five months, supporting the initial market VAR results. In the shortened 1993 to 2011 time period, returns no longer positively predict future trading. The result goes slightly the opposite way during this sample.

In addition to changing over time, overconfidence can also vary across stocks. If overconfidence is in part stock-specific or if investors do not hold fully diversified portfolios, self attribution bias will cause stock-level returns to influence stock-level overconfidence. Similarly, industry returns will influence stock-level overconfidence if investors specialize in certain industries or have industry-specific overconfidence. Using separately estimated stock-level VARs, Statman, Thorley, and Vorkink (2006) show that stock turnover is positively influenced by both past market returns and past individual stock returns. I employ a different econometric strategy and estimate a single panel VAR that includes stock-level turnover, illiquidity, and returns as well as industry returns.

The panel VAR specification allows me to employ stock and time fixed effects, eliminating the need for detrending the data. Specifically, I estimate:

$$Y_{i,t} = \alpha_t + f_i + \sum_{k=1}^{2} A_k Y_{i,t-k} + e_t \tag{2}$$

where $Y_{i,t}$ is a $4 \times 1$ vector of log stock turnover, log stock *illiq*, stock returns, and industry returns for stock $i$ in month $t$. $\alpha_t$ and $f_i$ are $4 \times 1$ vectors of time and stock fixed effects for each variable. I employ two lags for consistency with the market model. The time fixed effects control for the effect of market returns as well as any other market-level time variation. Prior to estimation, I eliminate the time fixed affects by time de-meaning all variables. The panel fixed effects are a little trickier because stock de-meaned lag variables are not orthogonal to the regression residual. Similarly, directly estimating stock fixed effects would produce biased and non-consistent estimates for all coefficients. Following Holtz-Eakin, Newey, and Rosen (1988), I take the first differences of all variables, resulting in:

$$Y_{i,t} - Y_{i,t-1} = (\alpha_t - \alpha_{t-1}) + \sum_{k=1}^{2} A_k \left(Y_{i,t-k} - Y_{i,t-1-k}\right) + e_t \tag{3}$$

which can be estimated using using $Y_{i,t-2}$ and $Y_{i,t-3}$ as instruments. I include all observations with at least three lagged observations. When there are breaks in the data. I treat observations before and after the break as if they were separate stocks. The only remaining complication is estimating standard errors. The lagged variables directly control for autocorrelation in the data, but there is likely cross-sectional correlation within time periods. To account for this I employ bootstrapped standard errors with a bootsrap that randomly samples (with replacement) time periods. When a time period is drawn, all observations in that time period are included. This preserves the data's cross-sectional correlation structure.

Table 5 reports the panel VAR coefficient estimates and standard errors. Turnover and illiquidity are both persistent – coefficients on their own first lags are approximately 0.2 and highly significant in both cases. Individual stock returns show a little reversal with an own-lag coefficient of -0.1. My primary interest is the coefficients of turnover and illiquidity on lagged returns and lagged industry returns. All four coefficients have the expected signs. Lagged stock returns predict decreased illiquidity and slightly (though insignificantly) predict increased turnover. Similarly, lagged industry returns predict increased turnover and decreased illiquidity (the illiquidity coefficient has an insignificant t-statistic, but its bootstrapped 95% confidence interval is entirely below zero). Figure 5 plots the most relevant impulse response functions of the panel VAR. As before, the impulse shocks are all one standard deviation. In panel A turnover is unaffected by individual stock returns. In the other three panels past returns forecast increased turnover and decreased illiquidity. A one standard deviation shock to individual stock returns forecasts a future decline in *illiq* of 2.7% (panel J). A one standard deviation shock to industry returns forecasts a 0.7% increase in turnover (panel M) and a 0.4% decrease in *illiq* (panel N). In untabulated results (available upon request) I repeat the panel VAR with the three different bid-ask spreads as alternative measures of illiquidity. Past stock returns consistently forecast future decreases in illiquidity. The other results are less clear, and there is some evidence that individual stock returns predict decreased turnover in the post-1993 sample.

As a final test of overconfidence, I sort stocks cross-sectionally based on momentum (stock-level returns from 12 months ago to 1 month ago). Table 6 shows turnover and illiquidity for portfolios formed from monthly momentum sorts. Turnover follows a U-shaped pattern, suggesting portfolio rebalancing or other trading motivations in extreme portfolios. Nonetheless, turnover is highest in the high momentum portfolios. Monthly turnover is 2.1% higher in decile 10 than in decile 1 with a 0.2% standard error. All illiquidity measures monotonically decrease with momentum except in the highest momentum deciles, where there is a small increase in illiquidity. Differences between deciles 1 and 10 are all negative and highly significant.

## 5 Asymmetric Information

The model's asymmetric information predictions are difficult to test because even if we can identify periods of high asymmetric information we generally can't tell whether they are due to precise private signals (high $\tau_s$) or weak public information (low $\tau_p$). Both of my identification strategies are likely to reflect a combination of high $\tau_s$ and low $\tau_p$. As a result, I am unable to differentially test propositions 2 and 3. Jointly, propositions 2 and 3 predict that asymmetric information should increase trading (only proposition 2 is operative since proposition 3 shows that public uncertainty does not affect trading volumes). I test this prediction of the model. On the other hand, propositions 2 and 3 make conflicting predictions about how asymmetric information affects liquidity (private information improves liquidity, but public uncertainty deteriorates it). Nonetheless, I analyze how asymmetric information relates to liquidity. This is not a test of the model, but it does inform whether proposition 2 or 3 is more empirically relevant for liquidity.

I first test for changes in turnover and liquidity around earnings announcements on the premise that asymmetric information is likely elevated at these times. To identify changes to turnover and illiquidity, I scale both by average values in the three months before an earnings announcement. I then analyze scaled turnover and illiquidity in the 21-trading-day window around earnings announcements. Frazzini and Lamont (2007) employ a similar methodology to study trading volume around earnings announcements.[3] My liquidity results are new. In this analysis I use bid-ask spreads to measure liquidity. $illiq_{it} = \frac{|Return_{it}|}{\$Vol_{it}}$ also spikes around earnings announcements, but this could be do to more volatility from public information as opposed to more sensitivity to buy and sell orders. Relying on bid-ask spread data limits the analysis to the 1993 to 2011 time period, during which there were 100,000 earnings announcements in sample firms. Data on earning announcements comes from Compustat.

Figure 6 plots equally weighted average scaled turnover and bid-ask spreads in event time around earnings announcements. Day 0 is the announcement day (or first trading day after the announcement). Other days represent trading days relative to the announcement. 95% confidence intervals are plotted in dashed lines. Panel A shows that turnover starts to increase the day before an announcement, spikes to 80% above normal levels on the announcement day, stays at that level for another day, and then decays. Even 10 days after an announcement, turnover remains 12% above normal levels. Panels B, C, and D plot the same analysis for daily, intraday quoted, and intraday effective bid-ask spreads, respectively. All three measures show the same pattern of widened bid-ask spreads on the announcement day and the day before and after it. On the announcement day itself, spreads are 11% to 16% wider than normal. Spreads are 3-11% higher than normal the day before and after the announcement. There is also a slight ramp up in spreads over the five days leading up to the announcement. By two days after the announcement, spreads largely return to normal

[3] Frazzini and Lamont's (2007) results are consistent with mine: they show that trading volume increases around earnings announcements. However, they do not interpret this as related to asymmetric information. Rather, their focus is the relationship between volume and prices. Lamont and Frazzini do not analyze liquidity.

levels.

Analyst dispersion is a second proxy for asymmetric information. Sadka and Scherbina (2007) show that in sorts on analyst dispersion, high dispersion stocks tend to be less liquid.[4] Table 6 shows turnover and illiquidity for decile portfolios formed monthly by sorts lagged dispersion. Dispersion itself is highly persistent. Current dispersion (unreported) has the same pattern and spread as lagged dispersion. Consistent with Sadka and Scherbina (2007), illiquidity increases with dispersion. The relationship is monotonic for all illiquidity measures with the exception of reductions between deciles 1 and 2. Decile 10 is significantly more illiquid than decile 1 across all illiquidity measures. Daily bid-ask spreads are 0.5% higher in decile 10. Intraday spreads are 0.2% to 0.3% higher. *illiq* is 0.5% higher. Turnover also increases monotonically as dispersion increases, and decile 10 turnover is a significant 5.3% higher than decile 1.

To control for omitted variables and time trends, I employ panel regressions with fixed effects for firms, years, and months. The resulting identification is based on changes to relative analyst dispersion over time for a given firm. Table 8 reports regression results. The analyzed variables are all logs so the coefficients can be interpreted as elasticities. Standard errors are multidimensionally clustered by stock and time. Across all specifications, the panel regressions support the cross-sectional decile results. As dispersion increases within firms turnover increases as do all measures of illiquidity. For turnover, the coefficient estimate is 1.9%. For *illiq* it is 20%. The bid-ask spread coefficients are around 10%. All five coefficients are highly significant.

## 6 Robustness Across Different Types of Stocks

My baseline results show that asymmetric information (proxied by analyst forecast dispersion and earnings announcements) increases trading and decreases liquidity. These baseline effects could vary across stocks or over time. For example stocks with more disagreement trading or less liquidity trading may respond differently to asymmetric information shocks than other stocks. To test for differences across stocks, I replicate my analyst forecast dispersion regressions with interactions with various stock characteristics. I also replicate my earnings announcement event studies for

[4] Sadka and Scherbina (2007) study the liquidity of portfolios sorted on analyst disagreement. I employ somewhat different illiquidity measures (they use effective spreads and a measure of price impact from intra-day trading). My panel regression approach is new, as are all of my turnover results.

different subsets of stocks.

The general theme of the results is that my baseline findings are robust. Across almost all sorts, asymmetric information tends to increase trading and decrease liquidity.

### *Size*

I sort stocks at the end of June in each year based on their current market capitalization. Big stocks have market capitalizations above the NYSE median. Small stocks have market capitalizations below the median. Results are in Table 9 and Figure 7.

- Turnover increases with analyst forecast dispersion only for big stocks.
- Analyst forecast dispersion decreases liquidity for all stocks.
- Size does not have a major impact on earnings announcement results.

### *Book-to-Market Ratios*

I sort stocks at the end of June based on book to market ratios at the end of the previous calendar year. Breakpoints for growth (low B/M ratio), neutral (medium B/M ratios), and value (high B/M ratios) are the NYSE 30th and 70th percentiles. Results are in Table 10 and Figure 8.

- Analyst dispersion decreases liquidity for all groups, but the effect decreases with B/M ratios. I.e., growth stock liquidity is more sensitive to analyst dispersion than value stock liquidity is.
- Similarly, turnover increases most around earnings announcements for growth stocks.
- Panel and earnings announcement illiquidity results are generally unaffected by B/M ratios.

### *Momentum*

I sort stocks monthly based on returns from twelve months ago to one month ago. Breakpoints for low, medium, and high momentum are the NYSE 30th and 70th percentiles. Results are in Table 11 and Figure 9.

- Turnover only increases with analyst forecast dispersion for medium and (most significantly) high momentum stocks.
- Analyst forecast dispersion has less of an impact on liquidity for medium and (most significantly) high momentum stocks.
- Earnings announcement results are insensitive to momentum.

### *Lagged Returns*

I sort stocks based on returns in the past month. Breakpoints for low, medium, and high prior month returns are the NYSE 30th and 70th percentiles.

- Results are consistent with the momentum sorts. Stocks with high past returns have higher turnover sensitivity and lower liquidity sensitivity to analyst forecast dispersion, and earnings announcement results are insensitive to past returns. Results are in Table 12 and Figure 10.
- The direct effect of lagged returns on turnover and liquidity are also clear in these results. Turnover is asymmetrically U-shaped in past returns, with high-return stocks having the highest future turnover. Liquidity increases with past returns.

### *Institutional Ownership*

I calculate institutional ownership (IO) for each stock at the end of each year using Thomson 13F data. I sort stocks at the end of the following June into low, medium, and high IO groups based NYSE 30th and 70th percentile breakpoints. Results are in Table 13 and Figure 11.

- High IO stocks tend to be more liquid and have higher turnover, but analyst forecast dispersion and earnings announcement results are insensitive to IO levels.

# Table 1: Data Summary

This table reports the sources, availability, and summary statistics for the main data items analyzed in this paper. The data sample is NYSE stocks with lagged prices greater than $5. Means and standard deviations are equally weighted across stocks. The reported values are averages of means and cross-sectional standard deviations calculated monthly in the relevant time period.

| | | Full Sample | | | | | 1926-1945 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Data Item** | **Source** | **Date Range** | **Obs** | **Obs/Month** | **Mean** | **Std Dev** | **Obs/Month** | **Mean** | **Std Dev** |
| turn | CRSP monthly | 1926-2011 | 1,130,018 | 1,095 | 6.22% | 8.07% | 585 | 6.03% | 13.45% |
| illiq | CRSP daily | 1926-2011 | 1,130,018 | 1,095 | 37.18% | 182.76% | 585 | 134.25% | 688.01% |
| bidask | CRSP daily | 1926-1941; 1993-2011 | 433,171 | 1,031 | 2.54% | 2.89% | 554 | 4.27% | 5.31% |
| qbidask | TAQ | 1993-2011 | 331,239 | 1,453 | 0.51% | 0.46% | | | |
| ebidask | TAQ | 1993-2011 | 331,239 | 1,453 | 0.36% | 0.35% | | | |
| disp | IBES | 1976-2011 | 347,864 | 805 | 17.14% | 100.81% | | | |

| | 1946-1975 | | | 1976-1992 | | | 1993-2011 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Data Item** | **Obs/Month** | **Mean** | **Std Dev** | **Obs/Month** | **Mean** | **Std Dev** | **Obs/Month** | **Mean** | **Std Dev** |
| turn | 1,091 | 2.32% | 3.39% | 1,302 | 4.90% | 4.93% | 1,453 | 13.78% | 12.62% |
| illiq | 1,091 | 15.54% | 59.98% | 1,302 | 2.10% | 5.36% | 1,453 | 0.56% | 3.50% |
| bidask | | | | | | | 1,433 | 1.09% | 0.85% |
| qbidask | | | | | | | 1,453 | 0.51% | 0.46% |
| ebidask | | | | | | | 1,453 | 0.36% | 0.35% |
| disp | | | | 696 | 20.64% | 123.86% | 903 | 14.02% | 80.18% |

## Table 2: Turnover Deciles

Decile portfolios are formed at the end of each month by sorting stocks by turnover in the previous month. The table reports market capitalization, turnover, and illiquidity measures for the next month. The reported values are equally weighted averages of all stocks in the decile portfolio. Standard errors for the 10-1 portfolio difference are reported in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. The data is for NYSE stocks with lagged prices greater than $5.

| **Decile** | **Lagged Turnover** | **Market Cap ($B)** | **Turnover** | **Illiq** | **Bid-Ask (Daily)** | **Bid-Ask (Quoted)** | **Bid-Ask (Effective)** |
|---|---|---|---|---|---|---|---|
| 1 | 0.84% | 1.14 | 1.22% | 166.62% | 6.08% | 0.99% | 0.73% |
| 2 | 1.76% | 2.64 | 2.25% | 46.77% | 3.51% | 0.62% | 0.44% |
| 3 | 2.41% | 2.60 | 2.93% | 31.12% | 2.69% | 0.52% | 0.36% |
| 4 | 3.04% | 2.28 | 3.60% | 24.15% | 2.33% | 0.46% | 0.32% |
| 5 | 3.75% | 2.01 | 4.30% | 21.54% | 2.15% | 0.43% | 0.30% |
| 6 | 4.62% | 1.77 | 5.15% | 20.24% | 2.01% | 0.42% | 0.29% |
| 7 | 5.76% | 1.55 | 6.23% | 18.19% | 1.87% | 0.41% | 0.29% |
| 8 | 7.41% | 1.34 | 7.68% | 15.59% | 1.73% | 0.41% | 0.29% |
| 9 | 10.27% | 1.12 | 10.04% | 14.06% | 1.62% | 0.42% | 0.29% |
| 10 | 22.71% | 0.89 | 18.87% | 12.06% | 1.42% | 0.43% | 0.31% |
| 10-1 | 21.87%*** | -0.24*** | 17.64%*** | -154.56%*** | -4.65%*** | -0.56%*** | -0.42%*** |
| | (0.63%) | (4.56%) | (0.54%) | (16.52%) | (0.31%) | (0.01%) | (0.01%) |
| **Date Range** | 1926-2011 | 1926-2011 | 1926-2011 | 1926-2011 | 1926-1941; 1993-2011 | 1993-2011 | 1993-2011 |

## Table 3: Turnover Panel Regressions

Results are for stock-level regressions of log illiquidity measures on lagged (by one month) log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. Data includes all NYSE stocks with lagged prices greater than $5.

| | **(1)** **ln(turn)** | **(2)** **ln(illiq)** | **(3)** **ln(bidask)** | **(4)** **ln(qbidask)** | **(5)** **ln(ebidask)** |
|---|---|---|---|---|---|
| **lagged ln(turn)** | 0.689*** | -0.561*** | -0.104*** | -0.147*** | -0.142*** |
| | (0.00465) | (0.0112) | (0.00947) | (0.00860) | (0.00837) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.831 | 0.913 | 0.887 | 0.900 | 0.874 |
| **Date Range** | 1926-2011 | 1926-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 4: VAR Results

turn and illiq are detrended log turnover and illiq (a measure of illliquidity), respectively. rmrf is the excess return of the CRSP value weighted market return over the risk free rate. turn and illiq were detrended using a Hodrick and Prescott (1997) filter with a penalty value of 14,400. Reported results are for a 2-lag VAR of turn, illiq, and rmrf. Bootstrapped standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. Turnover and illiq are equally weighted averages. Sample includes all NYSE stocks with lagged prices greater that $5 from 1926 to 2011.

| | **(1) turn** | **(2) illiq** | **(3) rmrf** |
|---|---|---|---|
| **Lag 1** | | | |
| **turn** | 0.4835*** | -0.1083** | 0.0137 |
| | (0.0392) | (0.0437) | (0.012) |
| **illiq** | -0.0634 | 0.4329*** | 0.0225** |
| | (0.0392) | (0.0507) | (0.011) |
| **rmrf** | 0.8625*** | -1.5128*** | 0.1133* |
| | (0.1905) | (0.1687) | (0.0612) |
| **Lag 2** | | | |
| **turn** | -0.0059 | 0.081** | -0.0049 |
| | (0.0432) | (0.0383) | (0.0094) |
| **illiq** | -0.0043 | 0.2444*** | 0.0167 |
| | (0.0366) | (0.045) | (0.0103) |
| **rmrf** | 0.3903** | 0.0793 | 0.0161 |
| | (0.1849) | (0.164) | (0.054) |
| **Constant** | -0.0076 | 0.0089 | 0.0053*** |
| | (0.007) | (0.0067) | (0.0018) |
| **R-Squared** | 0.38 | 0.52 | 0.05 |

## Table 5: Panel VAR Results

turn and illiq are monthly stock-level log turnover and illiq (a measure of illliquidity), respectively. ret is the monthly individual stock returns. ret_ind is the monthly return on the stock's industry. Industries are defined using the 10 industry groups on Ken French's website. Reported results are for a 2-lag VAR of turn, illiq, ret, and ret_ind. Bootstrapped standard errors controlling for cross-sectional correlation are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. Sample includes all NYSE stocks with lagged prices greater that $5 from 1951 to 2011.

| | **(1)** **turn** | **(2)** **illiq** | **(3)** **ret** | **(4)** **ret_ind** |
|---|---|---|---|---|
| **Lag 1** | | | | |
| **turn** | 0.2295*** | -0.1645*** | 0.0214* | 0.0007 |
| | (0.0312) | (0.0333) | (0.0125) | (0.0035) |
| **illiq** | -0.1209 | 0.2187*** | 0.025 | 0.0006 |
| | (0.0803) | (0.0696) | (0.0226) | (0.0055) |
| **ret** | 0.0558 | -0.2166** | -0.1021*** | -0.0001 |
| | (0.0935) | (0.0873) | (0.0278) | (0.0066) |
| **ret_ind** | 0.1776*** | -0.1159 | 0.1119** | 0.0515 |
| | (0.0638) | (0.074) | (0.0486) | (0.0713) |
| **Lag 2** | | | | |
| **turn** | -0.0196 | 0.0192 | 0.008 | 0.0004 |
| | (0.0204) | (0.0199) | (0.007) | (0.0019) |
| **illiq** | -0.041 | 0.0626** | 0.0139 | 0.0005 |
| | (0.0343) | (0.0297) | (0.0097) | (0.0024) |
| **ret** | -0.0116 | -0.0036 | -0.0325*** | -0.0018 |
| | (0.025) | (0.0249) | (0.009) | (0.0021) |
| **ret_ind** | 0.084** | -0.0388 | 0.0054 | -0.0212 |
| | (0.0403) | (0.0463) | (0.0293) | (0.0413) |
| **Stock FE** | Yes | Yes | Yes | Yes |
| **Time FE** | Yes | Yes | Yes | Yes |

## Table 6: Momentum Deciles

Decile portfolios are formed at the end of each month by sorting stocks by the 11-month return from 12 months ago to 1 month ago. The table reports market capitalization, turnover, and illiquidity measures for the next month. The reported values are equally weighted averages of all stocks in the decile portfolio. Standard errors for the 10-1 portfolio difference are reported in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. The data is for NYSE stocks with lagged prices greater than $5.

| **Decile** | **Momentum** | **Market Cap ($B)** | **Turnover** | **Illiq** | **Bid-Ask (Daily)** | **Bid-Ask (Quoted)** | **Bid-Ask (Effective)** |
|---|---|---|---|---|---|---|---|
| 1 | -30.36% | 0.85 | 7.63% | 62.37% | 3.56% | 0.76% | 0.55% |
| 2 | -14.21% | 1.53 | 5.97% | 42.26% | 2.94% | 0.60% | 0.43% |
| 3 | -5.75% | 1.81 | 5.51% | 32.60% | 2.59% | 0.52% | 0.37% |
| 4 | 1.14% | 1.96 | 5.22% | 30.29% | 2.41% | 0.48% | 0.34% |
| 5 | 7.53% | 2.03 | 5.12% | 26.29% | 2.23% | 0.46% | 0.33% |
| 6 | 14.10% | 2.11 | 5.23% | 26.01% | 2.16% | 0.44% | 0.31% |
| 7 | 21.46% | 2.16 | 5.39% | 22.80% | 2.08% | 0.43% | 0.30% |
| 8 | 30.73% | 2.15 | 5.82% | 20.96% | 2.01% | 0.43% | 0.30% |
| 9 | 44.71% | 1.98 | 6.68% | 23.09% | 2.05% | 0.43% | 0.31% |
| 10 | 91.76% | 1.32 | 9.75% | 33.66% | 2.20% | 0.48% | 0.34% |
| 10-1 | 122.12%*** | 0.47*** | 2.12%*** | -28.71%*** | -1.36%*** | -0.28%*** | -0.21%*** |
| | (1.87%) | (7.30%) | (0.19%) | (4.29%) | (0.08%) | (0.02%) | (0.01%) |
| **Date Range** | 1926-2011 | 1926-2011 | 1926-2011 | 1926-2011 | 1926-1941; 1993-2011 | 1993-2011 | 1993-2011 |

## Table 7: Analyst Dispersion Deciles

Decile portfolios are formed at the end of each month by sorting stocks by analyst dispersion in the past month. Analyst dispersion is the standard deviation of current year analyst earnings forecasts scaled by the mean forecast. The table reports market capitalization, turnover, and illiquidity measures for the next month. The reported values are equally weighted averages of all stocks in the decile portfolio. Standard errors for the 10-1 portfolio difference are reported in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. The data is for NYSE stocks with lagged prices greater than $5, coverage by at least two analysts, and December fiscal years.

| **Decile** | **Lagged Dispersion** | **Market Cap ($B)** | **Turnover** | **Illiq** | **Bid-Ask (Daily)** | **Bid-Ask (Quoted)** | **Bid-Ask (Effective)** |
|---|---|---|---|---|---|---|---|
| 1 | 0.01 | 9.20 | 7.69% | 0.54% | 0.85% | 0.37% | 0.25% |
| 2 | 0.02 | 7.25 | 8.09% | 0.35% | 0.79% | 0.33% | 0.23% |
| 3 | 0.02 | 5.83 | 8.42% | 0.36% | 0.82% | 0.35% | 0.24% |
| 4 | 0.03 | 4.96 | 8.86% | 0.37% | 0.85% | 0.36% | 0.25% |
| 5 | 0.04 | 4.32 | 9.17% | 0.40% | 0.88% | 0.38% | 0.26% |
| 6 | 0.05 | 4.11 | 9.58% | 0.42% | 0.91% | 0.39% | 0.28% |
| 7 | 0.07 | 4.44 | 10.09% | 0.47% | 0.98% | 0.42% | 0.30% |
| 8 | 0.10 | 4.09 | 10.90% | 0.59% | 1.05% | 0.46% | 0.33% |
| 9 | 0.16 | 2.83 | 12.18% | 0.67% | 1.13% | 0.51% | 0.36% |
| 10 | 1.22 | 1.96 | 13.04% | 1.01% | 1.32% | 0.62% | 0.45% |
| 10-1 | 1.21*** | -7.23*** | 5.34%*** | 0.46%*** | 0.47%*** | 0.26%*** | 0.20%*** |
| | (0.04) | (27.18%) | (0.32%) | (0.03%) | (0.03%) | (0.01%) | (0.01%) |
| **Date Range** | 1976-2011 | 1976-2011 | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 8: Analyst Dispersion Panel Regressions

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log dispersion. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance. Data includes all NYSE stocks with lagged prices greater than $5, at least 2 analyst forecasts, and fiscal years that end in December.

| | **(1)**<br>**ln(turn)** | **(2)**<br>**ln(illiq)** | **(3)**<br>**ln(bidask)** | **(4)**<br>**ln(qbidask)** | **(5)**<br>**ln(ebidask)** |
|---|---|---|---|---|---|
| **lagged ln(disp)** | 0.0194***<br>(0.00437) | 0.202***<br>(0.00720) | 0.0975***<br>(0.00472) | 0.106***<br>(0.00387) | 0.109***<br>(0.00386) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.715 | 0.880 | 0.895 | 0.910 | 0.884 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 9: Analyst Dispersion Panel Regressions – Size

Results are for stock-level regressions of monthly log turnover and log bid-ask spread measures on lagged (by one month) log dispersion of analyst earnings forecasts and log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

| | (1)<br>ln(turn) | (2)<br>ln(illiq) | (3)<br>ln(bidask) | (4)<br>ln(qbidask) | (5)<br>ln(ebidask) |
|---|---|---|---|---|---|
| **lagged ln(disp)** | -0.00861* | 0.175*** | 0.0833*** | 0.0970*** | 0.0980*** |
| | (0.00515) | (0.00870) | (0.00505) | (0.00469) | (0.00462) |
| **lagged ln(disp)** | 0.0653*** | -0.0256** | 0.0116 | -0.00418 | -0.000804 |
| ***big** | (0.00700) | (0.0115) | (0.00721) | (0.00608) | (0.00621) |
| **big** | 0.307*** | -1.111*** | -0.197*** | -0.312*** | -0.304*** |
| | (0.0263) | (0.0477) | (0.0280) | (0.0253) | (0.0259) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.723 | 0.895 | 0.897 | 0.916 | 0.890 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 10: Analyst Dispersion Panel Regressions – Book-to-Market Ratios

Results are for stock-level regressions of monthly log turnover and log bid-ask spread measures on lagged (by one month) log dispersion of analyst earnings forecasts and log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

| | **(1)**<br>**ln(turn)** | **(2)**<br>**ln(illiq)** | **(3)**<br>**ln(bidask)** | **(4)**<br>**ln(qbidask)** | **(5)**<br>**ln(ebidask)** |
|---|---|---|---|---|---|
| **lagged ln(disp)** | 0.0231*** | 0.142*** | 0.0799*** | 0.0884*** | 0.0899*** |
| | (0.00561) | (0.00998) | (0.00635) | (0.00573) | (0.00575) |
| **lagged ln(disp)** | 0.000293 | 0.0328*** | 0.0127** | 0.00620 | 0.00740 |
| ***Neutral BM** | (0.00575) | (0.0110) | (0.00611) | (0.00568) | (0.00577) |
| **lagged ln(disp)** | 0.00971 | 0.0724*** | 0.0177** | 0.0178** | 0.0201*** |
| ***Growth** | (0.00784) | (0.0152) | (0.00784) | (0.00730) | (0.00750) |
| **Neutral BM** | 0.0164 | -0.214*** | -0.0815*** | -0.126*** | -0.127*** |
| | (0.0190) | (0.0362) | (0.0214) | (0.0203) | (0.0207) |
| **Growth** | 0.111*** | -0.334*** | -0.112*** | -0.160*** | -0.158*** |
| | (0.0270) | (0.0559) | (0.0305) | (0.0295) | (0.0303) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.722 | 0.886 | 0.896 | 0.914 | 0.888 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 11: Analyst Dispersion Panel Regressions – Momentum

Results are for stock-level regressions of monthly log turnover and log bid-ask spread measures on lagged (by one month) log dispersion of analyst earnings forecasts and log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

| | **(1) ln(turn)** | **(2) ln(illiq)** | **(3) ln(bidask)** | **(4) ln(qbidask)** | **(5) ln(ebidask)** |
|---|---|---|---|---|---|
| **lagged ln(disp)** | 0.00728 | 0.207*** | 0.101*** | 0.104*** | 0.107*** |
| | (0.00500) | (0.00784) | (0.00562) | (0.00449) | (0.00441) |
| **lagged ln(disp)** | 0.0191*** | -0.0340*** | -0.0175*** | -0.0137*** | -0.0151*** |
| ***Medium Momentum** | (0.00390) | (0.00599) | (0.00443) | (0.00321) | (0.00324) |
| **lagged ln(disp)** | 0.0375*** | -0.0536*** | -0.0273*** | -0.0132*** | -0.0143*** |
| ***High Momentum** | (0.00535) | (0.00817) | (0.00651) | (0.00463) | (0.00466) |
| **Medium Momentum** | 0.00456 | -0.222*** | -0.152*** | -0.142*** | -0.155*** |
| | (0.0134) | (0.0205) | (0.0150) | (0.0124) | (0.0125) |
| **High Momentum** | 0.193*** | -0.504*** | -0.260*** | -0.205*** | -0.224*** |
| | (0.0189) | (0.0281) | (0.0219) | (0.0185) | (0.0191) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.724 | 0.886 | 0.897 | 0.914 | 0.889 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 12: Analyst Dispersion Panel Regressions – Prior Month Returns

Results are for stock-level regressions of monthly log turnover and log bid-ask spread measures on lagged (by one month) log dispersion of analyst earnings forecasts and log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

| | (1) ln(turn) | (2) ln(illiq) | (3) ln(bidask) | (4) ln(qbidask) | (5) ln(ebidask) |
|---|---|---|---|---|---|
| **lagged ln(disp)** | 0.000800 | 0.228*** | 0.104*** | 0.113*** | 0.116*** |
| | (0.00481) | (0.00759) | (0.00508) | (0.00409) | (0.00409) |
| **lagged ln(disp)** | 0.0187*** | -0.0357*** | -0.0101*** | -0.0126*** | -0.0136*** |
| ***Medium Lag Ret** | (0.00271) | (0.00392) | (0.00315) | (0.00247) | (0.00243) |
| **lagged ln(disp)** | 0.0299*** | -0.0391*** | -0.0112*** | -0.00914*** | -0.00960*** |
| ***High Lag Ret** | (0.00342) | (0.00440) | (0.00410) | (0.00291) | (0.00285) |
| **Medium Lag Ret** | -0.0391*** | -0.158*** | -0.1000*** | -0.108*** | -0.110*** |
| | (0.00951) | (0.0135) | (0.0107) | (0.00912) | (0.00901) |
| **High Lag Ret** | 0.0881*** | -0.258*** | -0.115*** | -0.106*** | -0.108*** |
| | (0.0118) | (0.0155) | (0.0131) | (0.0108) | (0.0109) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.718 | 0.881 | 0.895 | 0.911 | 0.885 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

## Table 13: Analyst Dispersion Panel Regressions – Institutional Ownership

Results are for stock-level regressions of monthly log turnover and log bid-ask spread measures on lagged (by one month) log dispersion of analyst earnings forecasts and log turnover. Robust multidimensionally clustered (by stock and time) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

| | **(1) ln(turn)** | **(2) ln(illiq)** | **(3) ln(bidask)** | **(4) ln(qbidask)** | **(5) ln(ebidask)** |
|---|---|---|---|---|---|
| **lagged ln(disp)** | 0.0269*** | 0.176*** | 0.0933*** | 0.106*** | 0.108*** |
| | (0.00815) | (0.0125) | (0.00773) | (0.00686) | (0.00399) |
| **lagged ln(disp) *Medium IO** | 0.00262 | 0.0161 | 0.00483 | -0.00359 | -0.00413 |
| | (0.00786) | (0.0135) | (0.00731) | (0.00683) | (0.00681) |
| **lagged ln(disp) *High IO** | -0.0130 | 0.0258* | 0.00347 | 0.000284 | 0.000121 |
| | (0.00952) | (0.0152) | (0.00851) | (0.00785) | (0.00786) |
| **Medium IO** | 0.122*** | -0.262*** | -0.0848*** | -0.122*** | -0.134*** |
| | (0.0294) | (0.0500) | (0.0280) | (0.0270) | (0.0270) |
| **High IO** | 0.196*** | -0.425*** | -0.149*** | -0.170*** | -0.196*** |
| | (0.0357) | (0.0609) | (0.0335) | (0.0320) | (0.0323) |
| **Stock FE** | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes |
| **Month FE** | Yes | Yes | Yes | Yes | Yes |
| **R-Squared** | 0.704 | 0.877 | 0.895 | 0.911 | 0.885 |
| **Date Range** | 1976-2011 | 1976-2011 | 1993-2011 | 1993-2011 | 1993-2011 |

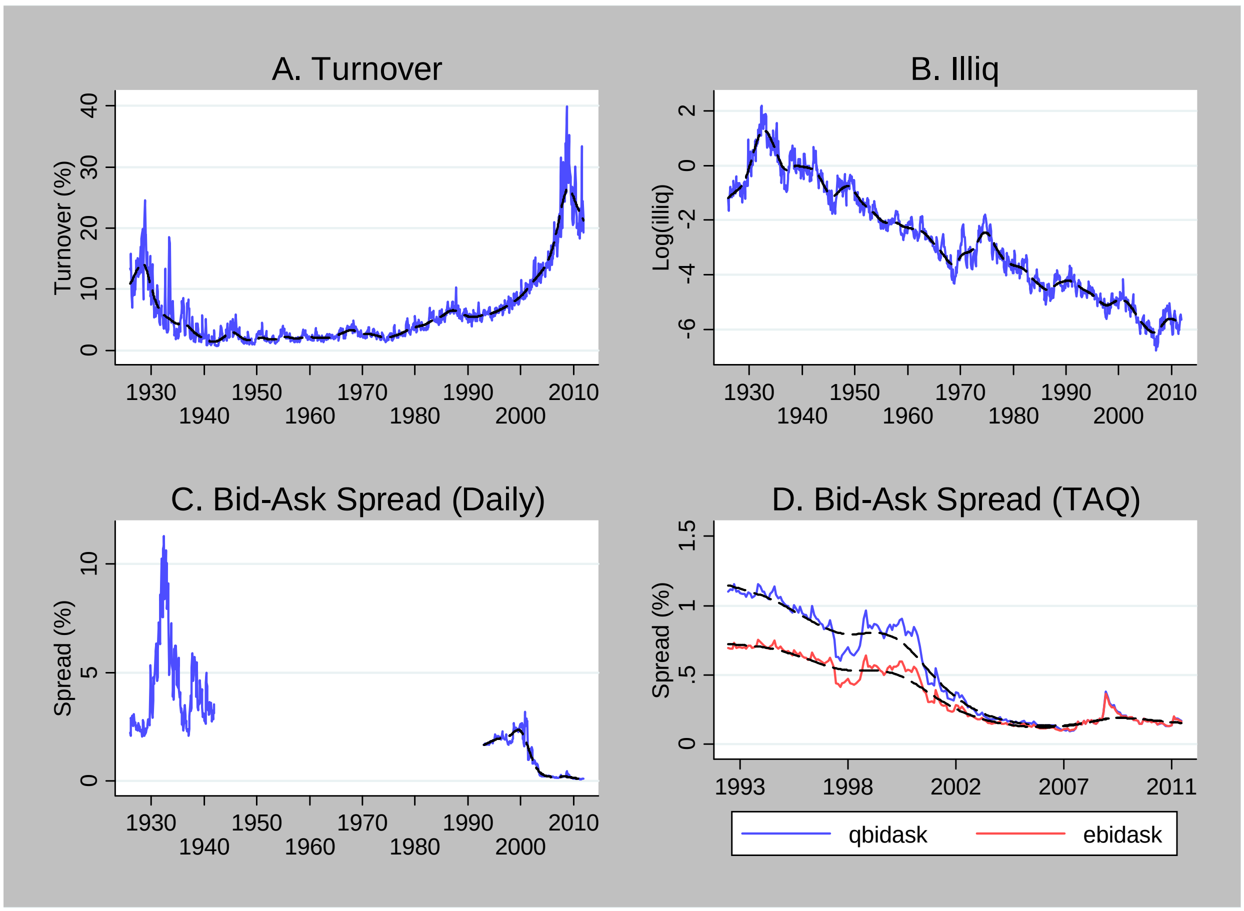


**Figure 1: Monthly Time Series.** Solid lines are the actual data. Dashed lines are trends calculated using a Hodrick Prescott filter with a penalty value of 14,400 on the log data.

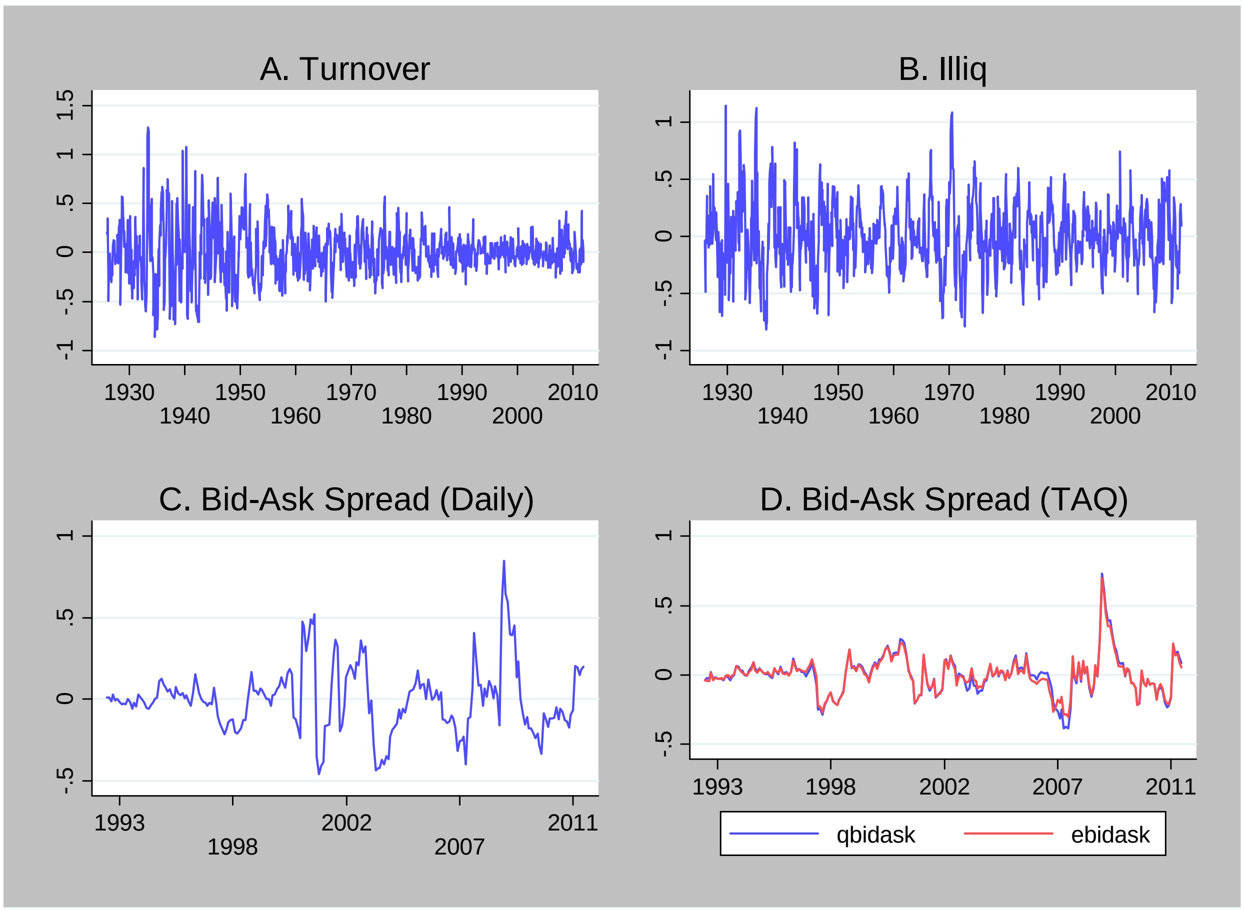


**Figure 2: Detrended Log Monthly Time Series.** The log time series were detrended using a Hodrick Prescott filter with a penalty value of 14,400.

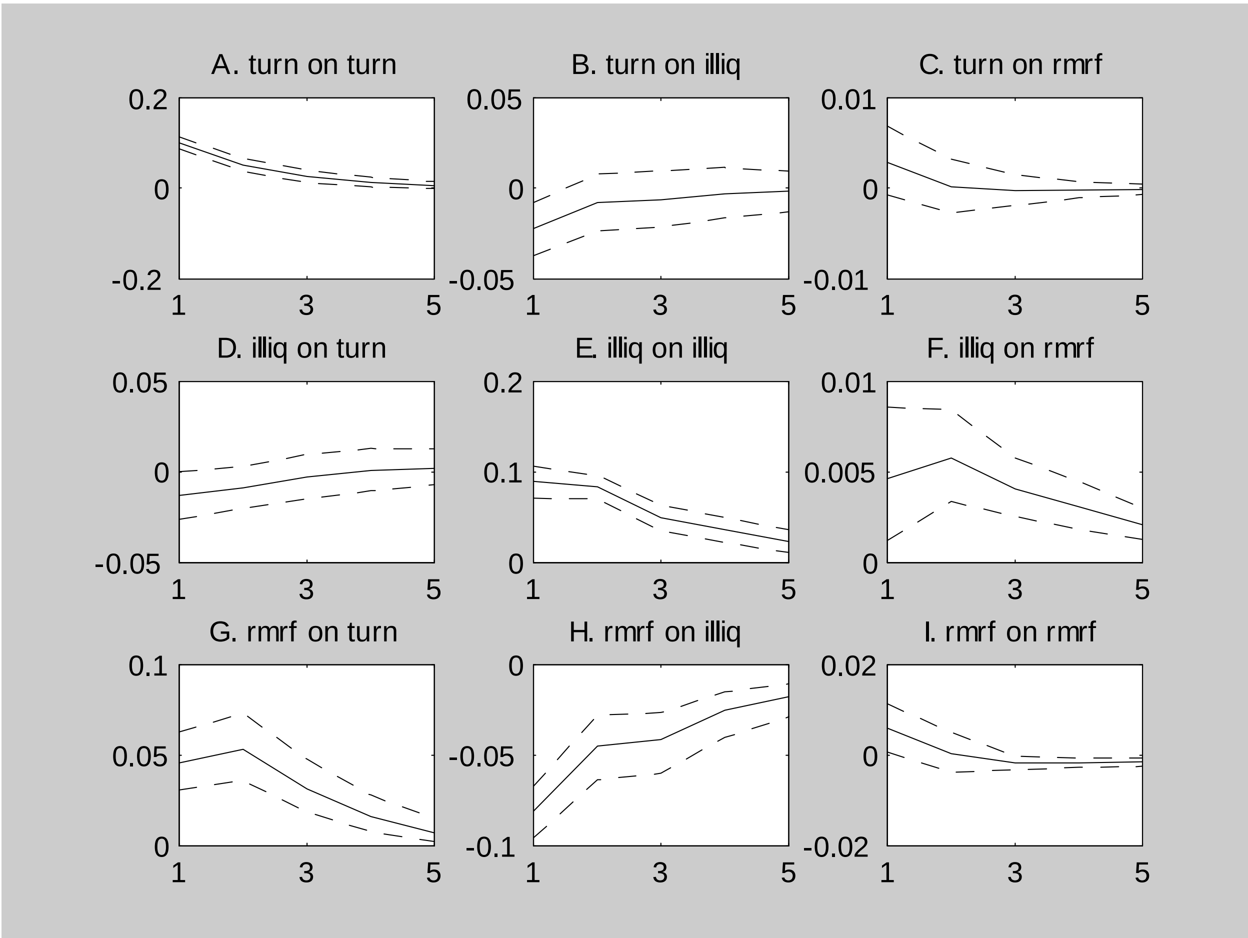


**Figure 3: Impulse Response Functions from *illiq* VAR.** The first variable in each panel title is the impulse variable. The second variable is the response variable. The solid lines are responses to one standard deviation shocks to the impulse variables after the number of lags indicated on the horizontal axis. The dashed lines are 95% confidence intervals. turn and illiq are detrended log market turnover and market illiq (a measure of illiquidity), respectively. rmrf is the excess return of the CRSP value weighted market index over the risk free rate.

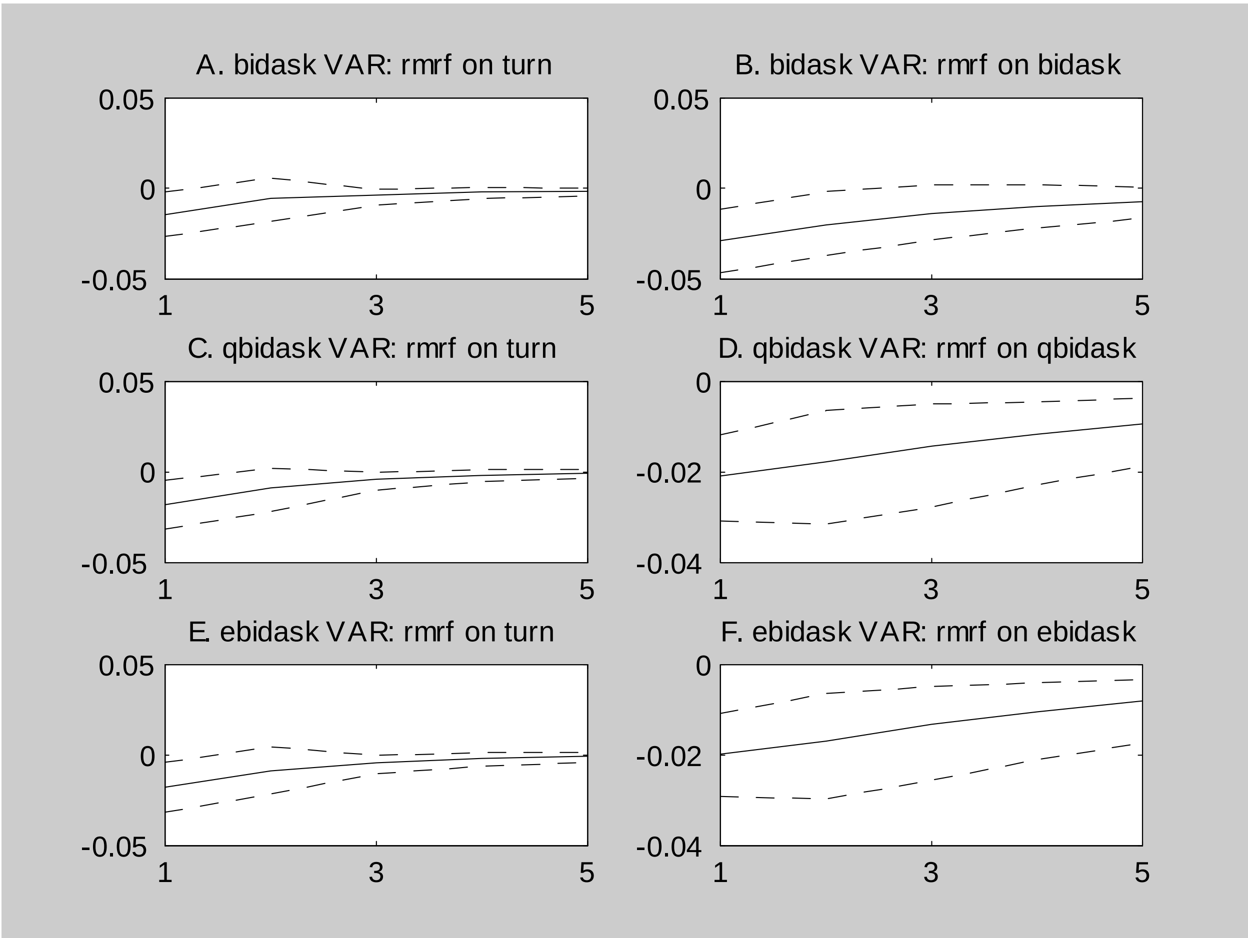


**Figure 4: Impulse Response Functions from** *bidask***,** *qbidask***, and** *ebidask* **VARs.** Each VAR includes detrended log market turnover ($turn$), CRSP value-weighted market returns in excess of the risk free rate ($rmrf$), and a detrended log measure of market illiquidity (daily bid-ask spreads in the first row, and intra-day quoted and effective bid ask spreads in the second and third rows, respectively. The first variable after the colon in each panel title is the impulse variable. The second variable is the response variable. The solid lines are responses to one standard deviation shocks to the impulse variables after the number of lags indicated on the horizontal axis. The dashed lines are 95% confidence intervals. For brevity only the most relevant impulse response functions are shown.

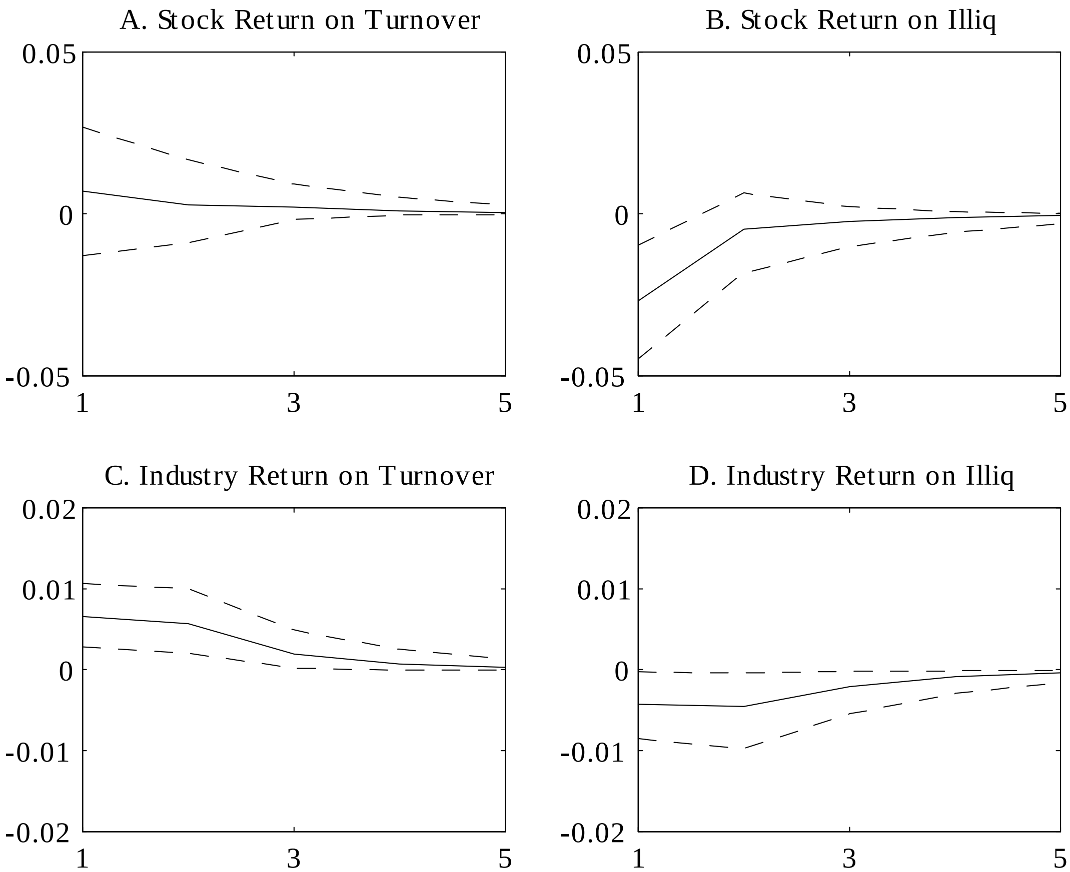


**Figure 5: Impulse Response Functions from panel VAR.** The panel VAR includes stock log turnover, stock log *illiq* (an illiquidity measure), stock returns, industry returns, and stock and time fixed effects. The first variable in each panel title is the impulse variable. The second variable is the response variable. Only the four impulses of most interest are shown. The solid lines are responses to one standard deviation shocks to the impulse variables after the number of lags indicated on the horizontal axis. The dashed lines are 95% confidence intervals. For brevity only the most relevant impulse response functions are shown.

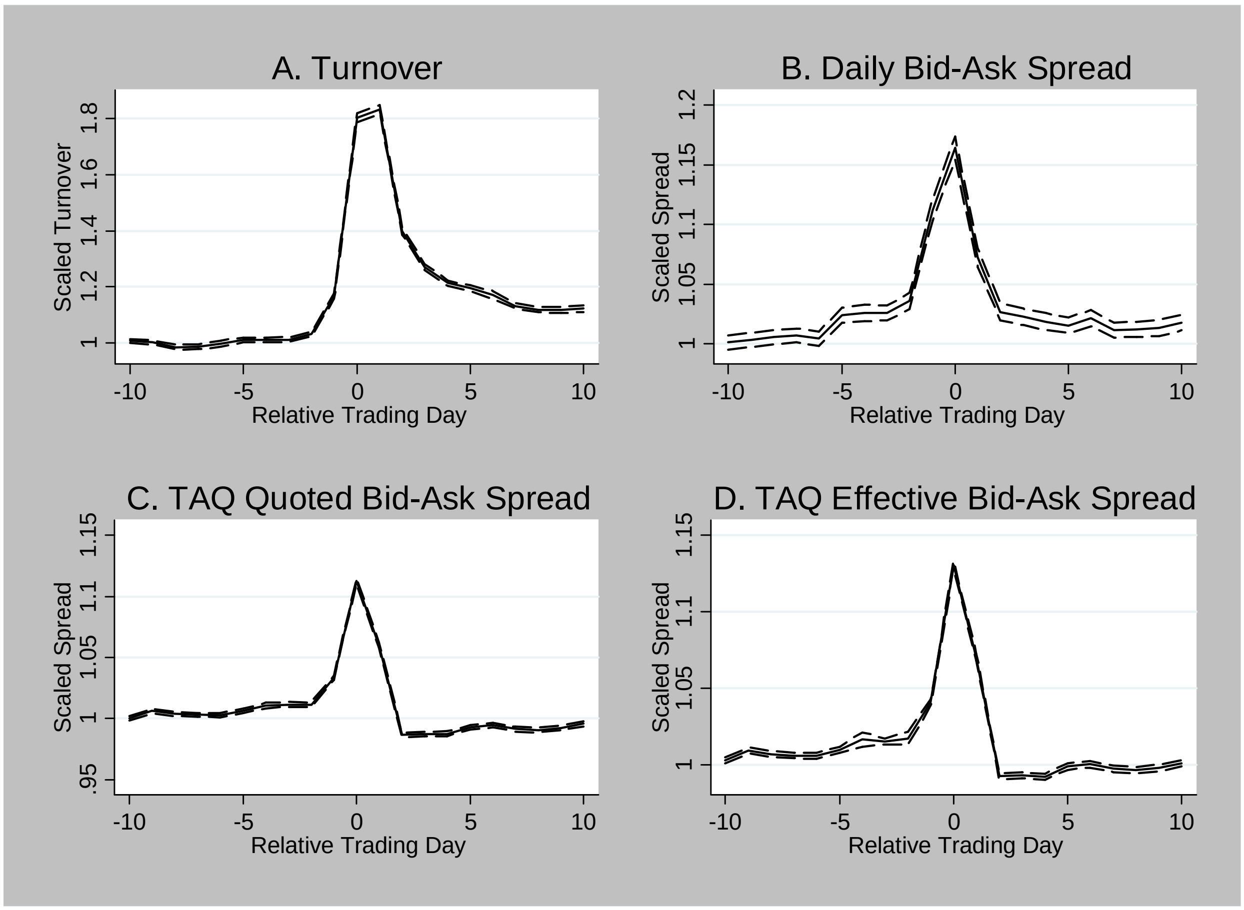


**Figure 6: Turnover and Liquidity Around Earnings Announcements.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

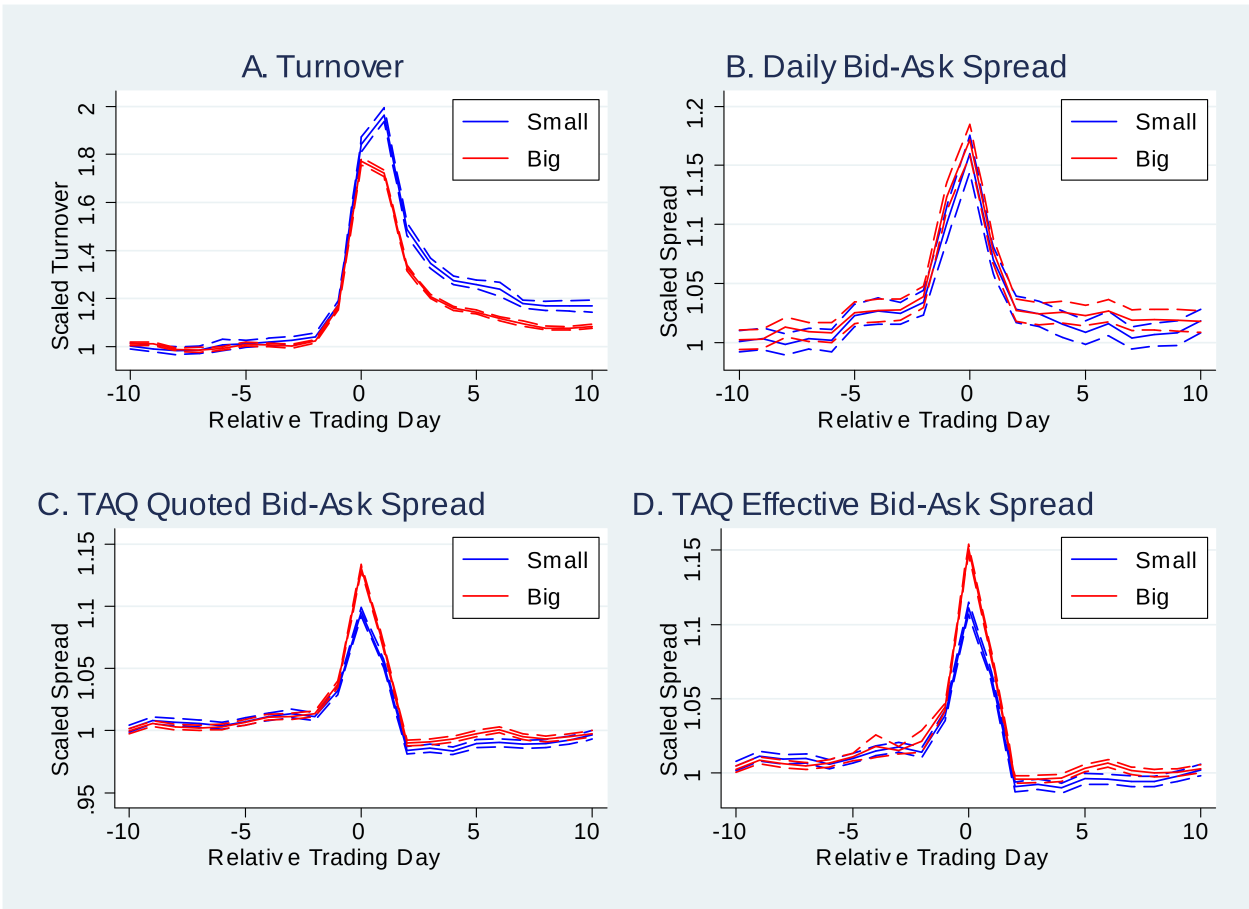


**Figure 7: Turnover and Liquidity Around Earnings Announcements by Size.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

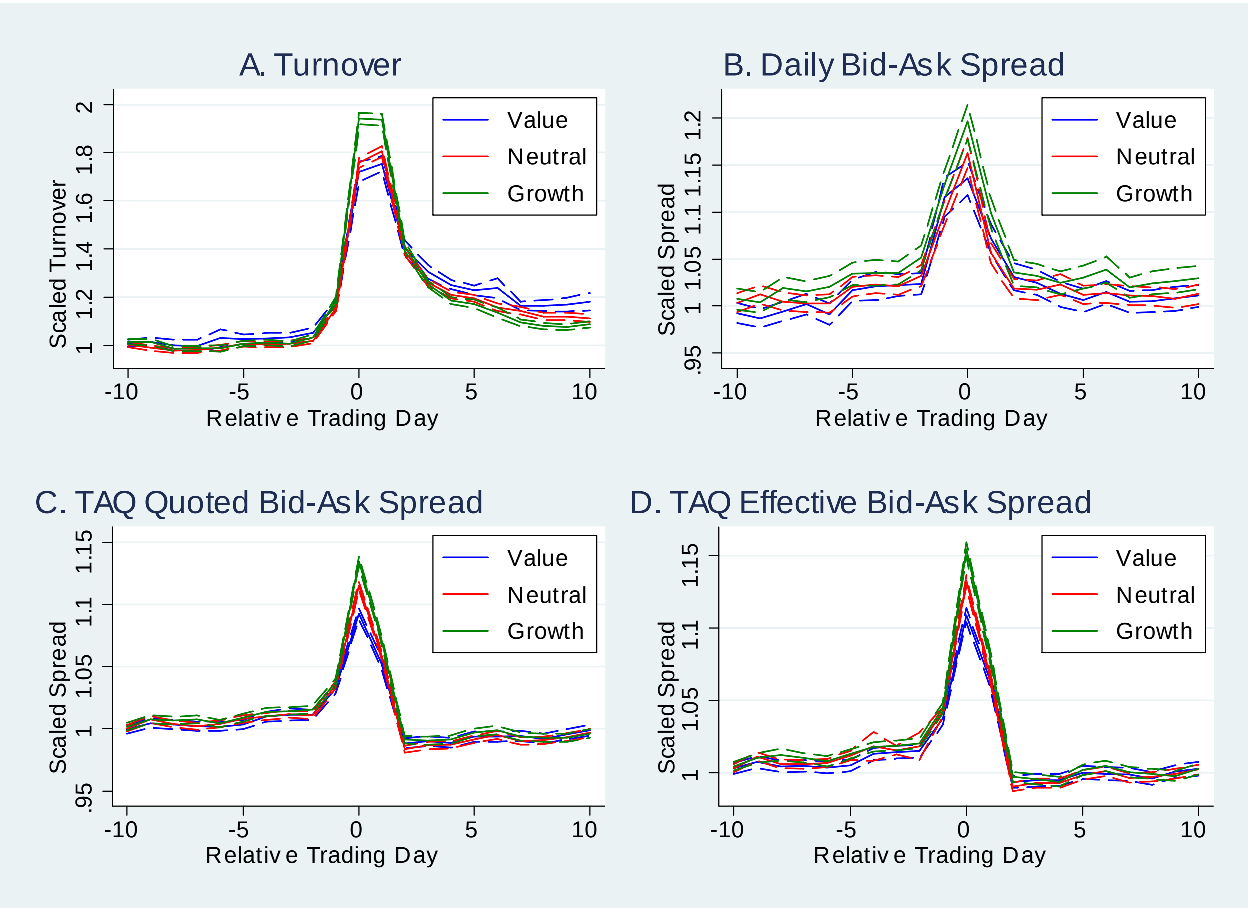


**Figure 8: Turnover and Liquidity Around Earnings Announcements by Book-to-Market Ratio.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

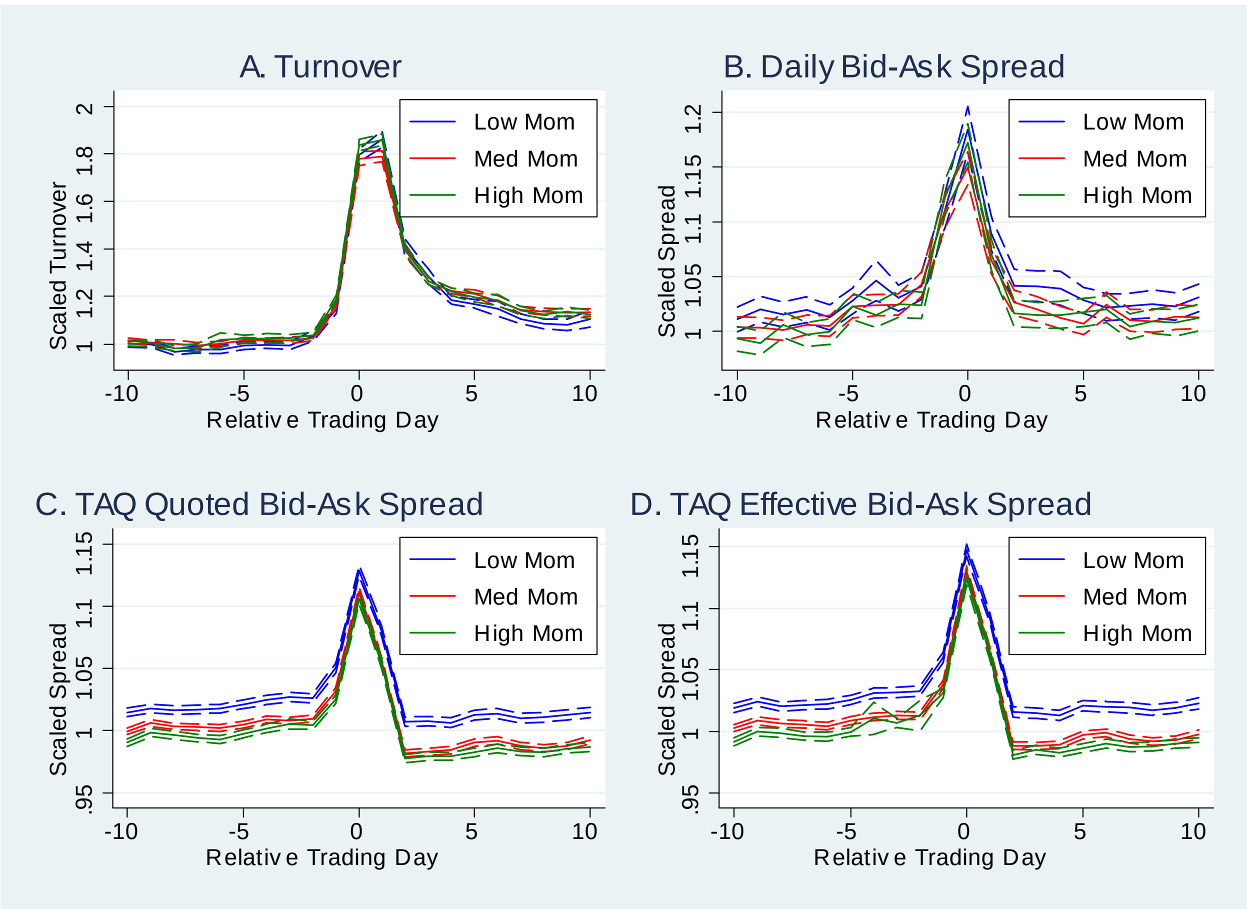


**Figure 9: Turnover and Liquidity Around Earnings Announcements by Momentum.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

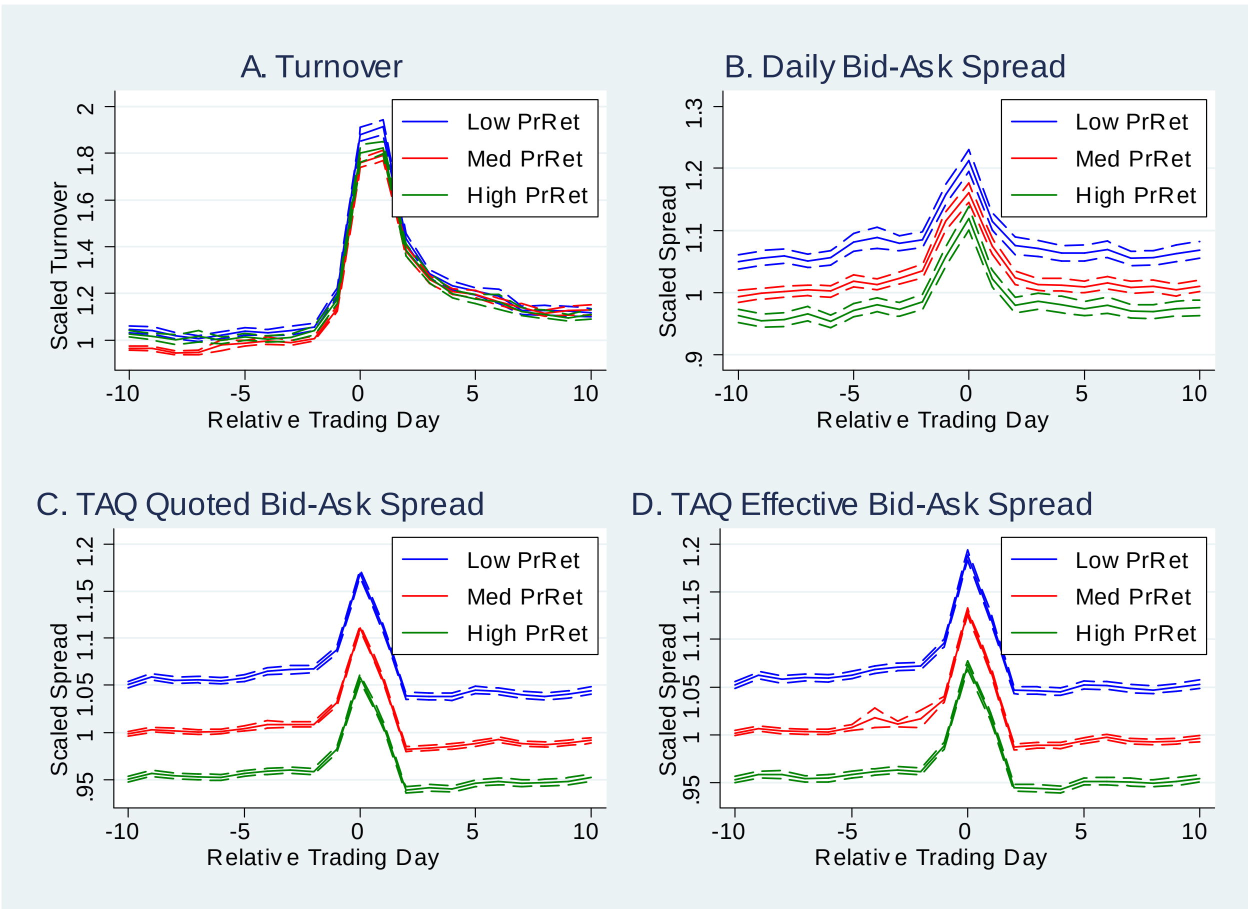


**Figure 10: Turnover and Liquidity Around Earnings Announcements by Prior Month Returns.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

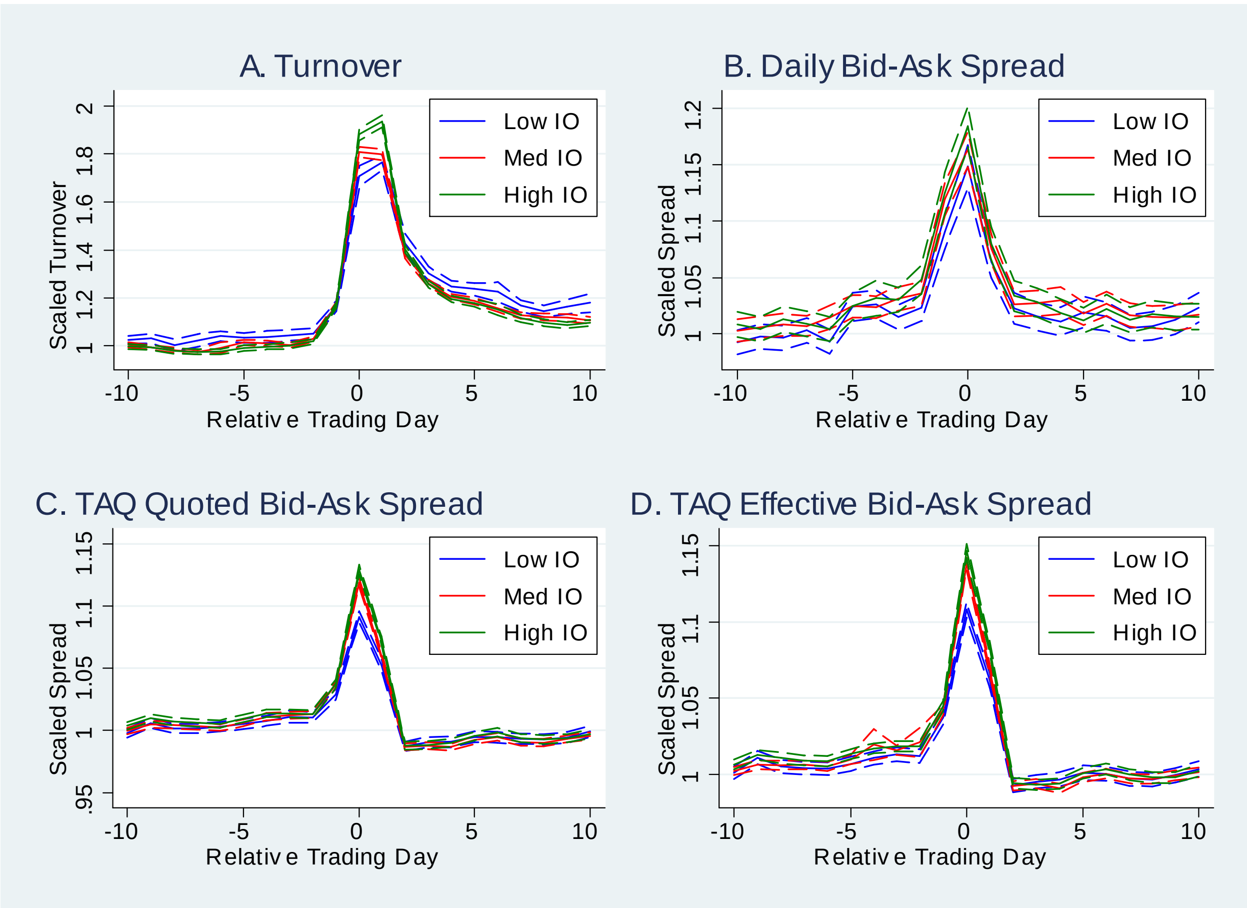


**Figure 11: Turnover and Liquidity Around Earnings Announcements by Institutional Ownership.** Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.