The Cross-Section of Price Efficiency

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Abstract

Inventory management by market makers can result in quoted prices deviating from unobserved fundamental prices. In a setting where prices have a factor structure, optimal inventory management implies that pricing errors of different securities are positively correlated if they load on the same risk factors. Using a state space model, I obtain estimates of 1-minute pricing errors for a panel of 1500 US stocks for the period 2016 – 2022. Daily cross-sectional regressions of pricing error correlations reveal that pricing error correlations increase in the similarity of factor betas. Investigating the role of liquidity demand in addition to liquidity supply, my results show that ETF flows are associated with higher pricing error correlations.

1 Introduction

In financial markets, observed trading prices can deviate from unobserved fundamental prices, or informationally efficient prices, resulting in pricing errors. The presence of such pricing errors can be motivated from a liquidity provider's optimal inventory control problem (Foucault, Pagano, and Roell, 2013; Hendershott and Menkveld, 2014). Even though such pricing errors are transitory, they affect transaction costs of liquidity demanding traders. In this paper, I systematically analyze pricing errors in the cross-section of stocks. Using a state space model, I identify pricing errors at the 1-minute frequency. Motivated by an inventory control model, I run cross-sectional regressions of pricing error correlations for a stock pair on the difference in their factor betas. In addition to this liquidity supply channel, I analyze the relationship between correlations

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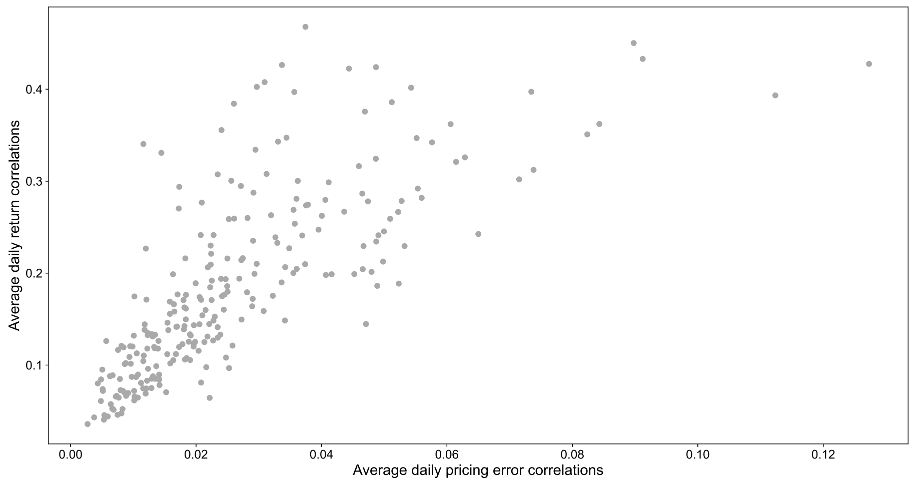
Figure 1: Average unconditional daily return and pricing error correlations for large stocks in 2019

This figure plots average daily return correlations (vertical axis) and pricing error correlations (horizontal axis) for large stocks in 2019. Large stocks refers to stocks that are in the top three NYSE market capitalization deciles at the beginning of the year.



in pricing errors and liquidity demand by ETFs, motivated by a literature that shows that ETF flows are associated with non-fundamental volatility and correlations in daily illiquidity measures (Ben-David, Franzoni, and Moussawi, 2018; Agarwal et al., 2018).

Figure 1 plots average unconditional daily pricing error correlations on the horizontal axis and average daily return correlations on the vertical axis for large stocks in 2019. Large stocks are stocks that were in the top three NYSE market capitalization deciles in the beginning of 2019. The relationship is positive: days on which pricing errors are on average more correlated are also days on which returns are more correlated. This suggests that pricing errors are systematic.

Institutional investors and mutual funds often trade a basket of stocks. Even though pricing errors in individual stocks may be small, such investors face pricing errors in transaction prices in multiple stocks. As Figure 1 suggests that pricing errors are systematic, individual pricing errors may not average out on aggregate. Moreover, investment mandates of institutional investors and mutual funds may cause them to trade in similar stocks in the sense that the stocks load on the same risk factors. This potentially aggravates the systematic impact of pricing errors.

To shed more light on the cross-section of pricing errors, I develop a simple inventory model based on Foucault, Pagano, and Roell (2013) in which market makers are setting quotes for stocks which prices, and therefore returns, are driven by a factor structure. As in standard inventory models, market makers adjust their quotes depending on the inventory they take, resulting in pricing errors. The underlying factor structure in asset prices connects different securities and affects the market makers' optimal quotes in different securities. This results in pricing errors being correlated across securities to the extent that they load on the same risk factors.

Guided by the implications of the theoretical model, I empirically examine the correlations of pricing errors in the cross-section of stocks. Therefore, I construct a balanced panel of 1500 stocks spanning the years 2016 – 2022. Using a state space model (Menkveld, Koopman, and Lucas, 2007) I obtain estimates for 1-minute pricing errors for the stocks in my sample. For every stock pair I compute daily correlations in pricing errors. Fama and MacBeth (1973) regressions of daily pricing error correlations on differences in the the stocks' Fama and French (1993) factor betas reveal a negative relationship between pricing error correlations and the absolute difference in the stocks' factor betas. This suggests a systematic component in pricing error correlations. My results are robust to controlling for industry similarity, linear and nonlinear stock pair characteristics, as well as differences in the microstructure of trading as captured by the difference in the stocks price and 5-minute return volatilities.

Motivated by a literature that documents a positive relationship between ETF flows and volatility as well as the co-movement of daily illiquidity measures (Ben-David, Franzoni, and Moussawi, 2018; Agarwal et al., 2018), I examine the impact of liquidity demanding flows by ETFs on pricing error correlations. I focus both and common holdings by ETFs and the exposure of a stock pair to ETF flows and ETF creations/ redemptions. Overall, the effect of liquidity demand is an order of magnitude smaller than the previously described liquidity supply channel. While common holdings do not appear to move correlations in pricing errors, larger differences in relative ETF flows are associated with a reduction in pricing error correlations for a stock pair. This is intuitive as actual flows are part of the liquidity provider's maximization problem. Also, this is consistent with the finding of Antón and Polk (2014) that common ownership by funds is more relevant in periods of high flows.

Both my theoretical models as well as empirical analysis build on the assumption that market makers take the latent risk factor structure spanning asset prices into consideration. Therefore, I relate to Conrad and Wahal (2020) who show that market risk is an important driver of inventory effects in assets prices. By systematically analyzing the cross-sectional effects of different risk factors on pricing errors, I contribute to the understanding of which risks drive intraday prices as well as price efficiency in securities.

My work complements Rösch, Subrahmanyam, and Van Dijk (2017) who study systematic drivers of market efficiency over the time-series by studying cross-sectional variation in price efficiency. Their work provides evidence consistent with the existence of systematic drivers of price efficiency in the time-series. In a similar spirit, Sadka (2006) shows that time-variation in liquidity explains a substantial part of momentum an post-earnings-announcement drift returns. Chordia, Roll, and Subrahmanyam (2000) as well as Hasbrouck and Seppi

(2001) study co-movement in liquidity and Pastor and Stambaugh (2003) show that liquidity is a priced risk factor. I contribute to this literature by studying systematic drivers of price efficiency in the cross-section of stocks. My findings show that pricing errors vary systematically in the cross-section of stocks, which can be rationalized by a model of optimal liquidity supply.

My work is closely related to Seasholes and Hendershott (2007) and Hendershott and Menkveld (2014) who link NYSE specialist inventories to price reversals and price pressures at a daily frequency. These findings provide evidence that market maker inventories move (closing) prices at lower frequencies. Rather than focusing on daily frequencies, I analyze intraday pricing errors as a result of aggregate liquidity demand. By analyzing intraday patterns in price efficiency, I follow Bogousslavsky and Collin-Dufresne (2023) who study the impact of the volatility of intraday order imbalances on liquidity in the cross-section and time series.

In addition, also using specialist inventories, Coughenour and Saad (2004) find that liquidity co-moves across stocks handled by the same specialist firms and Comerton-Forde et al. (2010) link specialist inventories to time variation in liquidity. Instead of analyzing co-movement in liquidity between different securities, I focus on co-movement in price efficiency in the cross-section of stocks. I complement the findings of Coughenour and Saad (2004) by showing that the underlying risk factor structure causes pricing errors to co-move in the cross section of stocks.

Van Binsbergen et al. (2023) relate different asset pricing anomalies to the buildup and resolution of long-lasting price wedges. Their model defines price wedges as the deviation from a model-implied price. My research aims to identify pricing errors based on a top-down approach based on filtering at a high frequency.

I study the effect of liquidity demanding ETF flows relative to liquidity supply on correlations in pricing errors. With this, I relate to Lou and Polk (2021) who provide evidence that crowded trades by arbitrageurs drive prices away from fundamentals. Antón and Polk (2014) relate correlations in Fama and French (1993) – Carhart (1997) residuals to common ownership by funds. Their results show that common ownership by mutual funds explains return correlations in the cross-section of stocks. Focusing on ETF flows and ownership, Ben-David, Franzoni, and Moussawi (2018) show that ETF flows increase volatility and Agarwal et al. (2018) relate common stock ownership by ETFs to co-movement in illiquidity. My paper contributes to this literature by analyzing to which extent common ETF ownership and exposure to ETF flows induces pricing errors co-move at high intraday frequencies. I complement their results by showing that ETF flows are associated with co-movement in pricing errors. At the same time, my results show that common factor exposure has explanatory power, even when controlling for liquidity demand from ETFs.

The remainder of the paper is structured as follows. Section 2 presents a simple inventory model in which security prices are driven by a factor structure. Section 3 presents my methodology before I discuss the data in Section 4. I present my main empirical results in Section 5. Finally, Section 6 concludes.

2 An Inventory Model with Factor Structure

In this Section I present an inventory model for a market maker in a setting in which security prices, and therefore returns, are driven by a factor structure. The model follows the inventory model of Foucault, Pagano, and Roell (2013).

2.1 Setup

There are two periods, $t = 1$ and $t = 2$. I consider trading in N assets that load on M underlying risk factors. The assets have a payoff structure given by

$$V_i = \sum_{j=1}^{M} \theta_{ij} f_j + \varepsilon_i, \quad i = 1, \dots, N \tag{1}$$

with

$$f_j = \mu_j + \eta_j, \quad j = 1, \dots, M. \tag{2}$$

The innovations $\varepsilon_i \sim N(0, \sigma_i^2),\ \forall i,\ \eta_j \sim N(0, \sigma_{fj}^2),\ \forall j$ are i.i.d. The payoff of each asset i has a factor structure in the sense that the payoff is a function of the factors $f_1, \dots, f_M$. Moreover, there is an idiosyncratic component to the assets' payoff given by ε_i. The payoff V_i of asset i is correlated with the payoff $V_{\tilde{i}},\ \tilde{i} \neq i$, that is, the payoff of another asset, if any of the factor loadings θ_{ij}, $\theta_{\tilde{i}j}$ are not zero for at least one j.

There are K risk-averse dealers with CARA utility function and risk aversion ρ in the market. The dealer market is competitive. Dealers begin period $t = 1$ with inventory $z_i^k,\ i = 1, \dots, N$ and a cash position c^k. The aggregate inventory position at the beginning of $t = 1$ is denoted by

$$Z_i = \sum_{k=1}^{K} z_i^k,\ i = 1, \dots, N. \tag{3}$$

In period $t = 1$, trading takes place and each dealer trades with one client. Trading takes pace by each client submitting their order of quantity q_i. Each dealer posts a supply schedule $y_i^k(p)$. Market clearing requires that

$$\sum_{k=1}^{K} y_i^k(p_i) = q_i,\ i = 1, \dots, N. \tag{4}$$

2.2 Dealer maximization

At date $t = 1$, each dealer chooses their supply schedule y_i^k for asset i that maximizes their expected utility at $t = 2$:

$$\mathbb{E}_1[-exp(-\rho W^k)] \tag{5}$$

with W^k being their final wealth at $t = 2$

$$W^k = c^k + \sum_{i=1}^{N} \left(V_i(z_i^k - y_i^k) + p_i y_i^k \right). \tag{6}$$

Given that the innovations ε_1, ε_2, η_1, and η_2 are normally distributed, this is equivalent to maximizing

$$\mathbb{E}_1[W^k] - \frac{\rho}{2}\mathbb{V}_1[W^k]. \tag{7}$$

2.3 Equilibrium

In equilibrium, markets must clear such that

$$\sum_{k=1}^{K} y_i^k = q_{i0}, \quad i = 1, \ldots, N. \tag{8}$$

Dealer k's inverse supply schedule for asset i is derived from their maximization problem and given by

$$p_i = \sum_{j=1}^{M} \theta_{ij}\mu_j - \rho \left((z_i^k - y_i^k) \left(\sum_{j=1}^{M} \theta_{ij}^2 \sigma_{fj}^2 + \sigma_i^2 \right) + \sum_{\tilde{i} \neq i} (z_{\tilde{i}}^k - y_{\tilde{i}}^k) \left(\sum_{j=1}^{M} \theta_{ij}\theta_{\tilde{i}j}\sigma_{fj}^2 \right) \right) \tag{9}$$

As can be seen, the supply schedule for asset i depends not only on the dealer's inventory for asset i, but also on the dealer's inventory for the other assets. This is because all asset payoffs are a function of the same underlying factor structure and dealers care about the risks the individual assets are exposed to. The dependence of dealer k's inverse supply schedule for asset i on their inventory in asset $\tilde{i} \neq i$ is scaled by the factor loadings on the respective underlying factors in asset prices. In addition, the dealers' quoted price schedules differ since their starting inventories in $t = 1$ differ.

The dealer quotes a bid-ask spread per unit traded in asset i of

$$s = 2\rho \left(\sum_{j=1}^{M} \theta_{ij}^2 \sigma_{fj}^2 + \sigma_i^2 \right), \tag{10}$$

taking their inventory and the quantity in the other assets as given. Note that while the quoted price schedules of the dealers differ due to the inventories with which they enter period $t = 1$, quoted spreads posted by the different dealers are the same. This is the same results as in Foucault, Pagano, and Roell (2013) in the sense that spreads depend on the dealers' inventory at the beginning of the period. Also in Bogousslavsky and Collin-Dufresne (2023) spreads are related to dealer inventory through order imbalance. The result differs from Hendershott and Menkveld (2014) in which spreads are orthogonal to dealer inventory.

Using the market clearing condition (8) yields that the equilibrium price is given by

$$p_i^* = \sum_{j=1}^{M} \theta_{ij}\mu_j - \bar{\rho}\left((Z_i - q_i)\left(\sum_{j=1}^{M} \theta_{ij}^2 \sigma_{fj}^2 + \sigma_i^2\right) + \sum_{\tilde{i}\neq i} (Z_{\tilde{i}} - q_{\tilde{i}})\left(\sum_{j=1}^{M} \theta_{ij}\theta_{\tilde{i}j}\sigma_{fj}^2\right)\right),$$

where Z_i and $Z_{\tilde{i}}$ are the aggregate inventories in assets i and $\tilde{i}$, respectively, as defined in (3), and $\bar{\rho} = \rho/K$ is the aggregate risk aversion coefficient of the dealers.

In equilibrium, dealer k trades

$$y^{k*}(p^*) = \frac{q}{K} + z^k - \frac{Z}{K}. \tag{11}$$

After trading took place, dealer k's inventory is therefore given by $\frac{Z}{K} - \frac{q}{K}$.

The midquote price for asset i before trading takes place can be defined as

$$m_i = \sum_{j=1}^{M} \theta_{ij}\mu_j - \bar{\rho}\left(Z_i \left(\sum_{j=1}^{M} \theta_{ij}^2 \sigma_{fj}^2 + \sigma_i^2\right) + \sum_{\tilde{i}\neq i} Z_{\tilde{i}} \left(\sum_{j=1}^{M} \theta_{ij}\theta_{\tilde{i}j}\sigma_{fj}^2\right)\right), \tag{12}$$

while the fundamental value of the asset is equal to the conditional expected payoff of asset i, given by

$$m_i^* = \sum_{j=1}^{M} \theta_{ij}\mu_j. \tag{13}$$

The difference between the midquote and the fundamental value can be interpreted as the price pressure exerted by dealers on the price, or the pricing error in the observed quotes. This pricing error is given by

$$-\bar{\rho}\left(Z_i \left(\sum_{j=1}^{M} \theta_{ij}^2 \sigma_{fj}^2 + \sigma_i^2\right) + \sum_{\tilde{i}\neq i} Z_{\tilde{i}} \left(\sum_{j=1}^{M} \theta_{ij}\theta_{\tilde{i}j}\sigma_{fj}^2\right)\right). \tag{14}$$

As can be seen from (14), the pricing error is negative (the midquote is below the fundamental value of the asset) if dealers are on aggregate long in asset i, $Z_i > 0$. This is the standard results from the literature that dealers adjust their quotes downward to facilitate selling if they have a long position in the asset (Amihud and Mendelson, 1980; Hendershott and Menkveld, 2014). At the same time, the pricing error for asset i also depends on the dealer's aggregate position in the other assets $\tilde{i}$. The sign of this effect depends on the signs of the factor loadings $\theta_{ij}\theta_{\tilde{i}j},\ j = i, \ldots, M,\ \tilde{i} \neq i$. The effect is always positive (that is, the pricing error increases) if all factor loadings are positive an the dealers have an aggregate long position in asset $\tilde{i}$, $Z_{\tilde{i}} > 0$.

Intuitively, in this case all assets load on the same risk factors and increase the dealers' aggregate risk exposure. Therefore, the dealers want to facilitate selling asset i even more and set their midquote lower, resulting in a more negative pricing error. If instead for some pair of factor loadings $\theta_{ij} > 0$, $\theta_{\tilde{i}j} < 0$ or $\theta_{ij} < 0$, $\theta_{\tilde{i}j} > 0$ (that is, the assets have opposite loadings on the risk factors), the dealers having an aggregate long position in asset $\tilde{i}$ increases the midquote, resulting in a less negative pricing error. This is because asset $\tilde{i}$ is a hedge for asset i regarding risk factor j. In this scenario, having a long position in asset $\tilde{i}$ decreases the overall risk exposure of the dealers to the risk factors.

Note that while the pricing error for asset i depends on the dealers' inventory in all assets, the bid-ask-spread depends only on inventory in asset i. As a result, pricing errors in different assets co-move if they load on the same underlying risk factors and dealer inventory positions co-move, while spreads do not co-move with inventory positions. In other words, spreads in asset i are orthogonal to inventory in asset $\tilde{i}$.

3 Methodology

This Section first describes the methodology used to identify pricing errors in Section 3.1, before turning the the empirical approach to model cross-sectional variation in pricing errors in Sections 3.2 and 3.3.

3.1 Identification of Pricing Errors

Central to the analysis is the identification of pricing errors at every point in time. Rather than relying on a model-based bottom-up approach to the identification of pricing errors as, for example, Van Binsbergen et al. (2023), I identify pricing errors using filtering based on the approach of Hasbrouck (1993) and the state space model of Menkveld, Koopman, and Lucas (2007) in a top-down way.

Observed (log) prices for stock i at time t can be decomposed into two latent components: a martingale efficient price component and a stationary pricing error:

$$p_{i,t} = m_{i,t} + s_{i,t} \tag{15}$$
$$m_{i,t} = m_{i,t-1} + w_{i,t} \tag{16}$$

where p_t are observed (midquote) prices, m_t are efficient prices, w_t are innovations in efficient prices, and s_t is the pricing error. To identify innovations in efficient prices, I incorporate information on trade flow. This yields the model:

$$p_{i,t} = m_{i,t} + s_{i,t} \tag{17}$$
$$m_{i,t} = m_{i,t-1} + \kappa \tilde{x}_{i,t} + \mu_{i,t} \tag{18}$$
$$s_{i,t} = \phi_i s_{i,t-1} + \psi x_{i,t} + \nu_{i,t} \tag{19}$$

where (17) is the observation equation, (18) is the state equation for latent efficient prices, and (19) is the state equation for latent pricing errors. Furthermore, the model assumes that $\nu_{i,t} \sim \mathcal{N}(0, \sigma^2_{i,\nu})$ and $\mu_{i,t} \sim \mathcal{N}(0, \sigma^2_{i,\mu})$. As discussed in Hendershott and Menkveld (2014) and Menkveld and Saru (2024), innovations in order flow contain information while imbalances in order flow affect liquidity (Brandt and Kavajecz, 2004; Evans and Lyons, 2008). Therefore, including signed order flow allows identifying pricing errors in the model. The identifying assumption that conditional on controlling for trade flow $\nu_{i,t}$ and $\mu_{i,t}$ are uncorrelated is consistent with similar applications of the model such as Hendershott and Menkveld (2014) and Brogaard, Hendershott, and Riordan (2014), among others.

The model is estimated stock-day-by-stock-day at a 1-minute frequency. Midquote prices are used as observed proxy for efficient prices. By using midquote prices, bid-ask bounces are not part of the pricing error. Trade flow $x_{i,t}$ is the signed order flow for every 1-minute interval.[1] Innovations in trade flow $\tilde{x}_{i,t}$ are obtained as the residual from an AR model with 15 lags. Using aggregate trade flow captures aggregate liquidity demand in the market. Furthermore, it can be interpreted as the aggregate inventory that all market makers in stock i absorb. This is aligned with the theoretical model presented in Section 2 in which midquotes and pricing errors depend on the aggregate position of all market makers. Moreover, using signed aggregated order flow captures order flow information that is in principle available to market participants subscribing to data feeds (George and Khoja, 2023).

The model is estimated by maximum likelihood and the Kalman filter is used to evaluate the likelihood function. The Kalman filter requires initial priors for the latent states characterized by a prior mean and a prior variance. I initialize the efficient price series with a diffuse prior. That is, the prior variance is set to κ with $\kappa \to \infty$. Pricing errors are initialized as stationary states with the prior variance set to the unconditional variance. After obtaining estimates for the

[1] I discuss details on trade signing in Section 4.

coefficients, I obtain estimates of the latent state variables – the efficient price as well as the pricing error – as smoothed states of the model. These smoothed states are conditional on all observations on the respective trading day in stock i. The smoothed states for the pricing error equation (19) are central to my analysis of pricing errors in the cross section of stocks.

Even though I require that there are at least 200 trading days per year with non-zero volume[2], there are time intervals with zero volume as well as quotes in the sample. The proposed state space model naturally deals with missing observations through extrapolation (Kalman filter) and interpolation (for the smoothed states).

3.2 Factor Structure in Returns

The theoretical model in Section 2 predicts that pricing errors of different stocks are connected through the stocks' loadings on underlying risk factors. To test this implication empirically, I run factor regressions to estimate the factor betas of different stocks. In the baseline version, I use the factors proposed by Fama and French (1993): the market factor, the size factor (SMB), and the value factor (HML).

I estimate the factor betas by running daily rolling time-series regressions of excess returns on the factors. The last 500 available return observations in CRSP are used for the rolling regressions. If there is a missing return observation in CRSP for a trading day within the estimation window, the respective day is left out of the estimation, but estimation is still performed for the overall window.

3.3 Cross-Sectional Variation in Pricing Error Correlations

Using the pricing error estimates obtained as smoothed states from the state space model, I compute the realized correlations in pricing errors for each stock pair in my sample, $\rho^s_{ij,t}$. Based on the factor betas for each stock pair, I compute the the absolute difference in their factor betas as $|\Delta\beta_{ij,t}|$. I then estimate daily cross sectional regressions for the realized correlations as

$$\begin{aligned}\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| \\ + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t},\end{aligned} \tag{20}$$

where $\rho^x_{ij,t}$ is the correlation in order flow for stock pair i, j, $|\Delta\beta^M_{ij,t-1}|$, $|\Delta\beta^{SMB}_{ij,t-1}|$, and $|\Delta\beta^{HML}_{ij,t-1}|$ are the absolute differences in the loadings on the Fama and French (1993) factors estimated based on a rolling regression as described in Section 3.2. Other included control variables are denoted by $\mathbf{X}\gamma$. All independent variables are standardized to facilitate economic interpretability.

[2]I discuss details on sample construction in Section 4.

I implement the estimation in a Fama and MacBeth (1973) fashion. Therefore, I estimate the cross-sectional regressions day-by-day and report time-series averages of the daily coefficients. I report Newey and West (1987) standard errors that are robust to time-series autocorrelation in the cross-sectional estimates of 20 lags.

This implementation is similar to Antón and Polk (2014) who estimate monthly regressions for realized correlations in four-factor abnormal returns in a Fama and MacBeth (1973) fashion. Agarwal et al. (2018) estimate a pooled regression for quarterly correlations in stock liquidity. In my setting, daily regressions in a Fama and MacBeth (1973) style a preferred as market conditions potentially driving the realized correlations only change slowly. Moreover, I estimate both the state space model as well as the cross-sectional regressions day-by-day. Aligning the frequencies alleviates concerns of mechanical correlations of the dependent and independent variables in equation (20) over different trading days. Moreover, the approach of obtaining smoothed states from the state space model and estimating their relationship with a set of independent variables is consistent with Chordia, Green, and Kottimukkalur (2018).

Correlations in order flow for stock pair i, j on day t, $\rho^x_{ij,t}$, are included in the model as the order flow series identify pricing errors in the state space model presented in Section 3.1. The inclusion of the absolute differences of the factor betas is motivated by the theoretical model presented in Section 2. The model predicts that as the absolute difference in the factor betas increases, correlations should decrease. By controlling for correlations in the order flow series, the differences capture correlation in pricing errors above and beyond correlation in pricing errors that is due to a potential factor structure in the order flow series.

Additional control variables contained in $\mathbf{X}\gamma$ are the absolute difference in log midquotes of stock pair i, j on date $t-1$,[3] the 5-minute midquote return volatilities of stocks i and j on date $t-1$, and the factor betas of stocks i and j as well as squared factor betas. I refer to the latter as linear and nonlinear characteristics controls. Including the difference in the midquote prices captures differences in the participation of traders as well as differences in liquidity related to the price level and the relative tick size (Weller, 2018; Li and Ye, 2023). 5-minute midquote return volatilities account for potential differences in liquidity as a result of volatility (Conrad and Wahal, 2020). Including the factor betas as well as their quadratic terms captures potential differences in the stocks that are related to their betas and follows Antón and Polk (2014).

The time convention of the independent variables in equation (20) captures which information is available to market makers on day t. As discussed before, correlations in order flow on day t, $\rho^x_{ij,t}$, are included as they mechanically drive correlations in pricing errors. The best estimate of the factor exposure of stock returns available to the market maker are the factor betas estimated including

[3] I run additional regressions confirming that results do not change if both the midquotes of stocks i and j are included as control variables.

all return observations until day $t-1$. Therefore, these betas are included in the model. For the other control variables, observations for $t-1$ are included.

4 Data

The data used in the main analysis come from TAQ and CRSP. I construct a balanced panel based on all common stocks listed on NYSE, Amex and NASDAQ from CRSP. The sample period spans January 1, 2016 – December 31, 2022.

For a stock to be included in the sample, I require a market capitalization of at at least USD 100 million and a stock price between USD 5 and USD 1000 at the end of the previous month. This is in line with, for example Hendershott and Menkveld (2014) or Bogousslavsky and Collin-Dufresne (2023). Furthermore, for a security to be included in the analysis I require the security to have at least 200 trading days displaying non-zero trading volume per year (Duarte, Hu, and Young, 2020). My final sample contains 1500 securities.

For each year, securities are assigned to market capitalization deciles based on the market capitalization at the end of the previous year. I use the market equity breakpoints for NYSE from Ken French's website for this.

TAQ data is cleaned according to the filters proposed by Holden and Jacobsen (2014). Trades are signed using the Lee and Ready (1991) algorithm, given it has been documented to perform well (Chakrabarty, Pascual, and Shkilko, 2015). Data from CRSP and TAQ is merged using the TCLINK linking files from WRDS. For the analysis, only observations within the trading hours between 9:30 a.m. and 4:00 p.m. are kept. As my interest is in intraday pricing errors that are potentially driven by high-frequency order imbalances (Bogousslavsky and Collin-Dufresne, 2023), I work with a data frequency of 1 minute.

The factor regressions use daily return data from CRSP. The daily return factors as well as the risk-free rate come from Ken French's website.

Descriptive statistics for my sample by year and market capitalization are presented in Table 1. The descriptive statistics suggest that there is considerable variation in key variables both in the time-series as well as in the cross-section. It is notable that both for high market capitalization stocks as well as for medium market capitalization stocks effective spreads increase over the sample period. Dollar trading volume increases over the sample period for all market capitalizations.

Given the cross-sectional differences documented in Table 1, I report results from estimating the state space model by year and market capitalization and perform my cross-sectional analysis both for the overall sample as well as for high market capitalization stocks only. This alleviates concerns that my results are driven by small, irregularly traded stocks.

Table 1: Descriptive Statistics

This table presents descriptive statistics for the stocks in the sample by calendar year and market capitalization. High market capitalization refers to stocks that are in the top three NYSE market capitalization deciles at the beginning of the respective year. Medium market capitalization refers to stocks that are in the middle four NYSE market capitalization deciles at the beginning of the respective year. Similarly, low market capitalization refers to stocks that are in the bottom three NYSE market capitalization deciles at the beginning of the respective year. $midquote_{it}$ refers to the dollar midquote and is from TAQ. $shares\_outst_{it}$ refers to the number of shares outstanding (in million) and is from CRSP. $market\_cap_{it}$ refers to the market capitalization in millions of dollars and is from CRSP. $espread_{it}$ refers to the share-volume-weighted effective spread in basis points and is from TAQ. $volatility_{it}$ refers to the 5-minute midquote return volatility in basis points as is computed based on data from TAQ. $volume_{it}$ refers to the daily trading volume in millions of dollars and is from TAQ.

Panel A: Full Sample

	2016	2017	2018	2019	2020	2021	2022
$midquote_{it}$	50.65	60.81	69.12	71.60	75.15	101.82	89.67
$shares\_outst_{it}$	240.13	239.17	238.02	235.03	234.49	236.33	234.37
$market\_cap_{it}$	11691.33	13774.95	15597.21	16319.71	18161.62	24458.70	23381.66
$espread_{it}$	18.06	16.22	17.08	15.33	19.67	16.66	16.30
$volatility_{it}$	20.00	17.07	20.24	18.61	31.51	21.31	23.67
$volume_{it}$	71.79	73.93	96.36	85.65	128.73	134.67	139.22

Table 1: – continued

Panel B: High Market Capitalization

	2016	2017	2018	2019	2020	2021	2022
$midquote_{it}$	82.94	96.99	111.69	121.11	139.77	191.28	161.63
$shares\_outst_{it}$	707.63	700.03	670.15	653.24	642.22	653.67	623.42
$market\_cap_{it}$	37336.60	43567.86	47673.79	49684.72	55965.70	76861.23	70348.92
$espread_{it}$	4.46	3.82	4.35	4.24	6.30	5.48	5.86
$volatility_{it}$	14.27	11.31	15.58	13.80	23.56	15.89	20.11
$volume_{it}$	217.27	218.61	282.51	247.61	382.22	405.80	408.16

Panel C: Medium Market Capitalization

	2016	2017	2018	2019	2020	2021	2022
$midquote_{it}$	46.49	56.42	60.91	61.24	58.35	81.14	71.94
$shares\_outst_{it}$	83.67	84.08	82.38	79.74	83.54	93.50	86.94
$market\_cap_{it}$	2684.90	3303.66	3502.74	3352.47	3202.13	4902.85	4130.28
$espread_{it}$	10.10	9.71	10.23	9.38	13.09	11.52	11.06
$volatility_{it}$	19.30	16.17	19.87	18.39	31.45	21.26	23.82
$volume_{it}$	24.67	27.48	29.90	26.28	31.66	38.04	32.55

Table 1: – continued

Panel D: Low Market Capitalization							
	2016	2017	2018	2019	2020	2021	2022
$midquote_{it}$	27.70	35.03	38.97	34.73	30.56	43.34	38.42
$shares\_outst_{it}$	26.99	28.71	28.39	27.72	27.65	30.14	30.25
$market\_cap_{it}$	523.25	697.96	756.42	665.03	581.46	902.30	790.50
$espread_{it}$	39.77	34.58	38.53	36.29	45.58	35.11	34.79
$volatility_{it}$	25.87	23.06	25.23	24.09	40.51	26.74	27.25
$volume_{it}$	3.48	5.20	5.27	4.18	5.47	6.23	4.81

5 Results

In this Section I present the main results. First, I discuss the results from estimating the state space model in Section 5.1. Then, I discuss the cross-sectional results in Section 5.2 before turning to the relationship with liquidity demand in Section 5.3. Section 5.4 discusses the robustness of my results.

5.1 State Space Results

The theoretical model presented in Section 2 suggests that pricing errors are more correlated for stocks that load in the same direction on the underlying risk factors. To empirically test this prediction, I first need estimates of pricing errors for every point in time. As described in Section 3, I obtain pricing error estimates as smoothed states form a state space model. I present the estimation results from estimating the state space model in Table 2.

In light of the descriptive statistics presented in Section 4, I present results by year and market capitalization. The volatilities of efficient price innovations – permanent volatility – as well as pricing error innovations – residual pricing error volatility – increase for lower market capitalization deciles. This holds across all years in the sample and is consistent with the results of Brogaard, Hendershott, and Riordan (2014) and Hendershott and Menkveld (2014). Note that these are only one component of the volatility of efficient price innovations and pricing errors, respectively. Both are also driven by the volatility of order flow innovations and order flow, respectively.

In this setting, order imbalances can be interpreted as the aggregate order flow liquidity providers face. That is, if the aggregate order imbalance is positive, liquidity providers on aggregate take a short position. Order imbalance innovations are informative across all market capitalizations for all years, as indicated by the the positive κ. The positive κ suggests that liquidity providers are on aggregate subject to adverse selection. This result is consistent with Menkveld and Saru (2024) who show that clients are relatively more informed than intermediaries at lower intraday frequencies.

In addition, order imbalances are positively associated with pricing errors for high and medium market capitalization stocks (ψ is positive). This result suggests that, on aggregate, liquidity providers raise their midquotes relative to the latent efficient price in response to a positive order imbalance (that is, when they sell on aggregate). This result is consistent with the theoretical model presented in Section 2 as well as the documented relationship between price pressures and specialist inventories (Hendershott and Menkveld, 2014). In response to taking a net short position, market makers want to facilitate selling to them and discourage more buying from them. They achieve this by raising both the bid and the offer price, increasing the midquote price.

It is notable that the impact of order imbalances on pricing errors is negative for small stocks across all years (ψ is negative). This is inconsistent with the previously described channel of market makers facilitating selling to them in response to taking a short position. Rather, a negative ψ suggests that market

Table 2: State space model estimation results

This table presents estimation results for the state space model

$$p_{i,t} = m_{i,t} + s_{i,t}, \qquad m_{i,t} = m_{i,t-1} + \kappa \tilde{x}_{i,t} + \mu_{i,t}, \qquad s_{i,t} = \phi_i s_{i,t-1} + \psi x_{i,t} + \nu_{i,t}$$

for each stock-day using log midquote prices as observable prices ($p_{i,t}$). x_t is order flow and $\tilde{x}_t$ are innovations in order flow obtained as the residual from an AR(10) model. The table reports average coefficients by year and market capitalization. High market capitalization refers to stocks that are in the top three NYSE market capitalization deciles at the beginning of the respective year. Medium market capitalization refers to stocks that are in the middle four NYSE market capitalization deciles at the beginning of the respective year. Similarly, low market capitalization refers to stocks that are in the bottom three NYSE market capitalization deciles at the beginning of the respective year. σ_μ and σ_ν are in *bp* and κ as well as ψ in $bp/1,000,000$ USD. Standard errors are double clustered by stock and day and reported in parentheses. * denotes significance at the 1% level.

	2016			2017			2018		
	high	medium	low	high	medium	low	high	medium	low
σ_μ	4.621*	6.164*	7.767*	3.696*	5.230*	7.122*	5.280*	6.522*	7.767*
	(0.120)	(0.139)	(0.151)	(0.069)	(0.084)	(0.108)	(0.127)	(0.147)	(0.203)
σ_ν	1.708*	2.580*	5.040*	1.418*	2.236*	4.387*	1.814*	2.445*	4.874*
	(0.052)	(0.070)	(0.173)	(0.030)	(0.045)	(0.130)	(0.052)	(0.071)	(0.230)
ϕ	0.252*	0.221*	0.189*	0.214*	0.195*	0.183*	0.194*	0.176*	0.170*
	(0.006)	(0.005)	(0.004)	(0.007)	(0.004)	(0.003)	(0.008)	(0.005)	(0.004)
κ	8.925*	75.117*	521.425*	6.836*	62.034*	448.182*	7.783*	67.519*	492.269*
	(0.546)	(2.662)	(64.547)	(0.294)	(2.500)	(38.002)	(0.420)	(4.101)	(28.562)
ψ	3.994*	19.610*	−143.012*	3.285*	11.808*	−23.798	3.755*	14.523*	−74.780*
	(0.245)	(1.043)	(37.006)	(0.126)	(0.788)	(29.096)	(0.190)	(1.104)	(15.657)

Table 2: – continued

	2019			2020			2021		
	high	medium	low	high	medium	low	high	medium	low
σ_μ	4.598*	6.052*	7.339*	7.711*	10.045*	12.223*	5.304*	7.078*	8.362*
	(0.082)	(0.092)	(0.129)	(0.286)	(0.324)	(0.389)	(0.112)	(0.133)	(0.154)
σ_ν	1.686*	2.447*	4.878*	2.724*	4.080*	7.909*	1.873*	2.775*	5.457*
	(0.043)	(0.065)	(0.224)	(0.135)	(0.227)	(0.497)	(0.047)	(0.082)	(0.214)
ϕ	0.229*	0.191*	0.154*	0.253*	0.206*	0.162*	0.230*	0.180*	0.161*
	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)
κ	7.202*	63.608*	535.538*	11.392*	104.811*	1032.641*	7.533*	61.343*	496.751*
	(0.429)	(2.323)	(28.520)	(0.688)	(4.545)	(74.845)	(0.523)	(2.396)	(23.911)
ψ	3.588*	18.244*	−95.977*	5.641*	31.508*	−184.126*	3.770*	17.434*	−61.809*
	(0.226)	(0.795)	(18.991)	(0.299)	(1.959)	(40.247)	(0.175)	(0.940)	(10.659)

Table 2: – continued

	2022		
	high	medium	low
σ_μ	6.915*	8.041*	8.522*
	(0.138)	(0.144)	(0.151)
σ_ν	2.293*	2.742*	5.255*
	(0.061)	(0.067)	(0.218)
ϕ	0.228*	0.176*	0.146*
	(0.009)	(0.006)	(0.004)
κ	8.706*	72.991*	618.215*
	(0.486)	(2.326)	(33.424)
ψ	4.543*	20.383*	−85.716*
	(0.184)	(0.807)	(16.422)

makers lower the midquote price in response to taking a short position. Two points are worth noting. First, there is relatively more heterogeneity in the stock-day estimates for low market capitalization stocks than for medium and high market capitalization stocks as can be seen by the relatively larger standard errors. Second, small stocks are traded less frequently than large and medium sized stocks (see Table 1). A potential explanation for the negative impact of order imbalances on pricing errors is a correction of pricing errors. If liquidity providers are subject to adverse selection, and the direction of the order imbalance as well as the trading price contain information, they adjust their quotes incorporating this information (Glosten and Milgrom, 1985). As a results, liquidity providers update their quotes in the direction of the trade. Moreover, this is consistent with liquidity demanding trades executing against potentially stale quotes (Budish, Cramton, and Shim, 2015; Aquilina, Budish, and O'Neill, 2021) and the finding of Brogaard, Hendershott, and Riordan (2014) that HFTs' market orders trade in the opposite direction of pricing errors.

While these results give an overview of the volatility of pricing errors in the cross-section as well as of the reaction of pricing errors to imbalances in order flow, they do not speak to the cross-sectional relationship between pricing errors. I address this in the next Section.

5.2 Cross-Sectional Results

Table 3 reports cross-sectional results for daily correlations in pricing errors. Based on the evidence presented in Tables 1 and 2, I report results for the full sample (Panel A) as well as for high market capitalization stocks only (Panel B).

In the first column, I present results for a reduced-form regression on specification (20), with only a constant and the correlation in signed order flow (that is, the correlation in the order imbalance) as independent variable. This specification serves as a benchmark for all other specifications as daily pricing error correlations are mechanically a function of daily order flow correlations. This is because in the state space model the order flow series as well as innovations in order flow are used to identify pricing errors and efficient price innovations, as described in Section 3. For better comparability of the results, I standardize correlations in signed order flow. As expected, pricing error correlations are positively related to correlations in signed order flow. This effect is stronger for the full sample than for large market capitalization stocks.

In the second column, I add standardized differences between the factor loadings on the Fama and French (1993) factors for each stock pair i, j. Consistent with the the theoretical model in Section 2, daily pricing error correlations for stock pair i, j decrease as the difference in the Fama and French (1993) factor betas increases.

The effect is both economically and statistically significant. The coefficients on the correlation in signed order flow and the differences in factor betas are of a similar magnitude. Therefore, a one-standard deviation increase in the correlation in signed order flow has a comparable effect to a one-standard devi-

Table 3: Cross-Sectional Results for Pricing Error Correlations

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors:

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t}.$$

Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ is the absolute difference in the SMB betas, and $|\Delta\beta^{HML}_{i,j,t-1}|$ is the absolute difference in the HML betas of stocks in i and j. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
Constant	0.01908*	0.01932*	0.01930*	0.01491*
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 76)
$\rho^x_{i,j,t}$	0.00868*	0.00296*	0.00290*	0.00265*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\|\Delta\beta^M_{i,j,t-1}\|$		−0.00214*	−0.00196*	−0.00232*
		(0.000 11)	(0.000 10)	(0.000 10)
$\|\Delta\beta^{SMB}_{i,j,t-1}\|$		−0.00163*	−0.00145*	−0.00206*
		(0.000 08)	(0.000 08)	(0.000 07)
$\|\Delta\beta^{HML}_{i,j,t-1}\|$		−0.00052*	−0.00019	−0.00350*
		(0.000 18)	(0.000 19)	(0.000 15)
$\|\Delta m_{t-1}\|$			−0.00078*	−0.00063*
			(0.000 06)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00167*	−0.00256*
			(0.000 13)	(0.000 10)
$\sigma(r^{5min}_{j,t-1})$			−0.00166*	−0.00245*
			(0.000 11)	(0.000 10)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 3: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02726*	0.02726*	0.02726*	0.01918*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 36)
$\rho^x_{i,j,t}$	0.00310*	0.00288*	0.00286*	0.00263*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 08)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00411*	−0.00421*	−0.00526*
		(0.000 20)	(0.000 20)	(0.000 23)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00251*	−0.00246*	−0.00331*
		(0.000 12)	(0.000 13)	(0.000 17)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00213*	−0.00209*	−0.00658*
		(0.000 27)	(0.000 28)	(0.000 27)
$\lvert\Delta m_{t-1}\rvert$			−0.00045*	−0.00049*
			(0.000 09)	(0.000 08)
$\sigma(r^{5min}_{i,t-1})$			−0.00007	−0.00266*
			(0.000 17)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00050*	−0.00268*
			(0.000 16)	(0.000 14)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

ation decrease in the difference between the market betas. For the full sample results, the effect is the strongest for the difference between the market betas. The effect is weaker for the differences between the SMB betas as well as the HML betas, respectively. In addition, the effect is similar in magnitude to the effect of common fund ownership on the correlation in Fama and French (1993) – Carhart (1997) residuals documented by Antón and Polk (2014). The finding that the economic effect is the strongest for differences in market betas is consistent with Conrad and Wahal (2020) who document that market risk drives inventory effects. My results additionally suggest that differences in the exposure to market risk drive price efficiency in the cross-section of stocks. Moreover, market risk is not the only systematic risk factor driving inventory effects in the cross-section of stocks, with the exposure to other risk factors having an economically meaningful effect as well.

Comparing the full sample results with the results for high-market capitalization stocks reveals interesting differences. Firstly, the results are overall stronger for high-market capitalization stocks than for the full sample. Secondly, the differences in loadings on the market factor still appear to be the most relevant driver of variation in pricing error correlations in the cross-section. At the same time, however, the effect for differences in SMB betas as well as for differences in HML betas increases, both in absolute terms as well as relative to the impact of correlations in signed order flow. These results alleviate the concern that my results are driven by small, irregularly traded stocks. In contrast, they appear to be driven by large, regularly traded stocks.

In the third column, I add controls for the differences in midquote prices on the previous trading day as well as the for the 5-minute return volatilities of stocks i and j. In addition, I add linear and nonlinear characteristic controls in column 4, following the specifications of Antón and Polk (2014). Overall, adding these controls leaves the results unchanged for both the full sample as well as for high market capitalization stocks only. If anything, the effect appears stronger once the full set of linear and nonlinear characteristic controls is added.

The literature suggests that different types of traders may be more active in a subset of stocks, dependent on the stocks' price as the relative tick size decreases in the trade price (Weller, 2018; Li and Ye, 2023). For instance, Weller (2018) uses the previous stock price as an instrument for the activity of algorithmic and high-frequency traders. Suppose market making and liquidity provision are fragmented in the cross-section of stocks, market makers are limited in their risk bearing capacity, face capital constraints (as in Stoll (1978)), and/or are only imperfectly able to trade with each other as in the theoretical model in Section 2. Then, one would expect pricing error correlations to be larger among the subset of stocks in which the respective market makers are active. If this fragmentation occurs along different price levels, this would be captured by the difference in the midquote prices. My result that an increase in the difference between the last midquote prices on the previous trading day is associated with a reduction in the correlation in pricing errors is consistent with this intuition.

Additionally, I include standardized midquote prices rather than the difference in midquote prices in untabulated results. I find that an increase in midquote prices of stock pair i, j is associated with a reduction in the pricing error correlation for the stock pair. This holds both for the overall sample as well as for high market capitalization stocks only. To the extent that the past stock price proxies for algorithmic and high-frequency trading activity, this is consistent with Brogaard, Hendershott, and Riordan (2014) and Hendershott, Jones, and Menkveld (2011) who document that high-frequency trading is associated with an improvement in liquidity and price efficiency.

The result that the effect is stronger for high market capitalization stocks is consistent across all specifications. A possible explanation is that as these stocks are more frequently traded, liquidity providers take positions more frequently. As a result, they adjust their quotes more frequently in response to their positions, resulting both more in frequent as well as more frequently changing pricing errors.

This result is relevant for institutional investors trading a basket of stocks. Even when these stocks may be liquid as measured by the bid-ask spread, the pricing errors are correlated in the cross-section. Moreover, pricing errors are systematic as shown in Figure 1.

The finding that the difference in market betas has the strongest economic effect is consistent with the literature documenting common factors in the time series of liquidity as well as price efficiency metrics (Conrad and Wahal, 2020; Rösch, Subrahmanyam, and Van Dijk, 2017). My results show that common factor also drive the cross-section of price efficiency.

5.3 Relationship with Liquidity Demand

The results in the previous sections are consistent with a liquidity supply channel as in the theoretical model presented in Section 2. However, Ben-David, Franzoni, and Moussawi (2018) show that ETFs increase the volatility in underlying securities through an arbitrage channel. Agarwal et al. (2018) show that common ETF ownership increases stock-level illiquidity to co-move. This raises the question whether the findings documented in Section 5.2 could be driven by a liquidity demand rather than by a liquidity supply channel. This could be the case if ETF flows have an underlying factor structure and marker maker set their quotes both facing their current inventory positions as well as anticipating future flows due to ETF arbitrage.

In this Section I explore the possibility that the results are indeed driven by a liquidity demand channel. Given the findings documented in the previous literature, I focus particularly on ETF ownership. Therefore, I obtain daily data on ETF constituents and ETF flows from ETF Global. Starting from the universe of all ETFs in ETF Global, I keep only ETFs classified as equity ETFs and drop levered ETFs, active ETFs, and ETNs. On average, there are 1,213 unique ETFs per month in my sample, with an upward trend over the sample period. This is comparable to the coverage of Agarwal et al. (2018). ETF Global contains daily data on ETF constituents, the weight of the constituents in the ETF, the number of shares held in the constituent, and aggregate ETF flows. Constituents in ETF Global are identified by their CUSIP. I merge the ETF constituents to their CRSP PERMNO based on historical CUSIP information in CRSP MSENAMES.

I compute several measures of (differences in) stock exposure to ETF ownership. First, I compute a measure capturing the exposure of stocks i and j to ETF flows. Therefore, I compute the inflow (outflow) into (out of) stock i as a result of its exposure to ETF ownership, scaled by stock i's market capitalization:

$$FLOW_{i,t} = \frac{\sum_{f=1}^{F} w_{i,t}^{f} FLOW_{t}^{f}}{S_{i,t} P_{i,t}} \tag{21}$$

where $w_{i,t}^{f}$ denotes the weight of stock i in ETF f and $FLOW_t^f$ is the inflow (outflow) experienced by ETF f on day t. To capture the difference in exposure of stocks i and j to ETF flows, I compute the absolute difference

$$|\Delta FLOW_{ij,t}| = |FLOW_{i,t} - FLOW_{j,t}|. \tag{22}$$

As the other independent variables, I standardize $|\Delta FLOW_{ij,t}|$ for every trading day. In a separate specification, I include standardized absolute exposures of stocks i and j to ETF flows, $|FLOW_{i,t}|$ and $|FLOW_{j,t}|$.

Next, I adopt the measure of Antón and Polk (2014) to estimate the common ownership of stock pair i, j by the ETFs in my sample:

$$CAPij, t = \frac{\sum_{f=1}^{F}(S_{i,t}^{f} P_{i,t} + S_{j,t}^{f} P_{j,t})}{S_{i,t} P_{i,t} + S_{j,t} P_{j,t}} \tag{23}$$

where the numerator sums the total holdings of all ETFs in the sample in stock pair i, j and the denominator scales by the total market capitalization of stocks i and j. The number of shares held by the ETFs in my sample comes from ETF Global, while data on prices and total shares outstanding come from CRSP. To facilitate economic interpretability, $CAP_{ij,t}$ is rank-transformed and standardized for every trading day. This measure is also used by Agarwal et al. (2018).

In addition, I compute a measure intended to capture changes in the number of shares held by ETFs, that is, ETF creations and redemptions. Therefore, I fist compute changes in ETF holdings in stock i, scaled by the number of shares outstanding in stock i

$$CREATIONS_{i,t} = \frac{\sum_{f=1}^{F}(S_{i,t}^{f} - S_{i,t-1}^{f})}{S_{i,t}}, \tag{24}$$

where $S_{i,t}^{f}$ is the number of shares ETF f holds in stock i on day t and $S_{i,t}$ is the number of shares outstanding of stock i on day t. This measure is positive for ETF creations and negative for ETF redemptions. Then, I compute a measure capturing the difference in the exposure of stocks i and j to ETF creations and redemptions:

$$|\Delta CREATION_{i,j,t}| = |CREATIONS_{i,t} - CREATIONS_{j,t}|. \tag{25}$$

Intuitively, scaling ETF creations and redemptions by the amount of shares outstanding captures the relative intensity of creations and redemptions.

To the extent that ETF ownership drives daily pricing error correlations, I expect common ETF ownership $CAP_{ij,t}$ to be psoitively associated with pricing error correlations (Antón and Polk, 2014; Agarwal et al., 2018). Similarly, I expect the coefficient on absolute ETF flows ($|FLOW_{i,t}|$ and $|FLOW_{j,t}|$) to be positive (Antón and Polk, 2014; Ben-David, Franzoni, and Moussawi, 2018). At the same time, I expect the coefficient on the difference in exposure to ETF flows ($|\Delta FLOW_{ij,t}|$) and the difference in exposure to ETF creations and redemptions ($|\Delta CREATIONSij, t|$) to be negative (Ben-David, Franzoni, and Moussawi, 2018).

According to Ben-David, Franzoni, and Moussawi (2018) ETF sponsors disseminate net-asset values at a 15-second frequency throughout the trading day. Since I analyze data at a lower frequency — at a 1-minute frequency – I am able to capture potential pricing errors arising as a consequence of ETF sponsor's arbitrage activity.

Results from estimating daily cross-sectional regressions for correlations in pricing errors including the above measures for exposure to ETF ownership

Table 4: Cross-Sectional Results Including Liquidity Demand Proxies

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t}$$

including proxies for liquidity demand. Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ and $|\Delta\beta^{HML}_{i,j,t-1}|$ are the absolute difference in the SMB and HML betas of stocks in i and j, respectively. All specifications include controls for the absolute difference in the midquotes of stocks i and j on trading day $t-1$, 5-minute midquote return volatilities for stocks i and j on trading day $t-1$, and linear as well as nonlinear characteristics controls. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
$Constant$	0.01492*	0.01495*	0.01487*	0.01491*
	(0.000 76)	(0.000 76)	(0.000 76)	(0.000 76)
$\rho^x_{i,j,t}$	0.00264*	0.00264*	0.00263*	0.00264*
	(0.000 06)	(0.000 06)	(0.000 06)	(0.000 06)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$	−0.00232*	−0.00231*	−0.00234*	−0.00232*
	(0.000 10)	(0.000 10)	(0.000 10)	(0.000 10)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$	−0.00205*	−0.00207*	−0.00199*	−0.00206*
	(0.000 07)	(0.000 07)	(0.000 07)	(0.000 07)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$	−0.00350*	−0.00351*	−0.00350*	−0.00351*
	(0.000 15)	(0.000 15)	(0.000 15)	(0.000 15)
$\lvert\Delta FLOW_{ij,t}\rvert$	−0.00004			
	(0.000 04)			
$\lvert FLOW_{i,t}\rvert$		0.00045*		
		(0.000 04)		
$\lvert FLOW_{j,t}\rvert$		0.00047*		
		(0.000 04)		
$CAP_{i,j,t}$			0.00097*	
			(0.000 05)	
$\lvert\Delta CREATION_{i,j,t}\rvert$				−0.00012*
				(0.000 03)

Table 4: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
Constant	0.01906*	0.01916*	0.01917*	0.01914*
	(0.001 36)	(0.001 35)	(0.001 36)	(0.001 36)
$\rho^x_{i,j,t}$	0.00263*	0.00263*	0.00263*	0.00263*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 08)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$	−0.00521*	−0.00526*	−0.00526*	−0.00525*
	(0.000 23)	(0.000 23)	(0.000 23)	(0.000 23)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$	−0.00327*	−0.00331*	−0.00331*	−0.00329*
	(0.000 17)	(0.000 17)	(0.000 17)	(0.000 17)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$	−0.00654*	−0.00659*	−0.00659*	−0.00657*
	(0.000 27)	(0.000 27)	(0.000 27)	(0.000 27)
$\lvert\Delta FLOW_{ij,t}\rvert$	−0.00110*			
	(0.000 08)			
$\lvert FLOW_{i,t}\rvert$		0.00013		
		(0.000 08)		
$\lvert FLOW_{j,t}\rvert$		0.00022*		
		(0.000 07)		
$CAP_{i,j,t}$			−0.00010	
			(0.000 08)	
$\lvert\Delta CREATION_{i,j,t}\rvert$				−0.00077*
				(0.000 07)

are presented in Table 4. All specifications include controls for the absolute difference in the midquotes of stocks i and j on trading day $t-1$, 5-minute midquote return volatilities for stocks i and j on trading day $t-1$, and linear as well as nonlinear characteristics controls.

Comparing the results with the results for differences in the Fama and French (1993) betas only (Table 3) reveals that the main findings are unchanged. Larger absolute differences in the factor betas are associated with lower daily pricing error correlations. This holds for both the full sample results as well as the results for high-market capitalization stocks.

For the full-sample results, the signs of the coefficients on measures of (differences in) stock exposure to ETF ownership are in line with the hypotheses that emerge from the literature: common ETF ownership as well as absolute flows from ETFs into stocks i and j are associated with higher pricing error correlations. Larger differences in the exposure to ETF flows and ETF creations and redemptions are associated with lower pricing error correlations. Comparing the economic magnitudes of the coefficients of the differences in factor betas and and the exposure to ETF ownership reveals that the effect of ETF ownership is in general an order of magnitude smaller than the effect of differences in factor betas.

For high-market capitalization stocks only, the signs of the coefficients on the measures of (differences in) stock exposure to ETF ownership are again in line with the hypotheses that emerge from the literature, except for common ownership ($CAP_{i,j,t}$). However, the effect of common ownership is insignificant at all conventional significance levels and the point estimate is economically small, constituting a precise zero. At the same time, I find a relatively stronger negative effect of the difference in exposures of stocks i and j to ETF flows ($|\Delta FLOW_{ij,t}|$). In comparison to the full sample results, the coefficient on $|\Delta FLOW_{ij,t}|$ is at least an order of magnitude larger. A possible explanation for this is that the large stocks in my sample are more common constituents of widely traded ETFs.

In addition, this result suggests the following: When analyzing the effect of ETF ownership at high (intraday) frequencies, it is not ETF ownership per se that drives prices. Rather, flows resulting from ETF ownership drive prices and pricing errors. This is intuitive as market makers/liquidity providers observe and react to the flows they observe, rather than to holdings by market participants (this is the case in inventory models as my model in Section 2 as well as in adverse-selection models such as Kyle (1985) and Glosten and Milgrom (1985)). Moreover, this is consistent with the result in Antón and Polk (2014) that common ownership is more relevant in periods of high (absolute) flows.

If the effect I document in Section 5.2 was solely driven by a liquidity demand channel rather than liquidity supply as in the theoretical model in Section 2, I expect the coefficients on the measures of (differences in) stock exposure to ETF ownership to be of at least a similar magnitude as the coefficients on the differences in the factor betas. In addition, I expect the size of the coefficients on the differences in factor betas to decrease. This is neither the case in the full sample results, nor in the high-market capitalization sample results.

Rather, my results suggest that intraday pricing errors as well as their daily correlations are driven by both liquidity supply as well as liquidity demand channels, with the economic effect of a liquidity supply channel being economically larger. With this I complement the literature that shows that correlations in daily liquidity metrics are driven by ETF ownership, and therefore liquidity demand (Agarwal et al., 2018). In this context, it should also be noted that I estimate my state space model which yields estimates of pricing errors on a stock-day level. By construction, this does not allow me to identify long-lasting pricing errors. At the same time, estimating the state space model on the stock-day level alleviates concerns that my results capture a mechanical relationship between pricing error correlations and the explanatory variables in my regressions over multiple days.

Bogousslavsky and Muravyev (2023) document an increase in trading during closing auctions related to the increasingly important role of ETFs in today's financial market architecture. Hendershott and Menkveld (2014) find price pressures in closing prices as a result of specialist inventory positions. My findings complement these results for higher frequencies. With this, I also relate to the literature studying the impact of common fund and ETF ownership on correlations of lower-frequency liquidity metrics and factor residuals (Antón and Polk, 2014; Agarwal et al., 2018).

5.4 Robustness Checks

I investigate the robustness of my results along several dimensions. In Appendix A, I present the results from robustness checks showing the robustness of my findings to additional factor model specifications. In addition to the Fama and French (1993) factors considered in the main analysis, I consider the Fama and French (1993) –Carhart (1997), the Fama and French (2015), and the He, Kelly, and Manela (2017) factors.[4] The results are consistent across all factor models. More similar factor loadings are associated with higher pricing error correlations. In addition, results are stronger in the sample of high-market capitalization stocks.

Next, I investigate the possibility that my results are driven by noise in high-frequency TAQ data due to exchange-to-SIP latency (Holden, Pierson, and Wu, 2023). Therefore, I re-estimate my state space model based on data that has been cleaned using the latency adjustment procedure of Holden, Pierson, and Wu (2023) rather than the Holden and Jacobsen (2014) algorithm. Detailed results are presented in Appendix B. Comparing the main results with the exchange-to-SIP latency-adjusted results reveals quantitatively similar results.

Stocks may be similar and their pricing errors be correlated due to industry similarity rather than due to the underlying risk factor structure. I explore this channel in Appendix C. Following Antón and Polk (2014), I capture a stock pair's industry similarity by the number of of equal consecutive SIC digits, starting from the first digit. While I find that a higher degree of of industry similarity is associated with higher pricing error correlations, the relationship between differences in factor betas and pricing error correlations is robust to controlling for industry similarity. This suggest that the relationship I uncover is distinct from industry similarity.

Finally, I shed light on the possibility that my results are driven by a differences in market volatility in Appendix D. Therefore, consider differences in daily coefficients between high- and low volatility periods. I define high-volatility (low-volatility) periods as trading days when the VIX closes in the top (bottom) three deciles of its sample distribution. The results provide only mixed evidence for variation in daily coefficients with market volatility. In line with the predictions of the theoretical model in Section 2, I can reject the null hypothesis that the relationship between pricing error correlations and absolute differences in factor betas turns positive for any of the sub-periods. At the same time, these results suggest that my results are not driven by high- or low market volatility periods.

[4] Moreover, including the He, Kelly, and Manela (2017) factor captures differences in intermediary risk capacity as dealers' cost of liquidity provision increases as their risk capacity decreases (Huang et al., 2023).

6 Conclusions

Motivated by an inventory model I study pricing errors in the cross-section of stocks. In a setting in which prices are a function of risk factors, theory predicts that pricing errors of different securities are correlated if they load on the same underlying risk factors. Using a state space model, I identify pricing errors at a 1-minute frequency and compute correlations in pricing errors for stock pairs for each trading day. My results indicate that absolute differences in factor betas are negatively related to correlations in pricing errors. The effect is economically meaningful and robust to controlling for differences in the microstructure of trading and several stock characteristics.

In addition to this liquidity supply channel, I investigate the role of liquidity demand. I study the relationship between pricing error correlations and liquidity demanding flows from ETFs, as well as ETF ownership. While my results reveal a null result for the relationship between common ownership by ETFs and pricing error correlations, I find that ETF flows contribute to pricing error correlations in the cross section of stocks. These channels co-exist with the liquidity supply channel and are generally smaller in magnitude.

My results reveal systematic drivers of price efficiency in the cross-section of stocks. This adds to the literature showing that market wide risks drive inventory effects in stocks (Conrad and Wahal, 2020).

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A Cross-Sectional Results with Additional Factors

In this Section I present additional results for different factor models. Table 5 presents results for the Fama and French (1993) – Carhart (1997), Table 6 presents results for the Fama and French (2015) factors, and Table 7 presents results for the He, Kelly, and Manela (2017) as well as the market factor. As before, I report results for the full sample as well as high-market capitalization stocks only.

Comparing with the results for the Fama and French (1993) factors shows consistent results. As before, the results are stronger for high-market capitalization stocks only, compared to the full sample results. This alleviates the concern that the results are driven by small, irregularly traded stocks. In addition, differences in market betas consistently appear to be the most important driver of differences in daily pricing error correlations. The economic magnitude of differences in the additional factors (UMD, RMW, and CMA) is overall smaller than the magnitude of differences in the Fama and French (1993) factors. Especially the CMA factor appears to have little traction in the overall sample. In the high-market capitalization sample, however, the coefficients on the CMA factor are in line with the intuition of the theoretical model presented in Section 2.

The He, Kelly, and Manela (2017) factor appears highly significant across all specifications. Moreover, its economic magnitude is sizeable, especially in the sample of high market capitalization stocks. As the factor captures intermediary capital, this lends additional evidence in favor of the hypothesis that the liquidity supplying side influences co-movement in pricing errors.

Table 5: Cross-Sectional Results for Pricing Error Correlations for Fama and French (1993) – Carhart (1997) Factors

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors and Fama and French (1993) – Carhart (1997) factors. Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ is the absolute difference in the SMB betas, $|\Delta\beta^{HML}_{i,j,t-1}|$ is the absolute difference in the HML betas, and $|\Delta\beta^{UMD}_{i,j,t-1}|$ is the absolute difference in the UMD (momentum) betas of stocks in i and j. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
Constant	0.01908*	0.01932*	0.01929*	0.01437*
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 77)
$\rho^x_{i,j,t}$	0.00868*	0.00296*	0.00289*	0.00262*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\|\Delta\beta^M_{i,j,t-1}\|$		−0.00227*	−0.00211*	−0.00238*
		(0.000 11)	(0.000 10)	(0.000 09)
$\|\Delta\beta^{SMB}_{i,j,t-1}\|$		−0.00169*	−0.00154*	−0.00198*
		(0.000 09)	(0.000 09)	(0.000 08)
$\|\Delta\beta^{HML}_{i,j,t-1}\|$		−0.00042	−0.00017	−0.00342*
		(0.000 17)	(0.000 17)	(0.000 15)
$\|\Delta\beta^{UMD}_{i,j,t-1}\|$		0.00004	0.00039*	−0.00093*
		(0.000 06)	(0.000 07)	(.000 07)
$\|\Delta m_{t-1}\|$			−0.00083*	−0.00066*
			(0.000 06)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00174*	−0.00248*
			(0.000 13)	(0.000 10)
$\sigma(r^{5min}_{j,t-1})$			−0.00170*	−0.00239*
			(0.000 11)	(0.000 10)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 5: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02726*	0.02726*	0.02726*	0.01796*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 39)
$\rho^x_{i,j,t}$	0.00310*	0.00288*	0.00286*	0.00261*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 07)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00423*	−0.00431*	−0.00542*
		(0.000 19)	(0.000 19)	(0.000 21)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00235*	−0.00232*	−0.00318*
		(0.000 12)	(0.000 13)	(0.000 17)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00157*	−0.00152*	−0.00659*
		(0.000 28)	(0.000 29)	(0.000 26)
$\lvert\Delta\beta^{UMD}_{i,j,t-1}\rvert$		−0.00130*	−0.00117*	−0.00239*
		(0.000 15)	(0.000 14)	(0.000 16)
$\lvert\Delta m_{t-1}\rvert$			−0.00054*	−0.00061*
			(0.000 09)	(0.000 09)
$\sigma(r^{5min}_{i,t-1})$			−0.00008	−0.00256*
			(0.000 16)	(0.000 16)
$\sigma(r^{5min}_{j,t-1})$			−0.00052*	−0.00258*
			(0.000 15)	(0.000 14)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 6: Cross-Sectional Results for Pricing Error Correlations for Fama and French (2015) Factors

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors and Fama and French (2015) factors. Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$, $|\Delta\beta^{HML}_{i,j,t-1}|$, $|\Delta\beta^{RMW}_{i,j,t-1}|$, and $|\Delta\beta^{CMA}_{i,j,t-1}|$ are the absolute difference in the SMB, HML, RMW, and CMA betas of stocks in i and j, respectively. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
$Constant$	0.01908*	0.01932*	0.01930*	0.01335*
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 75)
$\rho^x_{i,j,t}$	0.00868*	0.00297*	0.00291*	0.00261*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\|\Delta\beta^M_{i,j,t-1}\|$		−0.00213*	−0.00191*	−0.00217*
		(0.000 11)	(0.000 10)	(0.000 10)
$\|\Delta\beta^{SMB}_{i,j,t-1}\|$		−0.00164*	−0.00149*	−0.00203*
		(0.000 08)	(0.000 08)	(0.000 07)
$\|\Delta\beta^{HML}_{i,j,t-1}\|$		−0.00020	−0.00006	−0.00359*
		(0.000 13)	(0.000 13)	(0.000 14)
$\|\Delta\beta^{RMW}_{i,j,t-1}\|$		−0.00050*	−0.00002	−0.00115*
		(0.000 08)	(0.000 06)	(0.000 05)
$\|\Delta\beta^{CMA}_{i,j,t-1}\|$		0.00020*	0.00017*	−0.00103*
		(0.000 06)	(0.000 06)	(0.000 06)
$\|\Delta m_{t-1}\|$			−0.00083*	−0.00063*
			(0.000 07)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00171*	−0.00249*
			(0.000 12)	(0.000 10)
$\sigma(r^{5min}_{j,t-1})$			−0.00166*	−0.00240*
			(0.000 11)	(0.000 10)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 6: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02726*	0.02726*	0.02726*	0.01702*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 38)
$\rho^{x}_{i,j,t}$	0.00310*	0.00289*	0.00287*	0.00259*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 07)
$\lvert\Delta\beta^{M}_{i,j,t-1}\rvert$		−0.00390*	−0.00395*	−0.00448*
		(0.000 21)	(0.000 21)	(0.000 25)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00189*	−0.00185*	−0.00289*
		(0.000 12)	(0.000 12)	(0.000 15)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00107*	−0.00108*	−0.00669*
		(0.000 24)	(0.000 23)	(0.000 26)
$\lvert\Delta\beta^{RMW}_{i,j,t-1}\rvert$		−0.00182*	−0.00174*	−0.00233*
		(0.000 19)	(0.000 17)	(0.000 12)
$\lvert\Delta\beta^{CMA}_{i,j,t-1}\rvert$		−0.00084*	−0.00080*	−0.00311*
		(0.000 13)	(0.000 13)	(0.000 16)
$\lvert\Delta m_{t-1}\rvert$			−0.00059*	−0.00066*
			(0.000 08)	(0.000 08)
$\sigma(r^{5min}_{i,t-1})$			−0.00007	−0.00240*
			(0.000 15)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00047*	−0.00255*
			(0.000 14)	(0.000 14)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 7: Cross-Sectional Results for Pricing Error Correlations for He, Kelly, and Manela (2017) Factor

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors and the He, Kelly, and Manela (2017) factor as well as the market factor. Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{HKM}_{i,j,t-1}|$, is the absolute difference in the He, Kelly, and Manela (2017) factor betas of stocks in i and j, respectively. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
Constant	0.01908*	0.01932*	0.01930*	0.01544*
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 76)
$\rho^x_{i,j,t}$	0.00868*	0.00302*	0.00295*	0.00272*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00123*	−0.00079*	−0.00204*
		(0.000 09)	(0.000 08)	(0.000 09)
$\lvert\Delta\beta^{HKM}_{i,j,t-1}\rvert$		−0.00051*	−0.00048*	−0.00330*
		(0.000 15)	(0.000 14)	(0.000 13)
$\lvert\Delta m_{t-1}\rvert$			−0.00101*	−0.00081*
			(0.000 06)	(0.000 06)
$\sigma(r^{5min}_{i,t-1})$			−0.00168*	−0.00308*
			(0.000 12)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00176*	−0.00292*
			(0.000 11)	(0.000 13)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 7: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
Constant	0.02726*	0.02726*	0.02726*	0.02016*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 32)
$\rho^x_{i,j,t}$	0.00310*	0.00300*	0.00297*	0.00271*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 08)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00244*	−0.00227*	−0.00413*
		(0.000 17)	(0.000 18)	(0.000 19)
$\lvert\Delta\beta^{HKM}_{i,j,t-1}\rvert$		−0.00187*	−0.00188*	−0.00743*
		(0.000 20)	(0.000 20)	(0.000 32)
$\lvert\Delta m_{t-1}\rvert$			−0.00034*	−0.00047*
			(0.000 08)	(0.000 09)
$\sigma(r^{5min}_{i,t-1})$			−0.00024	−0.00313*
			(0.000 15)	(0.000 17)
$\sigma(r^{5min}_{j,t-1})$			−0.00109*	−0.00312*
			(0.000 15)	(0.000 16)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

B Latency Adjustment

When working with high-frequency data, the latency at which the data are recorded may influence results. Holden, Pierson, and Wu (2023) show that accounting for the exchange-to-SIP latency improves the performance of the Lee and Ready (1991) algorithm for trade classification. In light of these results, I explore in this Section whether my results may be driven by noise introduced by the exchange-to-SIP latency. As my state space model identifies pricing errors as well as efficient price innovations using signed aggregate trade flow (see Section 3.1 for details), noise in trade signing may carry over to the identification of pricing errors. Moreover, my methodology relies on the prevailing midquote series. This is another potential source of variation once I account for the exchange-to-SIP latency.

To account for this channel, I implement the latency-adjusted procedure proposed by Holden, Pierson, and Wu (2023) rather than the Holden and Jacobsen (2014) algorithm. Based on this, I re-estimate the state space model, obtain pricing error series relative to the latency-adjusted midquote series, and re-estimate my cross-sectional Fama and MacBeth (1973) regressions for correlations in daily pricing errors. Results for the Fama and French (1993) factor betas are presented in Table 8. Comparing with my main results presented in

Table 3 reveals robust findings. All results presented in Section 5.2 carry over when performing the analysis based on latency-adjusted data. Moreover, results are also quantitatively highly robust, with the coefficients reported in Table 8 generally being within the margin of error of the coefficients reported in Table 3. This alleviates the concern that my results are driven by noise in the data, caused by the exchange-to-SIP latency.

Table 8: Latency-Adjusted Cross-Sectional Results for Pricing Error Correlations

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors:

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t}.$$

The analysis follows the steps in the main section, with the difference that the TAQ data for the results presented here is cleaned based on the latency-adjusted procedure of Holden, Pierson, and Wu (2023) rather than the Holden and Jacobsen (2014) algorithm. Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ is the absolute difference in the SMB betas, and $|\Delta\beta^{HML}_{i,j,t-1}|$ is the absolute difference in the HML betas of stocks in i and j. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
Constant	0.01962*	0.01973*	0.01971*	0.01529*
	(0.000 74)	(0.000 74)	(0.000 74)	(0.000 74)
$\rho^x_{i,j,t}$	0.00439*	0.00426*	0.00416*	0.00375*
	(0.000 10)	(0.000 10)	(0.000 09)	(0.000 08)
$\|\Delta\beta^M_{i,j,t-1}\|$		−0.00208*	−0.00191*	−0.00230*
		(0.00011	(0.00010	(0.00009
$\|\Delta\beta^{SMB}_{i,j,t-1}\|$		−0.00158*	−0.00142*	−0.00205*
		(0.000 08)	(0.000 08)	(0.000 07)
$\|\Delta\beta^{HML}_{i,j,t-1}\|$		−0.00047*	−0.00017	−0.00350*
		(0.000 18)	(0.000 19)	(0.000 15)
$\|\Delta m_{t-1}\|$			−0.00071*	−0.00055*
			(0.000 06)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00156*	−0.00250*
			(0.000 13)	(0.000 09)
$\sigma(r^{5min}_{j,t-1})$			−0.00155*	−0.00239*
			(0.000 11)	(0.000 09)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 8: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02759*	0.02759*	0.02758*	0.01948*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 34)
$\rho^x_{i,j,t}$	0.00442*	0.00412*	0.00408*	0.00374*
	(0.000 11)	(0.000 10)	(0.000 10)	(0.000 09)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00400*	−0.00409*	−0.00506*
		(0.000 19)	(0.000 19)	(0.000 21)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00244*	−0.00239*	−0.00339*
		(0.000 12)	(0.000 13)	(0.000 17)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00201*	−0.00199*	−0.00646*
		(0.000 26)	(0.000 28)	(0.000 27)
$\lvert\Delta m_{t-1}\rvert$			−0.00034*	−0.00037*
			(0.000 09)	(0.000 08)
$\sigma(r^{5min}_{i,t-1})$			−0.00010	−0.00266*
			(0.000 18)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00047*	−0.00264*
			(0.000 16)	(0.000 13)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

C Industry Similarity

Stocks may be similar and their prices co-vary because they load on the same underlying risk factors. However, this may also be driven by industry similarity. Also, investors may invest in a specific industry (Antón and Polk, 2014), causing their liquidity demand to be correlated and potentially inducing correlation in pricing errors. To investigate this channel, I follow Antón and Polk (2014) and capture industry similarity for a stock pair i, j as the number of equal consecutive SIC digits, starting from the first digit ($NUMSIC_{i,j,t}$). As before, I standardize the measure to facilitate economic interpretation.

Results for the full sample as well as high market capitalization stocks are presented in Table 9. As expected, industry similarity (i.e., an increase in the number of similar SIC code digits) is associated with higher pricing error correlations. The effect is economically relevant and significant. At the same time, the effect of differences in factor betas remains significant, even when controlling for industry similarity. As in the main results presented in Section 5, differences in factor betas have a larger effect on pricing error correlations among high-market capitalization stocks. Overall, these results provide evidence that the relationship I uncover between pricing error correlations and similarities in factor loadings is distinct from industry similarity.

Table 9: Cross-Sectional Results for Pricing Error Correlations with Controls for Industry Similarity

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors:

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t}.$$

Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ is the absolute difference in the SMB betas, and $|\Delta\beta^{HML}_{i,j,t-1}|$ is the absolute difference in the HML betas of stocks in i and j. $NUMSIC_{i,j,t}$ captures industry similarity by the number of equal SIC code digits, starting from the first digit. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
$Constant$	0.01908*	0.01932*	0.01930*	0.01525*
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 76)
$\rho^x_{i,j,t}$	0.00868*	0.00293*	0.00287*	0.00263*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00208*	−0.00190*	−0.00225*
		(0.000 11)	(0.000 10)	(0.000 09)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00156*	−0.00138*	−0.00200*
		(0.000 08)	(0.000 08)	(0.000 07)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00034	0.00000	−0.00312*
		(0.000 18)	(0.000 18)	(0.000 15)
$NUMSIC_{i,j,t}$		0.00227*	0.00229*	0.00175*
		(0.000 05)	(0.000 05)	(0.000 05)
$\lvert\Delta m_{t-1}\rvert$			−0.00077*	−0.00063*
			(0.000 06)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00167*	−0.00253*
			(0.000 13)	(0.000 10)
$\sigma(r^{5min}_{j,t-1})$			−0.00170*	−0.00244*
			(0.000 11)	(0.000 10)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 9: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02726*	0.02726*	0.02726*	0.02022*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 35)
$\rho^x_{i,j,t}$	0.00310*	0.00278*	0.00276*	0.00256*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 07)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00382*	−0.00391*	−0.00474*
		(0.000 19)	(0.000 19)	(0.000 21)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00241*	−0.00234*	−0.00314*
		(0.000 12)	(0.000 13)	(0.000 17)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00169*	−0.00163*	−0.00578*
		(0.000 27)	(0.000 28)	(0.000 27)
$NUMSIC_{i,j,t}$		0.00460*	0.00459*	0.00390*
		(0.000 17)	(0.000 17)	(0.000 15)
$\lvert\Delta m_{t-1}\rvert$			−0.00046*	−0.00050*
			(0.000 09)	(0.000 08)
$\sigma(r^{5min}_{i,t-1})$			−0.00010	−0.00258*
			(0.000 17)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00059*	−0.00263*
			(0.000 15)	(0.000 14)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

D Differences by Market Volatility

As market volatility changes, pricing error correlations as well as their interaction with factor loadings may change as well. This channel is distinct from variation in pricing error correlations as a result of volatilities in the individual securities. I control for the latter channel by including 5-minute return volatilities for each stock in all specifications. In this Section I investigate the first channel.

I use differences in VIX closing prices to capture differences in market volatility. Over my sample period, I classify days on which VIX closing prices were in the top three deciles of its distribution over my sample period as high-volatility days. Conversely, I classify days on which VIX closing prices were in the bottom three deciles of its distribution over my sample period as low-volatility days.

Building on daily cross-sectional regressions as in the main analysis

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| \\ + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t},$$

I investigate whether there is systemic variation in the time series of daily coefficients with respect to market volatility. Results are presented in Table 10.

The results lend only mixed evidence for variation in daily coefficients with market volatility. There is some evidence consistent with variation between high- and low volatility periods for absolute differences in market betas and SMB betas. Also, I can reject the null hypothesis that the relationship between pricing error correlations and absolute differences in the factor betas turns positive for any of the specifications. This is in line with the theoretical predictions of the model in Section 2 which predicts a negative relationship between differences in factor betas and pricing error correlations. In addition, the results in Table 10 suggest that my results are neither driven by high- or low-volatility periods.

Table 10: Differences by Market Volatility in Cross-Sectional Results for Pricing Error Correlations

This table reports Fama and MacBeth (1973) estimates of daily cross-sectional regressions for correlations in pricing errors:

$$\rho^s_{ij,t} = a + b_0\rho^x_{ij,t} + b_1|\Delta\beta^M_{ij,t-1}| + b_2|\Delta\beta^{SMB}_{ij,t-1}| + b_3|\Delta\beta^{HML}_{ij,t-1}| + \mathbf{X}\gamma + \varepsilon_{ij,t}.$$

Pricing errors are obtained as smoothed states from estimating the state space model on the stock-day level. All independent variables are standardized to facilitate economic interpretability. $\rho^x_{i,j,t}$ is the correlation in the signed order flow series, $|\Delta\beta^M_{i,j,t-1}|$ is the absolute difference in the market betas of stocks i and j, obtained from a factor regression using the last 500 available return observations. Similarly, $|\Delta\beta^{SMB}_{i,j,t-1}|$ is the absolute difference in the SMB betas, and $|\Delta\beta^{HML}_{i,j,t-1}|$ is the absolute difference in the HML betas of stocks in i and j. $|\Delta m_{t-1}|$ is the absolute difference in the midquotes of stocks i and j on trading day $t-1$, and $\sigma(r^{5min}_{i,t-1})$ as well $\sigma(r^{5min}_{j,t-1})$ are the 5-minute midquote return volatilities for stocks i and j on trading day $t-1$. The specifications that control for linear and nonlinear characteristics include the (standardized) factor betas as well as squared terms of the factor betas for stocks i and j. $HIGHVIX$ is an indicator referring to trading days on which the VIX is in the top three deciles of its distribution over my sample period. $LOWVIX$ is an indicator referring to trading days on which the VIX is in the bottom three deciles of its distribution over my sample period. I report Newey and West (1987) standard errors robust to autocorrelation of up to 20 lags in the cross-sectional estimates. Standard errors are reported in parentheses. * denotes significance at the 1% level.

Table 10: – continued

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
$Constant$	0.01908*	0.01932*	0.01930*	0.0149*1
	(0.000 74)	(0.000 76)	(0.000 76)	(0.000 76)
$\rho^x_{i,j,t}$	0.00868*	0.00296*	0.00290*	0.00265*
	(0.001 01)	(0.000 07)	(0.000 07)	(0.000 06)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00231*	−0.00214*	−0.00263*
		(0.000 15)	(0.000 14)	(0.000 13)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert * HIGHVIX$		0.00029	0.00028	0.00060*
		(0.000 24)	(0.000 22)	(0.000 21)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert * LOWVIX$		0.00029	0.00029	0.00044*
		(0.000 18)	(0.000 16)	(0.000 15)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00189*	−0.00175*	−0.00235*
		(0.000 11)	(0.000 10)	(0.000 10)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert * HIGHVIX$		0.00076*	0.00081*	0.00033
		(0.000 17)	(0.000 16)	(0.000 16)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert * LOWVIX$		0.00009	0.00020	0.00061*
		(0.000 11)	(0.000 10)	(0.000 12)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00058	−0.00024	−0.00376*
		(0.000 30)	(0.000 31)	(0.000 22)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert * HIGHVIX$		−0.00029	−0.00017	0.00049
		(0.000 41)	(0.000 42)	(0.000 33)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert * LOWVIX$		0.00046	0.00033	0.00037
		(0.000 32)	(0.000 33)	(0.000 28)
$\lvert\Delta m_{t-1}\rvert$			−0.00078*	−0.00063*
			(0.000 06)	(0.000 04)
$\sigma(r^{5min}_{i,t-1})$			−0.00167*	−0.00256*
			(0.000 13)	(0.000 10)
$\sigma(r^{5min}_{j,t-1})$			−0.00166*	−0.00245*
			(0.000 11)	(0.000 10)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes

Table 10: – continued

	Panel B: High Market Capitalization			
	(1)	(2)	(3)	(4)
$Constant$	0.02726*	0.02726*	0.02726*	0.01918*
	(0.001 24)	(0.001 24)	(0.001 24)	(0.001 36)
$\rho^x_{i,j,t}$	0.00310*	0.00288*	0.00286*	0.00263*
	(0.000 08)	(0.000 08)	(0.000 08)	(0.000 08)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert$		−0.00480*	−0.00494*	−0.00610*
		(0.000 27)	(0.000 27)	(0.000 32)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert * HIGHVIX$		0.00130*	0.00139*	0.00219*
		(0.000 44)	(0.000 44)	(0.000 45)
$\lvert\Delta\beta^M_{i,j,t-1}\rvert * LOWVIX$		0.00099*	0.00106*	0.00062
		(0.000 33)	(0.000 33)	(0.000 38)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert$		−0.00291*	−0.00283*	−0.00385*
		(0.000 15)	(0.000 17)	(0.000 27)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert * HIGHVIX$		0.00077*	0.00063	0.00095*
		(0.000 28)	(0.000 29)	(0.000 34)
$\lvert\Delta\beta^{SMB}_{i,j,t-1}\rvert * LOWVIX$		0.00055*	0.00062*	0.00084*
		(0.000 18)	(0.000 19)	(0.000 30)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert$		−0.00217*	−0.00207*	−0.00708*
		(0.000 48)	(0.000 49)	(0.000 45)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert * HIGHVIX$		−0.00053	−0.00081	0.00063
		(0.000 58)	(0.000 59)	(0.000 59)
$\lvert\Delta\beta^{HML}_{i,j,t-1}\rvert * LOWVIX$		0.00065	0.00074	0.00100
		(0.000 51)	(0.000 54)	(0.000 58)
$\lvert\Delta m_{t-1}\rvert$			−0.00045*	−0.00049*
			(0.000 09)	(0.000 08)
$\sigma(r^{5min}_{i,t-1})$			−0.00007	−0.00266*
			(0.000 17)	(0.000 14)
$\sigma(r^{5min}_{j,t-1})$			−0.00050*	−0.00268*
			(0.000 16)	(0.000 14)
Linear characteristics	No	No	No	Yes
Nonlinear characteristics	No	No	No	Yes