Internet Appendix for:
"Disagreement and Liquidity"

A Model details

Alternative overconfidence specifications

Separately specified objective and perceived signal precision

The information structure is the same as in the general model except that agent's in group m perceive that signal y_m has precision $\tau_b > \tau_s$. This specification decouples τ_b and τ_s from one another and allows for consideration of changes to τ_s without changing τ_b.

Solving for the linear price function using the same approach described for the baseline model results in an equilibrium price of:

$$P = \frac{\tau_p \mu + \left(\left(M-1\right)\tau_s + \tau_b\right)\bar{y}}{\tau_p + \left(M-1\right)\tau_s + \tau_b} - \frac{\mu_X}{\eta\left(\tau_p + \left(M-1\right)\tau_s + \tau_b\right)} \tag{IA.1}$$

The directed trading volume of group m is:

$$Trade_m = \frac{\eta}{M}\left(\tau_b - \tau_s\right)\left(y_m - \overline{y}\right) \tag{IA.2}$$

Expected aggregate trading volume is $\frac{1}{2}\sum_m \sqrt{\frac{2\mathrm{Var}(Trade_m)}{\pi}}$ and $\mathrm{Var}(Trade_m)$ is:

$$\mathrm{Var}\left(Trade_m\right) = \frac{\eta^2}{M^2}\left(1 - \frac{1}{M}\right)\left(\frac{\tau_b^2}{\tau_s} - 2\tau_b + \tau_s\right) \tag{IA.3}$$

Illiquidity, which is defined the same as before is:

$$\lambda = \frac{M\left(\left(M-1\right)\tau_s + \tau_b\right)}{\eta\left(M-1\right)\left(\tau_b - \tau_s\right)\left(\tau_p + \left(M-1\right)\tau_s + \tau_b\right)} \tag{IA.4}$$

From equations (IA.3) and (IA.4), it can be seen that as private information becomes more precise (τ_s increases), trading and liquidity both decrease (i.e., $\mathrm{Var}(Trade_m)$ decreases and λ increases). Increasing τ_s to be closer to τ_b effectively decreases overconfidence, and directionally, these are the same effects that decreasing overconfidence (ψ) has in the baseline model.

Additive overconfidence

The information structure is the same as in the general model except that agents in group m perceive that signal y_m has precision $\tau_s + \kappa$, where $\kappa > 0$.

The equilibrium price is:

$$P = \frac{\tau_p \mu + (M\tau_s + \kappa)\,\bar{y}}{\tau_p + M\tau_s + \kappa} - \frac{\mu_X}{\eta\,(\tau_p + M\tau_s + \kappa)} \tag{IA.5}$$

The directed trading volume variance of group m is:

$$\mathrm{Var}\,(Trade_m) = \frac{\eta^2\kappa^2}{M^2}\left(1 - \frac{1}{M}\right)\frac{1}{\tau_s} \tag{IA.6}$$

Illiquidity, which is defined the same as before is:

$$\lambda = \frac{M\,(M\tau_s + \kappa)}{\eta\kappa\,(M-1)\,(\tau_p + M\tau_s + \kappa)} \tag{IA.7}$$

As private information becomes more precise (τ_s increases), trading and liquidity both decrease (i.e., $\mathrm{Var}(Trade_m)$ decreases and λ increases). As τ_s increases, additive overconfidence, κ, becomes small relative to objective information. This has the effect of decreasing relative overconfidence, with results that are again directionally the same as decreasing ψ in the baseline model.

General model solution

I assume that the price function is linear:

$$P = \alpha + \beta\overline{y} - \gamma\,(X - \mu_X) \tag{IA.8}$$

Claim 1. $\beta \neq 0$.

Proof. Assume $\beta = 0$. Thus, price is uninformative about private signals, and all agents have posterior beliefs of $\mathrm{E}_i[\theta|y_{m(i)}, x_{m(i)}, P] = \frac{\tau_p\mu + \psi\tau_s y_{m(i)}}{\tau_p + \psi\tau_s}$ and $\mathrm{Var}_i[\theta|y_{m(i)}, x_{m(i)}, P] = (\tau_p + \psi\tau_s)^{-1}$, resulting in asset demand $D_i\left[y_{m(i)}, x_{m(i)}, P\right] = \frac{\mathrm{E}_i[\theta|y_{m(i)}, x_{m(i)}, P] - P}{\frac{N}{\eta}\mathrm{Var}_i[\theta|y_{m(i)}, x_{m(i)}, P]} = \frac{\eta}{N}\left[\tau_p\mu + \psi\tau_s y_{m(i)} - (\tau_p + \psi\tau_s)\,P\right]$.

Solving $\sum_i D_i = X$ for the market clearing price implies $P = \frac{\tau_p \mu + \psi \tau_s \bar{y} - \frac{X}{\eta}}{\tau_p + \psi \tau_s}$. Thus, $\beta = \frac{\psi \tau_s}{\tau_p + \psi \tau_s} \neq 0$, a contradiction. ■

Given the price function described by equation (IA.8), agent i extracts a noisy signal for $\bar{y}_{-m(i)}$ from observing price, $y_{m(i)}$, and $x_{m(i)}$:

$$\begin{aligned} A_{m(i)} &= \frac{M}{\beta(M-1)}(P-\alpha) - \frac{1}{M-1} y_{m(i)} + \frac{\gamma M}{\beta(M-1)} \left(x_{m(i)} - \frac{\mu_X}{M} \right) \\ &= \bar{y}_{-m(i)} - \frac{\gamma M}{\beta} \left(\bar{x}_{-m(i)} - \frac{\mu_X}{M} \right) \end{aligned} \tag{IA.9}$$

Note that $A_{m(i)} \sim_i \mathcal{N}\left(\theta, \frac{1}{(M-1)\tau_s} + \left(\frac{\gamma}{\beta}\right)^2 \frac{M}{M-1} V\right)$ and $A_{m(i)}$ is independent of $y_{m(i)}$ and $x_{m(i)}$. Using Bayesian updating with signals $y_{m(i)}$ and $A_{m(i)}$ and substituting P, $y_{m(i)}$, $x_{m(i)}$ for $A_{m(i)}$ using (IA.9), agent i's posterior beliefs as a function of P, $y_{m(i)}$, $x_{m(i)}$ are:

$$\mathrm{E}_i[\theta | y_{m(i)}, x_{m(i)}, P] = \frac{\left(\begin{array}{c} \tau_p \mu - \frac{M\tau_A}{\beta(M-1)}\alpha + \left(\psi \tau_s - \frac{\tau_A}{M-1} \right) y_{m(i)} \\ + \frac{\gamma M \tau_A}{\beta(M-1)} \left(x_{m(i)} - \frac{\mu_X}{M} \right) + \frac{M\tau_A}{\beta(M-1)} P \end{array} \right)}{\tau_p + \psi \tau_s + \tau_A} \tag{IA.10a}$$

$$\mathrm{Var}_i[\theta | y_{m(i)}, x_{m(i)}, P] = (\tau_p + \psi \tau_s + \tau_A)^{-1} \tag{IA.10b}$$

where $\tau_A = \left(\frac{1}{(M-1)\tau_s} + \left(\frac{\gamma}{\beta}\right)^2 \frac{M}{M-1} V \right)^{-1}$ is the precision agent i attributes to $A_{m(i)}$.

Agent i's asset demand is:

$$\begin{aligned} D_i &= \frac{\mathrm{E}_i[\theta | y_{m(i)}, x_{m(i)}, P] - P}{\frac{N}{\eta} \mathrm{Var}_i[\theta | y_{m(i)}, x_{m(i)}, P]} \\ &= \frac{\eta}{N} \left(\begin{array}{c} \tau_p \mu - \frac{M\tau_A}{\beta(M-1)}\alpha + \left(\psi \tau_s - \frac{\tau_A}{M-1} \right) y_{m(i)} + \frac{\gamma M \tau_A}{\beta(M-1)} \left(x_{m(i)} - \frac{\mu_X}{M} \right) \\ - \left(\tau_p + \psi \tau_s + \left(1 - \frac{M}{\beta(M-1)} \right) \tau_A \right) P \end{array} \right) \end{aligned} \tag{IA.11}$$

The market clearing price must solve $X = \sum_i D_i$. Thus,

$$P = \frac{\tau_p \mu - \frac{1}{\eta}\mu_X - \frac{M\tau_A}{\beta(M-1)}\alpha + \left(\psi \tau_s - \frac{\tau_A}{M-1} \right) \bar{y} - \left(\frac{1}{\eta} - \frac{\gamma \tau_A}{\beta(M-1)} \right) (X - \mu_X)}{\tau_p + \psi \tau_s + \left(1 - \frac{M}{\beta(M-1)} \right) \tau_A} \tag{IA.12}$$

Equations (IA.8) and (IA.12) yield the following system of equations:

$$\begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix} \left(\tau_p + \psi\tau_s + \left(1 - \frac{M}{\beta\,(M-1)}\right)\tau_A\right) = \begin{bmatrix} \tau_p\mu - \frac{1}{\eta}\mu_X - \frac{M\tau_A}{\beta(M-1)}\alpha \\ \psi\tau_s - \frac{\tau_A}{M-1} \\ \frac{1}{\eta} - \frac{\gamma\tau_A}{\beta(M-1)} \end{bmatrix} \tag{IA.13}$$

Claim 2. The unique solution to equations (IA.13) is:

$$\alpha = \frac{\left(\eta^2\psi^2\tau_p\tau_s + MV\tau_p\right)\mu - \left(\eta\psi^2\tau_s + \frac{MV}{\eta}\right)\mu_X}{\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV} \tag{IA.14a}$$

$$\beta = \frac{\psi\tau_s\left(\eta^2\psi\,(M+\psi-1)\,\tau_s + MV\right)}{\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV} \tag{IA.14b}$$

$$\gamma = \frac{\eta^2\psi\,(M+\psi-1)\,\tau_s + MV}{\eta\left(\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV\right)} \tag{IA.14c}$$

Proof. Consider $\Gamma \equiv \frac{\gamma}{\beta}$. We already established that $\beta \neq 0$ so Γ is finite. Substituting Γ into (IA.13) and dividing the γ equation by the β equation yields:

$$\begin{aligned} \Gamma &= \frac{\frac{1}{\eta} - \Gamma\frac{\tau_A}{M-1}}{\psi\tau_s - \frac{\tau_A}{M-1}} \\ &= \frac{1}{\eta\psi\tau_s} \end{aligned} \tag{IA.15}$$

Plugging (IA.15) into the β equation of (IA.13) yields:

$$\beta = \frac{\psi\tau_s\left(\eta^2\psi\,(M+\psi-1)\,\tau_s + MV\right)}{\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV} \tag{IA.16}$$

Plugging (IA.15) and (IA.16) into the γ equation of (IA.13) yields:

$$\gamma = \frac{\eta^2\psi\,(M+\psi-1)\,\tau_s + MV}{\eta\left(\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV\right)} \tag{IA.17}$$

Finally, plugging (IA.15), (IA.16), and (IA.17) into the α equation of (IA.13) yields:

$$\alpha = \frac{\left(\eta^2\psi^2\tau_p\tau_s + MV\tau_p\right)\mu - \left(\eta\psi^2\tau_s + \frac{MV}{\eta}\right)\mu_X}{\eta^2\psi^2\tau_s\left(\tau_p + (M+\psi-1)\,\tau_s\right) + \left(\tau_p + \psi\tau_s\right)MV} \tag{IA.18}$$

■

Trading

Using equation (IA.11),

$$
\begin{aligned}
Trade_m &\equiv \sum_{i:m(i)=m} \left[D_i - \frac{M}{N} x_m \right] \\
&= \left\{ \frac{\eta}{M} \left(\psi \tau_s - \frac{\tau_A}{M-1} \right) (y_m - \overline{y}) \right\} - \left\{ \left(1 - \frac{\eta \gamma \tau_A}{(M-1)\beta} \right) (x_m - \overline{x}) \right\} \qquad \text{(IA.19)}
\end{aligned}
$$

All other trading derivations are in the main text of the paper.

Liquidity

Recall that illiquidity is defined as:

$$
\lambda \equiv \frac{\frac{dP}{dy_m}}{\frac{dTrade_m}{dy_m}}
$$

Taking derivatives of P (eq. IA.8) and $Trade_m$ (eq. IA.19) with respect to y_m and plugging in γ from (IA.14c) and Γ from (IA.15) yields:

$$
\begin{aligned}
\lambda &= \frac{-\gamma}{\left(\frac{N}{M}\right)\left(\frac{\eta}{N}\right)\left(\frac{\gamma M \tau_A}{\beta(M-1)} + \gamma \left(\tau_p + \psi \tau_s + \left(1 - \frac{M}{\beta(M-1)}\right) \tau_A \right)\right) - 1} \\
&= \frac{M \left(\eta^2 \psi^2 \tau_s + MV\right)\left(\eta^2 \psi (M + \psi - 1) \tau_s + MV\right)}{\eta (M-1) \left(\eta^2 \left(\psi^2 - \psi\right) \tau_s + MV\right)\left(\eta^2 \psi^2 \tau_s (\tau_p + (M + \psi - 1)\tau_s) + (\tau_p + \psi \tau_s) MV\right)} \\
&= \left\{ \frac{M}{(M-1)\eta (\tau_p + \psi \tau_s + \tau_A)} \right\} \\
&\quad + \left\{ \frac{\eta^2 \psi^2 \tau_s}{\eta^2 \psi^2 \tau_s + MV} \right\} \left\{ \frac{\tau_s}{\tau_p + \psi \tau_s + \tau_A} \right\} \left\{ \frac{\eta}{M} \left(\psi \tau_s - \frac{\beta}{M} (\tau_p + \psi \tau_s + \tau_A) \right) \right\}^{-1} \\
&= \{S\} + \{B1\}\{B2\}\{B3\}^{-1} \qquad \text{(IA.20)}
\end{aligned}
$$

Consistent with the baseline model, $\lim_{V \to 0} \frac{d\lambda}{d\psi} < 0$, $\lim_{V \to 0} \frac{d\lambda}{d\tau_s} < 0$, and $\lim_{V \to 0} \frac{d\lambda}{d\tau_p} < 0$. From (IA.20) one can see that $\frac{d\lambda}{d\tau_p} < 0$ for all V. However, $\frac{d\lambda}{d\psi}$ and $\frac{d\lambda}{d\tau_s}$ are not always negative.

Their signs are determined by complicated functions of the parameters. Considering limiting cases is instructive. We have already seen that $\frac{d\lambda}{d\psi}$ and $\frac{d\lambda}{d\tau_s}$ are negative in the limit as $V \to 0$. Both are also negative in the limit as $V \to \infty$. For interim values of V (i.e., positive, finite V), $\frac{d\lambda}{d\psi}$ and $\frac{d\lambda}{d\tau_s}$ can be positive or negative. Both follow a similar pattern. As $\psi \to 0$ or $\tau_s \to 0$, $\lambda \to \frac{M}{(M-1)\eta\tau_p}$, which is solely a supply impact – it includes no belief price response.[1,2] $\frac{d\lambda}{d\psi}$ and $\frac{d\lambda}{d\tau_s}$ initially have the same sign as $\eta^2\tau_p - V$ (i.e., $sign\left[\lim_{\psi\to 0}\frac{d\lambda}{d\psi}\right] = sign\left[\lim_{\tau_s\to 0}\frac{d\lambda}{d\tau_s}\right] = sign\left[\eta^2\tau_p - V\right]$). As ψ and τ_s increase, they eventually decrease λ, driving it to approach zero as $\psi \to \infty$ or $\tau_s \to \infty$.

Liquidity without overconfidence

Private information precision can enhance liquidity even without overconfidence. When $\psi = 1$ (which reproduces the model of Diamond and Verrecchia (1981)), illiquidity is:

$$\lambda_{\psi=1} = \frac{M\left(\eta^2\tau_s + MV\right)\left(\eta^2\tau_s + V\right)}{\eta\left(M-1\right)\left(\eta^2\tau_s\left(\tau_p + M\tau_s\right) + \left(\tau_p + \tau_s\right)MV\right)V} \tag{IA.21}$$

and its derivative with respect to private information precision is:

$$\frac{d\lambda}{d\tau_s}_{\psi=1} = \frac{M\left(\eta^6\tau_p\tau_s^2 + \eta^4\tau_s\left(2\tau_p - M\tau_s\right)MV + \eta^2\left(\tau_p - 2\tau_s\right)M^2V^2 - M^2V^3\right)}{\eta\left(M-1\right)\left(\eta^2\tau_s\left(\tau_p + M\tau_s\right) + \left(\tau_p + \tau_s\right)MV\right)^2 V} \tag{IA.22}$$

The $V \to 0$ limit is uninteresting because without endowment shocks or overconfidence, illiquidity is infinite.

As $V \to \infty$, $\lambda_{\psi=1} \to \frac{M}{(M-1)\eta(\tau_p+\tau_s)}$ and $\frac{d\lambda}{d\tau_s}_{\psi=1} \to \frac{-M}{(M-1)\eta(\tau_p+\tau_s)^2} < 0$. Under infinite supply variance, liquidity trading swamps informed trading so trades carry no information. Thus, only the supply channel is operative, and the supply illiquidity channel always decreases as information (public or private) increases.

For interim values of V, λ starts off as solely a supply effect: $\lim_{\tau_s\to 0}\lambda_{\psi=1} = \frac{M}{(M-1)\eta\tau_p}$. As τ_s increases, the supply illiquidity channel decreases, but the belief illiquidity channel increases at least initially. For large V, the decreasing supply channel is more powerful. For small V, the increasing belief channel is more powerful. Specifically, $\lim_{\tau_s\to 0}\frac{d\lambda}{d\tau_s}_{\psi=1} = \frac{M\left(\eta^2\tau_p - V\right)}{\eta\tau_p^2(M-1)V}$. For large τ_s,

[1] Though I restrict my attention to overconfidence ($\psi > 1$) in other parts of the paper, it is useful to generalize and consider underconfidence ($\psi < 1$) here to get a full picture of the relationship between λ and ψ.

[2] The total risk tolerance of agents not receiving the shock is $\frac{(M-1)\eta}{M}$ and their posterior variance is τ_p^{-1}.

only the belief channel is operative, and $\lim_{\tau_s \to \infty} \lambda_{\psi=1} = \frac{\eta}{(M-1)V}$. Note that this is a positive constant whereas $\lim_{\tau_s \to \infty} \lambda = 0$ when $\psi > 1$. The belief channel consistently increases with τ_s when V is small, but when V is large, τ_s eventually decreases the belief channel, thereby decreasing overall illiquidity as well. Specifically, $sign\left[\lim_{\tau_s \to \infty} \frac{d\lambda}{d\tau_s}_{\psi=1}\right] = sign\left[\eta^2\tau_p - M^2V\right]$. Another point of interest is to compare illiquidity at the two limits of τ_s: $\frac{\lim_{\tau_s \to \infty} \lambda_{\psi=1}}{\lim_{\tau_s \to 0} \lambda_{\psi=1}} = \frac{\eta^2\tau_p}{MV}$.

The overall relationship between private information and illiquidity without overconfidence is as follows: For high supply variance ($V > \eta^2\tau_p$), private information decreases illiquidity; for low supply variance ($V < \frac{\eta^2\tau_p}{M^2}$), private information increases illiquidity; and for moderate supply variance ($\frac{\eta^2\tau_p}{M^2} < V < \eta^2\tau_p$), illiquidity is a hump-shaped function of private information. Within the moderate case, τ_s decreases illiquidity overall when $V > \frac{\eta^2\tau_p}{M}$ and increases illiquidity overall when $V < \frac{\eta^2\tau_p}{M}$.

B Empirical details and supplemental analysis

The 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.

Data and methodology

I consider trading and liquidity of New York Stock Exchange (NYSE) stocks between 1926 and 2011. Focusing on the NYSE avoids differences in market structure and reporting across exchanges. Limiting attention to the NYSE also mitigates the impact of small stocks. The sample is also limited to stocks with share prices above $5 at the end of the previous month.

Table IA.1 and Figure IA.1 summarize the data. Means represent equally weighted averages across stocks. Standard deviations are cross-sectional. Trading volume is the most straight-forward data item because it is directly observable in CRSP monthly data from 1926 to 2011. 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 then rose to 20% in 2011 with a peak of 40% in 2008. The time trend is clearest in Figure IA.1, panel A. Table IA.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. The first measure of illiquidity I consider 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 IA.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 IA.1, panel B plots $\log(illiq)$ over time.

Bid-ask spread is another measure of illiquidity, and corresponds to price response to trading 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 IA.1 and panels C and D of Figure IA.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 in the early 2000's. The drop-off in daily bid-ask spreads was 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).[3]

Changes in private information relative to public information are identified in two ways. First, periods around earnings announcements are likely to have elevated private information and public uncertainty. 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 private information relative to public information. Analyst dispersion may represent or cause public uncertainty and could also stem from more private information. Dispersion is measured as 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 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 IA.1, are available from I/B/E/S starting in 1976. Valid dispersion data is available for about 60% of the stocks in the 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 variables in Table IA.1 and Figure IA.1 show significant time trends and changing standard deviations. Regressions analyze log variables to make changes more comparable over time. Panel analysis controls for time and firm fixed effects. For market vector autoregression (VAR) analysis, log time series are detrended using a Hodrick and Prescott (1997) filter. The dashed lines in Figure IA.1 plot the trends. Figure IA.2 shows the detrended time series.

[3] 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.

Fact 1: Trade and liquidity are positively correlated

I first examine the reduced form relationship between turnover and liquidity in the cross section. At the end of each month, stocks are sorted into decile portfolios based on turnover in the past month. Table IA.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.

A potential concern with the decile sort methodology is that lagged turnover is likely correlated with omitted variables. To control for omitted variables, the panel regressions in Table 1 include stock, bond, and month fixed effects. The resulting identification is based on changes to turnover over time for a given firm. Table IA.3 reports supplemental stock results using *illiq* and alternative bid-ask spread measures. Consistent, with Table 1, turnover is negatively related to all illiquidity measures.

Fact 2: As private information increases relative to public information, trade increases and liquidity decreases

Figure IA.3 plots daily and quoted transaction-level bid-ask spreads around earnings announcements. Results are similar to the effective bid-ask spread results plotted in Figure 6.

Table IA.4 reports turnover and illiquidity for decile portfolios formed monthly by sorts lagged analyst 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.

Table IA.5 reports analyst dispersion panel regression results for alternative illiquidity measures. Consistent with results in Table 2, analyst earnings forecast dispersion is positively related to all illiquidity measures.

The results show that as information heterogeneity (proxied by analyst forecast dispersion and earnings announcements) increases, trade increases and liquidity decreases. These relationships could vary across stocks. To test for differences across stocks, I add stock characteristic interactions to the analyst forecast dispersion regressions and replicate the earnings announcement event studies for different subsets of stocks. Results are robust across most stock characteristics. Across almost all sorts, as information heterogeneity increases, trading tends to increase and liquidity tends to decrease.

Size

I sort stocks at the end of June in each year based on their current market capitalization. Large stocks have market capitalizations above the NYSE median. Small stocks have market capitalizations below the median. Results are in Table IA.6 and Figure IA.4.

- Turnover increases with analyst forecast dispersion only for large 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 IA.7 and Figure IA.5.

- Analyst dispersion decreases liquidity for all groups, but the effect decreases with B/M ratios. Thus, growth stock liquidity is more sensitive to analyst dispersion than value stock liquidity is.
- 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 IA.8 and Figure IA.6.

- 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 in Table IA.9 and Figure IA.7.

- 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.

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 IA.10 and Figure IA.8.

- 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.

Fact 3: Trade and liquidity are elevated following high past returns

Table IA.11 reports parameter estimates and bootstrapped standard errors for the stock market VAR.

Figure IA.9 plots impulse response functions for the stock market VAR, including responses that are omitted from Figure 7 for brevity. 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 IA.9

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 (row 3) 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 IA.11 and Figure IA.9 on bid-ask spreads, which are unfortunately only available in uninterrupted time series starting in 1993. Figure IA.10 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 last 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.

Table IA.12 reports panel VAR coefficient estimates and standard errors. The primary coefficients of interest are 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 (with an insignificant t-statistic for illiquidity).

As a final test, stocks are sorted cross-sectionally based on momentum (stock-level returns from 12 months ago to 1 month ago). Table IA.13 reports 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.

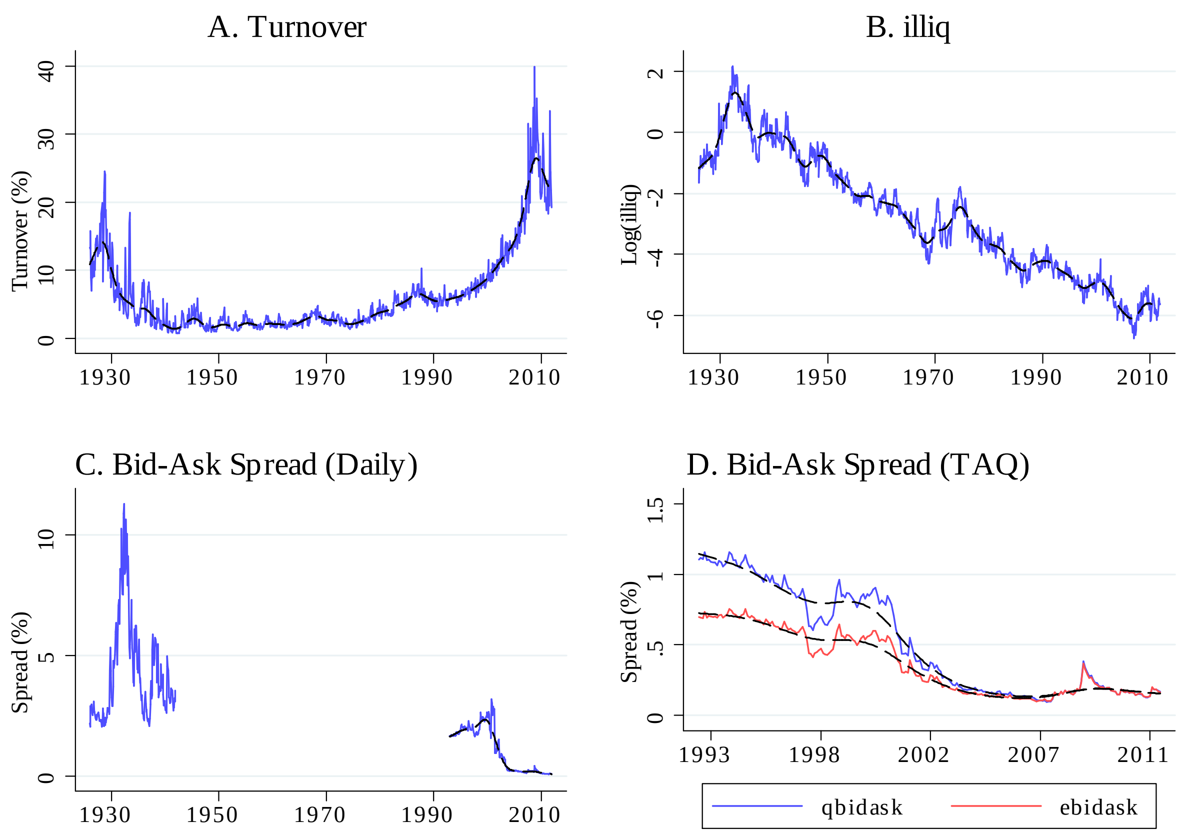

Figure IA.1: Monthly Time Series. Solid lines are the actual data. Dashed lines are trends calculated using a Hodrick Prescott filter with a penalty value of 14,400 on the log data.

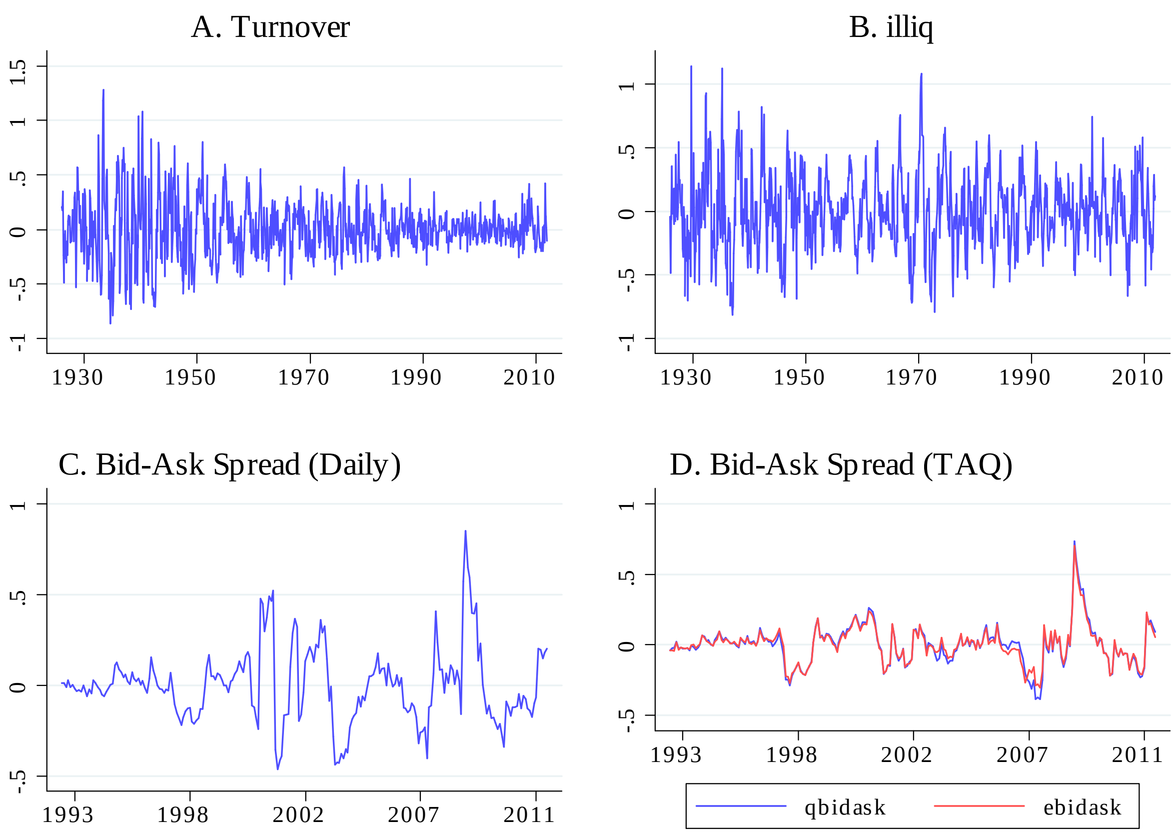

Figure IA.2: Detrended Log Monthly Time Series. The log time series were detrended using a Hodrick Prescott filter with a penalty value of 14,400.

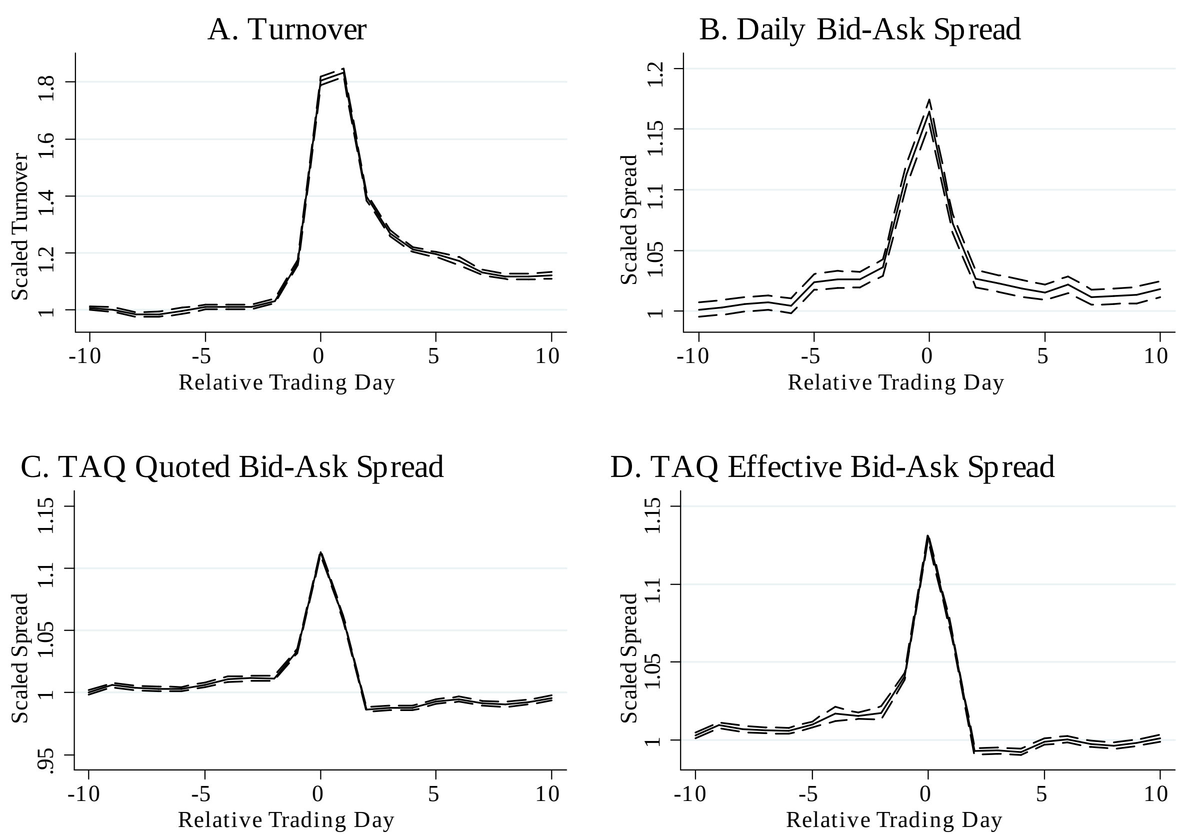

Figure IA.3: Turnover and Liquidity Around Earnings Announcements. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

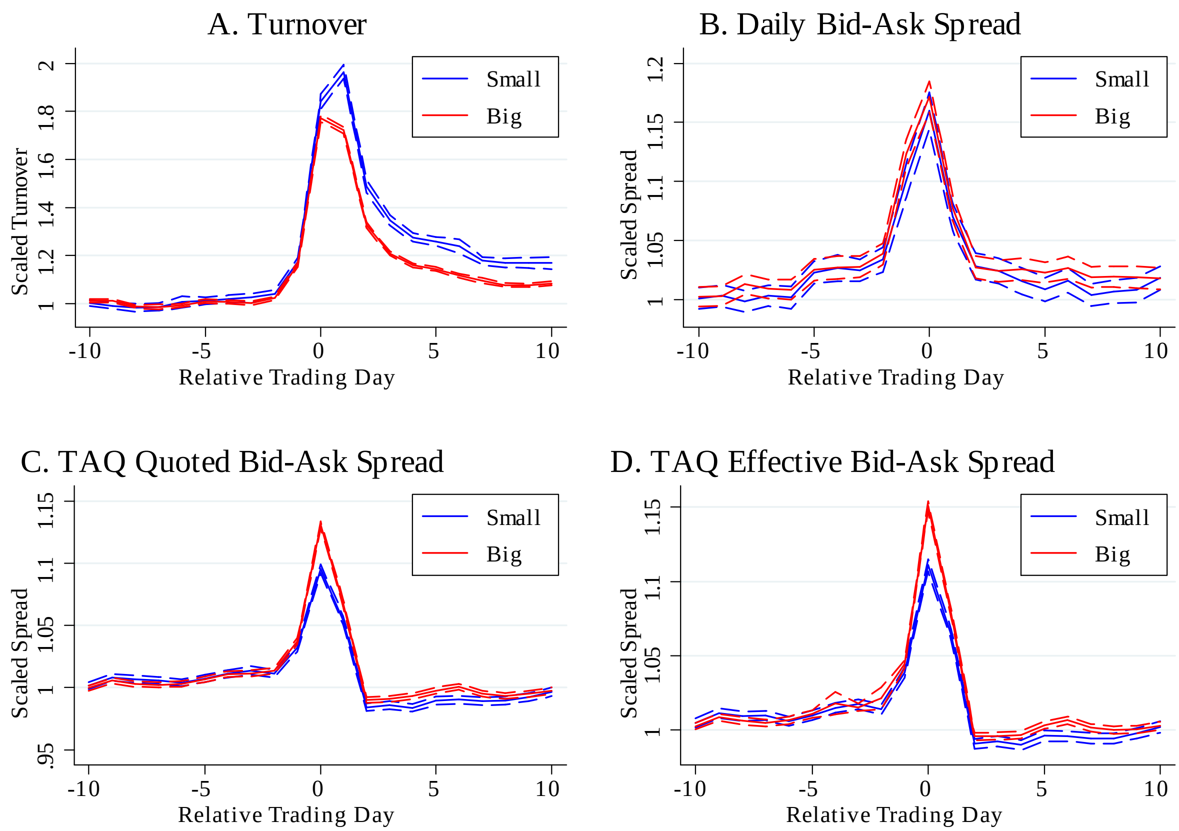

Figure IA. 4: Turnover and Liquidity Around Earnings Announcements by Size. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

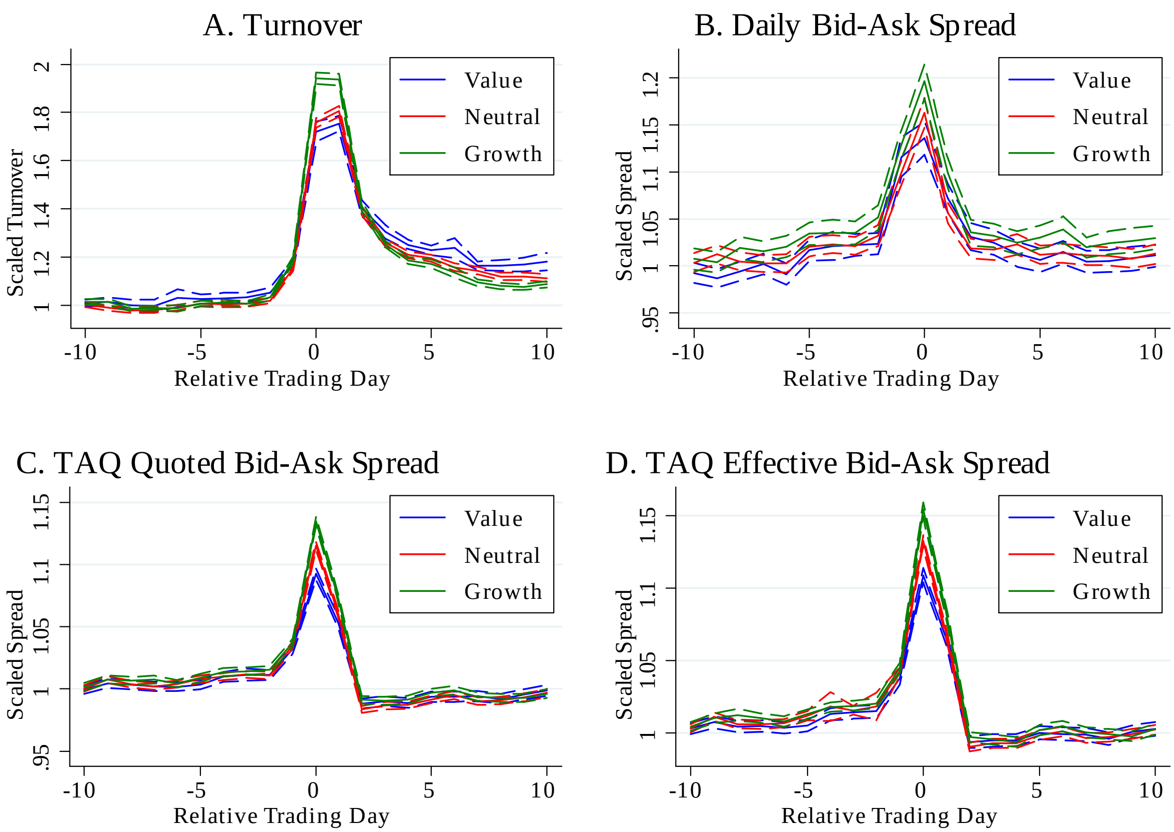

Figure IA.5: Turnover and Liquidity Around Earnings Announcements by Book-to-Market Ratio. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence intervals. Day 0 is the day of the earnings announcement.

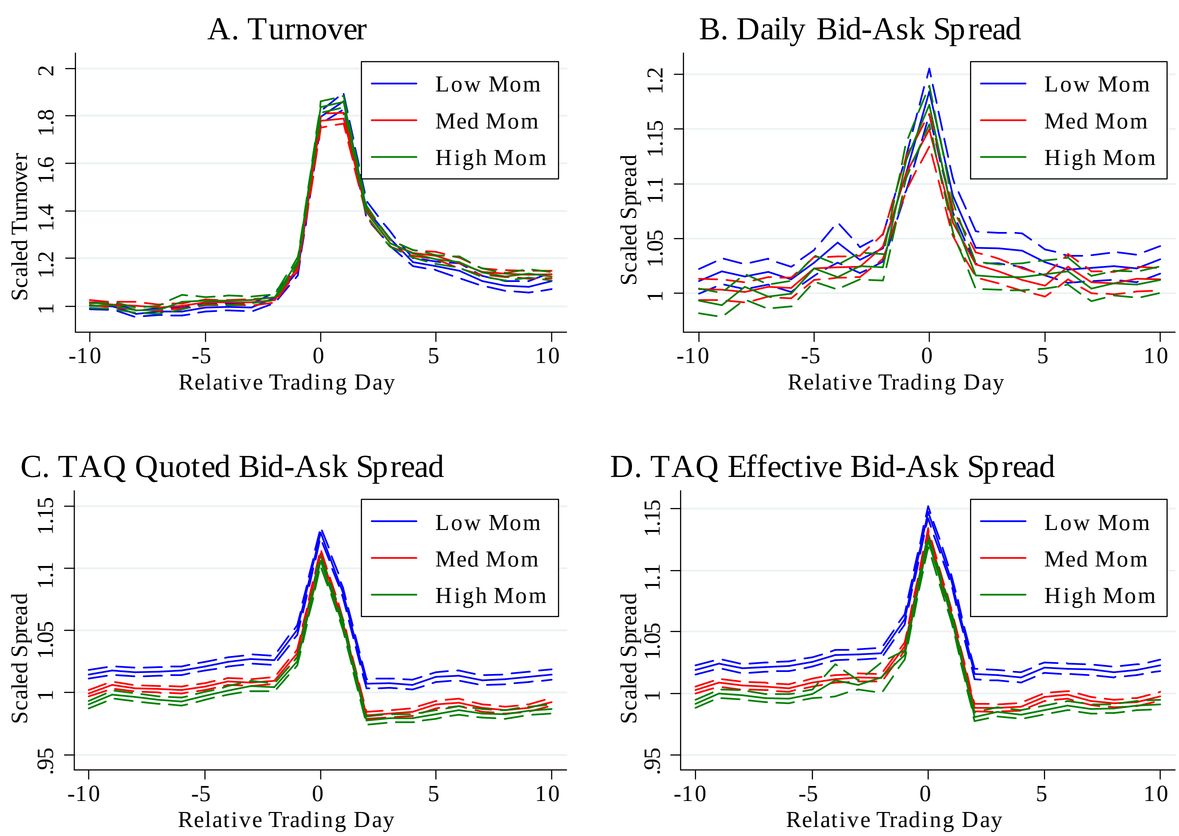

Figure IA.6: Turnover and Liquidity Around Earnings Announcements by Momentum. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95% confidence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

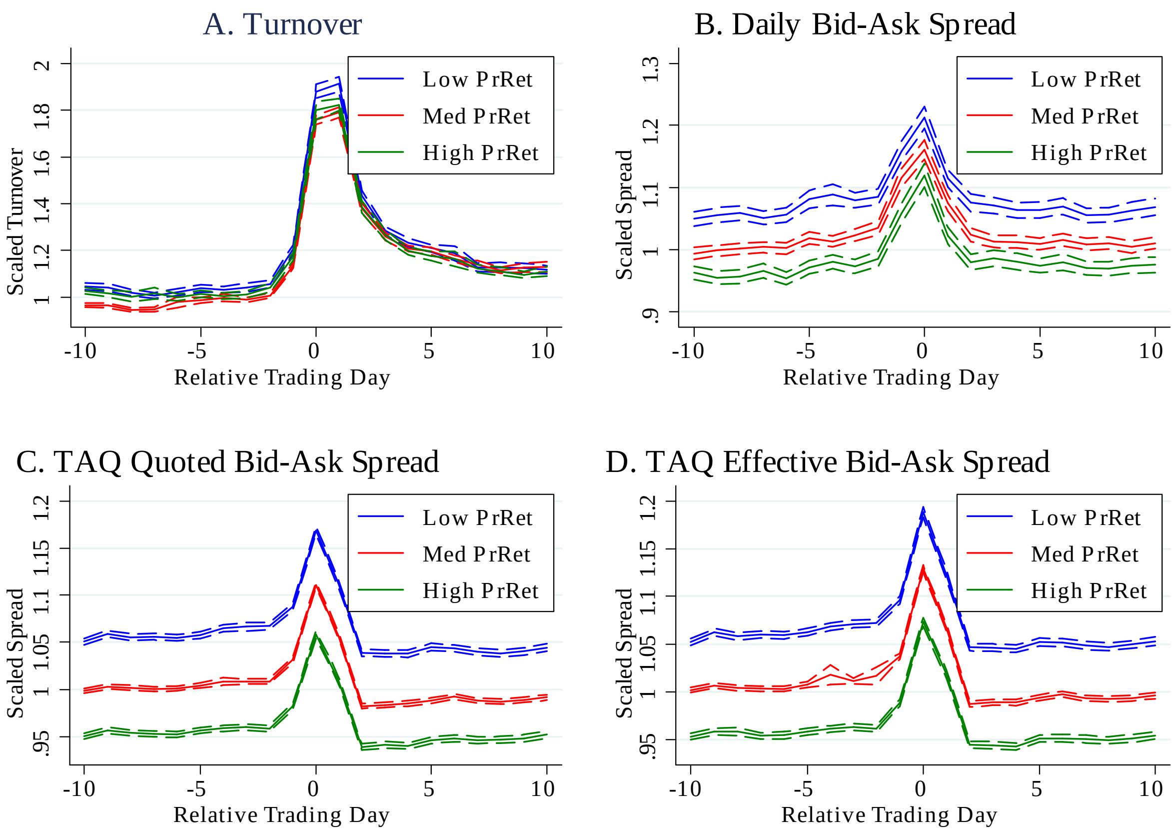

Figure IA.7: Turnover and Liquidity Around Earnings Announcements by Prior Month Returns. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are 95%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

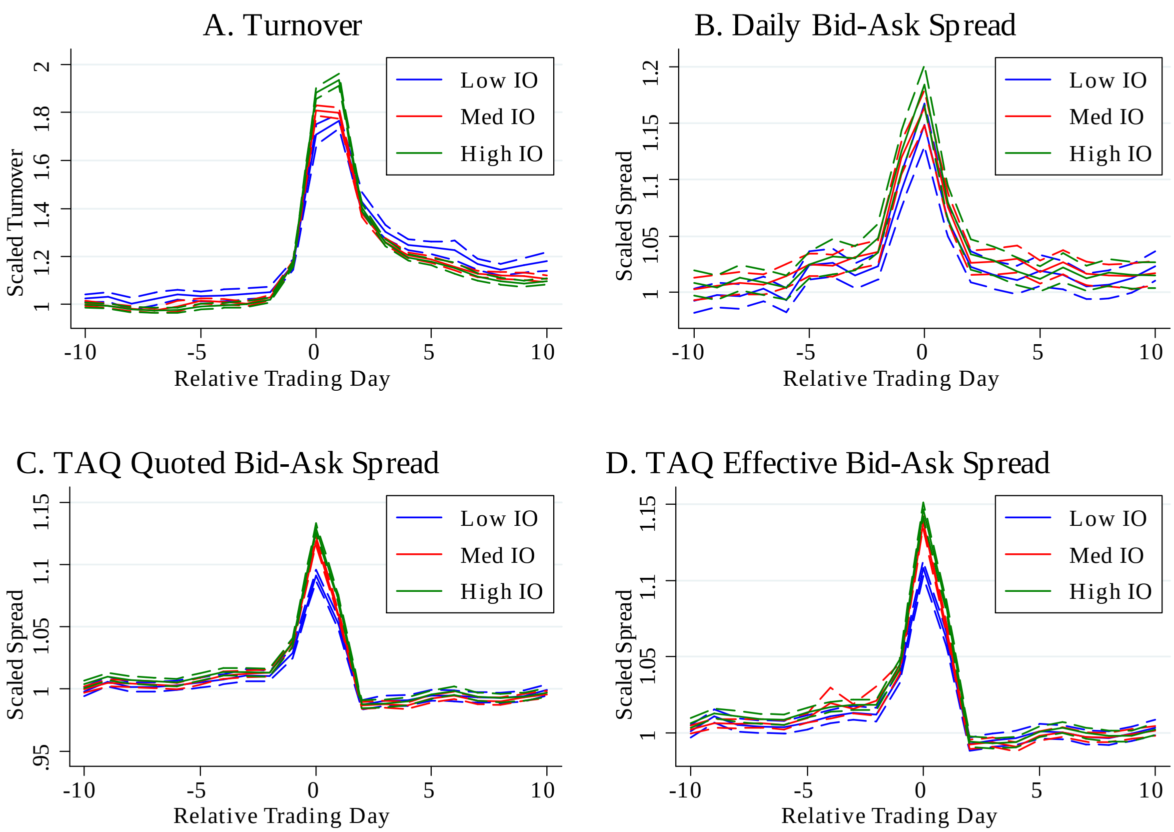

Figure IA.8: Turnover and Liquidity Around Earnings Announcements by Institutional Ownership. Turnover and bid-ask spreads are scaled by average daily values over the three calendar months before the earnings announcement. Solid lines are equally weighted averages across all stocks. Dashed lines are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

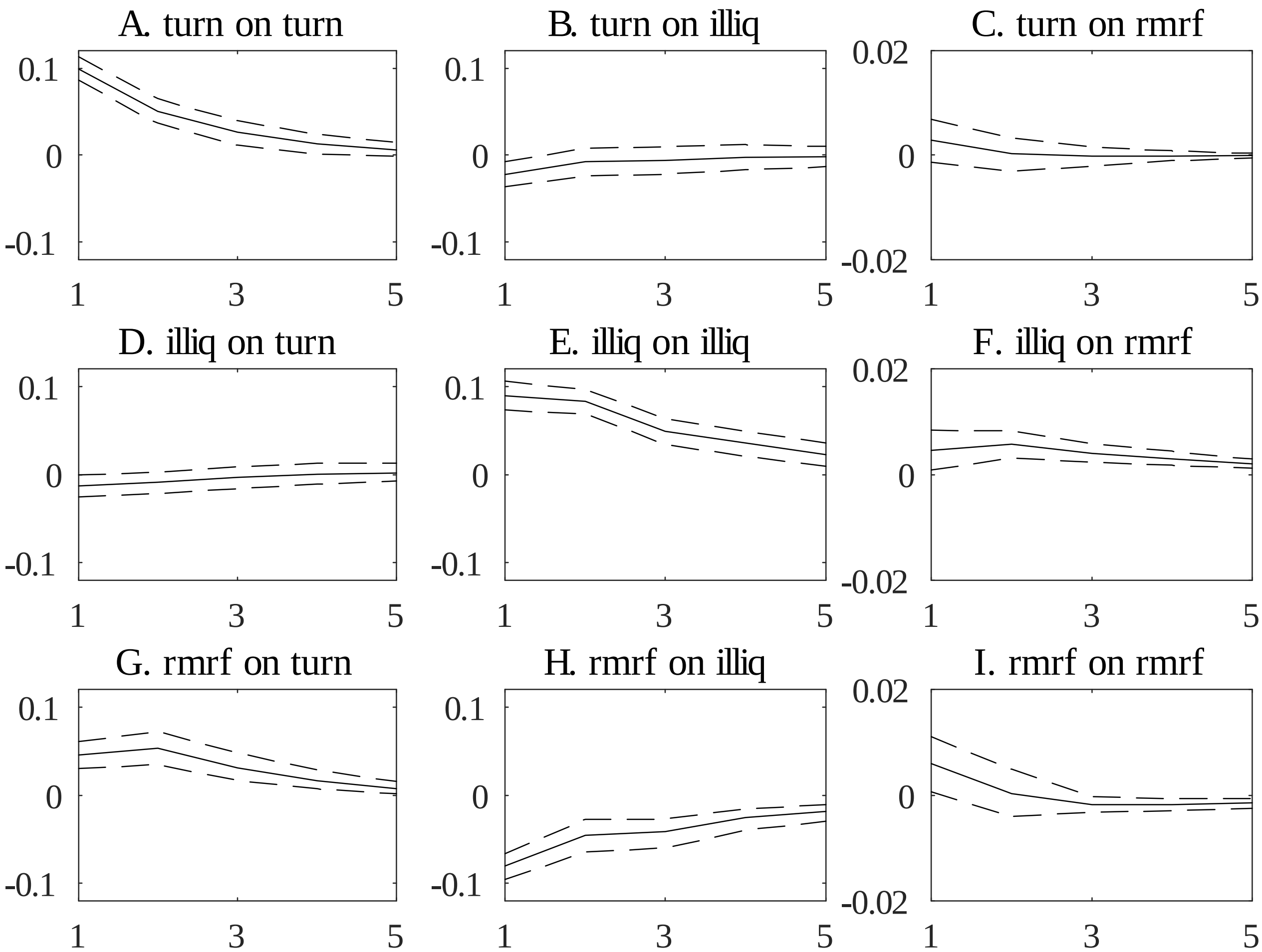

Figure IA.9: Impulse Response Functions from ***illiq*** **VAR.** The first variable in each panel title is the impulse variable. The second variable is the response variable. The solid lines are responses to one standard deviation shocks to the impulse variables after the number of lags indicated on 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.

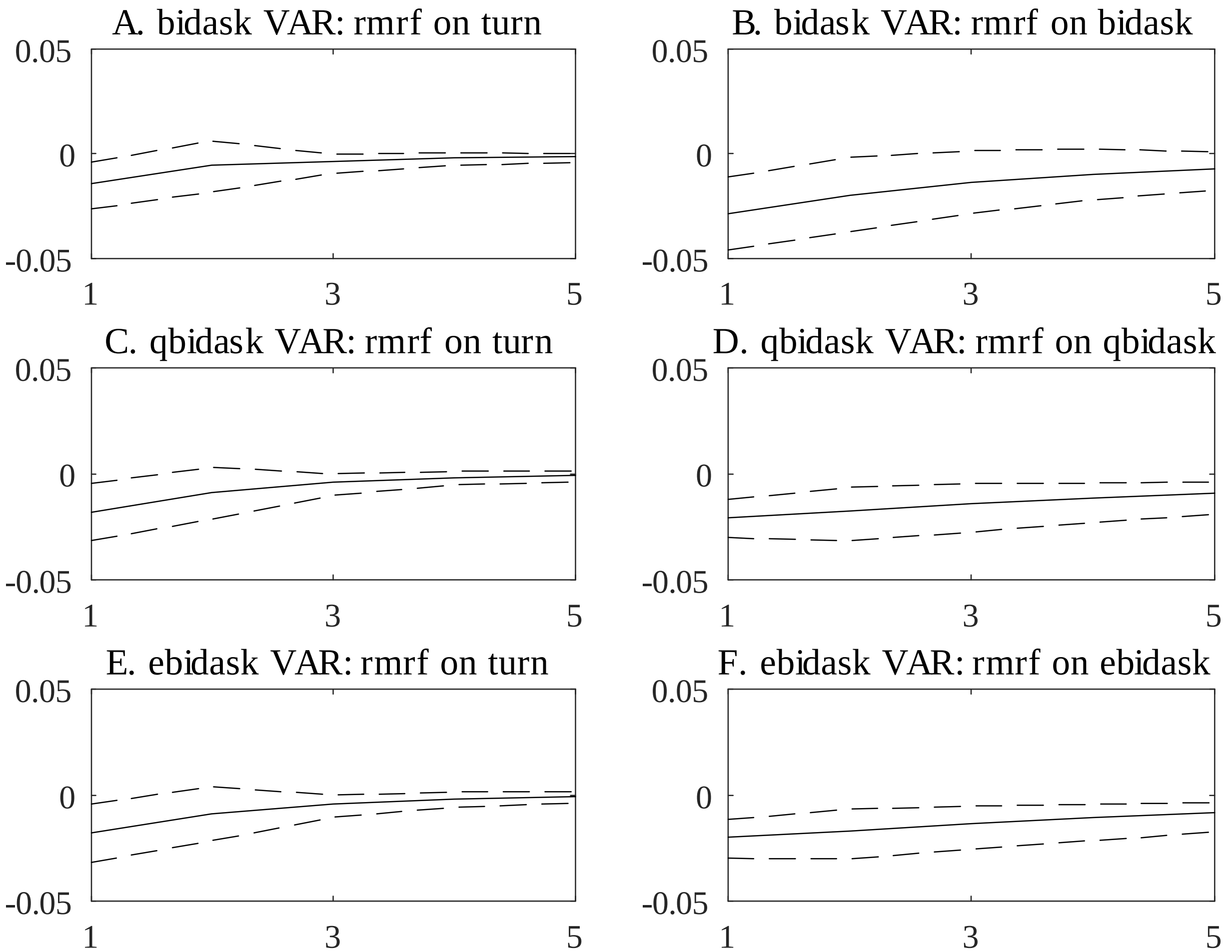

Figure IA.10: Impulse Response Functions from ***bidask*****,** ***qbidask*****, and** ***ebidask*** **VARs.** Each VAR includes detrended log market turnover ($turn$), CRSP value-weighted market returns in excess of the risk free rate ($rmrf$), and a detrended log measure of market illiquidity (daily 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.

Table IA.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 IA.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 IA.3: Turnover Panel Regressions

Results are for stock-level panel regressions of log illiquidity measures on log turnover. Robust clustered (by stock) 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) $\log(illiq)$	(2) $\log(bidask)$	(3) $\log(qbidask)$	(4) $\log(ebidask)$
Log Turnover	-0.667***	-0.112***	-0.164***	-0.158***
	(0.010)	(0.007)	(0.006)	(0.006)
Stock FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	1,128,984	326,781	331,239	331,238
R^2	0.925	0.908	0.914	0.889
Date Range	1926-2011	1993-2011	1993-2011	1993-2011

Table IA.4: 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 IA.5: Analyst Dispersion Panel Regressions

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) 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) log($turn$)	(2) log($illiq$)	(3) log($bidask$)	(4) log($qbidask$)	(5) log($ebidask$)
Lagged Log Analyst Dispersion	0.016***	0.207***	0.100***	0.107***	0.110***
	(0.004)	(0.007)	(0.004)	(0.003)	(0.004)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	341,431	341,398	199,582	201,948	201,948
R^2	0.729	0.888	0.919	0.926	0.901
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.6: Analyst Dispersion Panel Regressions – Size

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

	(1) log($turn$)	(2) log($illiq$)	(3) log($bidask$)	(4) log($qbidask$)	(5) log($ebidask$)
Lagged Log Analyst Dispersion	-0.012**	0.180***	0.086***	0.098***	0.099***
	(0.005)	(0.008)	(0.004)	(0.004)	(0.004)
Lagged log($disp$) × Big	0.065***	-0.027**	0.009	-0.005	-0.001
	(0.007)	(0.011)	(0.006)	(0.006)	(0.006)
Big	0.305***	-1.121***	-0.220***	-0.321***	-0.311***
	(0.026)	(0.046)	(0.025)	(0.023)	(0.024)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	331,395	331,363	193,007	195,294	195,294
R^2	0.737	0.902	0.922	0.931	0.908
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.7: Analyst Dispersion Panel Regressions – Book-to-Market Ratios

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

	(1) log($turn$)	(2) log($illiq$)	(3) log($bidask$)	(4) log($qbidask$)	(5) log($ebidask$)
Lagged Log Analyst Dispersion	0.020***	0.145***	0.083***	0.090***	0.092***
	(0.005)	(0.010)	(0.006)	(0.005)	(0.005)
Lagged log($disp$) × Neutral BM	-0.001	0.034***	0.009	0.004	0.005
	(0.006)	(0.011)	(0.006)	(0.005)	(0.006)
Lagged log($disp$) × Growth	0.009	0.075***	0.017**	0.017**	0.020***
	(0.008)	(0.015)	(0.008)	(0.007)	(0.007)
Neutral BM	0.013	-0.212***	-0.093***	-0.133***	-0.133***
	(0.019)	(0.036)	(0.020)	(0.019)	(0.020)
Growth	0.109***	-0.330***	-0.119***	-0.163***	-0.160***
	(0.026)	(0.056)	(0.030)	(0.029)	(0.030)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	331,309	331,277	192,974	195,261	195,261
R^2	0.735	0.893	0.921	0.929	0.905
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.8: Analyst Dispersion Panel Regressions – Momentum

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

	(1) $\log(turn)$	(2) $\log(illiq)$	(3) $\log(bidask)$	(4) $\log(qbidask)$	(5) $\log(ebidask)$
Lagged Log	0.004	0.210***	0.097***	0.103***	0.106***
Analyst Dispersion	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Lagged $\log(disp)$	0.019***	-0.033***	-0.014***	-0.013***	-0.015***
× Medium Momentum	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Lagged $\log(disp)$	0.039***	-0.049***	-0.013***	-0.008**	-0.011***
× High Momentum	(0.004)	(0.007)	(0.004)	(0.003)	(0.004)
Medium Momentum	0.001	-0.222***	-0.150***	-0.145***	-0.158***
	(0.011)	(0.018)	(0.012)	(0.010)	(0.010)
High Momentum	0.195***	-0.495***	-0.226***	-0.196***	-0.218***
	(0.015)	(0.023)	(0.014)	(0.012)	(0.013)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	332,972	332,939	192,876	195,170	195,170
R^2	0.738	0.893	0.922	0.930	0.907
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.9: Analyst Dispersion Panel Regressions – Prior Month Returns

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

	(1) log(*turn*)	(2) log(*illiq*)	(3) log(*bidask*)	(4) log(*qbidask*)	(5) log(*ebidask*)
Lagged Log	-0.002	0.229***	0.103***	0.112***	0.115***
Analyst Dispersion	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Lagged log(*disp*)	0.018***	-0.033***	-0.008***	-0.011***	-0.012***
× Medium Lag Ret	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Lagged log(*disp*)	0.030***	-0.031***	-0.005**	-0.004**	-0.005***
× High Lag Ret	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Medium Lag Ret	-0.040***	-0.153***	-0.095***	-0.106***	-0.107***
	(0.008)	(0.011)	(0.008)	(0.007)	(0.007)
High Lag Ret	0.089***	-0.242***	-0.101***	-0.095***	-0.098***
	(0.008)	(0.010)	(0.007)	(0.006)	(0.006)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	341,232	341,200	199,427	201,789	201,789
R^2	0.731	0.888	0.920	0.927	0.902
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.10: Analyst Dispersion Panel Regressions – Institutional Ownership

Results are for stock-level regressions of log turnover and log illiquidity measures on lagged (by one month) log analyst forecast dispersion. Robust clustered (by stock) standard errors are in parentheses. * represents 10% significance, ** represents 5% significance, *** represents 1% significance.

	(1) log(*turn*)	(2) log(*illiq*)	(3) log(*bidask*)	(4) log(*qbidask*)	(5) log(*ebidask*)
Lagged Log	0.024***	0.182***	0.096***	0.108***	0.111***
Analyst Dispersion	(0.008)	(0.012)	(0.007)	(0.006)	(0.006)
Lagged log(*disp*)	0.001	0.016	0.004	-0.004	-0.005
× Medium IO	(0.008)	(0.013)	(0.007)	(0.007)	(0.007)
Lagged log(*disp*)	-0.015	0.024	0.001	-0.002	-0.002
× High IO	(0.009)	(0.015)	(0.008)	(0.008)	(0.008)
Medium IO	0.119***	-0.260***	-0.089***	-0.120***	-0.132***
	(0.028)	(0.050)	(0.027)	(0.026)	(0.026)
High IO	0.193***	-0.426***	-0.154***	-0.173***	-0.199***
	(0.034)	(0.060)	(0.032)	(0.031)	(0.031)
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	293,155	293,124	193,030	195,317	195,317
R^2	0.721	0.887	0.921	0.928	0.904
Date Range	1976-2011	1976-2011	1993-2011	1993-2011	1993-2011

Table IA.11: 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 than $5 from 1926 to 2011.

	(1) *turn*	(2) *illiq*	(3) *rmrf*
Lag 1			
turn	0.4835***	-0.1083**	0.0137
	(0.0392)	(0.0437)	(0.0120)
illiq	-0.0634	0.4329***	0.0225**
	(0.0392)	(0.0507)	(0.0110)
rmrf	0.8625***	-1.5128***	0.1133*
	(0.1905)	(0.1687)	(0.0612)
Lag 2			
turn	-0.0059	0.0810**	-0.0049
	(0.0432)	(0.0383)	(0.0094)
illiq	-0.0043	0.2444***	0.0167
	(0.0366)	(0.0450)	(0.0103)
rmrf	0.3903**	0.0793	0.0161
	(0.1849)	(0.1640)	(0.0540)
Observations	1024	1024	1024
R^2	0.380	0.520	0.045
Date Range	1926-2011	1926-2011	1926-2011

Table IA.12: 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 than $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***	0.0250	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)	(0.0740)	(0.0486)	(0.0713)
Lag 2				
turn	-0.0196	0.0192	0.0080	0.0004
	(0.0204)	(0.0199)	(0.0070)	(0.0019)
illiq	-0.0410	0.0626**	0.0139	0.0005
	(0.0343)	(0.0297)	(0.0097)	(0.0024)
ret	-0.0116	-0.0036	-0.0325***	-0.0018
	(0.0250)	(0.0249)	(0.0090)	(0.0021)
ret_ind	0.0840**	-0.0388	0.0054	-0.0212
	(0.0403)	(0.0463)	(0.0293)	(0.0413)
Stock FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	751,221	751,221	751,221	751,221
Date Range	1951-2011	1951-2011	1951-2011	1951-2011

Table IA.13: 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