February 7, 2014

An Empirical Analysis of Co-Movements in High- and Low-Frequency Metrics for Financial Market Efficiency

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Abstract

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Several high- and low-frequency metrics for financial market efficiency have been proposed in distinct lines of research. We explore the joint dynamics of these metrics. High-frequency metrics co-move across individual stocks, and also co-move with lower-frequency metrics based on monthly reversal, momentum, and price-scaled anomalies. The systematic component of efficiency extracted from the time-series of high- and low-frequency metrics varies with funding liquidity and hedge fund flows, and variables that affect the efficacy of market-making. Thus, microstructural efficiency metrics share a common factor with lower-frequency metrics, and events and policies that affect funding liquidity can impact variations in this factor.

In a financial market that is relatively free of frictions and of high quality (i.e., one that is "efficient"), prices accurately reflect fundamentals, and, in doing so, obey the law of one price that assets with identical cash flows sell for the same price. The finance literature uses a number of distinct metrics to capture the efficiency of a market. For example, microstructure research considers high-frequency metrics such as intraday return predictability, pricing errors, and variance ratios (Andrade, Chang, and Seasholes, 2008; Hasbrouck, 1993; Bessembinder, 2003). One may also consider the extent to which markets obey the law of one price (such as put-call parity deviations - viz. Finucane, 1991; Cremers and Weinbaum, 2010), or measure the strength of longer-horizon return anomalies (for example, the well-known reversal and momentum effects of Jegadeesh, 1990, and Jegadeesh and Titman, 1993).

The above metrics for efficiency have largely been investigated separately in the literature. However, we note that they all are intimately linked to arbitrage activity and market making capacity, both of which facilitate convergence of prices to their efficient market benchmarks. In turn, arbitrage and market-making are stimulated by availability of capital, market liquidity, and the ease of short-selling, and these attributes vary over time, which suggests market efficiency metrics may also have a time-varying component.[1] Similarly, the efficiency of price formation is likely to vary across individual securities, since there is considerable cross-sectional variation in various attributes that affect the efficacy of arbitrage.[2]

The idea that efficiency metrics vary over time and across securities raises the ques-

[1]See, for example, D'Avolio (2002), Duffie (2010), Mitchell, Pulvino, and Stafford (2002), and Shleifer and Vishny (1997), for theoretical and empirical explorations of how arbitrage efficacy can cause market efficiency to vary over time. Indeed, earlier literature suggests that secular changes in institutional trading influence market efficiency dynamics, where efficiency is defined (inversely) by the extent of short-horizon return predictability from past order flow (Boehmer and Kelley, 2009). Other work demonstrates that arbitrageurs are more effective in maintaining accurate prices during times when arbitrage capital is relatively easy to access (Mitchell and Pulvino, 2012; Hu, Pan, and Wang, 2012).

[2]Benston and Hagerman (1974), and Nagel (2005), provide evidence of cross-sectional variation in illiquidity and short-sales constraints, respectively.

tion to what extent market efficiency metrics co-move across individual securities. This question is relevant since investors, exchange officials, and policy-makers should care about whether efficiency is prone to fluctuation in a systematic way. Furthermore, since variation in arbitrage frictions may affect short-horizon return predictability, efficiency metrics related to the law of one price (such as put-call parity deviations), and metrics for longer-term return anomalies (such as reversal and momentum) in a similar way, they could also give rise to co-movement across different metrics for efficiency. Evidence of such co-movement would be important since it would link the microstructure literature on short-horizon, market quality-based metrics for efficiency to the asset pricing literature that addresses longer-horizon phenomena.

Motivated by the above observations, in this paper, we do the following. We first compute three daily market efficiency measures for individual stocks: short-horizon (intraday) return predictability based on past order flow, Hasbrouck's (1993) pricing errors, and put-call parity deviations in the corresponding options markets, using 738 S&P 500 constituents over a long sample period of fifteen years. We then construct market-wide high-frequency measures of efficiency from these stock-level measures, and estimate the extent of co-movement in these measures from regressions of the individual stock measures on the market-wide measures. These analyses uncover material co-movement in the high-frequency efficiency measures.

Subsequently, we aggregate these efficiency measures to obtain their market-wide equivalents, and analyze co-movement between the three aggregate efficiency measures, a high-frequency variance-ratio-based measure of aggregate market quality,[3] and the time-series of profits from reversals (Jegadeesh, 1990), momentum (Jegadeesh and Titman,

[3]This efficiency measure is based on the observation that for a random walk price process, the variance of long-horizon returns is n times the variance of short-horizon returns, where n is the number of short-horizon intervals in the longer horizon; see, for example, Bessembinder (2003).

1993), and a price-scaled (specifically, earnings/price-based) anomaly.[4] To our knowledge, such an attempt to link the various efficiency metrics does not yet appear in the literature. We find that these high- and low-frequency measures are almost all positively cross-correlated and the majority of these correlations are significant, suggesting the existence of a systematic market efficiency factor. We extract the factor via principal component analysis from the monthly time-series of our seven market-wide efficiency measures and show that this first component explains over one-third of the joint variation in the efficiency measures.[5]

We next propose that this systematic component varies across time because of variation in funding liquidity proxied by variables such as hedge fund flows and short rates, in financial market liquidity measures such as bid-ask spreads, as well as in microstructural variables that affect market-making efficacy such as volatility and trading activity. We find that the systematic component is strongly related to hedge fund flows, the TED spread (a common indicator of funding liquidity), returns to the banking sector, market volatility, and the aggregate number of transactions in the stock market. We find no significant relation between the systematic efficiency component and measures of financial market liquidity, which suggests that the systematic efficiency component exhibits variations beyond those due to the traditional liquidity proxies. Overall, almost 60% of the time-variation in the systematic component of market-wide efficiency can be explained

[4]Fama and French (1996) point out that momentum is left unexplained by traditional risk-based factor models; Fama (1998) argues that momentum is among very few anomalies that survives closer scrutiny. Cooper (1999) and Mase (1999) provide evidence suggesting that investor overreaction accounts for monthly return reversals. These papers suggest that both momentum and reversals are arbitrageable anomalies. We do not include very long-term reversals (DeBondt and Thaler, 1985), because of controversy about the power of statistical tests documenting this phenomenon (Fama, 1998). While we include earnings/price as a proxy for price-scaled anomalies (viz. Basu, 1983); qualitatively similar results are obtained using book/market and cash flow/price ratios.

[5]In related work, Gagnon and Karolyi (2010) analyze daily time-series variations in price discrepancies in American Depositary Receipts (or ADRs) and cross-listed securities relative to home-market prices, and relate these variations to arbitrage proxies. Our work complements their analysis by considering sources of common variation across several high- and low-frequency metrics.

by our regressors.[6]

We view our demonstration of systematic variation in market efficiency metrics as relevant for at least three reasons. First, we show that metrics for efficiency, rather than being static concepts, exhibit significant time-variation and co-movement across individual stocks. Second, we take a step towards linking a vast literature on microstructural efficiency with longer-horizon efficiency metrics such as reversals and momentum. Third, we go beyond the well-known link between funding liquidity and market liquidity and demonstrate a further connection between funding liquidity and common variation in high- and low-frequency metrics for the efficiency of price formation.

This paper is organized as follows. In Section 1, we discuss the estimation of microstructural efficiency measures. Section 2 documents systematic variation in these measures, as well as in daily put-call parity deviations, across individual stocks. Section 3 demonstrates that high- and low-frequency measures of efficiency have a common component; and Section 4 analyzes determinants of time-series variation in this component. Section 5 concludes.

1. Microstructural Efficiency Measures

We begin by estimating two high-frequency measures of efficiency and quality obtained from intraday data for individual stocks. First, we estimate the intraday predictability

[6]Many recent and important papers explore efficiency-related issues. Griffin, Kelly, and Nardari (2010) examine market efficiency metrics across countries. Brennan and Wang (2010) compute mispricing measures from monthly return data by estimating specific forms of autocorrelation structures in factor model residuals. Jylhä, Rinne, and Suominen (2012) examine the relation between hedge fund flows and monthly reversals. Pasquariello (2012) finds that investors demand significant risk premia to hold stocks that perform poorly during times of large deviations of arbitrage bounds across countries in foreign exchange markets and ADRs. We complement these papers by examining co-movements across microstructural and longer-horizon metrics for efficiency, and relating the systematic component to several determinants of the efficacy of arbitrage, such as measures of funding liquidity, as well as financial market liquidity and return volatility.

of returns from order flow. Several papers, including Boehmer and Wu (2007), Chan and Fong (2000), Chordia, Roll, and Subrahmanyam (2005), and Hasbrouck and Ho (1987), explore and provide evidence of such return predictability, which we use as an inverse indicator of microstructural market efficiency. In particular, Chordia, Roll, and Subrahmanyam (2005) argue that such predictability arises from a temporary disequilibrium because of dealers' inability to accommodate autocorrelated order imbalances. Their evidence suggests that trading by astute arbitrageurs removes all return predictability over intervals of five minutes or more, but some predictability remains at shorter horizons. In line with these prior studies, we estimate the intraday return predictability of each individual stock for each day in the sample based on regressions of the returns over short intervals within the day on order imbalance (volume of buyer- minus seller-initiated trades) in the previous interval. A lower R^2 from these regressions indicates a greater degree of efficiency. In our baseline specification, we use one-minute intervals, but in robustness tests we also use two-minute intervals as well as intraday return predictability from lagged returns (return autocorrelation) instead of order imbalance. We refer to Appendix A, Section A.1, for a detailed exposition of the predictability regressions.

Second, we estimate Hasbrouck's (1993) pricing error measure based on intraday trades and quotes. Hasbrouck defines a stock's price as the sum of a random walk component and a transitory pricing error, which captures temporary deviations from the efficient price. In line with Hasbrouck (1993) and Boehmer and Kelley (2009), we estimate vector autoregression models based on intraday data for each individual stock for each day in the sample to separate variation in the stock's efficient price (the random walk component) from variation in its pricing error (the stationary component). As in Boehmer and Kelley (2009), we use the daily standard deviation of the intraday pricing errors as an inverse measure of informational efficiency of individual stocks. Section A.2 of Appendix A discusses the estimation of the Hasbrouck measure in detail.

To estimate the preceding microstructural efficiency measures, we obtain data on all trades and quotes as well as their respective sizes for individual U.S. stocks from the Thomson Reuters Tick History (TRTH) database, which contains global tick-by-tick trade and quote data across asset classes. TRTH is increasingly used in studies on high-frequency data, see, e.g., Lau, Ng, and Zhang (2012) and Marshall, Nguyen, and Visaltanachoti (2012).[7] Our sample consists of all 738 NYSE stocks that were an S&P 500 constituent at any time during our sample period of 1996-2010. We include only NYSE stocks to prevent issues with differences in trading volume definitions across NYSE and Nasdaq, see, e.g., Gao and Ritter (2010). We apply a variety of filters to the data that are described in Appendix B. We are able to use 3.9 billion transactions, signed by the Lee and Ready (1991) method, in our analyses.

Table 1 presents summary statistics of the return and order imbalance variables that serve as inputs to our predictability regressions. For these variables, the table reports cross-sectional summary statistics (the mean, standard deviation, as well as the median and the 25th and 75th percentiles) of the stock-by-stock time-series averages. The average number of trades per day is around 1,650. The average daily dollar trading volume is 0.042 or US$42m. The median mid-quote return is equal to 0.01 basis point, which corresponds to four basis points per day. There is a slight positive average order imbalance over the one-minute intervals in our sample.

Panel A of Table 2 presents the results of the intraday return predictability regressions. As described in Appendix A, the baseline predictability measure (*OIB predictability*) is obtained from regressions of one-minute mid-quote returns (computed using quotes associated with trades) on lagged dollar order imbalance. For robustness, we also estimate four alternative predictability measures. The *allquotes* measure is based on returns com-

[7]To verify that our results do not depend on using TRTH instead of NYSE's Trade and Quote (TAQ) database, we compare the results based on TRTH to those based on TAQ for all S&P 100 stocks over the period 1996-2000 and find that they are almost identical. Details are available from the authors.

puted using all quotes within each interval rather than only using quotes associated with trades; the *2minutes* measure is based on two-minute instead of one-minute intervals; the *oib#* measure is based on order imbalance expressed in number of trades rather than dollars; and the *autocorrelation* measure is based on regressions of one-minute returns on their one-minute lagged counterparts, instead of past order flows.

Consistent with prior research, Panel A of Table 2 shows that order imbalance positively predicts future returns over short intervals. The average coefficient on lagged order imbalance across the approximately 1.8 million stock-day regressions ranges from 0.839 for the *oib#* measure to 2.504 for the *OIB predictability* measure. The return autocorrelation coefficient is also positive at 0.021. The first number in parentheses below the average coefficient ("t-stat avg") is the average t-statistic across all stock-day regressions. Although for all but one measure the simple average t-statistic does not exceed critical values associated with conventional confidence levels, the t-statistics of the individual stock-day regressions can be based on as few as 20 intraday observations. The second number in parentheses in each column ("t-stat cross") is the t-statistic computed from the cross-sectional distribution of estimated coefficients by stock-day, and thus exploits the power obtained from the large cross-section of predictability regressions. These t-statistics are highly significant and indicate that intraday returns exhibit significant predictability from lagged order imbalance or returns.[8] Panel A of Table 2 also shows that a large fraction (around 60-90%, depending on the predictability measure) of the coefficients on lagged order imbalance and on lagged returns in the individual stock-day predictability regressions are positive, and that 30-65% of these coefficients are significant on an individual basis. The average R^2 of the regressions ranges from 1.3% for *allquotes*

[8] These cross-sectional t-statistics (pooled t-statistics to be more precise) are based on the assumption that the estimation errors in the estimated coefficients are independent across the stock-day regressions for each efficiency measure. Unreported results based on a random selection of calendar days and stocks from our sample suggest that the corrections are nowhere near large enough to make the cross-sectional t-statistics insignificant.

to 3.4% for *oib#*. Although these R^2s are modest, we note that predicting stock returns is challenging and that the results are in line with prior work on high-frequency return predictability (Chordia, Roll, and Subrahmanyam, 2005). The degree of predictability varies considerably over time, as well as in the cross-section. For example, in 1996 the average *OIB predictability* R^2 ranges from 2.3% for Mobil Corporation to 13.1% for LSI Corporation and the interquartile range is 1.75%.

Overall, Panel A of Table 2 provides evidence that the degree of intraday return predictability is robust across various specifications of the predictability regressions. In the remainder of paper, we therefore focus on the baseline *OIB predictability* measure.

One issue that arises is how predictability of intraday returns from order flow is related to market illiquidity, studied extensively in Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2000), and Huberman and Halka (2001). We find evidence that liquidity proxies and order-flow-based return predictability are only weakly correlated. Specifically, unreported tests show very low time-series correlations between return predictability and three common illiquidity measures: the proportional quoted bid-ask spread (*PQSPR*), the proportional effective spread (*PESPR*, defined as two times the absolute difference between the transaction price and the quote midpoint, scaled by the quote midpoint), and the Amihud (2002) illiquidity proxy (*Amihud*). Later, we report that the degree of co-movement in the predictability measures across stocks is not affected when we first orthogonalize the predictability measures with respect to common illiquidity measures.

We also note that, as pointed out by Chordia, Roll, and Subrahmanyam (CRS) (2008), illiquidity does not necessarily imply any return predictability from order flow or past returns. In Kyle (1985), even though markets are illiquid, prices are martingales because market makers are risk-neutral. This observation, in fact, motivates CRS' analysis of how liquidity *influences* efficiency, as opposed to being a concept that is interchangeable with efficiency. On the other hand, in inventory-based models, return predictability from order flow can arise if market makers have capital constraints or limited risk-bearing capacity that prevent them from conducting arbitrage trades that mitigate the predictability (Stoll, 1978). So, in a sense, our measure of predictability, or lack thereof, is a measure of the efficacy of such short-horizon arbitrage.

Panel B of Table 2 presents cross-sectional summary statistics of the stock-by-stock time-series averages of the high-frequency efficiency measures. The average value of the *OIB predictability* measure (the R^2 of the baseline predictability regression) across the 738 stocks in our sample is equal to 2.74%, with an interquartile range of 1.13%. The average value of the *Hasbrouck* measure is 1.31, which is roughly in line with the values reported in Hasbrouck (1993) and Boehmer and Kelley (2009). The substantial interquartile range of 0.73 indicates that the value of the *Hasbrouck* efficiency measure also varies substantially across stocks.

To further enrich our analysis, we supplement the two microstructural measures (*OIB predictability* and *Hasbrouck*) with a law of one price measure derived from options markets. The use of this measure enhances our understanding of co-movements in market efficiency by extending the notion to derivatives markets for individual stocks. This *put-call parity* measure is estimated using the OptionMetrics database as the absolute difference between the implied volatilities of a call and a put option of the same series (i.e., pairs of options on the same underlying stock with the same strike price and the same expiration date), averaged across all option pairs for each stock. We use end-of-day quotes from all option series with positive implied volatilities, expiring in two weeks to one year, and with a call delta between 0.3 and 0.7.[9] We discard stock-days with fewer than three valid underlying option series. We are able to estimate the *put-call parity* measure for 695 of the 738 stocks in our sample, for on average 114 of the 180 months in our sample period. The average number of underlying (put and call) option series is seven, with a minimum of four and a maximum of 31. The mean absolute put-call parity deviation (expressed in terms of implied volatility) across stock-days in the sample is 1.68%, with an interquartile range of 0.93% (see Panel B of Table 2).

In the next section, we investigate common components in the time-varying efficiency of individual stocks.

2. Co-Movement in High-Frequency Efficiency Measures Across Stocks

We now set out to accomplish one of our primary goals by examining whether there is significant co-movement in high-frequency measures of market efficiency across stocks. To estimate the extent of co-movement in the measures across stocks, we run time-series regressions of changes in the efficiency measures of individual stocks on contemporaneous, lead, and lagged changes in market-wide efficiency measures. Specifically, we estimate the degree of co-movement in efficiency for each stock i in the following regression:

$$\Delta Eff_{i,d} = \alpha_i + \beta_i \Delta MktEff_{i,d} + \gamma_i \Delta MktEff_{i,d-1} + \delta_i \Delta MktEff_{i,d+1} + \eta_{i,d}, \quad (1)$$

where $\Delta Eff_{i,d}$ is the change in the efficiency measure of stock i on day d, and $\Delta MktEff_{i,d}$ is the change in market-wide efficiency (defined as the equally-weighted average efficiency across all stocks in our sample excluding stock i). [In unreported robustness tests, we

[9] This measure is also used in Cremers and Weinbaum (2010). These authors note that while, strictly speaking, put-call parity does not hold as an equality for the American options on individual stocks, a lower discrepancy in implied volatilities from binomial models nonetheless is indicative of more efficient options and stock markets and vice versa.

perform these "market model" regressions based on levels of the measures rather than changes, and based on the contemporaneous measure as the only independent variable (that is, no lead and lagged market-wide measures), and obtain similar results.]

2.1 Full Sample Co-Movements in Microstructural Efficiency Across Stocks

We estimate Eq. (1) by stock over the full sample period 1996-2010 based on daily estimates of three different high-frequency efficiency estimates: *OIB predictability*, *Hasbrouck*, and *put-call parity*. Since the *OIB predictability* measure is defined as the R^2 from the predictability regression in Eq. (2) in Appendix A, which is bounded within the interval [0,1], we use its logistic transformation, $\ln[R^2/(1\text{-}R^2)]$, as the stock level efficiency measure, and the logistic transformation of the equally-weighted average R^2 across stocks as the market-wide efficiency measure.

Table 3 presents the results of our regressions to estimate co-movement in each of the three high-frequency efficiency measures across individual stocks. The table reveals evidence of significant co-movement across stocks. The average coefficient on contemporaneous changes in the market-wide efficiency measures across the 738 individual stock regressions is positive and economically substantial for all efficiency measures, ranging from 0.766 for the *OIB predictability* measure to 0.915 for the *put-call parity* measure. The average t-statistic of this coefficient is significant at the 10% level or better in all cases, and is particularly high for the *Hasbrouck* and *put-call parity* measures.

The cross-sectional t-statistics (computed from the cross-sectional distribution of estimated coefficients by stock) exploit the power obtained from the cross-section of regressions for each individual stock and are 21.3 for *OIB predictability*, 80.1 for *Hasbrouck*, and 30.3 for *put-call parity*, which indicates highly significant co-movement in efficiency across individual stocks for all three high-frequency efficiency measures. We note that the cross-sectional t-statistics are calculated under the assumption that the estimation errors in the estimated coefficients are independent across the stock-month regressions, a presumption we examine in more detail below.

For each of the three efficiency measures, the vast majority (at least 89%) of the individual coefficients on contemporaneous changes in market-wide efficiency are positive. At least 53% (*OIB predictability*) and up to 95% (*Hasbrouck*) of the coefficients are positive and significant on an individual basis. There is little evidence that the lead and lagged changes in market-wide efficiency are important in explaining time-variation in the efficiency of individual stocks. The average adjusted R^2s of the predictability regressions are 0.27% for *OIB predictability*, 7.26% for *Hasbrouck*, and 4.86% for *put-call parity*. Overall, Table 3 presents evidence of common variation in high-frequency efficiency measures across stocks.

In unreported tests, we assess the extent to which our finding of co-movement in the efficiency measures of individual stocks is due to underlying co-variation in illiquidity measures documented, for example, by Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001). To this end, we first orthogonalize the daily changes in each of the three high-frequency efficiency measures at the stock-level with respect to changes in that stock's illiquidity proxy (the proportional quoted spread, *PQSPR*; we obtain similar results with the effective spread (*PESPR*) or the *Amihud* measure). We then run co-movement regressions akin to Eq. (1) of orthogonalized changes in stock-level efficiency on contemporaneous, lead, and lagged orthogonalized changes in market efficiency (defined as the equally-weighted average changes in efficiency, orthogonalized with respect to changes in illiquidity proxies, across all stocks in our sample excluding stock i). The bottom line is that the degree of co-movement in efficiency is roughly equally strong for the high-frequency efficiency measures that have been orthogonalized with respect to illiquidity measures, suggesting that co-movements in high-frequency efficiency measures are not due to commonality in widely-used liquidity measures. Detailed results are available from the authors.

2.2 Co-Movements in Microstructural Efficiency Across Portfolios

The degree of co-movement in efficiency measures uncovered in Table 3 is mitigated by both estimation noise and idiosyncratic components in the efficiency of individual stocks. Looking at portfolios of stocks might alleviate estimation noise and expose a stronger image of commonality. From the perspective of portfolio management, analyzing the co-movement of efficiency measures for a portfolio of stocks with those of the market is relevant, since investors that manage different portfolios of securities might be concerned about the risk that multiple portfolios are simultaneously exposed to variation in pricing efficiency.

Table 4 examines the degree of co-movement in efficiency measures for size portfolios. At the beginning of each year, we sort stocks into quartile portfolios based on their market capitalization. We then compute the daily efficiency measure of each portfolio as the equally-weighted average efficiency measure across all stocks in the portfolio on that day. Subsequently, we run full sample period regressions of daily changes in the efficiency measures of the four size portfolios on contemporaneous, lead, and lagged changes in the market equivalent (computed as the equally-weighted average efficiency measures across the stocks not in the subject portfolio).

Table 4 shows strong co-movement in efficiency measures at the portfolio level for all four size quartiles based on all three high-frequency efficiency measures. The coefficients on contemporaneous changes in market efficiency are all positive and statistically significant. The *t*-statistics are very high, indicating that the contemporaneous coefficients are all 15 or more standard deviations away from zero. The portfolio level R^2s of the co-movement regressions in Eq. (1) are considerably greater than the individual stock level R^2s reported in Table 3. Where the average adjusted R^2s for individual stocks in Tables 3 are below 1% for the *OIB predictability* measure and around 5-7% for *Hasbrouck* and *put-call parity*, the portfolio level counterparts range from 8.9% to 21.8% for the four size portfolios based on the *OIB predictability* measure, from 69.2% to 85.6% based on *Hasbrouck* , and from 34.9% to 62.7% based on *put-call parity.* The evidence in Table 4 suggests that estimation noise dampens the degree of co-movement in efficiency measures reported in Table 3, and that the biggest stocks in our sample tend to exhibit the lowest degree of co-movement.

2.3 Monthly Co-Movements in High-Frequency Efficiency Measures Across Stocks

Another potential explanation for the modest R^2s in Table 3 is that estimation of Eq. (1) over the full sample period could underestimate the degree of co-movement in efficiency measures, since these regressions restrict the coefficients to be the same across the 15-year sample period, while the degree of co-movement might vary over time. Table 5 reports the results of estimating Eq. (1) for each stock each month (instead of over the full sample period) based on daily efficiency estimates within the month.

The results of the monthly stock level regressions in Table 5 differ in two important aspects from those of the full sample regressions in Table 3. First, although the coefficients on contemporaneous changes in market efficiency measures are again positive and economically sizable for all three efficiency measures, the average t-statistics and the fraction of individual coefficients that is positive and significant are smaller than in Table 3. This is not surprising, since the individual t-statistics are now based on at most around 20 daily observations within a month. We note that the cross-sectional t-statistics that exploit the power obtained from the more than 70,000 stock-month regressions are still highly significant.

Second, the average (adjusted) R^2s are considerably higher when the degree of co-movement in efficiency measures across stocks is assessed at the monthly frequency. The average (adjusted) R^2 is now 21.2% (6.6%) for the *OIB predictability* measure, 26.3% (12.6%) for *Hasbrouck*, and 24.6% (10.5%) for *put-call parity*. The finding that restricting the coefficients in Eq. (1) to be the same over the full sample period (as in Table 3) depresses the R^2s relative to the monthly regressions in Table 5 is suggestive of material time-variation in the degree of co-movement in efficiency measures across stocks.

In an unreported analysis (available upon request) we explore the extent to which the cross-sectional t-statistics reported in Table 5 need to be corrected for the effect of cross-equation dependence in estimation error. Under the simplifying assumptions that the residual variances are homogeneously distributed across stocks, and that pairwise residual correlations all equal ρ, the ratio of the true standard error to that under independence can be expressed as $[1 + (N - 1)\rho]^{0.5}$, where ρ is the correlation between each pair of residuals. (This implies that for negative ρ, the standard errors used in Table 5 are too large and the reported t-statistics are too small.) The sample statistics of the correlations between the residuals of the stock-month efficiency co-movement regressions across stocks, estimated on an annual basis, reveal little evidence of cross-equation dependence. For each of the three high-frequency efficiency measures and for each year, the average correlation between the residuals is very close to zero and the p-values are never significant.

3. Covariation Between Market-Wide High- and Low-Frequency Efficiency Measures

The previous section uncovered evidence of significant co-movement in high-frequency efficiency measures across individual stocks. In this section, we consider whether there is co-movement across market-wide efficiency measures. In other words, we examine systematic variation across different measures of market efficiency and quality at the aggregate market level. The underpinning argument is that the efficacy of both long- and short-horizon arbitrage is governed by the availability of capital or funding liquidity, as well as market-making efficacy, so that both intraday and longer-horizon versions of efficiency could tend to vary systematically over time. An opposing hypothesis is that measures of high-frequency market quality and longer-horizon market efficiency capture different aspects of the functioning of a financial market, which would imply that research on the microstructural quality of a market may not have direct implications for its efficient functioning in a broader sense. We test these contrasting notions by assessing whether high-frequency, microstructural measures of market quality are linked to broader, longer-horizon market efficiency measures.

3.1 Aggregate High- and Low-Frequency Efficiency Measures

We aggregate the three stock-level high-frequency efficiency measures (*OIB predictability*, *Hasbrouck*, and *put-call parity*) to monthly, market-level measures by first averaging across stocks each day, and then averaging across days within the month. We add a further high-frequency measure of aggregate market efficiency used in Bessembinder (2003): namely, a variance ratio that examines how closely the market adheres to a random walk benchmark. The *variance ratio* measure is defined as $|1-13\times VAR(30-\text{min})/VAR(OC)|$, where $VAR(30-\text{min})$ is the return variance estimated from 30-minute, market-wide (equally-weighted) mid-quote returns within a day and $VAR(OC)$ is the return variance estimated from open-to-close, market-wide mid-quote returns. The scaling factor 13 is based on the number of 30-minute intervals within the 6.5 hour trading day. We discard stock-days with fewer than four non-zero 30-minute returns. The variance ratio is estimated each month and tends to unity as serial dependence in asset returns tends to zero as per Bessembinder (2003); therefore, it measures how closely the market adheres to a random walk.[10]

We now consider low-frequency measures of efficiency. Such measures are typically identified as "anomalies" in the context of the Fama (1970) definitions of semi-strong and weak-form efficiency. We include three measures based on longer-horizon return anomalies that are prominent in the asset pricing literature: namely, monthly reversals, momentum, and predictability of returns from price-scaled ratios. While there are a large number of cross-sectional anomalies (Fama and French, 2008; McLean and Pontiff, 2012), our focus on reversals and momentum (Jegadeesh, 1990; Jegadeesh and Titman, 1993), which are based on past returns, accords with our usage of the short-horizon predictability of returns from past returns and order flow as a high-frequency metric. In addition, we include one price-scaled anomaly based on the earnings/price ratio, which has been well-known at least since Basu (1983).[11] Specifically, we consider the following market-wide low-frequency efficiency measures:

- *reversal*: returns on a portfolio that is long losers and short winners over the past month.

[10] Variance ratios are computed from equally-weighted mid-quote returns and do not utilize traded prices, mitigating the problem of non-synchronous trading. We use variance ratios at the aggregate market level, because our exploratory analyses and those of Andersen, Bollerslev, and Das (2001) suggest that return outliers at high frequencies render intraday variances unreliable at the individual stock level. Our use of 30-minute-to-daily variance ratios is similar to the hourly-daily measure computed by Bessembinder (2003).

[11] As pointed out in Footnote 4, we obtain similar results when we use book/market, or cash flow/price as the sorting variables.

- *momentum*: returns on a portfolio that is long winners and short losers over the past twelve months, skipping the first month (i.e., months $m-12$ up to and including $m-2$, where m is the current month).

- *E/P*: returns on a portfolio that is long high earnings/price stocks and short low earnings/price stocks.

The monthly time-series of returns on the *reversal* and *momentum* factors are computed as the monthly average of the daily returns on those factors as obtained from Ken French's website.[12] The monthly returns on the *E/P* factor are from the same website.

Table 6 presents summary statistics for the monthly market-wide high-frequency (*OIB predictability*, *Hasbrouck*, *put-call parity*, and *variance ratio*) and low-frequency (*reversal*, *momentum*, and *E/P*) efficiency measures. The time-series means of the market-wide *OIB predictability*, *Hasbrouck*, and *put-call parity* measures are very similar to the means reported in Panel B of Table 2, which were computed as the cross-sectional average of the time-series average of each efficiency measure by stock. The mean absolute deviation of the variance ratio from unity is 0.31, and the mean daily rewards for *reversal*, *momentum*, and *E/P* are 8.6, 2.6, and 3.0 basis points, respectively.[13] The time-series standard deviation and interquartile range indicate substantial time-series variation in all measures.

[12]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/. As per the website, the momentum factor is formed as follows: "We use six value-weight portfolios formed on size and prior (2-12) returns to construct Mom. The portfolios, which are formed daily, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The daily size breakpoint is the median NYSE market equity. The daily prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. [The momentum factor] is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios." The reversal and E/P factors are formed similarly, except that the prior 2-12 months' return is replaced by the prior month's return and the E/P ratio, respectively.

[13]While positive returns on the *reversal*, *momentum*, and *E/P* factors can arguably be interpreted as a departure from market efficiency, it is less clear that negative returns on these factors are signs of efficient pricing. However, our results do not materially change when we set negative returns on these factors to zero.

3.2 Correlations Across Market-Wide Efficiency Measures

Table 7 shows the matrix of rank correlations between the seven different monthly market-wide efficiency measures. All seven measures are inverse indicators of the degree of market efficiency. Of the 21 correlations, 20 are positive, and 14 are significant at the 10% level or better. This is indication of non-trivial co-movement in aggregate market efficiency across different efficiency measures.

The correlations between the four market-wide high-frequency measures (*OIB predictability*, *Hasbrouck*, *put-call parity*, and *variance ratio*) are all statistically significant at the 1% level and have substantial economic magnitudes. The three market-wide low-frequency efficiency measures (*reversal*, *momentum*, and *E/P*) are weakly correlated among each other (only the correlation between *reversal* and *E/P* is significant), but each of the low-frequency measures is significantly correlated with at least one of the high-frequency measures. The *reversal* measure shows significant correlations with *OIB predictability*, *Hasbrouck*, as well as *put-call parity*, while *E/P* is significantly correlated with the *OIB predictability*, *Hasbrouck*, and *variance ratio* measures. *Momentum* tends to behave relatively independently of the other efficiency measures, and is only significantly correlated with *OIB predictability*, at the 10% level.

3.3 Constructing an Efficiency Factor Based on High- and Low-Frequency Measures

Given the evidence of common variation in aggregate market efficiency across different measures in Table 7, we now seek to extract a systematic efficiency factor via principal component analysis (PCA). We follow Hasbrouck and Seppi (2000) and extract the principal components based on the correlation matrix. We find that the first principal component explains 36.4% of the total variation in the seven monthly time-series of market-wide efficiency measures. Moreover, the loadings of the seven different efficiency measures on the first principal component are all of the same sign. The second to seventh components account for 17%, 15%, 12%, 12%, 7%, and 0.5% of the variance, respectively. Overall, this evidence points to strong common variation in both microstructural and longer-horizon measures of market efficiency.

Since the first principal component explains over one-third of the total variation, explains almost twenty percent more variation than the next component, and exhibits same-sign factor loadings across all seven efficiency measures, we use this component as representative of systematic variation in aggregate market efficiency. To get a time-series of the first principal component, we standardize each efficiency measure to have zero mean and unit standard deviation, and multiply the matrix of standardized efficiency measures by the vector of the loadings of each measure on the component.[14] The resulting systematic efficiency factor is an inverse indicator of the degree of market efficiency.

Figure 1 shows the monthly time-variation in this systematic efficiency factor. The figure indicates that systematic efficiency has gradually improved until 2008, when the financial crisis caused a major disruption in efficient pricing, after which the degree of efficiency returned to pre-crisis levels.

4. Determinants of Time-Variation in the Aggregate Efficiency Measure

We now turn to an analysis of the drivers of systematic variation in aggregate market efficiency, measured by the first principal component described above. First, to the extent that fluctuations in the funding liquidity of the financial system have pervasive effects

[14] The resulting time series of the first principal component correlates positively with all of the efficiency measures in Table 7, with p-values less than 0.01 in five of seven cases (for the sixth and seventh cases, the *momentum* and E/P measures, the p-values are 0.04 and 0.05, respectively).

on market making and arbitrage activity (e.g., Brunnermeier and Pedersen, 2009; Aoun, 2010; Mancini-Griffoli and Ranaldo, 2011), the systematic component of efficiency can be affected by changes in funding liquidity. Second, arbitrage activity is also affected by trading cost measures such as bid-ask spreads, so that variation in these measures can result in systematic variation in efficiency. Third, systematic variation in efficiency can be induced by anticipated volatility and levels of trading activity, both of which influence market making efficacy (viz. Stoll, 1978), and/or by investor sentiment (Lo, 2004), which may cause waves of price fluctuations around efficient benchmarks.

We collect data on four different proxies for funding liquidity. *Hedge fund flow* is the monthly percentage money inflow into hedge funds. Greater hedge fund inflows should spur arbitrage activity.[15] *TED spread* is the difference between the three-month LIBOR and the three-month T-bill rate from the FRED database of the Federal Reserve Bank of St. Louis and is a widely used indicator of funding liquidity (Brunnermeier, Nagel, and Pedersen, 2008; Brunnermeier, 2009).[16] *Reserves* is the amount of funds held by U.S. depository institutions in their accounts at the Federal Reserve in excess of their required reserve balances and contractual clearing balances (in US$b.), obtained from FRED. In light of the recent debate on whether the buildup of excess reserves during the recent financial crisis suppressed the provision of funding liquidity by the banking sector (Keister and McAndrews, 2009), we interpret larger reserves as an indication of lower funding liquidity. In the baseline regressions, we include this variable in levels, but we obtain similar results when we include it in first differences. *Bank returns* is the monthly total return on the Dow Jones U.S. financial industry index taken from TRTH. Following Hameed, Kang, and Viswanathan (2010), we argue that a rise in the market value of the

[15]We thank Matti Suominen and LIPPER-TASS for data on hedge fund flows. The sample includes all hedge funds that report their returns in U.S. dollars and have a minimum of 36 monthly return observations over our sample period.

[16]The notion is that the TED spread may proxy for counterparty risk, which, when elevated, can lead to decreased funding liquidity.

financial industry is likely to be associated with a stronger aggregate balance sheet of the funding sector.

As trading cost measure, we include *PQSPR*, defined as the average across stocks of the monthly time-series average of the daily proportional quoted bid-ask spread of each stock (averaged across all observations), computed from TRTH data.

Regarding the third category of determinants, we argue that reduced fundamental uncertainty can make deviations from efficient pricing less likely across the board (by improving market making efficacy) and we use the forward-looking *VIX* (volatility index) obtained from TRTH as a proxy for market-wide uncertainty. We define *#trades* as the total number of trades per month across all the stocks in our sample. We include this variable to account for the marked increase in turnover and decrease in average trade size over our sample period which has been related to the advent of algorithmic trading that could affect market making efficacy (Hendershott, Jones, and Menkveld, 2011). Finally, Baker and Wurgler (2006) show that waves of investor sentiment affect many stocks at the same time. To test the hypothesis that fluctuations in market-wide investor sentiment affect systematic variation in efficiency by affecting pricing accuracy, we use their sentiment index, higher scores of which indicate more optimistic investor sentiment. Since we would expect pricing inaccuracies to potentially arise when sentiment is either unusually pessimistic or unusually optimistic and since values of the sentiment index roughly center around zero, we define *sentiment* to be the absolute value of this index. Table 8 presents summary statistics of the variables in each of the three categories of potential determinants of the systematic component of aggregate efficiency.

We are interested in what factors explain time-variation in the systematic component of efficiency. We run time-series regressions of the first principal component on the contemporaneous determinants in the three categories. Prior to usage as a dependent variable, we detrend the first principal component with linear and quadratic trend terms; we find that efficiency has significantly trended downward, which is consistent with recent improvements in trading technology and the rise of high frequency trading (Chordia, Roll, and Subrahmanyam, 2011).[17] Fluctuations in the dependent variable are an inverse indicator of movements in aggregate market efficiency.

Table 9 presents the estimated coefficients and their associated t-statistics in each of four regressions to explain time-variation in this variable. The regression reported in the first column includes only the funding liquidity measures. We find that the coefficients on *hedge fund flow* and *bank returns* are negative and significant (at the 5% and 1% level, respectively), and the coefficient on *reserves* is positive and significant at the 10% level. Thus, an increase in hedge fund inflows or returns to the banking sector, or a decrease in bank reserves held at the Federal Reserve are associated with an improvement in the systematic component of market efficiency, which is consistent with intuition. The economic magnitudes of these effects are substantial. A one standard deviation increase in *hedge fund flow* is associated with a 0.27 standard deviation decrease in the systematic component of efficiency (which is an inverse measure of aggregate market efficiency).[18] The corresponding economic effects of *bank returns* and *reserves* are also non-trivial at 0.20 and 0.15 standard deviations, respectively.

In the regression reported in the second column of Table 9, the coefficient on *PQSPR* is positive (in line with expectations), but not statistically significant. In unreported robustness checks, we find similar results when we include the Amihud (2002) illiquidity

[17]Detrending addresses the possible concern that trends in dependent and explanatory variables could lead to spurious conclusions. The results below are largely unchanged whether we detrend the principal component, or whether we detrend the individual efficiency measures and then extract the principal component.

[18]This economic magnitude is computed by multiplying the coefficient on *hedge fund flow* of -0.119 in the first column of Table 9 by the time-series standard deviation of this variable of 1.806 (from Table 8) and then dividing by the time-series standard deviation of the detrended first principal component of the seven aggregate market efficiency measures, which is equal to 0.798 (not tabulated).

proxy instead of *PQSPR*.

We present coefficients for the third and last category of determinants in the third column of Table 9. The coefficient on *VIX* is positive and significant, indicating that decreased ex ante uncertainty is associated with increased efficiency, as is intuitive. A one standard deviation reduction in *VIX* is associated with a 0.73 standard deviation improvement in market efficiency. *#trades* is not related to common variation in efficiency in this specification. The coefficient on *sentiment* is positive and significant at the 5% level. The economic magnitude of the effect of *sentiment* is more modest than that of some of the other variables, at 0.15 standard deviation units per unit standard deviation move in *sentiment*.

The fourth column of Table 9 includes all of our explanatory variables. The coefficients on *hedge fund flow*, *bank returns*, *reserves*, and *VIX* continue to have the expected sign and by and large preserve their statistical and economic significance. However, we now also find a significantly positive effect of the *TED spread*, in line with the idea that a relaxation of funding constraints improves market efficiency. The economic magnitude of this effect is considerable. A one standard deviation decrease in *reserves* is associated with a 0.29 standard deviation improvement in the systematic component of market efficiency.

We also find that the coefficient on *#trades* is now negative and significant at the 1% level in the presence of the other variables. The negative sign implies that, controlling for other determinants of efficiency, an increase in the number of trades is associated with greater market efficiency, which is consistent with the notion that increased market activity leads to greater camouflage for arbitrageurs and increases their efficacy. An increase in the number of trades could also be associated with increased algorithmic trading in later years of our sample (Hendershott, Jones, and Menkveld, 2011), which, under the presumption that some of this trading is arbitrage-driven, could enhance market efficiency. The economic significance of the effect of *#trades* is sizable. A one standard deviation increase in this variable is associated with a 0.53 standard deviation improvement in the systematic component of the efficiency measures.

Taken together, the results in Table 9 indicate that the aggregate market efficiency measure varies over time with funding liquidity, market volatility, and trading activity. As indicated by the raw and adjusted R^2s reported in Table 9, the determinants in these three categories jointly explain almost 60% of the time-variation in the systematic component of time-variation in efficiency measures.

5. Summary and Concluding Remarks

Many well-known high- and low-frequency efficiency metrics have been proposed in distinctly different lines of work within the finance literature. We attempt to unify these areas of research by exploring the joint dynamics of these metrics. Our underlying premise is that these metrics might co-move with each other because they all are linked to the ease of arbitrage, which varies systematically across stocks and time.

We show that various high-frequency market efficiency measures (specifically, intraday return predictability from order flow, Hasbrouck's (1993) pricing errors, and daily put-call parity deviations) exhibit significant co-movement across stocks, which persists after accounting for dynamics in liquidity proxies. Next, we correlate market-wide equivalents of these short-horizon efficiency measures with market-wide variance ratios, and with the well-known reversal, momentum, and price-scaled anomalies. We find that almost all of these short- and long-horizon market efficiency measures are positively cross-correlated, with the majority of correlations being statistically significant. This finding links microstructural measures of market efficiency and quality to a measure based on the law of one price, and to broader, longer-horizon measures of market efficiency.

We extract the common component of market efficiency via the first principal component of the aggregate market efficiency measures. We show that this measure of systematic variation in efficiency depends on funding liquidity (measured by variables such as hedge fund flows and the TED spread), market volatility, and traditional variables that measure the efficacy of market making such as trading activity. Particularly, the results suggest that the hedge fund industry plays a valuable role in enhancing market efficiency.

Recognizing that market efficiency has a systematic component opens new vistas for research. First, it would be worth exploring whether there is a global component to variation in market efficiency. This would allow us to ascertain whether worldwide growth in the financial sector (e.g., in the money management industry), and global improvements in funding liquidity might lead to systematic improvement in the quality of price formation in markets across the world. Second, it would be worth investigating whether systematic variations in market efficiency metrics extends to other asset classes such as fixed income securities, foreign exchange, and derivatives. These and other issues are left for future research.

Appendix A: Estimation of Microstructural Efficiency Measures

This appendix describes the estimation of the two stock-level, microstructural efficiency measures: intraday return predictability and Hasbrouck's (1993) pricing errors.

A.1. Intraday Return Predictability

For each individual stock for each day in the sample, we estimate the intraday return predictability using regressions of the returns over short intervals within the day on order imbalance (volume of buyer- minus seller-initiated trades) in the previous interval. Chordia, Roll, and Subrahmanyam (2005) show that prices cease to be predictable from order flow in 30 minutes or less in 1996, and around five minutes in 2002. Since our sample period lasts till 2010, it is desirable for us to use intervals shorter than five minutes to still capture meaningful predictability in the later part of the sample period. In light of this consideration, we estimate predictability based on intraday returns and order imbalances measured over one-minute intervals (with a robustness check based on two-minute intervals).

We estimate the extent of short-horizon return predictability from order flow for each stock i and day d in the sample as the R^2 from the following regression, using intraday data aggregated over one-minute intervals:

$$R_{i,d,t} = a_{i,d} + b_{i,d} OIB_{i,d,t-1} + \epsilon_{i,d,t}, \tag{2}$$

where $R_{i,d,t}$ is the return of stock i in one-minute interval t on day d based on the mid-quote associated with the last trade to the mid-quote of the first trade in the interval (to avoid the bid-ask bounce), and $OIB_{i,d,t-1}$ is the order imbalance for the same stock and day in the previous interval $t-1$, computed as the difference between the total dollar amount of trades initiated by buyers and sellers ($OIB\$$). A lower R^2 from the regression in Eq. (2) indicates greater efficiency.[19] We require at least 20 one-minute intervals per day for a stock in order to estimate Eq. (2) for that stock. We refer to the efficiency measure based on this regression specification as the *OIB predictability* measure.

To assess the robustness of our results to changes in the specification of the predictability regressions, we also estimate four alternative return predictability measures, each named after the single feature that distinguishes it from the *OIB predictability* measure. The *allquotes* measure is based on returns computed using all quotes within each interval rather than only using quotes associated with trades; the *2minutes* measure is based on two-minute instead of one-minute intervals; and the *oib#* measure is based on order imbalance expressed in number of trades rather than dollars. We also present and discuss the results using the R^2 from the regression of one-minute returns on their one-minute lagged counterparts, instead of past order flows, and label this the *autocorrelation* measure. In unreported tests, we also estimate an intraday predictability measure based on regressions that include lagged order imbalance in dollars and in trades as well as lagged returns simultaneously, and find slightly stronger return predictability based on all three variables.

A.2. Hasbrouck's (1993) Pricing Errors

Hasbrouck (1993) proposes a method to decompose stock prices into random walk and stationary components. He refers to the stationary component, the difference between the efficient price and the actual price, as the pricing error. Hasbrouck argues that its dispersion is a natural measure for pricing efficiency. We follow Hasbrouck and estimate vector autoregression (VAR) models to estimate these components. We follow Boehmer and Kelley (BK) (2009) by estimating a five-lag VAR model based on intraday data for

[19] As the ratio of explained to total variance, R^2 is a convenient, dimensionless measure of the extent of return predictability that is easy to compare across stocks and time. However, variation in R^2 may also be driven by variation in total variance. In unreported tests, we therefore use the slope coefficient $b_{i,d}$ in Eq. (2) as an alternative stock-specific efficiency measure. The main results are unaffected.

each stock-day with at least one hundred trades. The endogenous variables of the model are: (i) the logarithmic gross return, from quote midpoints associated with trades (using midquote returns avoids the bid-ask bounce, but using returns from actual trade prices does not alter the main results), (ii) a trade sign indicator, (iii) the signed volume (that is, the sign of the trade times the number of shares traded), and (iv) the sign of the trade times the square root of the number of shares traded. We sign all trades with trade prices above the prevailing quote midpoint as buyer initiated, and as seller initiated if they are below the quote midpoint. If the trade occurred at the prevailing quote midpoint, we set the sign of the trade to zero (following Hasbrouck, 1993). As in Hasbrouck (1993), we also set all lagged variables at the beginning of each day to zero. As in BK, we obtain the standard deviation (estimated by stock-day) of the intraday pricing error estimates from the vector moving average representation of the VAR system (Beveridge and Nelson, 1981) using Eq. (16) in Hasbrouck (1993). Also (as do BK) we use the logarithmic transformation of the daily standard deviation of the intraday pricing error (scaled by 10,000) as our stock-level *Hasbrouck* measure.[20]

[20]The logarithmic transformation helps mitigate the influence of outliers. We obtain similar results, if, instead of taking the logarithmic transformation, we winsorize the daily stock-level *Hasbrouck* measure at the 95% level.

Appendix B: Data Filters

This appendix describes the data filters applied to the high-frequency data. We collect data on all trades and quotes for all 738 NYSE stocks that were an S&P 500 constituent at any time during 1996-2010 from the Thomson Reuters Tick History (TRTH) database. We drop 14 stocks from the sample with less than one year of data over this period. Our data start in 1996, which is the earliest year available in the TRTH database.

We discard trades that fall outside the continuous trading session (9:30 am till 4:00 pm U.S. EST/EDT) on the NYSE (in total 9,348,169 trades). We also discard trades with a negative price (9,497 trades) or a price that is more than 10% different from the trade price of the ten surrounding trades (3,688 trades). We further drop trades of more than 100,000 shares (954,669 trades) since large trades are often negotiated before they get reported (Glosten and Harris, 1988). We discard quotes outside the continuous trading session (8,089,672 quotes), quotes with a non-positive bid or ask price (5,154 quotes), quotes of which the bid price exceeds the ask price (1 quote). We also discard a number of quotes we regard as outliers, defined as those for which (i) the bid (ask) price is more than 10% different from the average bid (ask) price of the ten surrounding quotes, (ii) the ask price is more than $5 higher than the bid price, or (iii) the proportional quoted spread is greater than 25%. A total of 9,407,538 quotes are discarded because of these criteria. We note that while the absolute numbers of trades and quotes excluded because of these data screens are large, they are small relative to the total number of trades and quotes in the sample. Our data screens lead us to discard a mere 0.2% of all trades.

Our final sample consists of 738 stocks and 3,941,515,119 trades. To prevent survivorship bias, we use data for these stocks over the entire period for which we have data during 1996-2010, and not only during the period over which they were an S&P

500 constituent. We sign trades using the Lee and Ready (1991) algorithm.[21] Because of a decrease in reporting errors since 1998 (Madhavan, Richardson, and Roomans, 2002), we do not use a delay between a trade and its associated quote. We are able to sign 3,939,064,997 trades, which corresponds to 99.94% of all trades in our final sample.

To estimate Eq. (2), we require at least one signed trade in both the interval over which we calculate the return as well as the previous interval. This leads us to drop a non-negligible fraction of the intraday intervals in the early years of the sample period, but since 2000 almost all stocks have at least one trade in almost all of the intraday intervals. We discard stock-days for which we have fewer than 20 one-minute intervals with valid data on the stock return within that interval and on the order imbalance or return in the preceding interval (in total 157,454 stock-day observations), and days for which TRTH reports a data gap that overlaps with the continuous trading session (in total 56 days). Our data filters allow us to estimate Eq. (2) for on average 2,445 days over the period 1996-2010 across the 738 stocks in our sample.

[21] The Lee/Ready algorithm classifies a trade as buyer- (seller-) initiated if it is closer to the ask (bid) of the prevailing quote. If the trade is exactly at the midpoint of the quote, the trade is classified as buyer- (seller-) initiated if the last price change prior to the trade is positive (negative). Of course, there is inevitably some assignment error, so the resulting order imbalances are imperfect estimates. Lee and Radhakrishna (2000) and Odders-White (2000) indicate that the Lee/Ready algorithm is quite accurate for NYSE stocks, suggesting that assignment errors should have minimal impact on the results.

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Table 1 – Cross-sectional summary statistics of time-series averages (1996-2010)

This table reports the cross-sectional (across the 738 S&P500 stocks in the sample) mean, standard deviation, first quartile, median, and third quartile of the time-series average by stock of the daily number of trades (*#trades*), trading volume in US$b. (*dollar volume*), average one-minute mid-quote returns in basis points (*1-min mid-quote return*), percentage annualized volatility of one-minute mid-quote returns (*1-min return volatility*), average difference between the total number of trades initiated by buyers and sellers (order imbalance in number of trades) over one-minute intervals (*1-min oib#*), and the average difference between the total dollar amount of trades initiated by buyers and sellers (order imbalance in US$) over one-minute intervals (*1-min oib$*). The first column indicates the number of stocks over which the summary statistics are computed. The sample includes all 738 NYSE-listed stocks that were part of the S&P500 at any time during 1996-2010. Data to compute all variables in the table are from TRTH.

	#Stocks	Mean	SD	25%	Median	75%
#trades	738	1,651	1,367	667	1,347	2,243
dollar volume	738	0.042	0.051	0.013	0.025	0.049
1-min mid-quote return	738	0.00	0.03	-0.00	0.01	0.02
1-min return volatility	738	30.65	9.61	24.24	28.39	34.60
1-min oib#	738	0.116	0.123	0.043	0.101	0.171
1-min oib$	738	7,523	10,308	1,441	3,943	9,321

Table 2 – Stock-level high-frequency efficiency measures (estimated by stock-day, 1996-2010): Return predictability regressions and cross-sectional summary statistics

Panel A reports the average of the return predictability regression results from Eq. (2) in Appendix A, estimated daily based on intraday data for all 738 S&P500 stocks in the sample. Each column presents the results of a different way to estimate the predictability of one-minute returns from lagged order imbalance (*OIB*) or lagged returns. Section A.1 of Appendix A discusses all five measures in detail. The first number in each column is the average slope coefficient across all stock-day predictability regressions. The *OIB* coefficient has been scaled by 10^9 for the *OIB predictability*, *allquotes*, and *2minutes* regressions and by 10^4 for the *oib#* regressions. The average t-statistics ("t-stat avg") and the cross-sectional t-statistics ("t-stat cross") are in parentheses below the coefficients. "% positive" is the percentage of positive coefficients, and "% + significant" is the percentage with t-statistics greater than 1.645 (the 5% critical level in a one-tailed test). Intercepts have been suppressed to conserve space. The last three rows of Panel A report the average R^2 and adjusted R^2 across all stock-day regressions and the number of stock-day predictability regressions estimated across all stocks.

Panel B reports the cross-sectional mean, standard deviation, first quartile, median, and third quartile of the time-series average by stock of three daily stock-level high-frequency efficiency measures: *OIB predictability*, *Hasbrouck*, and *put-call parity*. *OIB predictability* is from Panel A. *Hasbrouck* is the daily standard deviation of intraday pricing errors extracted from a decomposition of observed prices into efficient prices and a stationary component (Hasbrouck, 1993). For details we refer to section A.2 of Appendix A. The *put-call parity* measure is calculated as the absolute difference between the implied volatilities of a call and a put option of the same series (i.e., pairs of options on the same underlying stock with the same strike price and the same expiration date), averaged across all option pairs for each stock (based on end-of-day quotes from all option series with positive implied volatilities, expiring in two weeks to one year, and with a call delta between 0.3 and 0.7). The first column indicates the number of stocks over which the summary statistics are computed. The sample includes all 738 NYSE-listed stocks that were part of the S&P500 at any time during 1996-2010. Data to compute returns and order imbalances are from TRTH. Data to compute *put-call parity* are from OptionMetrics.

Panel A: Intraday return predictability regressions with dependent variable $Return_t$

Efficiency measure:	*OIB predictability*	*allquotes*	*2minutes*	*oib#*	*autocorrelation*
OIB_{t-1}	2.504	1.158	2.277	0.839	
$Return_{t-1}$					0.021
t-stat avg	(1.340)	(0.689)	(0.839)	(1.984)	(0.316)
t-stat cross	(34.121)	(18.403)	(33.877)	(740.091)	(225.112)
% positive	83.04	70.32	73.77	89.46	57.02
% + significant	48.84	30.07	35.07	64.75	28.70
R^2	2.31	1.30	2.25	3.37	1.59
adj. R^2	1.54	0.52	1.32	2.60	0.76
# regressions (stock-days)	1,804,304	1,804,401	1,846,814	1,801,188	1,727,449

Panel B: Cross-sectional summary statistics of time-series average high-frequency efficiency measures

	#Stocks	Mean	SD	25%	Median	75%
OIB predictability	738	2.74	1.51	1.87	2.25	3.00
Hasbrouck	738	1.31	0.64	0.88	1.16	1.61
put-call parity	695	1.68	0.89	1.10	1.45	2.03

Table 3 – Regressions of daily changes in individual stock efficiency on changes in market efficiency (estimated by stock over the full sample period 1996-2010)

This table reports the average of the co-movement regression results from Eq. (1) estimated for all 738 S&P500 stocks over the full sample period 1996-2010. The dependent variable $\Delta Eff_{i,d}$ is the change in the efficiency of stock i on day d. The independent variable $\Delta MktEff_d$ is the change in market-wide efficiency on day d, computed as the equally-weighted average efficiency of all individual stocks on day d, excluding stock i. Each co-movement regression also includes a one-day lead and lag of changes in market-wide efficiency. Each of the three columns in the table presents the results of the co-movement regressions based on a different high-frequency efficiency measure. In the first column (*OIB predictability*), $Eff_{i,d}$ is measured by the R^2 of the daily predictability regressions in Eq. (1) estimated for stock i on day d (as reported in Panel A of Table 2). In the second column (*Hasbrouck*), $Eff_{i,d}$ is measured by the daily standard deviation of the intraday pricing errors by stock (Hasbrouck, 1993). In the final column (*put-call parity*), $Eff_{i,d}$ is measured by the absolute difference in implied volatility between put and call options of the same series by stock-day. We refer to Table 2 and Appendix A for a description of these efficiency measures. Each column presents the average slope coefficients across the co-movement regressions estimated by stock. The average t-statistics ("t-stat avg") and the cross-sectional t-statistics ("t-stat cross") are in parentheses below the coefficients. "% positive" is the percentage of positive coefficients, and "% + significant" is the percentage with t-statistics greater than 1.645 (the 5% critical level in a one-tailed test). Intercepts have been suppressed to conserve space. The last three rows of the table report the average R^2 and adjusted R^2 across all co-movement regressions and the number of regressions. The sample includes all 738 NYSE-listed stocks that were part of the S&P500 at any time during 1996-2010. Data to compute the *OIB predictability* and *Hasbrouck* measures are from TRTH. Data to compute *put-call parity* are from OptionMetrics.

	Dependent variable: $\Delta Eff_{i,d}$		
Efficiency measure:	*OIB predictability*	*Hasbrouck*	*put-call parity*
$\Delta MktEff_d$	0.766	0.888	0.915
t-stat avg	(1.748)	(10.939)	(7.596)
t-stat cross	(21.311)	(80.109)	(30.272)
% positive	89.43	99.59	97.41
% + significant	53.52	95.53	88.63
$\Delta MktEff_{d-1}$	0.062	0.005	0.023
t-stat avg	(0.138)	(0.099)	(0.107)
t-stat cross	(1.959)	(0.709)	(1.409)
% positive	56.10	55.01	45.47
% + significant	6.78	7.99	19.57
$\Delta MktEff_{d+1}$	0.073	0.000	0.019
t-stat avg	(0.119)	(0.072)	(-0.061)
t-stat cross	(2.200)	(0.074)	(1.041)
% positive	52.03	51.08	45.18
% + significant	7.45	9,76	16.26
R^2	0.54	7.52	5.14
adj. R^2	0.27	7.26	4.86
# regressions	738	738	695

Table 4 – Regressions of daily changes in the efficiency of size portfolios on changes in market efficiency (estimated by size portfolio over the full sample period 1996-2010)

This table reports the average of the co-movement regression results from Eq. (1) estimated for four portfolios of the 738 S&P500 stocks in the sample sorted based on their market capitalization at the beginning of the year. The dependent variable $\Delta Eff_{p,d}$ is the change in the efficiency of size portfolio p on day d, which is computed as the equally-weighted average efficiency across the stocks in the portfolio. The independent variable $\Delta MktEff_d$ is the change in market-wide efficiency on day d, computed as the equally-weighted average efficiency of all individual stocks not in the subject portfolio on day d. Each co-movement regression also includes a one-day lead and lag of changes in market-wide efficiency. Each of the four columns in the table presents the slope coefficients in the co-movement regressions for one of the four size quartile portfolios based on each of the three different high-frequency efficiency measures: *OIB predictability*, *Hasbrouck*, and *put-call parity*. We refer to Table 2 and Appendix A for a description of these efficiency measures. The t-statistics ("t-stat") are in parentheses below the coefficients. We note that we do not report cross-sectional t-statistics since we run one regression per size portfolio for each efficiency measure. For each regression, we also report the R^2 and adjusted R^2. The sample includes all 738 NYSE-listed stocks that were part of the S&P500 at any time during 1996-2010. Data to compute the *OIB predictability* and *Hasbrouck* measures are from TRTH. Data to compute *put-call parity* are from OptionMetrics.

Dependent variable: $\Delta Eff_{p,d}$				
Size portfolio:	smallest	2	3	largest
Efficiency measure: *OIB predictability*				
$\Delta MktEff_d$	0.578	0.643	0.542	0.479
t-stat	(22.469)	(25.630)	(21.142)	(15.324)
$\Delta MktEff_{d-1}$	-0.026	0.049	0.027	0.035
t-stat	(-1.140)	(2.186)	(1.172)	(1.251)
$\Delta MktEff_{d+1}$	0.009	0.034	0.032	0.024
t-stat	(0.410)	(1.537)	(1.410)	(0.862)
R^2	19.29	21.84	16.18	8.99
adj. R^2	19.22	21.77	16.11	8.91
Efficiency measure: *Hasbrouck*				
$\Delta MktEff_d$	0.811	0.942	1.021	0.986
t-stat	(72.481)	(117.020)	(101.626)	(75.323)
$\Delta MktEff_{d-1}$	0.039	0.005	-0.013	-0.012
t-stat	(3.885)	(0.660)	(-1.563)	(-1.081)
$\Delta MktEff_{d+1}$	0.047	-0.010	-0.024	-0.016
t-stat	(4.733)	(-1.384)	(-2.599)	(-1.357)
R^2	69.23	85.64	82.74	72.24
adj. R^2	69.21	85.63	82.73	72.22

Table 4, continued

Size portfolio:	smallest	2	3	largest
Efficiency measure: *put-call parity*				
$\Delta MktEff_d$	0.666	0.792	0.844	1.046
t-stat	(40.754)	(67.356)	(64.152)	(42.153)
$\Delta MktEff_{d-1}$	0.099	0.045	-0.003	-0.021
t-stat	(6.578)	(4.115)	(-0.217)	(-0.909)
$\Delta MktEff_{d+1}$	0.108	-0.013	-0.005	0.042
t-stat	(7.149)	(-1.163)	(-0.406)	(1.797)
R^2	34.94	62.75	60.99	39.66
adj. R^2	34.89	62.72	60.96	39.61

Table 5 – Regressions of daily changes in individual stock efficiency on changes in market efficiency (estimated by stock-month, 1996-2010)

This table reports the average of the co-movement regression results from Eq. (1) estimated by stock-month (instead of over the full sample period as in Table 3) for all 738 S&P500 stocks over the sample period 1996-2010. The dependent variable is the change in the efficiency of stock i on day d. The independent variables are the contemporaneous, lead, and lagged changes in market-wide efficiency on day d, computed as the equally-weighted average efficiency of all individual stocks on day d, excluding stock i. Each of the columns in the table presents the results of the co-movement regressions based on each of the three different high-frequency efficiency measures: *OIB predictability*, *Hasbrouck*, and *put-call parity*. We refer to Table 2 and Appendix A for a description of these efficiency measures. Each column presents the average slope coefficients across the co-movement regressions estimated by stock-month. The average t-statistics ("t-stat avg") and the cross-sectional t-statistics ("t-stat cross") are in parentheses below the coefficients. "% positive" is the percentage of positive coefficients, and "% + signif." is the percentage with t-statistics greater than 1.645 (the 5% critical level in a one-tailed test). Intercepts have been suppressed to conserve space. The last three rows of the table report the average R^2 and adjusted R^2 across all stock-month co-movement regressions and the number of stock-month regressions. The sample includes all 738 NYSE-listed stocks that were part of the S&P500 at any time during 1996-2010. Data to compute the *OIB predictability* and *Hasbrouck* measures are from TRTH. Data to compute *put-call parity* are from OptionMetrics.

	Dependent variable: $\Delta Eff_{i,d}$		
Efficiency measure:	*OIB predictability*	*Hasbrouck*	*put-call parity*
$\Delta MktEff_d$	0.724	0.913	0.727
t-stat avg	(0.140)	(0.964)	(0.591)
t-stat cross	(27.436)	(183.598)	(58.961)
% positive	55.70	78.69	66.87
% + significant	6.06	24.68	16.11
$\Delta MktEff_{d-1}$	0.068	0.009	0.037
t-stat avg	(0.012)	(0.004)	(0.016)
t-stat cross	(2.508)	(1.858)	(2.960)
% positive	50.61	50.17	49.91
% + significant	6.90	6.48	7.20
$\Delta MktEff_{d+1}$	0.087	-0.000	0.033
t-stat avg	(0.009)	(0.003)	(0.010)
t-stat cross	(3.306)	(-0.047)	(2.931)
% positive	50.55	50.00	49.52
% + significant	6.70	6.58	7.24
R^2	21.21	26.26	24.58
adj. R^2	6.58	12.55	10.50
# regressions	85,203	85,715	71,959

Table 6 – Summary statistics of monthly market-wide efficiency measures (1996-2010)

This table reports the time-series mean, standard deviation, first quartile, median, and third quartile of seven monthly market-wide efficiency measures: *OIB predictability*, *Hasbrouck*, *put-call parity*, *variance ratio*, *reversal*, *momentum*, and *E/P*. Each of the three high-frequency efficiency measures (*OIB predictability*, *Hasbrouck*, and *put-call parity*) is aggregated from daily stock-level efficiency measures by first averaging across stocks each day, and then averaging across days within the month. We refer to Table 2 and Appendix A for a description of the stock-day efficiency measures. *Variance ratio* is the monthly absolute difference (in %) between one and the scaled ratio of the 30-minute mid-quote return variance to the open-to-close mid-quote return variance. *Reversal* and *momentum* are the average daily returns (in basis points) each month on portfolios that are long losers and short winners over the past month and long winners and short losers over the past twelve months skipping the first month, respectively. *E/P* is the average daily return (in basis points) each month on portfolios that are long (short) stocks with high (low) earnings to price ratios. All seven measures are inverse indicators of the degree of market efficiency. Data to compute the market-wide efficiency measures are from TRTH, OptionMetrics, and the website of Ken French.

	# Obs.	Mean	SD	25%	Median	75%
OIB predictability	180	2.63	2.01	0.93	1.26	4.40
Hasbrouck	180	1.19	0.83	0.52	1.20	2.09
put-call parity	180	1.56	0.68	0.94	1.39	2.03
variance ratio	180	0.31	0.21	0.14	0.29	0.43
reversal	180	8.58	24.74	-2.97	5.82	16.95
momentum	180	2.56	28.58	-7.38	3.25	16.66
E/P	180	2.96	15.95	-5.47	3.14	10.75

Table 7 – Correlations between monthly market-wide efficiency measures (1996-2010)

This table reports Spearman correlation coefficients between seven different monthly market-wide efficiency measures: *OIB predictability*, *Hasbrouck*, *put-call parity*, *variance ratio*, *reversal*, *momentum*, and *E/P*. We refer to Table 6 for a description of these efficiency measures. All seven measures are inverse indicators of the degree of market efficiency. Data to compute the efficiency measures are from TRTH, OptionMetrics, and the website of Ken French. *p*-values are in parentheses (one-tailed test). Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	OIB predictability	*Hasbrouck*	*put-call parity*	*variance ratio*	*reversal*	*momentum*	*E/P*
OIB predictability	1						
Hasbrouck	0.882***	1					
	(0.00)						
put-call parity	0.476***	0.735***	1				
	(0.00)	(0.00)					
variance ratio	0.287***	0.328***	0.157**	1			
	(0.00)	(0.00)	(0.02)				
reversal	0.229***	0.258***	0.198***	0.094	1		
	(0.00)	(0.00)	(0.00)	(0.10)			
momentum	0.098*	0.036	0.046	-0.052	0.016	1	
	(0.09)	(0.32)	(0.27)	(0.76)	(0.42)		
E/P	0.127**	0.113*	0.017	0.142**	0.125**	0.010	1
	(0.05)	(0.07)	(0.41)	(0.03)	(0.05)	(0.44)	

Table 8 – Summary statistics of potential determinants of systematic variation in aggregate market efficiency (1996-2010)

This table reports the time-series mean, standard deviation, first quartile, median, and third quartile of three categories of potential determinants of monthly time-variation in the systematic component of aggregate market efficiency: (i) Funding liquidity: percentage money inflows into hedge funds (*hedge fund flow*), *TED spread* (FRED ID: USD3MTD156N minus TB3MS), the amount of funds held by U.S. depository institutions in their accounts at the Federal Reserve in excess of their required reserve balances and contractual clearing balances (in US$b.) (*reserves*), and monthly returns on the Dow Jones U.S. financial industry index (*bank returns*; RIC: .DJUSFN); (ii) Frictions impeding arbitrage: market-wide proportional quoted spread based on daily stock-level proportional quoted bid-ask spreads ($PQSPR$); (iii) Sources of mispricing: VIX index (VIX), market-wide number of trades (*#trades*) in millions, and the absolute value of the sentiment index from Baker and Wurgler (2006) (*sentiment*).

	# Obs.	Mean	SD	25%	Median	75%
(i) Funding liquidity						
hedge fund flow (%)	180	0.614	1.806	-0.052	0.904	1.629
TED spread (%)	180	0.574	0.440	0.242	0.482	0.722
reserves (US$b.)	180	135.627	328.062	1.267	1.578	1.865
bank returns (%)	180	0.260	5.782	-1.798	0.995	3.414
(ii) Frictions impeding arbitrage						
PQSPR (%)	180	0.233	0.170	0.082	0.174	0.414
(iii) Sources of mispricing (fundamental uncertainty, trading, sentiment)						
VIX (%)	180	22.22	8.38	16.61	20.98	25.48
#trades	180	21.892	19.117	5.121	17.015	33.882
sentiment	180	0.436	0.473	0.119	0.324	0.515

Table 9 – Regressions to explain systematic variation in aggregate market efficiency (1996-2010)

This table presents the results of four time-series regressions to explain monthly time-variation in the systematic component of aggregate market efficiency, defined as the first principal component of the seven monthly aggregate market efficiency measures from Table 6: *OIB predictability*, *Hasbrouck*, *put-call parity*, *variance ratio*, *reversal*, *momentum*, and *E/P*. We refer to Table 6 for a description of these efficiency measures. To get a time-series of the first principal component, we standardize each efficiency measure to have zero mean and unit standard deviation, and multiply the matrix of standardized efficiency measures by the vector of the loadings of each measure on the component. We then detrend the first principal component with linear and quadratic trend terms. The resulting dependent variable in the regressions is an inverse indicator of the degree of market efficiency. The (contemporaneous) independent variables are described in Table 8 and are grouped into three categories: (i) funding liquidity, (ii) frictions impeding arbitrage, and (iii) sources of mispricing. Intercepts have been suppressed to conserve space. Newey-West t-statistics are in parentheses. For each regression, we also report the R^2 and adjusted R^2 and number of monthly time-series observations. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Dependent variable: *first principal component of seven monthly aggregate market efficiency measures*				
(i) Funding liquidity				
hedge fund flow	-0.119**			-0.074*
	(-2.18)			(-1.95)
TED spread	0.291			0.532**
	(0.70)			(2.44)
reserves	0.000*			0.001***
	(1.73)			(4.15)
bank returns	-0.027***			-0.020***
	(-2.68)			(-2.61)
(ii) Frictions impeding arbitrage				
PQSPR		1.676		-1.628
		(0.95)		(-1.22)
(iii) Sources of mispricing (fundamental uncertainty, trading, sentiment)				
VIX			0.066***	0.037***
			(10.91)	(4.72)
#trades			-0.006	-0.022***
			(-1.14)	(-4.77)
sentiment			0.247**	0.376***
			(2.03)	(3.56)
R^2	27.26	4.30	52.59	60.44
adj. R^2	25.59	3.77	51.78	58.59
# Obs.	180	180	180	180

Figure 1 – Monthly time-variation in the systematic component of aggregate market efficiency (1996-2010)

This figure shows monthly time-variation in the systematic component of aggregate market efficiency, defined as the first principal component of the seven monthly aggregate market efficiency measures from Table 6: *OIB predictability*, *Hasbrouck*, *put-call parity*, *variance ratio*, *reversal*, *momentum*, and *E/P*. We refer to Table 6 for a description of these efficiency measures. To get a time-series of the first principal component, we standardize each efficiency measure to have zero mean and unit standard deviation, and multiply the matrix of standardized efficiency measures by the vector of the loadings of each measure on the component. The resulting systematic efficiency component is an inverse indicator of the degree of market efficiency. Data to compute the market-wide efficiency measures are from TRTH, OptionMetrics, and the website of Ken French.