Tumbling Titans? The Changing Patterns of Price Discovery in the U.S. Equity Market

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Abstract

After the implementation of Regulation NMS in 2007, the U.S. equity market became highly fragmented. The traditional exchanges, in particular the New York Stock Exchange (NYSE), lost substantial trading volume to the off-exchange market. We investigate the extent to which this development has been accompanied by a fragmentation of price discovery across established exchanges and off-exchange trading venues. The results of analyzing high frequency data of 91 U.S. stocks over a period of six years show that the contribution of the NYSE to price discovery has sharply declined; as of 2012, it even was overtaken by the Nasdaq. Trading in the off-exchange market also contributes to price discovery with rapidly increasing shares. Using daily estimates, we document a positive link between liquidity and price discovery contributions and offer evidence that liquidity Granger-causes price discovery for NYSE, Nasdaq, and trades reported through trade-reporting facilities.

Keywords: Equity Markets, Price Discovery, Market Fragmentation, Off-Exchange Markets, Liquidity

JEL: G1, G15

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1 Introduction

The U.S. equity markets have undergone substantial modifications in the past decade. Formerly, the trading floor of the New York Stock Exchange (NYSE) buzzed with brokers, who handled the vast majority of the U.S. equity business, while today it struggles to maintain a share in equity trading. In addition to competition from other stock exchanges, such as the Nasdaq, trading activity moved to electronic communication networks (ECNs), dark pools, and internalizing dealers and brokers.

The implementation of Regulation NMS in 2007, intensified this competition and the U.S. equity market structure has become highly fragmented (Buti et al., 2017). The shift of trading volume, away from the primary exchanges and toward alternative trading venues, has raised concerns about the effects of off-exchange trading on market quality. Substantial literature deals with the effects of increasing fragmentation in trading volume on market quality. For example, O'Hara and Ye (2011) examine U.S. stock market data, shortly after the reporting of off-exchanges transactions via a trade reporting facility (TRF) became obligatory, and find that more fragmented stocks have lower transaction costs and faster execution speeds. In addition, they report that higher short-term volatility is associated with greater fragmentation. They conclude that there is no evidence of a harmful effect of fragmentation on market quality. Kwan and McInish (2015) also note that traders circumvent time priority in traditional markets by executing orders in dark pools, resulting in volume migration away from lit markets. For the European market, Degryse et al. (2014) document a similar effect: Fragmentation lowers liquidity in traditional markets, so market quality declines. In particular, investors who only send their orders to lit markets face full pre-trade transparency but declining liquidity.

Previous research has mostly relied on a specific and limited time frame. The aim of this study is to provide a more general view by analyzing several time periods, altogether six years using data on over 90 large-cap constituents of the S&P 500, in order to reveal the role of the traditional exchanges with respect to price discovery and liquidity prior and after the implementation of Regulation NMS. Specifically, we examine contributions to price discovery using high frequency data over a six-year time period spanning 2004-2005, 2007-2008, and 2011-2012. Our main question are a) whether the previously documented decline in market shares of the NYSE and Nasdaq occurred at a specific point in time and can directly be associated with the regulatory changes implemented through Regulation NMS in 2007, b) whether the decline in market share is accompanied by a corresponding decline in contributions to price discovery, and c) whether price discovery leads liquidity or vice versa.

The results show that price discovery in the U.S. equity markets has become fragmented. At the beginning of the last decade the NYSE was the predominant market in terms of both trading volume and price discovery. With the implementation of Regulation NMS in 2007, however, its contribution to price discovery sharply declined and, during 2012, was even overtaken by the Nasdaq. Moreover, trading in off-exchange markets contributes increasingly to price discovery though the informational contribution of off-exchange transactions is not as pronounced as its share in terms of liquidity. This study also relies on panel regressions as well as Granger-causality tests to examine the link between contributions to price discovery and liquidity. We confirm the positive link between liquidity and price discovery for traditional exchanges and we show that liquidity Granger-causes price discovery contributions for more than half of the sample stocks.

The remainder of the paper is structured as follows: Section 2 describes the market structure of the U.S. stock markets. Section 3 contains details on the data and the price discovery measures, and Section 4 presents the empirical results for the estimated price discovery measures as well as the link between price discovery and liquidity. Finally, Section 5 concludes.

2 The Changing Structure of U.S. Equity Markets

U.S. equity markets can be broadly categorized into two groups: markets that are highly transparent to investors and markets, which generally lack transparency in the sense that investors cannot observe information on quotes and liquidity prior to trading. The first group corresponds to traditional established exchanges, such as the NYSE, Nasdaq, and regional exchanges. The second group, also referred to as the off-exchange market, exhibits a more fragmented structure.

Off-exchange business includes transactions that occur in alternative trading systems (ATSs), such as electronic communications networks (ECNs), dark pools, internalized trades, and other over-the-counter transactions. Similar to traditional exchanges ECNs offer pre- and post-trade transparency, but they are subject to different regulation standards, because they do not provide all functions of a primary exchange. In recent years, two of the largest ECNs became operational as exchanges: Direct Edge successfully transitioned to full exchange status in July 2010, followed by the BATS Exchange, or BZX Exchange, which became a U.S. primary listing venue in December 2011.[1] Dark pools are undisplayed liquidity pools that systematically facilitate the execution of orders. These orders are not visible to other market participants and account for approximately 10% of consolidated volume (Preece, 2012). Prior to 2007, these off-exchange markets played a minor role and the majority of transactions were conducted on the primary exchanges.[2] The introduction of Regulation NMS in 2007 prompted the adoption of new rules, including regulations concerning the intermarket trading-through of orders. This new rule implies that trades must be routed to the exchange that displays the best quotes, thereby fostering the competition between different trading venues. However, participating exchanges must meet certain requirements related to transparency and order execution speed. The goal of this regulation

[1] On January 31, 2014, Direct Edge and BATS Global Markets merged operations, placing Direct Edge's EDGX and EDGA exchanges under the BATS Global Markets brand, along with BATS BYX and BZX exchanges.

[2] According to Securities and Commission (2013), prior to the introduction of Reg NMS, the NYSE executed 79% of the volume in its listing.

is to promote fair competition and eliminate the advantage that prior rules gave to slower markets.[3] These regulatory changes affected the structure of the U.S. equity market in different ways. The NYSE implemented a hybrid market in 2007, partly in response to the new regulations. [4] The NYSE increased its automation electronic trading facilities, in order to meet the execution speed requirements demanded by Reg NMS rules (Hendershott and Moulton, 2011). The new reporting standards also required off-exchange transactions to be reported through a TRF. Prior to March 2007, off-exchange volume had to be reported through a registered exchange. Accordingly, it was not possible to distinguish between transactions completed through an exchange and transactions only reported there. After 2007 though, this distinction has been possible, and growing competition among different trading venues and a growing share of off-exchange transactions became obvious.

The increasing dispersion of liquidity across different trading venues and the growing number of orders that were matched and executed in the off-exchange markets prompted discussions about the effect of dark market trading on the overall quality of U.S. stock markets (compare Weaver, 2011; Hatheway et al., 2017; O'Hara and Ye, 2011; Jiang et al., 2012). Overall, evidence about the effect of dark trading on market quality is mixed. The impact of increasing fragmentation of the U.S. equity market on the multiple exchange price discovery process has been studied only rarely, mostly by analyzing periods of a few months only. Since price discovery is one of the main tasks of an exchange, measuring price discovery contributions over time is of great importance for investors, seeking to trade on informationally efficient markets, for exchanges, in particular the traditional markets, which face increasing competition from off-exchange venues, and for regulatory authorities that need to monitor the short and long run impacts of new regulations.

[3] For details on Regulation NMS, see Securities and Exchange Commission (2005).

[4] See Hendershott and Moulton (2011) for a comprehensive analysis concerning the effects of the implementation of NYSE's hybrid market structure on market quality.

3 Measuring Contributions to Price Discovery

We use the two standard methods to quantify price discovery contributions, the Gonzalo-Granger (GG) measure based on ideas in Gonzalo and Granger (1995) and the information shares (HIS) proposed by Hasbrouck (1995).[5] Both approaches have their merits and drawbacks. Consistent with theoretical considerations, the approach by Hasbrouck (1995) explicitly models the efficient price as a martingale, however, it only delivers upper and lower bounds of a market's contribution to price discovery. These bounds diverge with increasing contemporaneous correlation between different market prices.

In contrast, the Gonzalo-Granger measure is unique, but has to face critique based on the fact that the common factor, interpreted as the underlying efficient price, is not explicitly assumed to follow a martingale. We use both measures, however, for the latest period (2011-2012) mainly analyze the Gonzalo-Granger measure, because the increased trading intensity on all markets lead to such wide Hasbrouck-information share bounds that a precise assessment of each market's price discovery contribution is impossible. The Gonzalo-Granger measure has previously been applied only to the two-markets case. We present a generalization the n-markets case in the Appendix.

3.1 Hasbrouck (1995) Information Shares

Estimates of both price discovery measures, the Hasbrouck-Information Shares and the Gonzalo-Granger measure, rely on a vector equilibrium correction representation of price changes in n markets (Δp_t):

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{j=1}^{k} \Gamma_j \Delta p_{t-j} + \varepsilon_t \tag{1}$$

[5] For a comprehensive discussion and comparison of both measures we refer the interested reader to a special issue on price discovery by the Journal of Financial Markets, Volume 5, Issue 3, 259-390.

with a $(n \times n-1)$ cointegrating matrix β, $(n \times n-1)$ adjustment coefficient matrix α, $(n \times n)$ autoregressive parameter matrices Γ_j, and the $(n \times 1)$ vector of price innovations ε_t. These innovations have a zero mean and are serially uncorrelated ($\mathbb{E}[\varepsilon_t \varepsilon_s'] = 0 \ \forall s \neq t$), but are possibly contemporaneously correlated ($\mathbb{E}[\varepsilon_t \varepsilon_t] = \Sigma_\varepsilon$, with positive definite covariance matrix Σ_ε).

The space of cointegration vectors features the rows

$$\beta' = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ 1 & 0 & -1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \dots & -1 \end{bmatrix}.$$

This form of the cointegration matrix implies one stochastic trend common to all price series, which according to Hasbrouck (1995), reveals the underlying efficient price and which follows a random walk,

$$m_t = m_{t-1} + u_t, \qquad \mathbb{E}[u_t] = \mathbb{E}[u_t u_s] = 0 \ \forall s \neq t, \qquad \mathbb{E}[u_t^2] = \sigma_u^2 < \infty. \tag{2}$$

The determination of price discovery in Hasbrouck (1995) follows from the decomposition of the variance of the efficient price innovation u_t in Equation (2) into components that are attributable to the n different markets. The variance of the efficient price innovations is given by

$$\sigma_u^2 = \psi' \Sigma_\varepsilon \psi = \psi' B B' \psi, \tag{3}$$

where ψ denotes the vector of long-run impact coefficients of price innovations. ψ' is given by the identical rows of

$$\Xi = \beta_\perp [\alpha_\perp' (I_n - \sum_{i=1}^{q-1} \Gamma_i) \beta_\perp]^{-1} \alpha_\perp', \tag{4}$$

where $a_\perp$ describes the orthogonal complement of a (Johansen, 1995). The matrix B contains the contemporaneous effects of innovations. To achieve identification, B is replaced by the matrix C derived from the Cholesky decomposition of Σ_ε, the covariance matrix of correlated innovations (ε). The Hasbrouck-information share of market i follows as

$$IS_i = \frac{([\psi' C]_i)^2}{\psi' C C' \psi}, \tag{5}$$

where i denotes the i'th element of the row vector $[\psi' C]$. The Cholesky decomposition of the covariance matrix of Σ_ε implies that the first market's information share is maximised as it is not contemporaneously affected by other market's price innovations. Analogously the information share of the market ordered last is minimized. Permuting the ordering of the variables results in upper and lower information share bounds. The bounds diverge depending on the contemporaneous correlation between the VECM residuals in Equation (1).

3.2 Gonzalo and Granger Measure

Based on Gonzalo and Granger (1995) contribution to price discovery are measured as the weight of each market price innovations in the increment of a common, permanent factor. Following Lehmann (2002), we define the price series as

$$p_t = \iota w' p_t + \delta z_t, \tag{6}$$

where $w' p_t$ refers to the price of a weighted portfolio of the same security from different markets. The weights $w = (w_1 \dots w_n)'$ are normalized to sum to 1. ι equals the unity vector. $z_t = \beta' p_t$ refers to the stationary error correction terms with cointegration matrix β as defined in Equation (1). δ measures the transitory effects and relates to the portfolio weights w by:

$$\iota w' + \delta \beta' = I_n. \tag{7}$$

This representation belongs to the general class of permanent-transitory decompositions for which the permanent component or common factor is $I(1)$, but not necessarily a random walk. Replacing p_t with structural model, $p_t = \imath f_t + s_t$, where s_t denotes the stationary component and f_t is the nonstationary common component, it can be shown that the portfolio weights w and the weights of the stationary component are directly related. Gonzalo and Granger (1995) identify a special parameterization according to the additional prerequisite that the transitory component z_t does not Granger-cause the common factor f_t, which implies

$$\lim_{\tau \to \infty} \frac{\partial \mathbb{E}[f_{t+\tau}|I_t]}{\partial z_t} = 0.$$

This assumption establishes the link between the Gonzalo-Granger weights and the adjustment coefficients in Equation (1) as

$$w = \alpha_{\perp},$$

which states that w is orthogonal to all $n-1$ vectors of adjustment coefficients in α and its length is normalized such that its coefficients sum to 1. The resulting price discovery measure of market i is then given by

$$GG_i = \frac{w_i}{\sum_{j=1}^{n} w_j}. \tag{8}$$

A detailed derivation of this result is given in the Appendix.

4 Empirical Results

4.1 Data

We analyze transaction data of 91 stocks, which have continuously been traded on NYSE, Nasdaq, and at least one more exchange during the years under consideration, which are 2004-2005, 2007-2008, and 2011-2012. These three periods each are associated with a different regulatory environment and representable for the changing landscape of the U.S. equity markets. The years 2004 and 2005 represent the pre-Reg NMS period, 2007 and 2008 cover the time of regulatory changes brought about by Reg NMS as well as venue specific changes, such as the transformation of the NYSE to a hybrid market, while 2011 and 2012 are the basis to examine the post Reg NMS period. The sample stocks are selected by choosing the 150 largest (in terms of market capitalization) companies of the S&P 500 index, as of January 1st, 2004. Due to the restriction that the stocks have to be traded on several markets between 2004 and 2012, the sample was reduced to 91 stocks.

We use transaction prices from the NYSE Trades and Quotes (TAQ) database. We focus on transaction prices rather than quotes, as quotes for off-exchange markets are not available, while transactions are reported via TRFs from 2007 onwards. Since our main interest is to analyze the changes in the role of the two large traditional markets, NYSE and Nasdaq, we mainly consider three price series: NYSE transaction prices, Nasdaq transaction prices, and transaction prices on all the remaining exchanges as the third series. Transactions are recorded every second. In order to use the full set of available information, we keep all recorded prices in one market, and retain the last observed price in another market, if necessary, to align prices across markets. If an exchange records several transactions with the same time stamp, we use the average price. Table A.1 in the Appendix lists the included companies.

4.2 Market Shares

Table 1 shows market shares of the different exchanges in terms of both the number of transactions (upper panel) and total trading volume (lower panel). In the first three years under consideration, the NYSE dominates in both measures, even though its share appears to decline. As of 2007, Nasdaq's share (in terms of transactions) had risen to almost one-third of the overall market. At the same time, the market share of the other markets grew from 12% in 2005 to 32% in 2007, while the NYSE's share fell from 76% to 38%.

Insert Table 1 here

Two important regulatory changes drive this reallocation of market shares. First, some of the jumps in market shares are attributable to revised reporting standards. After March 5, 2007, off-exchange transactions had to be reported through reporting facilities of the FINRA, which are affiliated with a registered securities exchanges and provide a mechanism for the reporting of transactions, that have been completed in the off-exchange market (i.e., through ECNs, dark pools or internalization). Currently, there are two active TRFs, the FINRA/Nasdaq and the FINRA/NYSE. Prior to March 2007, off-exchange volume had to be reported through a registered exchange, which made it impossible to distinguish between transactions completed through an exchange and those only reported by the exchange. Second, in late 2006, the Securities and Exchange Commission (SEC) implemented Regulation National Market System (Reg NMS), which had far-reaching consequences. This regulation contains a bundle of comprehensive and substantive rules, designed to "modernize and strengthen the regulatory structure of the U.S. equity markets" (Securities and Exchange Commission, 2005). A key provision was its Order Protection Rule, which provides price protection to top-of-the-book orders across all electronically linked exchanges of the NMS. Orders on all exchanges are displayed in a common electronic book (i.e., consolidated tape, and each exchange is obliged to route its orders to the exchange with the best price, which helps prevent "trade throughs". These rules foster significant competition to attract the most order flow among exchanges, and they were designed to strengthen the position of regional exchanges and alternative trading venues relative to formerly dominant platforms, that is, the NYSE and Nasdaq. To offer order protection under Reg. NMS, exchanges must achieve status as a fast electronic market, which was the major motivation for NYSE to introduce its hybrid market in late 2006, thus customers could choose between traditional floor trading and automatic electronic order execution. Subsequently, the share of transactions executed through the NYSE decreased considerably.

In 2008, the NYSE's market share fell even lower, while Nasdaq's remained constant and the share accounted for by other markets is rising. In 2011 and 2012, trading activity on NYSE and Nasdaq was considerably lower than the other exchanges, which accounted for almost two-thirds of all transactions. Among these transactions, off-exchange trades reported through TRFs account for the largest part followed by the former ECNs (BATS and Direct Edge) and NYSE Arca. Regional exchanges process approximately 4% of all transactions. Measuring market share in terms of total volume, the NYSE share is much larger than that relative to the number of transactions. For the Nasdaq and the other trading venues, the opposite is true. Thus, on the NYSE, larger but fewer transactions tend to be executed, whereas on other markets, transactions appear to be executed more frequently but with a smaller volume. Caglio and Mayhew (2012) argue that exchanges might divide large orders into several small orders on purpose to gain more tape revenue.

4.3 Price Discovery in U.S. Equity Markets

Table 2 contains the sample averages of the estimated Hasbrouck-Information Shares and Gonzalo-Granger measures.[6] In 2004 and 2005, the NYSE accounted for the majority of price discovery, according to both measures. Similar to the decline of the NYSE's market share in these years, its informational contribution slightly diminished, though it retained

[6] Detailed results are given in Appendix B, Tables A1 and A2

the dominant role. Even though the Nasdaq gained some importance in 2007, the shift in trading activity was not accompanied by a similarly sized shift in informational contributions. The plots of the kernel densities of the bootstrapped Gonzalo-Granger measure (Figure 1) and Hasbrouck-Information Shares (Figure 2) offer similar results. Furthermore, the overlapping distributions of the lower bound, midpoint, and upper bound of Hasbrouck-Information Shares indicate that the measure is very precise in this period.

Insert Table 2 here

Contrary to what we might expect from the jump in market shares, the informational contribution of the other markets did not rise considerably. Instead, Nasdaq's Gonzalo-Granger measure increased to 31 %, and the NYSE experienced further reduction in its informational contributions. This trend continued in 2008, when the NYSE, accounting for roughly one third, relinquished informational leadership to the Nasdaq. In 2011 and 2012 price discovery seemed almost evenly distributed among NYSE, Nasdaq and the other group.

Insert Figures 1 and 2 here

For insights into the changes in 2007-2008, we estimated price discovery measures on a monthly basis. Figure 3 shows the results for 2007, revealing the change in February 2007, which broadly corresponds to the moment when the reporting standards for off-exchange transactions were revised. In particular, for the Nasdaq, off-exchange volume could be separated from actual Nasdaq transactions. From that date on, Nasdaq contributed increasingly to price discovery, while other markets kept lagging farther behind. Obviously, it is not sheer transaction volume that drives price discovery. This finding is consistent with the idea that much of the off-exchange volume consists of internalized trades, such as broker/dealers execute orders against their own books instead of routing them to an exchange, dark pools, or other ECNs with mostly uninformed liquidity traders (see Weaver, 2011 Jiang et al., 2012). This result is in line with the finding in Comerton-Forde and Putnins (2015) that the contribution of dark and block trading to price discovery increases less than proportionally to their volume share, such that dark trades contain less private information than lit trades on average.

Insert Figure 3 here

Both the Gonzalo-Granger measure and Hasbrouck-Information Shares provide evidence that the Nasdaq is taking a leading role in price discovery in the second quarter of 2008, which it maintained until the end of 2008. The other markets also were growing more important; by the end of 2008, according to the Gonzalo-Granger measure, they overtook the NYSE in terms of price discovery.

For the 2011-2012 period, it is interesting to investigate these other markets in detail, in order to figure out the main competitors of the traditional markets. In particular we are interested in the role of the ECNs, BATS and Direct Edge, which shortly prior (Direct Edge) and during (BATS) this period acquired exchange status.

Concerning TRFs, we expect a minor contribution to price discovery, due to their large share of internalized transactions, as Jiang et al. (2012) indicate with 2008 TAQ data. We thus divide the observations from other exchanges into three groups: transactions in the newly established exchanges Direct Edge and BATS, transactions reported through TRF, and the remaining regional exchanges. With increasing trading frequency in 2011-2012 the contemporaneous correlation between prices across the different trading venues increased, leading to the diverging bounds of the Hasbrouck-Information Shares in Table 2. Thus the midpoint becomes a rather inaccurate measure of contribution to price discovery. In the following analysis, we therefore focus on the Gonzalo-Granger measure.

Insert Figure 4 here

The results in Figure 4 show that BATS/Direct Edge contribute most to price discovery. Together these two exchanges account for almost half of the price discovery. The contribution of TRF transactions is rather low, at about 20 % during 2011 and 2012. The informational quality of TRF transactions thus is not as great as previously predicted, perhaps because transactions taking place on BATS and Direct Edge prior to 2008 that were reported through a TRF increased the contribution of TRF transactions to price discovery. However, because BATS and Direct Edge acquired exchange status shortly thereafter, these transactions can more adequately be described as originating from lit markets. The analysis of 2011 and 2012 data shows that the contribution of the off-exchange market to price discovery is rather small, after we account for Direct Edge and BATS transactions.

4.4 Liquidity, Trading Characteristics, and Price Discovery

The link between liquidity and contributions to price discovery has been subject to previous research, most of which relies on cross-sectional analyses and reveal a positive relationship. For example, Frijns et al. (2015) and Eun and Sabherwal (2003), both study cross-listed Canadian U.S. stocks and report a positive impact of trading volume and trading activity on their price discovery measure of a market. Theissen (2002) confirms the link for different trading platforms by examining both electronic and floor trading of German stocks and uncovering a positive relation between information shares and market shares.

To complement these studies, we adopt a panel approach as well as Granger-causality tests and thereby analyze the impact of liquidity on price discovery for the case of different trading venues within one country. We use daily Gonzalo-Granger measures for the sample stocks for the years 2011 and 2012, during which period no major regulatory changes or potential structural breaks occurred. We run separate regressions using the Gonzalo-Granger measure of the NYSE, Nasdaq, and other markets (all remaining trading venues). To measure liquidity, we use the relative trading frequency, that is the number of transactions on a trading venue relative to overall number of trades in this stock. As an alternative measure, we use relative volume, which denotes the trading volume of a specific stock on a specific venue, relative to the cumulated volume of this specific stock across all trading venues. To account for further trading characteristics that might impact price discovery, we also include the percentage of intermarket sweep orders (ISO) on each market, relative to regular trades. These ISOs are limit orders that get executed automatically on an exchange even if another offers a better quote. To comply with order protection rules, the submission of an ISO requires concurrently submitting orders to the markets with better prices. The inclusion of this variable is motivated by Chakravarty et al. (2012), who reveal that ISO trades are mostly used by institutional traders and are considered more informative than regular trades. Finally, we include the daily standard deviation of each market's returns as a measure of market center-specific volatility.

Table 3 contains results for stock-specific fixed-effects panel regressions of NYSE (column 1),and Nasdaq (column 2) Gonzalo-Granger measures as well as those of all remaining trades (column 3). In all three panels, we observe a significant positive effect of relative trading frequency on a market's price discovery contribution. Relative trading volume also shows a significant positive effect for the NYSE, but for the other markets, we observe insignificant parameters, probably due to the high correlation.[7] For the traditional exchanges, increases in the relative trading frequency on the other market decrease the price discovery contributions of their own trades. Thus price discovery takes place where liquidity is higher – at least in the comparison of the two largest traditional exchanges.

Regarding the percentage of ISOs, Table 3 shows a positive effect of Nasdaq ISOs on the Nasdaq and NYSE price discovery contributions, but relative ISOs in the remaining markets relate negatively to NYSE and Nasdaq price discovery contributions. This finding implies that ISOs originating on the Nasdaq have a special role, especially when we note

[7]Omitting relative trading frequency leads to significant positive estimates for relative trading volume for all three markets.

that the NYSE ISOs have no significant impact on either their own or the other markets.

Insert Table 3 here

Higher volatility of own market returns implies decreasing price discovery contributions in all three markets. Consistent with previous studies, high volatility increases opportunity costs, so informed investors draw away from a market with such levels of volatility, which in turn decreases its contributions to price discovery (Jiang et al., 2012). The NYSE Gonzalo-Granger measures also decrease with higher Nasdaq return volatility, whereas the other markets' volatility increases the NYSE price discovery consistent with the idea that higher volatility drives informed investors away from that particular trading venue. The Nasdaq information shares are less dependent on NYSE trading characteristics. Neither NYSE return volatility nor the percentage of NYSE ISOs significantly affects Nasdaq price discovery. Consequently, with respect to its largest competitor, relative liquidity that matters mostly for the Nasdaq. The third category incorporates all remaining trades and exhibits patterns consistent with the idea that relative liquidity increases and market return volatility decreases contributions to price discovery.

The question of whether liquidity predicts price discovery, or vice versa, is still unanswered, therefore we use our time series of daily information shares and liquidity measures to conduct Granger-causality tests based on a vector autoregressive model, including five lags as selected by the Schwartz information criterion. Table 4 summarizes the results, detailing the number of companies for which Granger-causality is detected, that is, for which the null hypothesis of no Granger-causality is rejected at a 5% significance level. Liquidity is measured by the relative volume traded (relative trading intensity produces qualitatively similar results).

Insert Table 4 here

We find that liquidity causes price discovery more often than vice versa when transactions are partitioned into NYSE, Nasdaq, and other trades. For the NYSE and Nasdaq, liquidity causes price discovery for more than half of the sample stocks. At the same time, we reject the null hypothesis of Granger-causality between a market's contribution to price discovery and liquidity for only a small proportion of the companies.

5 Conclusion

During the past decade, the landscape of the U.S. equity market has changed substantially. Whereas formerly the greatest amount of trading took place on traditional exchanges, the emergence of numerous trading platforms created a highly fragmented market today in terms of trading volume. The rules implied by Reg NMS favor fast electronic trading platforms, which rapidly increased the shares of such platforms in trading. An important question thus revolves around whether the migration of trading volume, away from the traditional exchanges and towards the off-exchange market, has been accompanied by a shifting role for those markets in the price discovery process. We examine price discovery in the U.S. equity market for the pre- and post-Reg MNS period, using a large set of high frequency stock data. The results show that the NYSE has lost its dominance in the price discovery process to Nasdaq and the off-exchange markets. Regarding developments during 2011 and 2012, our findings reveal that the former ECNs, BATS and Direct Edge have become the main competitors of the traditional exchanges with respect to price discovery. The landscape of the U.S. equity market also appears subject to ongoing changes, such that it requires further monitoring and studies of the informational linkages across different markets and trading venues. We confirm a positive link between liquidity and contributions to price discovery for the NYSE, Nasdaq. The Granger-causality test results also indicate that liquidity causes price discovery for the majority of our sample stocks, emphasizing the fundamental need for stock exchanges, and particularly, the NYSE, to offer an attractive trading environment and maintain their market share.

Appendix

Gonzalo and Granger shares for the n market case

Based on Gonzalo and Granger (1995) contribution to price discovery are measured as the weight of each market price innovations in the increment of a common, permanent factor. The relation between these weights and the adjustment coefficients within the VECM given in Equation 1 previously has only been derived for the two-market case. In the following we show the derivation for the n-market case. Following Lehmann (2002), we define the price series as

$$p_t = \iota w' p_t + \delta z_t, \tag{9}$$

where $w'p_t$ refers to the price of a weighted portfolio of the same security from different markets, where the weights $w = (w_1 \dots w_n)'$ are normalized to sum to 1. ι equals the unity vector. $z_t = \beta' p_t$ refers to the stationary error correction terms with cointegration matrix β as defined in Equation 1. δ measures the transitory effects and relates to the portfolio weights w by:

$$\imath w' + \delta\beta' = I_n. \tag{10}$$

This representation belongs to the general class of permanent-transitory decompositions for which the permanent component or common factor is $I(1)$, but not necessarily a random walk. To clarify the dimensions, we write Equation 9 in matrix form and replace $z_t = \beta' p_t$, which then reads as

$$\begin{bmatrix} p_{1t} \\ p_{2t} \\ \vdots \\ p_{nt} \end{bmatrix} = \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} [w_1 \ w_2 \ \dots \ w_n] \begin{bmatrix} p_{1t} \\ p_{2t} \\ \vdots \\ p_{nt} \end{bmatrix} + \begin{bmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n-1} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} & \delta_{n2} & \dots & \delta_{n\ n-1} \end{bmatrix} \begin{bmatrix} 1 & -1 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & -1 \end{bmatrix} \begin{bmatrix} p_{1t} \\ p_{2t} \\ \vdots \\ p_{nt} \end{bmatrix}.$$

Replacing p_t with structural model, $p_t = \imath f_t + s_t$, where s_t denotes the stationary component and f_t is the nonstationary common component, it becomes

$$
\begin{aligned}
\begin{bmatrix} p_{1t} \\ p_{2t} \\ \vdots \\ p_{nt} \end{bmatrix}
&= \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} w' \left(\begin{bmatrix} f_t \\ f_t \\ \vdots \\ f_t \end{bmatrix} + \begin{bmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{bmatrix} \right) + \begin{bmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n-1} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} & \delta_{n2} & \dots & \delta_{n\ n-1} \end{bmatrix} \begin{bmatrix} 1 & -1 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & -1 \end{bmatrix} \left(\begin{bmatrix} f_t \\ f_t \\ \vdots \\ f_t \end{bmatrix} + \begin{bmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{bmatrix} \right) \\
&= \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} f_t + \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} w' \begin{bmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{bmatrix} + \begin{bmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n-1} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} & \delta_{n2} & \dots & \delta_{n\ n-1} \end{bmatrix} \begin{bmatrix} 1 & -1 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & -1 \end{bmatrix} \begin{bmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{bmatrix} \\
&= \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} f_t + \left\{ \begin{bmatrix} \iota_1 \\ \iota_2 \\ \vdots \\ \iota_n \end{bmatrix} [w_1\ w_2\ \dots\ w_n] + \begin{bmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n-1} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} & \delta_{n2} & \dots & \delta_{n\ n-1} \end{bmatrix} \begin{bmatrix} 1 & -1 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & -1 \end{bmatrix} \right\} \begin{bmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{bmatrix}.
\end{aligned}
$$

Terms in braces are the unity matrix as outlined in Equation 10. Thus, the portfolio weights w and the weights of the stationary component are directly related:

$$
\begin{bmatrix} \delta_{11} + \delta_{12} + \ldots + \delta_{1n-1} & -\delta_{11} & \dots & -\delta_{1n-1} \\ \delta_{21} + \delta_{22} + \ldots + \delta_{2n-1} & -\delta_{21} & \dots & -\delta_{2n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} + \delta_{n2} + \ldots + \delta_{nn-1} & -\delta_{n1} & \dots & -\delta_{nn-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} - \begin{bmatrix} w_1 & w_2 & \dots & w_n \\ w_1 & w_2 & \dots & w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_1 & w_2 & \dots & w_n \end{bmatrix}.
$$

Gonzalo and Granger (1995) identify a special parameterization according to the additional prerequisite that the transitory component z_t does not Granger-cause the common factor f_t, which implies

$$\lim_{\tau \to \infty} \frac{\partial \mathbb{E}[f_{t+\tau}|I_t]}{\partial z_t} = 0,$$

and establishes the link between the Gonzalo-Granger weights and the adjustment coefficients in Equation (1) as follows: starting from

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{j=1}^{k} \Gamma_j \Delta p_{t-j} + \varepsilon_t = \alpha z_{t-1} + \Gamma(L)\Delta p_{t-1} + \varepsilon_t,$$

we develop a VECM representation for $\Delta f_t = w'\Delta p_t$ and $\Delta z_t = \beta'\Delta p_t$ given by

$$\underset{n\times 1}{\begin{bmatrix} \underset{1\times 1}{\Delta f_t} \\ \underset{n-1\times 1}{\Delta z_t} \end{bmatrix}} = \underset{n\times n}{\Pi}\,\underset{n\times 1}{\Delta p_t} = \begin{bmatrix} w' \\ \beta' \end{bmatrix} \begin{bmatrix} \Delta p_{1t} \\ \Delta p_{2t} \\ \vdots \\ \Delta p_{nt} \end{bmatrix} = \begin{bmatrix} w_1 & w_2 & \dots & w_n \\ 1 & -1 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & -1 \end{bmatrix} \begin{bmatrix} \Delta p_{1t} \\ \Delta p_{2t} \\ \vdots \\ \Delta p_{nt} \end{bmatrix}$$

$$= \Pi[\alpha z_{t-1} + \Gamma(L)\Delta p_{t-1} + \varepsilon_t]$$

$$= \alpha^{\Pi} z_{t-1} + \Gamma^{\Pi}(L) \begin{bmatrix} \Delta f_{t-1} \\ \Delta z_{t-1} \end{bmatrix} + \varepsilon_t^{\Pi}$$

where $$\alpha^{\Pi} = \Pi\alpha = \begin{bmatrix} w'\alpha^1 & w'\alpha^2 & \dots & w'\alpha^{n-1} \\ \alpha_1^1 - \alpha_2^1 & \alpha_1^2 - \alpha_2^2 & \dots & \alpha_1^{n-1} - \alpha_2^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_1^1 - \alpha_n^1 & \alpha_1^2 - \alpha_n^2 & \dots & \alpha_1^{n-1} - \alpha_n^{n-1} \end{bmatrix} = \begin{bmatrix} \underset{1\times n-1}{\alpha_f} \\ \underset{n-1\times n-1}{\alpha_z} \end{bmatrix},$$

$$\Gamma^{\Pi}(L) = \Pi\Gamma(L)\Pi^{-1} \left(\text{since } \Pi\Gamma(L)\Delta p_t = \Pi\Gamma(L)\Pi^{-1}\Pi\Delta p_t = \Pi\Gamma(L)\Pi^{-1} \begin{bmatrix} \Delta f_t \\ \Delta z_t \end{bmatrix} \right),$$

$$\varepsilon_t^{\Pi} = \begin{bmatrix} w'\varepsilon_t \\ \varepsilon_{1t} - \varepsilon_{2t} \\ \vdots \\ \varepsilon_{1t} - \varepsilon_{nt} \end{bmatrix} = \begin{bmatrix} \underset{1\times 1}{\varepsilon_{ft}^{\Pi}} \\ \underset{n-1\times 1}{\varepsilon_{zt}^{\Pi}} \end{bmatrix}$$

and where α_i^j denotes the coefficient of the i'th price series in the j'th cointegrating relation (i.e., the (i,j)-element of α). To eliminate the first difference Δz_t, we write

$$
\begin{aligned}
\begin{bmatrix} \Delta f_t \\ z_t \end{bmatrix} &= \begin{bmatrix} 0 & 0 & \dots & 0 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} z_{t-1} + \alpha^{\Pi} z_{t-1} + \Gamma^{\Pi}(L) \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & (1-L) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (1-L) \end{bmatrix} \begin{bmatrix} \Delta f_{t-1} \\ z_{t-1} \end{bmatrix} + \varepsilon_t^{\Pi} \\
&= \begin{bmatrix} 0 & w'\alpha^1 & w'\alpha^2 & \dots & w'\alpha^{n-1} \\ 0 & 1+\alpha_1^1-\alpha_2^1 & \alpha_1^2-\alpha_2^2 & \dots & \alpha_1^{n-1}-\alpha_2^{n-1} \\ 0 & \alpha_1^1-\alpha_3^1 & 1+\alpha_1^2-\alpha_3^2 & \dots & \alpha_1^{n-1}-\alpha_3^{n-1} \\ \vdots & \vdots & \ddots & \vdots & \\ 0 & \alpha_1^1-\alpha_n^1 & \alpha_1^2-\alpha_n^2 & \dots & 1+\alpha_1^{n-1}-\alpha_n^{n-1} \end{bmatrix} \begin{bmatrix} \Delta f_{t-1} \\ z_{t-1} \end{bmatrix} + \\
&\quad \begin{bmatrix} \Gamma_{11}^{\Pi}(L) & \Gamma_{12}^{\Pi}(L)(1-L) & \dots & \Gamma_{1n}^{\Pi}(L)(1-L) \\ \Gamma_{21}^{\Pi}(L) & \Gamma_{22}^{\Pi}(L)(1-L) & \dots & \Gamma_{2n}^{\Pi}(L)(1-L) \\ \vdots & \vdots & \ddots & \vdots \\ \Gamma_{n1}^{\Pi}(L) & \Gamma_{n2}^{\Pi}(L)(1-L) & \dots & \Gamma_{nn}^{\Pi}(L)(1-L) \end{bmatrix} \begin{bmatrix} \Delta f_{t-1} \\ z_{t-1} \end{bmatrix} + \varepsilon_t^{\Pi} \\
&= \begin{bmatrix} \Gamma_{11}^{\Pi}(L) & w'\alpha^1+\Gamma_{12}^{\Pi}(L)(1-L) & \dots & w'\alpha^{n-1}+\Gamma_{1n}^{\Pi}(L)(1-L) \\ \Gamma_{21}^{\Pi}(L) & 1+\alpha_1^1-\alpha_2^1+\Gamma_{22}^{\Pi}(L)(1-L) & \dots & \alpha_1^{n-1}-\alpha_2^{n-1}+\Gamma_{2n}^{\Pi}(L)(1-L) \\ \vdots & \vdots & \ddots & \vdots \\ \Gamma_{n1}^{\Pi}(L) & \alpha_1^1-\alpha_n^1+\Gamma_{n2}^{\Pi}(L)(1-L) & \dots & 1+\alpha_1^{n-1}-\alpha_n^{n-1}+\Gamma_{nn}^{\Pi}(L)(1-L) \end{bmatrix} \begin{bmatrix} L & 0 & \dots & 0 \\ 0 & L & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & L \end{bmatrix} \\
&\quad \begin{bmatrix} \Delta f_t \\ z_t \end{bmatrix} + \varepsilon_t^{\Pi}
\end{aligned}
$$

such that

$$
\begin{aligned}
\varepsilon_t^{\Pi} &= B^{\Pi}(L) \begin{bmatrix} \Delta f_t \\ z_t \end{bmatrix} \\
&= \begin{bmatrix} 1-\Gamma_{11}^{\Pi}(L)L & -[w'\alpha^1+\Gamma_{12}^{\Pi}(L)(1-L)]L & \dots & -[w'\alpha^{n-1}+\Gamma_{1n}^{\Pi}(L)(1-L)]L \\ -\Gamma_{21}^{\Pi}(L)L & 1-[1+\alpha_1^1-\alpha_2^1+\Gamma_{22}^{\Pi}(L)(1-L)]L & \dots & -[\alpha_1^{n-1}-\alpha_2^{n-1}+\Gamma_{2n}^{\Pi}(L)(1-L)]L \\ \vdots & \vdots & \ddots & \vdots \\ -\Gamma_{n1}^{\Pi}(L)L & -[\alpha_1^1-\alpha_n^1+\Gamma_{n2}^{\Pi}(L)(1-L)]L & \dots & 1-[1+\alpha_1^{n-1}-\alpha_n^{n-1}+\Gamma_{nn}^{\Pi}(L)(1-L)]L \end{bmatrix} \begin{bmatrix} \Delta f_t \\ z_t \end{bmatrix}
\end{aligned}
$$

and

$$\begin{bmatrix} \Delta f_t \\ z_t \end{bmatrix} = B^{\Pi}(L)^{-1} \begin{bmatrix} \varepsilon_{ft}^{\Pi} \\ \varepsilon_{zt}^{\Pi} \end{bmatrix}$$

The long-run impact of z_t on f_t is 0 if that of ε_{zt}^{Π} on Δf_t is 0, which in turn is given by the elements in the first row, columns 2 to n of $B^{\Pi}(L)^{-1}$, evaluated at $L = 1$. These elements are 0 if those of $B^{\Pi}(1)$ are 0, which is the case for

$$w'\alpha^1 = w'\alpha^2 = \ldots = w'\alpha^{n-1} = 0.$$

Thus, the parameterization of w that leads to no Granger causality of z_t for the common factor f_t is the one for which w is orthogonal to all $n-1$ vectors of adjustment coefficients in α and its length is normalized such that the coefficients sum to 1:

$$w = \alpha_{\perp}.$$

Thereby the relation between the common factor weights and the VECM presentation is established and the resulting price discovery measure of market i is given by

$$GG_i = \frac{w_i}{\sum_{j=1}^{n} w_j}. \tag{11}$$

Detailed Estimation Results

Insert Table A.1 here

Insert Table A.2 here

Insert Table A.3 here

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Figures and Tables

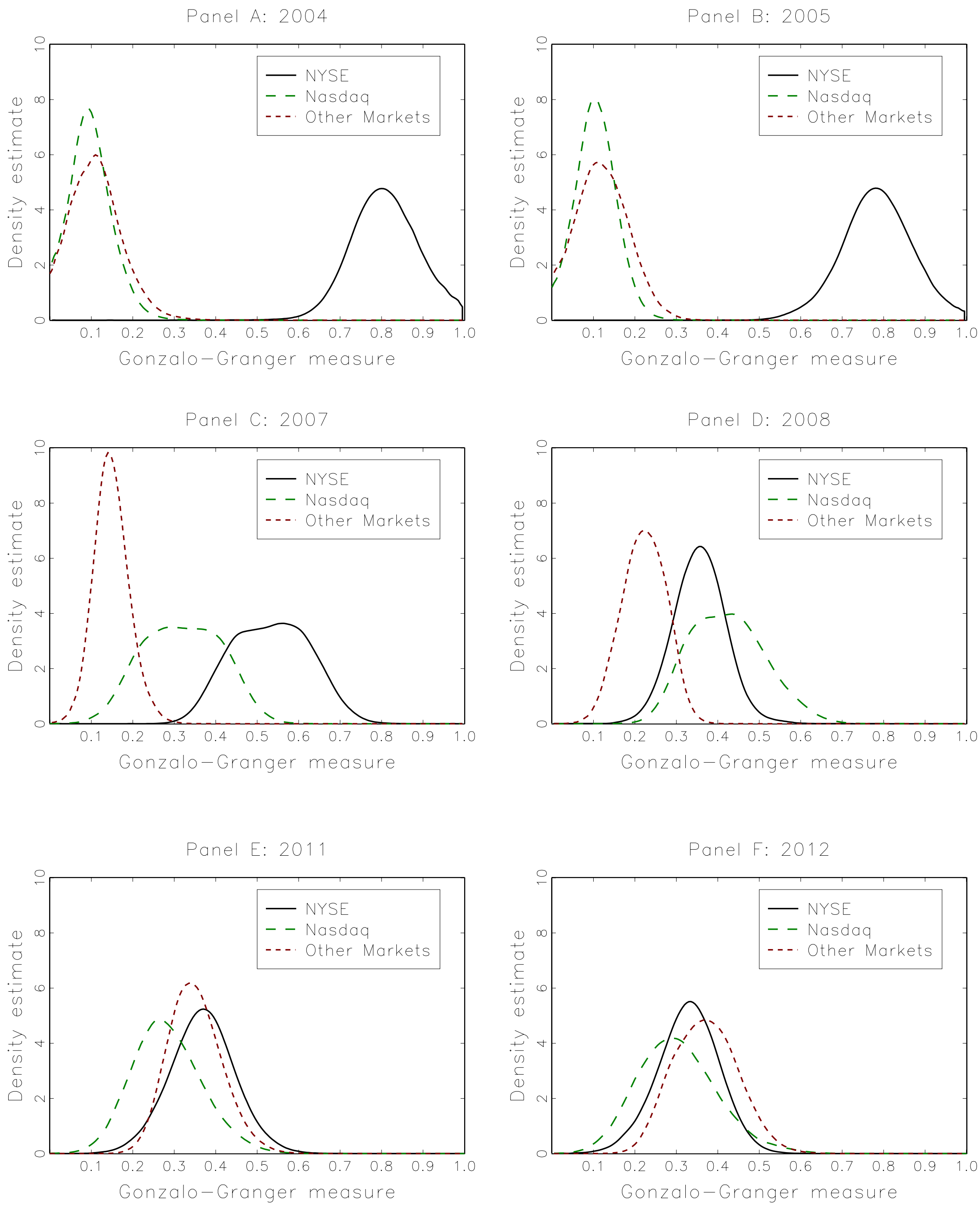

Figure 1: Kernel Densities of Gonzalo-Granger Measures. The figure shows the kernel densities of the bootstrapped Gonzalo-Granger measure averaged across all stocks. The beta kernel with adaptable bandwidth is used.

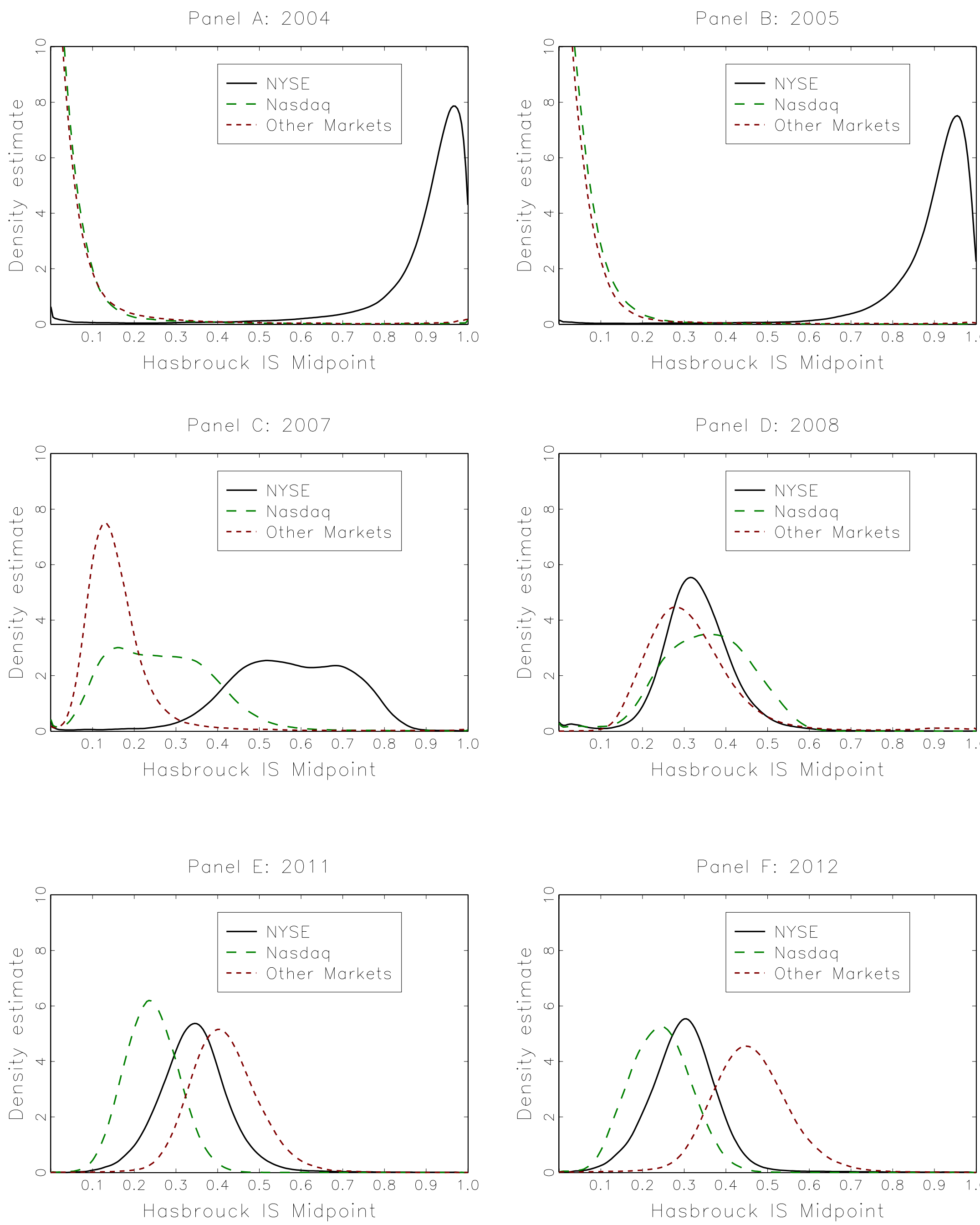

Figure 2: Kernel Densities of Hasbrouck-Information Shares. The figure shows the kernel densities of the bootstrapped Hasbrouck-Information Shares averaged across all stocks. The beta kernel with adaptable bandwidth is used.

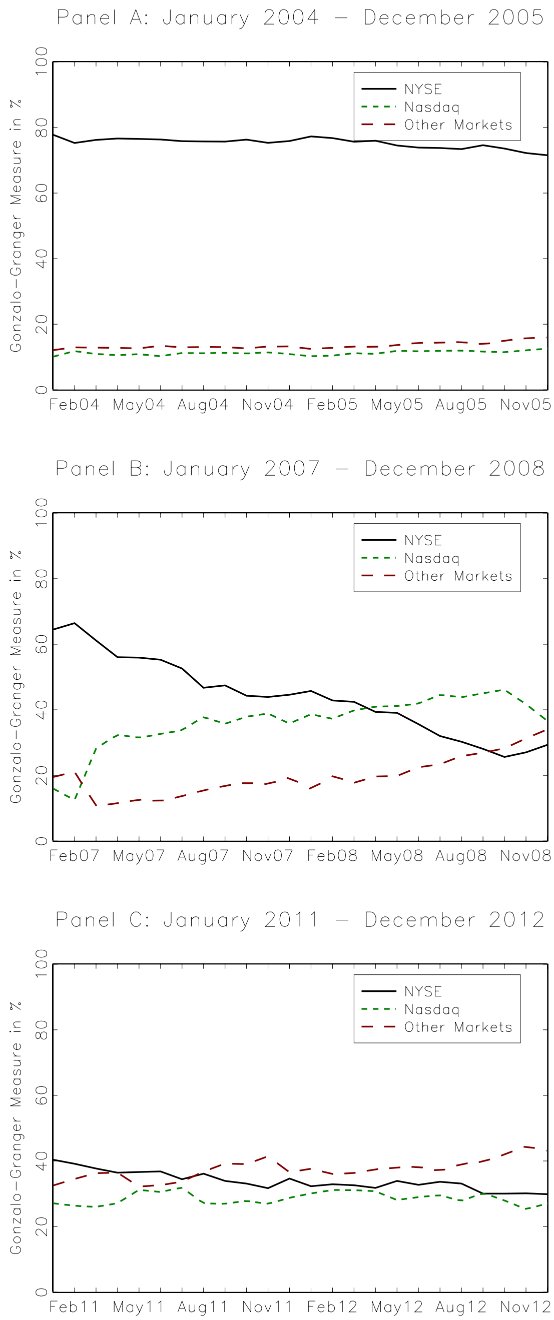

Figure 3: Monthly time series of Gonzalo-Granger measures. The figure shows the time series plots of the Gonzalo-Granger measures for NYSE, Nasdaq, and other markets for the pre Reg. NMS period (Panel A), the period of changing regulations due to Reg. NMS (Panel B), and the post Reg. NMS period (Panel C).

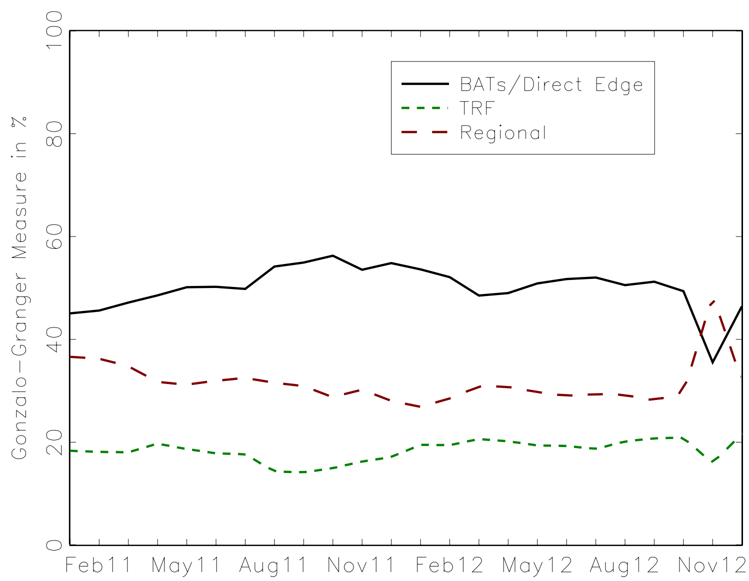

Figure 4: Monthly Time Series of Gonzalo-Granger Measures for Non-Traditional Markets.
The figure shows the time series plots of the Gonzalo-Granger measures for BATS/Direct Edge, TRF trades, and the regional markets during 2011 and 2012.

	2004	2005	2007	2008	2011	2012
			By number of transactions			
NYSE	75.8	68.8	37.8	20.9	16.3	12.8
Nasdaq	13.5	19.6	30.0	31.0	20.5	19.5
Other Markets	10.7	11.8	32.1	48.1	63.1	67.5
...of which						
Regional	6.8	4.6	2.1	3.3	4.4	5.0
TRF	(-)	(-)	10.4	19.9	19.7	23.5
BATS	(-)	(-)	(-)	2.9	14.6	16.1
Direct Edge	(-)	(-)	(-)	(-)	11.2	10.9
			By total trading volume			
NYSE	83.7	80.3	49.8	29.0	23.8	20.0
Nasdaq	10.0	13.6	20.7	24.6	16.4	16.2
Other Markets	6.3	6.2	29.6	46.3	59.7	63.6
...of which						
Regional	4.9	3.4	2.3	3.4	3.4	4.1
Pacific/Arca	1.4	2.8	12.1	16.4	11.0	10.2
TRF	(-)	(-)	15.2	24.6	25.8	28.6
BATS	(-)	(-)	(-)	1.9	10.6	11.7
Direct Edge	(-)	(-)	(-)	(-)	8.9	9.0

Table 1: Market Shares in Percent. The table provides the market shares (in %) of NYSE, Nasdaq, and other markets for the 91 sample stocks, in terms of the number of transactions and total trading volume (including opening volume).

		NYSE	Nasdaq	Other Markets		NYSE	Nasdaq	Other
2004	HIS^{low}	91.2	3.1	3.4				
	HIS^{mid}	92.2	3.8	4.0	GG	82.8	8.2	9.0
	HIS^{up}	93.2	4.4	4.6				
2005	HIS^{low}	88.6	4.1	4.0				
	HIS^{mid}	90.1	5.1	4.8	GG	79.5	9.7	10.8
	HIS^{up}	91.6	6.3	5.6				
2007	HIS^{low}	49.4	14.0	6.0				
	HIS^{mid}	61.7	25.0	13.3	GG	53.8	31.0	15.2
	HIS^{up}	76.3	38.2	22.8				
2008	HIS^{low}	20.2	20.1	12.7				
	HIS^{mid}	35.9	37.5	26.6	GG	34.5	42.4	23.2
	HIS^{up}	56.2	59.5	45.3				
2011	HIS^{low}	14.5	8.0	24.2				
	HIS^{mid}	33.4	24.1	42.5	GG	35.9	28.0	36.1
	HIS^{up}	59.3	47.1	67.8				
2012	HIS^{low}	12.0	8.8	29.1				
	HIS^{mid}	29.1	24.4	46.5	GG	32.1	29.6	38.3
	HIS^{up}	52.5	46.2	70.3				

Table 2: Hasbrouck-Information Shares and Gonzalo-Granger Measures. Hasbrouck-Information Shares (HIS) and Gonzalo-Granger measure (GG). The table shows the mean of Hasbrouck-information share (lower bound, midpoint, and upper bound) and the mean of the Gonzalo-Granger measure across the 91 stocks in the sample (in %).

	Dependent Variable: Gonzalo-Granger Measure of		
	NYSE	Nasdaq	Other Markets
Intercept	0.5404***	0.5605***	0.5214***
	(0.0051)	(0.0067)	(0.0071)
Trading Freq. NYSE	0.2228***	-0.1422***	0.0686***
	(0.0200)	(0.0195)	(0.0208)
Trading Freq. Nasdaq	-0.0648**	0.2207***	
	(0.0227)	(0.0292)	
Trading Freq. Other Mkts			0.1516 ***
			(0.0196)
Volume NYSE	0.0403***	0.0124	-0.0798
	(0.0138)	(0.0139)	(0.0179)
Volume Nasdaq	-0.0017	-0.0261	
	(0.0185)	(0.0223)	
Volume Other Mkts			-0.0285
			(0.0175)
ISO NYSE	0.0024	-0.0075	0.0048
	(0.0044)	(0.0049)	(0.0043)
ISO Nasdaq	0.0207***	0.0167***	-0.0368***
	(0.0031)	(0.0044)	(0.0045)
ISO Other Markets	-0.0426***	-0.0570***	0.0985***
	(0.0067)	(0.0079)	(0.0050)
Volatility NYSE	-0.0896***	-0.0201	0.1105**
	(0.0313)	(0.0169)	(0.0451)
Volatility Nasdaq	-0.0789**	-0.0563**	0.1358**
	(0.0365)	(0.0270)	(0.0608)
Volatility Other Mkts	0.1909***	0.0858***	-0.2784***
	(0.0566)	(0.0328)	(0.0864)
R^2	0.2204	0.3309	0.2542
Number of Stocks	91	91	91
Number of Time Series Obs.	481	481	481

Table 3: Determinants of NYSE, Nasdaq, and Other Markets Price Discovery Contributions. The table shows fixed-effects regression results. The dependent variable is the logistic transformation of the NYSE (column 1), Nasdaq (column 2) and other markets' Gonzalo-Granger measures. Trading Freq. denotes the trading frequency on the corresponding market relative to total trading frequency, volume is the relative volume on the corresponding market relative to overall volume, ISO denotes the percentage of ISO on a market relative to regular transaction on that market, and volatility denotes the intraday standard deviation of returns on the corresponding market. Standard errors are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level respectively.

	Volume $\rightarrow_{Granger}$ IS	IS $\rightarrow_{Granger}$ Volume
NYSE	54	6
Nasdaq	48	8
Other Markets	38	13

Table 4: Granger-Causality Tests Results. The table shows the results of Granger-causality tests using the corresponding market's price discovery contribution, estimated by the Gonzalo-Granger measure and relative trading frequency with a vector autoregressive model. The first column indicates the number of stocks for which we detect Granger-causality, running from relative trading frequency to the information share series at the 5% significance level, and the second column indicates the reverse direction.

Symbol	Name	Listing Exchange	Sector
aa	Alco Corporation	NYSE	Basic Materials
abt	Abott Laboratories	NYSE	Healthcare
adi	Analog Devices, Inc.	Nasdaq	Technology
afl	Aflac Incorporated	NYSE	Financial
aig	American International Group, Inc.	NYSE	Financial
all	The Allstate Corporation	NYSE	Financial
avp	Avon Products, Inc.	NYSE	Consumer Goods
axp	Amerian Express Company	NYSE	Financial
ba	The Boeing Company	NYSE	Industrial Goods
bac	Bank of America Corporation	NYSE	Financial
bax	Baxter International Inc.	NYSE	Healthcare
bbt	BB&T Corporation	NYSE	Financial
bby	Best Buy Co., Inc.	NYSE	Services
bk	The Bank of New York Mellon Corporation	NYSE	Financial
bmy	Bristol-Myers Sqibb Company	NYSE	Healthcare
bsx	Boston Scientific Corporation	NYSE	Healthcare
c	Citigroup Inc.	NYSE	Financial
cah	Cardinal Health, Inc.	NYSE	Services
cat	Caterpillar Inc.	NYSE	Industrial Goods
ccl	Carnival Corporation	NYSE	Services
cl	Colgate-Palmolive Company	NYSE	Consumer Goods
cop	ConocoPhillips	NYSE	Basic Materials
cvx	Chevron Corporation	NYSE	Basic Materials
d	Dominion Energy, Inc.	NYSE	Utilities
dd	E.I. du Pont de Nemours	NYSE	Basic Materials
dis	The Walt Disney Company	NYSE	Services
dow	The Dow Chemical Company	NYSE	Basic Matericals
duk	Duke Energy Corporation	NYSE	Utilities
emc	EMC Corporation	NYSE	Technology
emr	Emerson Electric Co.	NYSE	Industrial Goods
exc	Exelon Corporation	NYSE	Utilities
f	Ford Motor Company	NYSE	Consumer Goods
fdx	FedEx Corporation	NYSE	Services
frx	Forest Laboratories	NYSE	Healthcare
gci	Ganett Co., Inc.	NYSE	Services
gd	General Dynamics Corporation	NYSE	Industrial Goods
ge	General Electric Company	NYSE	Industrial Goods
gis	General Mills, Inc.	NYSE	Consumer Goods
gm	General Motors Company	NYSE	Consumer Goods
gps	The Gap, Inc.	NYSE	Services
gs	The Goldman Sachs Group, Inc.	NYSE	Financial
hd	The Home Depot, Inc.	NYSE	Services
hig	The Hartford Financial Services Group, Inc.	NYSE	Financial
hon	Honeywell International Inc.	NYSE	Industrial Goods
hpq	HP Inc.	NYSE	Technology
ibm	International Business Machines Corporation	NYSE	Technology
ip	International Paper Company	NYSE	Consumer Goods
itw	Illinois Tool Works Inc.	NYSE	Industrial Goods
jnj	Johnson & Johnson	NYSE	Healthcare
jpm	JPMorgan Chase & Co.	NYSE	Financial
k	Kellogg Company	NYSE	Consumer Goods
kmb	Kimberly-Clark Corporation	NYSE	Consumer Goods
ko	The Coca-Cola Company	NYSE	Consumer Goods

Table A.1: The table lists the ticker symbols, company names, listing exchange, and the sector of the sample stocks. Continued on next page.

Symbol	Name	Listing Exchange	Sector
kss	Kohl's Corporation	NYSE	Services
lly	Eli Lilly and Company	NYSE	Healthcare
lmt	Lockheed Martin Corporation	NYSE	Industrial Goods
low	Lowe's Companies, Inc.	NYSE	Services
mcd	McDonald's Corporation	NYSE	Services
mdt	Medtronic plc	NYSE	Healthcare
met	MetLife, Inc.	NYSE	Financial
mmc	Marsh & McLennan Companies, Inc.	NYSE	Financial
mmm	3M Company	NYSE	Industrial Goods
mo	Altria Group, Inc.	NYSE	Consumer Goods
mrk	Merck & Co., Inc.	NYSE	Healthcare
nem	Newmont Mining Corporation	NYSE	Basic Materials
noc	Northrop Grumman Corporation	NYSE	Industrial Goods
omc	Omnicom Group Inc.	NYSE	Services
oxy	Occidental Petroleum Corporation	NYSE	Basic Materials
pep	PepsiCo, Inc.	Nasdaq	Consumer Goods
pfe	Pfizer Inc.	NYSE	Healthcare
pg	The Procter & Gamble Company	NYSE	Consumer Goods
pgr	The Progressive Corporation	NYSE	Financial
pnc	The PNC Financial Services Group, Inc.	NYSE	Financial
pru	Prudential Financial, Inc.	NYSE	Financial
slb	Schlumberger Limited	NYSE	Basic Materials
so	The Southern Company	NYSE	Utilities
sti	SunTrust Banks, Inc.	NYSE	Financial
stt	State Street Corporation	NYSE	Financial
syk	Stryker Corporation	NYSE	Healthcare
t	AT&T Inc.	NYSE	Technology
tgt	Target Corporation	NYSE	Services
twx	Time Warner Inc.	NYSE	Services
tyc	Tyco International	NYSE	Industrial Goods
unh	United Health Group Incorporated	NYSE	Healthcare
unp	Union Pacific Corporation	NYSE	Services
usb	U.S. Bancorp	NYSE	Financial
utx	United Technologies Corporation	NYSE	Industrial Goods
vz	Verizon Communications Inc.	NYSE	Technology
wag	Walgreen and Co	NYSE	Healthcare
wfc	Wells Fargo & Company	NYSE	Financial
wlp	WellPoint, Inc.	NYSE	Healthcare
wmt	Walmart Inc.	NYSE	Services
xom	Exxon Mobil Corporation	NYSE	Basic Materials
zmh	Zimmer Holdings, Inc.	NYSE	Healthcare

Table A.1: The table lists the ticker symbols, company names, listing exchange, and the sector of the sample stocks.

		NYSE				Nasdaq				Other Markets			
		GG	IS^{low}	IS^{up}	IS^{mid}	GG	IS^{low}	IS^{up}	IS^{mid}	GG	IS^{low}	IS^{up}	IS^{mid}
2004	Mean	82.8	91.2	93.2	92.2	8.2	3.1	4.4	3.8	9.0	3.4	4.6	4.0
	Min	72.9	84.0	88.6	86.5	-6.1	1.9	2.3	2.1	3.4	1.4	2.1	1.9
	Median	83.1	91.7	93.6	92.5	8.4	3.0	4.2	3.6	8.7	3.2	4.3	3.8
	Max	92.4	94.7	96.4	95.4	13.7	5.8	8.3	7.0	22.5	6.8	9.0	7.3
2005	Mean	79.5	88.6	91.6	90.1	9.7	4.1	6.3	5.1	10.8	4.0	5.6	4.8
	Min	62.2	71.1	78.8	74.8	-13.6	2.0	2.8	2.5	3.7	2.0	2.8	2.4
	Median	80.8	90.3	92.5	91.3	9.5	3.4	5.0	4.2	9.5	3.7	4.9	4.3
	Max	91.1	93.7	95.5	94.5	18.2	11.3	17.8	14.4	30.8	9.4	14.2	11.7
2007	Mean	53.8	49.4	76.3	61.7	31.0	14.0	38.2	25.0	15.2	6.0	22.8	13.3
	Min	35.2	26.6	53.3	44.5	15.9	5.5	16.4	10.5	10.1	2.7	15.9	9.7
	Median	54.2	48.3	77.5	61.8	30.8	13.1	39.2	25.2	14.7	5.5	22.6	13.0
	Max	70.8	70.4	87.4	78.4	48.3	26.2	67.5	44.2	25.6	19.3	34.4	26.3
2008	Mean	34.5	20.2	56.2	35.9	42.4	20.1	59.5	37.5	23.2	12.7	45.3	26.6
	Min	21.7	6.6	43.1	22.3	28.6	11.3	37.4	23.6	13.8	3.0	33.2	18.6
	Median	34.3	19.1	55.6	35.5	42.7	20.8	60.9	38.3	22.9	12.4	44.8	26.0
	Max	52.7	40.4	77.4	57.1	61.5	29.6	88.3	53.7	32.3	28.3	59.3	37.8
2011	Mean	35.9	14.5	59.3	33.4	28.0	8.0	47.1	24.1	36.1	24.2	67.8	42.5
	Min	22.1	6.3	29.6	18.6	16.7	3.9	29.1	15.5	28.0	11.3	58.7	33.5
	Median	36.4	14.2	60.8	34.3	27.6	7.6	46.4	24.3	35.4	22.8	67.2	42.0
	Max	49.2	25.8	74.7	46.2	46.8	18.6	68.1	33.1	49.9	43.7	81.2	54.5
2012	Mean	32.1	12.0	52.5	29.1	29.6	8.8	46.2	24.4	38.3	29.1	70.3	46.5
	Min	19.9	4.7	24.0	15.5	17.1	3.6	26.7	14.3	25.6	13.2	60.1	33.9
	Median	32.7	11.9	54.2	29.8	29.2	8.4	47.2	24.8	38.1	27.8	70.3	45.9
	Max	41.6	19.2	66.1	39.0	51.5	19.7	69.4	34.1	53.8	47.9	83.6	59.8

Table A.2: The table reports means and quantiles across the intraday average parameters of the 91 stocks in the sample. The cointegrating relation is non-demeaned, there is no constant in the VECM, and 12 to 17 lagged first differences are included, depending on the year.

		NYSE				Nasdaq				Other Markets			
		GG	IS^{low}	IS^{up}	IS^{mid}	GG	IS^{low}	IS^{up}	IS^{mid}	GG	IS^{low}	IS^{up}	IS^{mid}
2004	Mean	75.9	90.1	92.4	91.2	11.0	3.6	5.0	4.3	13.0	3.9	5.2	4.5
	Min	69.4	83.7	86.3	85.1	8.0	1.9	2.3	2.1	9.0	1.6	2.6	2.3
	Median	76.1	90.7	92.8	91.6	11.0	3.4	4.8	4.1	12.8	3.6	4.8	4.2
	Max	82.0	93.7	96.1	94.6	14.3	6.8	8.8	7.8	18.8	8.2	9.4	8.8
2005	Mean	74.2	87.4	90.8	89.1	11.6	4.4	6.8	5.6	14.2	4.4	6.3	5.3
	Min	61.6	71.2	79.2	75.2	7.3	2.1	3.2	2.6	10.1	2.3	3.3	2.8
	Median	74.5	88.8	91.3	90.0	11.3	4.0	5.7	4.9	13.9	4.2	5.8	5.1
	Max	80.0	92.5	94.9	93.7	18.6	11.2	17.6	14.3	21.0	9.8	14.9	12.3
2007	Mean	52.4	48.0	75.8	60.7	31.9	14.2	39.2	25.5	15.8	6.2	23.8	13.8
	Min	35.1	26.3	53.2	44.2	17.7	5.9	18.0	11.4	10.2	2.6	17.3	10.5
	Median	53.2	46.7	76.9	60.5	31.7	13.4	40.5	25.9	15.4	5.7	23.7	13.2
	Max	66.0	66.5	85.9	75.6	47.9	25.6	68.0	43.9	25.7	19.4	35.3	26.5
2008	Mean	34.8	20.3	56.8	36.1	41.5	19.3	59.0	36.7	23.6	12.9	46.3	27.2
	Min	21.9	6.9	43.2	22.1	29.0	11.4	38.0	23.7	14.3	3.2	33.5	18.7
	Median	34.7	19.5	55.9	35.6	41.9	19.9	60.6	37.6	23.2	12.9	45.6	26.4
	Max	52.4	40.1	77.1	56.8	59.1	26.6	87.5	51.3	32.4	28.6	61.9	38.2
2011	Mean	35.7	14.4	59.4	33.3	28.3	8.0	47.4	24.2	36.0	24.1	68.0	42.5
	Min	22.7	6.4	29.7	18.6	17.8	4.1	31.2	16.6	28.1	11.4	58.6	33.5
	Median	36.1	14.1	61.0	34.0	27.8	7.5	46.3	24.2	35.4	23.0	67.5	42.0
	Max	48.3	25.2	74.5	45.8	46.6	18.4	67.9	32.5	49.7	43.8	81.2	54.4
2012	Mean	32.0	11.9	52.6	29.1	30.1	8.9	46.7	24.6	37.9	28.9	70.2	46.4
	Min	20.4	4.8	23.8	15.3	18.2	3.7	27.9	14.9	25.9	13.2	59.8	33.9
	Median	32.8	11.7	54.6	29.9	29.4	8.5	47.1	24.7	37.7	27.6	70.1	45.7
	Max	41.3	18.9	66.3	38.6	51.2	19.5	69.4	34.0	53.1	48.3	83.5	59.0

Table A.3: The table reports means and quantiles across the 91 stocks in the sample. In the calculation of the intraday average for each stock, only days where the estimated Gonzalo-Granger common factor weights are strictly positive are considered. The cointegrating relation is non-demeaned, there is no constant in the VECM, and 12 to 17 lagged first differences are included, depending on the year.