DO COMMON STOCKS HAVE PERFECT SUBSTITUTES? PRODUCT MARKET COMPETITION AND THE ELASTICITY OF DEMAND FOR STOCKS

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Abstract—Though common stocks are one of the most important assets in an economy, little is known about their demand curves. I estimate demand curves for 144 NYSE stocks using a unique data set of all orders, including off-equilibrium orders, during three months in 1990 and 1991. Connecting asset pricing with industrial organization, I find that stocks of firms in less competitive industries are more elastic because they have closer substitutes than stocks in more competitive industries. Tests that exploit the 1991 Gulf War shock and S&P 500 Index additions confirm these results.

I. Introduction

At the end of 2011, corporate equities accounted for $8.14 trillion of the assets owned by households in the United States. This compares to $6.71 trillion in savings deposits and $4.77 trillion in consumer durable goods (Board of Governors, 2012). Moreover, the aggregate dollar value of transactions of stocks listed on the New York Stock Exchange (NYSE) was about $11.7 trillion in 2011. The transaction of common stocks is clearly important. Accordingly, there is a vast literature in financial economics that seeks to understand stock prices. However, prior research has paid relatively little attention to one of the most fundamental economic aspects of stocks: the price elasticity of demand.

In this paper, I argue that the elasticity of a firm's stock is related to the competitive intensity of the firm's industry. As with any other good, stocks with close substitutes are expected to have more elastic demand than stocks with poor substitutes. Strategic interactions in oligopolistic industries create dependencies between firm outcomes. In contrast, the actions of firms in competitive industries have little impact on rivals' outcomes. This intuition is confirmed in the empirical results of MacKay and Phillips (2005) and the theoretical models of Raith (2003) and Irvine and Pontiff (2009). Given a common demand shock and firm-specific cost shocks, they show that greater competitive intensity leads to less correlated profits and greater firm-specific profit volatility. Since stock prices reflect the future discounted profits of a firm, a firm with greater idiosyncratic profit volatility has fewer substitutes. Hence, greater product market competition is predicted to lead to less elastic demand curves for stocks.

Using unique data for 144 common stocks on the NYSE over a three-month period, I find that the time-series and cross-sectional average (median) of the elasticity of demand is 6.9 (5.9). I form these estimates by reconstructing the limit-order book for each stock in the sample at 30-minute intervals. Since the limit-order book is a collection of off-equilibrium prices and quantities demanded, it represents an estimate of the demand curve for prices less than the market price. Under the assumption of constant elasticity, I then estimate the elasticity of the entire demand curve.[1]

My results show that a stock's elasticity is negatively and significantly related to the competitiveness of the firm's industry. First, using product market elasticity estimates from Hall (1986, 1988) and Domowitz, Hubbard, and Petersen (1988), I find that stock returns of firms in more competitive industries have smaller co-movement with overall industry returns compared to firms in less competitive industries. Second, stocks in above-median-competitiveness industries have an average stock price elasticity of 6.4 compared to 8.7 for stocks in below-median-competitiveness industries. These results support the idea that firms in less competitive industries have better substitutes and more elastic stock demand curves.

I also consider additional factors that may explain stock price elasticity. First, uninformed liquidity traders do not condition their demand on price. In contrast, informed investors are highly sensitive to price changes (Grossman & Stiglitz, 1980). Therefore, stock price elasticity is expected to be greater for stocks with more informed investors. I measure informed trading using standard measures developed in prior papers (e.g., Kyle, 1985). Second, if investors simultaneously form different beliefs about the value of a stock using common information, as argued in Miller (1977) and Harris and Raviv (1993), greater heterogeneity of beliefs will produce steeper demand curves. I use share turnover and dispersion in analysts' forecast estimates to measure heterogeneous beliefs.

I find that both information asymmetry and heterogeneous beliefs are correlated with stock price elasticity. Stocks with below-median share turnover have an average stock price elasticity of 9.5 compared to 5.7 for stocks with above-median turnover. Similarly, Kyle's λ is positively related to stock price elasticity. However, after controlling for firm size, volatility, and industry fixed effects, these relations are not significant. Product market competition remains negatively related to stock price elasticity after including all controls.

The main results are robust to alternative empirical approaches. First, the limit-order book may not represent the complete demand curve. Limit orders may be strategic bets by liquidity providers rather than true valuations. Likewise,

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[1] Prior studies rely on exogenous demand shocks from specific events (e.g., index additions) to estimate elasticity. See Shleifer (1986), Holthausen, Leftwich, and Mayers (1987), Loderer et al. (1991), Kandel, Sarig, and Wohl (1999), Kaul, Mehrotra, and Morck (2000), and Kalay, Sade, and Wohl (2004).

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because the limit-order book is changing dynamically, it may omit important parts of the true demand curve at any one time. To address these concerns, I estimate realized stock price elasticity using additions and deletions to the S&P 500 Index as an exogenous demand shock, following prior research (Shleifer, 1986). Using these estimates, I find that stock price elasticity is significantly and negatively related to product market elasticity, consistent with the main results.

Second, to account for possible omitted variables, I run fixed-effects difference-in-difference tests that exploit the exogenous shock created by the start of the first Gulf War in January 1991. Empirical tests show that the elasticity of oil stocks doubled after the war started, though the elasticity of nonoil stocks remained constant. The change in stock price elasticity for oil stocks seems most likely related to the availability of closer substitutes caused by the increased level and inelasticity of precautionary demand for oil.

Third, following research in finance, I decompose stock returns in two ways. First, I decompose individual stock returns into idiosyncratic and market-wide returns. I calculate the R^2 from a regression of a stock's returns on market-wide risk factors. I also record the maximum R^2 from the set of regressions of a stock's returns on every other stock in the market individually. Cross-sectionally, both R^2 measures are highly correlated, suggesting systematic risk factors have poor explanatory power (Roll, 1988). I find that stock price elasticity is negatively related to R^2, indicating that firms with greater comovement have less elastic demand curves, contrary to the substitutability hypothesis. A variety of alternative interpretations of R^2 may help to explain these results. Second, I decompose yearly stock returns into cash flow and expected return news, following Vuolteenaho (2002). I find that firms in less competitive industries have relatively greater industry co-movement of cash flow news than expected return news. This finding supports the main results of the paper using a different method and time frame to estimate comovement and substitutability.

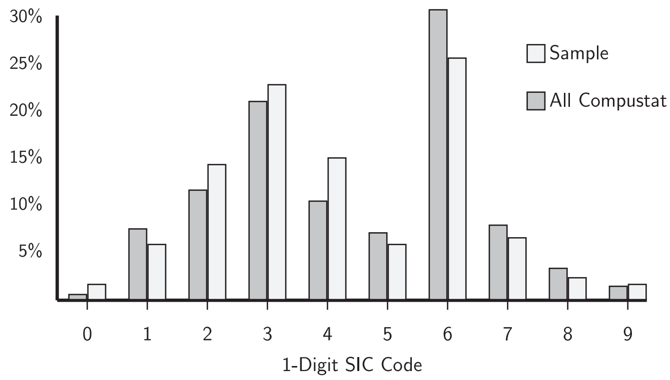
The central contribution of this paper is to provide the first evidence that product market competition is negatively related to the elasticity of demand for common stocks. This result is related to a line of research showing that stock return co-movement has decreased over time (Campbell et al., 2001) is smaller in developed markets (Morck, Yeung, & Yu, 2000), and is smaller in industries that adopt new technologies (Chun et al., 2008). My results suggest that greater competitive intensity in developed markets, in more recent years, and in innovative industries (Bils & Klenow, 2004) leads to less elastic demand curves, where stocks have lower systematic comovement. Consistent with this view, Irvine and Pontiff (2009) show that idiosyncratic stock volatility is positively related to competitive intensity. Other papers in finance have also investigated explanations for cross-sectional variation in elasticity (Loderer, Cooney, & Drunen, 1991; Chacko, Jurek, & Stafford, 2008; Petajisto, 2009). This paper is unique: it provides a strong connection between stock elasticity and industry structure.

TABLE 1.—PRICE ELASTICITY OF DEMAND AND SAMPLE FIRM CHARACTERISTICS

	Mean	Median	Standard Deviation	Minimum	Maximum
Stock price elasticity	6.893	5.863	4.404	0.617	27.112
NYSE percentiles					
Market equity	53.591	60.0	30.306	5	100
Prior returns	49.600	52.5	32.778	5	100
Book to market	53.878	55.0	29.563	5	100
Earnings to price	53.878	52.5	27.941	5	100

Price elasticity of demand estimates are time-series averages of the negative of the e coefficient in the regression $\ln(q) = \alpha + e \ln(p)$, where p is price and q is quantity demanded (supplied) from the limit order book. NYSE percentiles are measured at the half-decile. Statistics over 112 observations, data availability permitting.

FIGURE 1.—DISTRIBUTION OF COMPUSTAT VERSUS SAMPLE INDUSTRY CLASSIFICATIONS



Percentage of firms in each one-digit SIC code in 1990 for the universe of firms on the Compustat database and for the sample used in this paper.

II. Data and Methodology

A. Estimates of the Price Elasticity of Demand

The primary data for this paper are from the TORQ (Trades, Orders, Reports, and Quotes) database. This database contains transactions, quotes, and order processing data from the NYSE for 144 stocks selected by stratified random sampling over equity capitalization deciles. All orders, quotes, and trades for these stocks that were handled by the automated SuperDOT routing system over the three months of November 1990 to January 1991 are included in this database. At that time, about 75% of all orders were processed through the SuperDOT system (Hasbrouck, Sofianos, & Sosebee, 1993).[2] I exclude all REITs, closed-end funds, and ADRs from the sample and keep only regular common shares. (See Hasbrouck, 1992, for a complete description of the data.)

Though the sample I use is relatively small compared to other studies in financial economics, the firms are representative of the overall market. Table 1 presents characteristics of the firms compared to all NYSE firms. The sample closely matches the overall market with medians slightly higher than the NYSE medians for size, prior returns, book-to-market, and earnings-to-price ratios. Figure 1 presents the distribution

[2] A majority of order volume at the NYSE was submitted through the SuperDOT system, though not a majority of dollar volume (Lee & Radhakrishna, 2000). This biases my estimate of elasticity downward.

of industry affiliation at the one-digit SIC code level for all firms on Compustat in 1990 and the same distribution for my sample. The two distributions are highly similar. A Kolmogorov-Smirnov test cannot reject the hypothesis that the two distributions are drawn from the same population (p-value $= 0.675$). This provides confidence that the results of the paper are not driven by sample selection bias and are generalizable to all NYSE stocks.

Because the TORQ database contains off-equilibrium orders, it allows the unique possibility of estimating the demand and supply schedules of NYSE stocks at any time during the three-month period by constructing the limit-order book. A limit order is an order to buy (sell) a specific number of shares of a security at no more (less) than a specific price during a specific time, such as the current day, or until canceled or filled. The limit-order book is the collection of unexecuted limit orders prioritized first by price and then by time of arrival. Thus, the limit-order book presents a locus of quantities demanded for given prices.

To build the limit-order book, I follow the procedure of Kavajecz (1999). This procedure produces a list of unexecuted limit orders at every point in time. To infer the demand schedule from the limit-order book I cumulate the quantities on the book for prices that are better than or equal to the order price. In other words, the quantity demanded at price p is the sum of all shares of buy-limit orders at prices greater than or equal to p. These cumulated limit orders constitute a demand schedule for prices less than the current price. For each stock and for each of the 63 days in the sample, I construct the demand schedules from the limit-order book every 30 minutes from 10:00 a.m. until 4:00 p.m., yielding 819 observations per firm. I begin daily estimations at 10:00 a.m. because opening trades are different from regular trading hours and because not all stocks open exactly at 9:00 a.m. every day (Bessembinder, 2003).

Elasticity is defined as the percentage change in the quantity demanded for a 1 percentage point change in the price. Thus, the estimate of elasticity will vary depending on at which point of the demand curve it is estimated. To address this, I assume that the demand curves follow a constant elasticity specification. This allows me to estimate elasticity with only a partial picture of the entire demand curve.[3]

From the demand schedules, I estimate 819 measures of elasticity for each firm from the following equation:

$$\ln(q) = a + e\ln(p) + \varepsilon, \tag{1}$$

where q is quantity demanded at a given price p. Throughout this paper, I follow the convention that higher elasticity means flatter demand curves and more sensitivity of quantity demanded to price changes. Therefore, I take the negative of e as the measure of price elasticity. Each estimate of e is specific to one firm at one time. Because the limit-order books for some firms are much more extensive than others, to estimate elasticity consistently, at least five data points are required for any firm-time regression (16th percentile of all demand schedule sample sizes). For each firm, I calculate the average elasticity across all date-times available to produce one estimate per stock.

The estimated mean and median elasticity across all stocks are presented in table 1. The mean elasticity is 6.9, and the median is 5.9. Thus, consistent with prior studies, I find that stocks have downward-sloping demand curves.[4] I also find substantial variation in elasticity. The standard deviation of the estimates is 4.4 across the sample stocks. The range of estimates of elasticity is also wide, from a minimum of 0.617 to a maximum of 27.112.

The estimates of elasticity are persistent over time. In untabulated results, I regress daily elasticity on its one-day lag, controlling for firm fixed effects. The coefficient on lagged elasticity is 0.627 (p-value < 0.001) and the R^2 is 0.717. This result holds after controlling for the risk factors of Fama and French (1993). As a comparison, the autoregression coefficient for the bid-ask spread is 0.352, for returns it is -0.125, and for stock turnover (daily volume/shares outstanding) it is 0.117.

The TORQ data provide particular benefits for this study. In addition to the off-equilibrium nature of the data, the time period of the data is beneficial. Prior to June 1991, only NYSE specialists could see all the orders in the limit-order book. Boehmer, Saar, and Yu (2005) find that greater transparency leads traders to break large quantities demanded into smaller trades and to trade off the exchange. Thus, traders respond to greater transparency by attempting to hide their true demand. Since the NYSE was less transparent when the TORQ data were collected in 1990 and early 1991, it offers a unique view of stock demand that is less likely biased by trading strategies.

However, the TORQ data have limitations. First, market orders are not included. Additional demand at the equilibrium price will shift the demand curve to the right but should not affect the overall shape of the demand curve. Second, the data cannot account for latent demand from investors who stand ready to place a limit order if the price falls. Including these unseen orders would make the demand schedule more elastic as quantities demanded would increase for those prices furthest from the market price.[5] Third, I cannot distinguish strategic bets by liquidity providers from investors' true valuations. Investors may submit orders over time to profit from

[3] Other studies have estimated stock elasticity using different methods, though they tend to produce similar results. Kalay et al. (2004) computes elasticity for the opening auction of Israeli stocks for various measures of quantities, such as the number of shares outstanding and opening volume. Bagwell (1992) computes elasticities for Dutch auction repurchases by normalizing prices and quantities so that prices are 100 at opening and quantities are relative to total volume per day. Kim, Lee, and Morck (2004) find that elasticity estimates using Korean data are highly correlated using either the method of Bagwell or the constant elasticity method that I employ.

[4] Other papers finding finite elasticities are Wurgler and Zhuravskaya (2002), Kaul, Mehrotra, and Morck (2000), Kandel et al. (1999), Bagwell (1992), and Shleifer (1986).

[5] Hollifield, Miller, and Sandås (2004), Foucault, Kadan, and Kandel (2005), and Hollifield et al. (2006) discuss the effects of market versus limit orders for liquidity.

temporary imbalance in the order flow. Fourth, large trades may be completed in the "upstairs" market, where brokers match trades off the trading floor. However, Hasbrouck, Sofianos, and Sosebee (1993) report that in 1993, only 27% of block trades were actually facilitated upstairs. Finally, Sofianos and Werner (2000) report that orders for stocks that are smaller and less liquid are more likely handled by floor brokers rather than electronically and thus will not be included in the SuperDOT data. Since less liquid stocks are where floor brokers submit proportionally more trades, these stocks will appear even less liquid in my analysis.

Since my focus is on cross-sectional variation in elasticity, these concerns will bias my results only if they are also correlated with product market competition and substitutability. For instance, Keim and Madhavan (1996) show that block trades occur in firms of all sizes, and so their omission is unlikely to generate bias. Of most concern is the likelihood that an investor strategically submits market orders rather than a limit order. These stocks are likely to be the least liquid and have greater information asymmetry and at the same time are likely to be small and operate in younger industries. To address these possible biases, I present robustness checks in section IV using measures of elasticity based on S&P 500 index changes, differences-in-differences tests that account for possible firm-specific omitted variables, and I investigate the effect of industry maturity on my estimates.

B. *Measures of Substitutability*

Like any other good, stocks with closer substitutes will have more elastic demand curves. If a stock has close substitutes, small deviations from the stock's true price will lead investors to make large shifts in quantities demanded to substitute assets, generating an elastic demand curve. I consider two approaches to measure the substitutability of a firm's stock: one based on industrial organization theory, the other based on a statistical approach.

First, I argue that the competitive intensity of a firm's industry will be related to its stocks' substitutability. Stocks represent claims on a firm's future cash flows. Firms with cash flows that are correlated with other firms' cash flows will have more substitutable stocks. I propose that the competitive intensity of a firm's industry affects the correlation of its cash flows with other firms' cash flows, and hence, its stocks' substitutability.

Previous theoretical work has shown that competitive intensity affects profit volatility. First, in Raith (2003), increased competition from substitute products leads to greater volatility in profits. This occurs because greater substitutability makes demand more elastic, which leads to more volatility in firm-specific profits. Second, in the Cournot duopoly model of Irvine and Pontiff (2009), a common demand shock drives positive correlations in firms' profits, while idiosyncratic cost shocks drive negative correlations. An idiosyncratic cost shock for one firm causes the profit to increase for the other firm. However, for reasonable parameter estimates, the positive correlation of the common demand shock outweighs the negative correlation driven by the cost shocks. Irvine and Pontiff (2009) show that the correlation between the profits of two Cournot competitors decreases as competitive intensity increases.

Empirical results support these predictions. MacKay and Phillips (2005) find that competitive intensity is positively related to greater dispersion in risk, leverage, and profitability. Irvine and Pontiff (2009) present evidence that idiosyncratic stock return volatility increases following industry deregulation. Finally, Gatev, Goetzmann, and Rouwenhorst (2006) find that utility firms exhibit high within-industry comovement in stock prices (though this could be caused by regulation rather than a lack of competition). Overall, prior evidence suggests that greater competition leads to greater heterogeneity and less correlation in profitability.

To measure product market competition, I use product demand elasticities as a measure of pricing power. Less elastic demand implies the ability to price above marginal cost and is a direct measure of competitive intensity in an industry. Product market elasticities have been estimated for a large number of SIC codes in a series of influential papers that identify industry markup over marginal cost using cyclical variation in input costs. Solow (1957) shows that the growth of total factor productivity (the part of output growth not explained by growth in labor input also known as the "Solow residual") is procyclical. Hall (1986) shows that the procyclicality of the Solow residual will be spurious if price does not equal marginal cost. Instead, the procyclicality is driven in part by noncompetitive pricing. To measure markups, Hall uses instrumental variables, such as defense spending, that shift output but are unrelated to productivity. The method was refined in Hall (1988), Domowitz et al. (1988), and Norrbin (1993).[6]

Since the time period of the estimates of elasticity reported in these prior studies is appropriate for my study, I use the reported estimates in my analysis and do not attempt to improve on their methods. Based on the four-digit SIC code reported in CRSP, I record the elasticity from the most detailed industry level available. If different papers report different elasticities for the same industry level, I record the elasticity from the most recent paper, as the methodology was improved over time by taking into account intermediate inputs.

The average product market elasticity is 3.34 with a standard deviation of 3.33. Some examples of the estimates of elasticities are 1.02 for Pipelines (SIC 46), 1.72 for Railroad Transportation (SIC 40), 4.83 for Primary Metals (SIC 33), and 8.58 for Stone, Clay, Glass, and Concrete Products (SIC 32).

[6] Though industry concentration is sometimes linked to competition, simply having few firms dominating sales in an industry does not imply that firms have pricing power (Demsetz, 1968). Indeed, Domowitz et al. (1988) show that markups are only weakly related to industry concentration.

In contrast to the product market–based measures of substitutability, a related line of research, starting with Roll (1988), investigates the co-movement of individual stock returns with industry and market portfolios. Greater co-movement between an individual stock and a particular portfolio implies that both are affected by the same events. Other papers have shown that emerging markets have greater stock price co-movement than more developed markets (Morck et al., 2000; Wurgler, 2000), individual volatility increased from the 1960s to the 1990s (Campbell et al., 2001; Wei & Zhang, 2006), and firms that use information technology more intensively have greater firm-specific stock return variation (Chun et al., 2008).

Following these papers, in the second approach to measuring substitutability, I calculate the degree to which a stock co-moves with its particular industry, market-wide portfolios, and individual stocks. First, for each stock on CRSP that is not missing any observations over the period November 1, 1989, to October 31, 1990, I regress the stock's daily returns on the returns of an equally weighted portfolio of all stocks in the firm's industry, excluding the firm itself. I run identical regressions that also include the CRSP value-weighted index and mimicking portfolios to capture risk related to size and book-to-market characteristics, as described in Fama and French (1993). For each industry, I record the cross-sectional median of the coefficient on the industry portfolio. Thus, these measures capture the degree to which a median firm's returns in an industry co-move with the overall industry returns, before and after accounting for market-wide risk factors.

Second, I record the statistical maximum degree of substitutability for each stock where substitutes are limited to one other single stock. For every stock in the sample, I calculate the R^2 from a regression of the daily returns of the sample stock on a constant term and the returns of every other common stock in CRSP over the prior year, individually. From this set of R^2s I record the maximum R^2. I limit attention to the co-movement from just one matched stock for computational reasons, but I acknowledge that a portfolio of assets will provide a better match than will a single stock.[7] An additional caveat is that because the matched firms that generate these R^2s are discovered by purely statistical means and lack a theoretical basis, it is possible that the R^2s do not persist in other time periods.

Third, I calculate a risk-adjusted R^2 from a regression of the stock's daily excess return (relative to the risk-free rate) on the Fama-French risk factors (Fama & French, 1993). In contrast to the prior variables, this variable measures co-movement for each sample stock with one common portfolio of risk factors. While firm-specific matching portfolios will likely provide closer substitutes, this variable is more likely to capture a persistent measure of the inverse of idiosyncratic volatility, which Wurgler and Zhuravskaya (2002) argue is a key determinant of elasticity. I acknowledge that both R^2 measures are imperfect proxies for substitutability. More accurately, they reflect what type of information moves stock prices, whether it is common to the market or to just one other firm.

C. *Other Related Variables*

Heterogeneous beliefs and information asymmetry may also help to explain cross-sectional differences in elasticity. To measure heterogeneity in beliefs, I use the dispersion of analysts' earnings forecasts. Data for these estimates are collected from the Institutional Brokers Estimate System (I/B/E/S) Summary History data set. For each of the 144 firms in the TORQ sample, I calculate the average coefficient of variation using the monthly means and standard deviations of earnings-per-share (EPS) estimates over the twelve months prior to October 31, 1990. In addition, I use share turnover as a measure of heterogeneity of beliefs. This is computed as the mean of daily volume over the prior year divided by the number of shares outstanding on October 31, 1990. Diether, Malloy, and Scherbina (2002) show that both dispersion in analysts' forecasts and share turnover are good proxies for differences in opinion among investors.

To measure informed trading, I use the bid-ask spread decomposition of Madhavan, Richardson, and Roomans (1997) (MRR), the probability of information-based trading (PIN) measure of Easley, Hvidkjaer, and O'Hara (2004), and the adverse selection cost measure (λ) of Kyle (1985). Following MRR, I estimate the ratio of the information component of the spread to the overall implied spread, using trade and quote data from the Institute for the Study of Security Markets (ISSM) database. I calculate Kyle's λ following the model of Glosten and Harris (1988) and as calculated in Brennan and Subrahmanyam (1995). I also record the most recent PIN measure for my sample period as calculated in Easley et al. (2004) and obtained from Soeren Hvidkjaer's website.

Both PIN and λ are designed to measure informed trading by identifying how much prices move in response to buy and sell orders. Informed investors' trades convey information, and so their trades have an impact on stock prices, whereas noise traders do not. Thus, by observing equilibrium price changes for a given order flow, one can infer whether informed investors are trading. If trading does not affect prices, it can be inferred that the traders are uninformed. Since PIN and λ are empirically estimated using only equilibrium outcomes, they cannot identify the shape of the demand curve. Instead, the same equilibrium prices and order flow can be realized with demand curves of different slopes. Nevertheless, I argue that the demand curves for stocks with more informed investors should be more elastic because informed investors are expected to be more sensitive to prices than are liquidity traders. Since liquidity traders do not condition their trades on price, their demand curves are steep. Together with product market elasticity, the measures of asymmetric information and heterogeneous beliefs provide possible

[7] Wurgler and Zhuravskaya (2002) argue that finding the optimal portfolio weights on the vast set of available assets is likely infeasible, and even if one could find the optimal portfolio, transaction costs would likely erase any arbitrage gains if many assets were included.

explanations for cross-sectional variation in stock price elasticity. However, they are not mutually exclusive but, rather, likely interrelated. For instance, with no frictions, informed trading would cancel the effects of heterogeneous beliefs. Therefore, my goal is not to test the explanations against each other but to consider the variables as proxies for elasticity, with different interpretations.

Finally, in cross-sectional tests I control for firm size (using logged book assets), daily stock return volatility over the prior year, and industry fixed effects. The incomplete information model of Merton (1987) predicts that the change in expected returns for an increase in firm size is an increasing function of firm volatility and firm size. Risk-averse investors require greater returns for greater volatility and for holding a larger fraction of their wealth in one stock. Since prices move inversely to expected returns, the elasticity of the stock price is the inverse of the elasticity of expected returns. Therefore, Merton's model predicts a negative relationship between stock price elasticity and both firm size and volatility.[8]

III. Empirical Results on the Cross-Section of Elasticity

Table 2 presents univariate relationships between the elasticity of stock demand and measures of substitutability, heterogeneity of beliefs, and informed trading. Each entry reports the elasticity of demand according to the row variable. High (Low) indicates stocks that have characteristics that are greater (smaller) than the median of the row variable.

Firms with above-median product market demand elasticity have significantly lower stock price elasticity (6.2) compared to firms with below-median product market elasticity (8.6). This provides the first evidence that firms in more competitive industries have lower stock price elasticity. Industry co-movement is not significantly related to elasticity, though greater risk-adjusted industry co-movement is positively associated with stock price elasticity, as predicted, though just outside the bounds of conventional levels of statistical significance. In contrast, both risk-adjusted and maximum R^2 measures are negatively and significantly associated with stock price elasticity in contrast to the substitutability hypothesis.

The variables that measure heterogeneous beliefs and information asymmetry are related to stock elasticity in expected ways, though not always significantly. Stocks with high levels of turnover have significantly lower elasticity than stocks with low levels of turnover. This is consistent with the argument that differences in beliefs cause steeper demand curves. Second, stocks with higher levels of informed trading have higher stock price elasticity. In particular, Kyle's λ has a strong and significant positive relationship with stock price elasticity. This is consistent with the idea that informed investors are more sensitive to deviations in price. PIN and the MRR-informed trading measures are positively related, but they are not statistically significant. Finally, table 2 shows that larger firms and more volatile firms have significantly lower stock price elasticity, as Merton (1987) predicted.

TABLE 2.—ELASTICITY OF DEMAND: UNIVARIATE RELATIONSHIPS

	Low	High	Difference	p-value
Substitutability				
Product market elasticity	8.558	6.235	−2.323**	0.014
Industry comovement	7.548	7.250	−0.298	0.762
Risk-adjusted industry comovement	6.554	7.939	1.385	0.121
Risk-adjusted R^2	8.703	5.978	−2.725***	0.003
Maximum R^2	7.975	5.892	−2.083**	0.027
Heterogeneity of beliefs				
Analyst dispersion	7.289	6.322	−0.967	0.287
Turnover	9.476	5.747	−3.728***	< 0.001
Informed trading				
MRR information	7.263	8.207	0.944	0.342
Kyle's lambda	5.888	9.352	3.465***	< 0.001
PIN	6.299	7.661	1.363	0.153
Size and volatility				
Log(Assets)	7.493	6.127	−1.366*	0.098
Volatility	9.299	5.527	−3.771***	< 0.001

Low and high are defined by the median of the row variable. p-values are from a two-tailed t-test assuming unequal variances. Statistically significant at *10%, **5%, and ***1%.

Next, table 3 presents the correlation matrix for all of the variables. Consistent with table 2, stock price elasticity is negatively and significantly correlated with product market elasticity, share turnover, and firm size and positively correlated with risk-adjusted industry co-movement and informed trading, as measured by Kyle's λ and PIN. Table 3 also shows that product market elasticity is orthogonal to heterogeneous beliefs, informed trading, firm size, and stock volatility but negatively correlated with stock price elasticity and risk-adjusted industry co-movement, implying that in more competitive industries, firms co-move less with their industry rivals, as predicted.

The results in table 3 show that many of the variables associated with stock price elasticity are highly correlated. Simple industry co-movement is correlated with risk-adjusted industry co-movement (0.55, p-value < 0.01). The three measures of informed trading are highly correlated, with a correlation of 0.47 between Kyle's λ and MRR and 0.39 between λ and PIN. The two R^2 measures are positively correlated (correlation coefficient of 0.87), though for brevity, I tabulate only risk-adjusted R^2 in table 3. R^2 is negatively correlated with stock price elasticity as in the univariate tests but uncorrelated with product market elasticity. I also find a strong negative correlation between R^2 and proxies for informed trading (MRR, PIN, and λ), consistent with evidence in Durnev, Morck, and Yeung (2004). Finally, firm size and stock price volatility are highly correlated with a number of variables. Larger firms have higher industry co-movement, less dispersion in analyst forecasts, and less informed trading. Stocks with greater volatility have lower comovement with their industry and greater analyst dispersion. Finally, volatility is negatively related to firm size.

In regression estimates presented in table 4, I find that product market elasticity is negatively and significantly related to stock price elasticity after controlling for firm size,

[8] Using logged market equity in place of logged book assets does not change any of the paper's results.

TABLE 3.—CORRELATIONS BETWEEN MAIN VARIABLES

	Stock Price Elasticity	Product Market Elasticity	Industry Co-Move	Risk-Adjusted Industry Co-Move	Risk-Adjusted R^2	Analyst Dispersion	Turnover	MRR Information	Kyle's Lambda	PIN	Log Assets
Product market elasticity	−0.22**										
	(0.02)										
Industry co-movement	−0.05	0.06									
	(0.61)	(0.53)									
Risk-adjusted	0.23**	−0.34***	0.55***								
industry co-movement	(0.01)	(< 0.01)	(< 0.01)								
Risk-adjusted R^2	−0.25***	0.00	0.22**	0.08							
	(0.01)	(0.98)	(0.01)	(0.37)							
Analyst dispersion	−0.06	0.00	−0.12	−0.20*	−0.31***						
	(0.60)	(0.99)	(0.25)	(0.06)	(< 0.01)						
Turnover	−0.29***	0.06	0.19**	−0.03	0.17*	−0.06					
	(< 0.01)	(0.54)	(0.03)	(0.70)	(0.05)	(0.57)					
MRR information	0.14	0.11	−0.05	−0.18*	−0.29***	−0.04	−0.22**				
	(0.15)	(0.25)	(0.60)	(0.05)	(< 0.01)	(0.74)	(0.02)				
Kyle's lambda	0.29***	−0.05	−0.02	0.02	−0.27***	0.09	−0.12	0.47***			
	(< 0.01)	(0.61)	(0.83)	(0.83)	(< 0.01)	(0.39)	(0.16)	(< 0.01)			
PIN	0.22**	0.01	−0.42***	−0.36***	−0.51***	0.05	−0.22**	0.28***	0.39***		
	(0.03)	(0.95)	(< 0.01)	(< 0.01)	(< 0.01)	(0.69)	(0.03)	(0.01)	(< 0.01)		
Log(Assets)	−0.18*	−0.20**	0.06	0.17*	0.65***	−0.27***	0.32***	−0.37***	−0.15	−0.36***	
	(0.06)	(0.03)	(0.51)	(0.08)	(< 0.01)	(0.01)	(< 0.01)	(< 0.01)	(0.13)	(< 0.01)	
Volatility	−0.33***	0.13	−0.38***	−0.30***	−0.30***	0.33***	−0.09	0.09	−0.16*	0.49***	−0.36***
	(< 0.01)	(0.15)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(0.30)	(0.36)	(0.08)	(< 0.01)	(< 0.01)

This table presents correlation coefficients in the first row and p-values in the second row. Statistically significant at *10%, **5%, and ***1%.

TABLE 4.—CROSS-SECTIONAL DETERMINANTS OF THE PRICE ELASTICITY OF DEMAND FOR STOCKS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Product market elasticity	−0.239**						−0.241***
	(0.012)						(0.007)
Risk-adjusted industry co-movement		2.253					0.146
		(0.477)					(0.971)
Risk-adjusted R^2			−6.451**				−3.124
			(0.015)				(0.277)
Analyst dispersion				−0.739			−1.547
				(0.430)			(0.170)
Turnover					−0.134		0.005
					(0.616)		(0.987)
MRR information						1.354	1.327
						(0.429)	(0.302)
Log(Assets)	−0.995***	−0.908***	−0.609*	−1.128***	−0.866***	−1.126***	−1.309***
	(0.003)	(0.004)	(0.076)	(0.002)	(0.008)	(0.002)	(0.002)
Volatility	−0.995***	−1.086***	−1.239***	−0.999***	−1.104***	−2.254***	−1.857***
	(0.002)	(0.001)	(< 0.001)	(0.001)	(0.001)	(< 0.001)	(0.001)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105	104	106	88	109	101	78
Adjusted R^2	0.210	0.183	0.203	0.209	0.176	0.253	0.290

Coefficients are from ordinary least squares regressions. Numbers in parentheses are p-values from a heteroskedasticity robust t-test. The dependent variable is the price elasticity of demand. Statistically significant at *10%, **5%, and ***1%.

volatility, and industry effects. It remains significant after including industry co-movement, heterogeneous beliefs, and informed trading, none of which is significant by itself. Thus, even after controlling for a host of alternative variables, there is a strong negative relationship between the elasticity of a firm's product market and its stock price elasticity.

Consistent with the prior results, risk-adjusted R^2 is negatively and significantly related to stock price elasticity in the regression analysis. This indicates that firms with greater idiosyncratic volatility have flatter demand curves, contradictory to the substitutability argument. This could reflect that stocks with low R^2s have greater information asymmetry, which is associated with greater stock price elasticity. Indeed, in a regression setting, once I control for informed trading, the negative relation between stock price elasticity and R^2 is insignificant. Given that these R^2 measures are possibly related to a wide variety of factors, including corporate governance and institutional ownership (Campbell et al., 2001) and that the R^2 measures are imperfect proxies for substitutability, it is difficult to interpret these results.

Overall, the results in this section present consistent evidence that competitive intensity affects the shape of the demand curves for stocks. The stock returns of firms in less competitive industries co-move more with their competitors than do the stocks of firms in more competitive industries. The availability of better substitutes in the stock market produces more elastic demand for stocks in less competitive industries.

These findings may help to better understand a number of relations documented in prior papers. First, based on my results, the greater competitive intensity found in developed economies and in more recent years would lead to increased firm heterogeneity and thus less elastic demand curves. This is consistent with the cross-country results in Morck et al. (2000) and the time-series results in Campbell et al. (2001). Similarly, the link between innovation-induced creative destruction and firm-specific heterogeneity in Chun et al. (2008) is consistent with less elastic demand curves in more competitive industries. Finally, the positive relation between informed trading and stock price elasticity, documented above, is also consistent with the theory of Jin and Myers (2006), which shows that greater transparency (relatively less informed trading) leads to reduced co-movement (less elasticity) as investors bear greater firm-specific risk.

IV. Robustness Tests

In this section, I provide evidence that the main results of the paper are robust to different measures of elasticity, possible firm-specific omitted variables, and industry maturity. I also connect my results to prior research that decomposes stock returns by different sources of information.

A. *Stock Price Elasticity Estimates from S&P 500 Index Changes*

The limit-order book data I use in the main analysis has limitations. For robustness, in this section, I use a completely different estimate of elasticity. Following a large literature starting with Shleifer (1986), I use exogenous changes in demand following inclusion or deletion of a stock from the S&P 500 Index. I estimate elasticity as the ratio of the abnormal turnover, AT_i, to the abnormal returns at the announcement of the index change, AR_i ($ELAS_{S\&P} = AT_i/AR_i$). Under the assumption of symmetric supply and demand functions, the greater is the ratio, the steeper is the slope of the supply curve (since demand shifts trace out the supply curve).[9]

The S&P 500 index additions and deletions data are from Chen, Noronha, and Singal (2004). These data include all changes to the S&P 500 Index from 1965 to 2000, exclusive of index changes due to cosmetic firm name changes, changes due to other major events such as acquisitions, and irregular changes that do not require changes in index fund holdings. After accounting for data availability, there are 658 index additions and 203 deletions. Due to survivorship issues, the number of additions is much larger than deletions.

Abnormal returns on each day are calculated as the raw return adjusted by the return of a portfolio of ten stocks matched by NYSE deciles of market equity and prior returns (Ahern, 2009). Abnormal turnover is the daily volume normalized by the number of shares outstanding (turnover), adjusted by the average daily turnover during the period $(-239, -6)$ relative to the announcement date (Shleifer, 1986). Since elasticity is a ratio of these two estimates, I remove outliers by omitting the top and bottom 1% of estimates.

The average cumulative abnormal return over the announcement and following day for stocks added to the index is 3.27%; for deletions it is −2.90%. The average abnormal turnover in the announcement period is 0.95% compared to an average daily turnover of 0.38% in the prior year. The average estimated stock price elasticity ($ELAS_{S\&P}$) is 16.3% for additions and −6.20% for deletions.[10] This means that for a 1% increase in the stock price, the average stock added to the S&P 500 index experienced an increase of 0.163% in stock turnover on the announcement and following day.

Regression results are as follows:

$$\begin{aligned} &ELAS_{S\&P} \\ &\quad = \underset{(0.163)}{-4.552} \quad - \underset{(0.048)}{0.665} \times ELAS_{PM} \quad + \underset{(<0.001)}{1.311} \times SIZE \qquad (2) \\ &R^2 = 0.075,\ N = 494,\ \text{robust } p\text{-values in parentheses} \end{aligned}$$

The negative and significant coefficient on product market elasticity ($ELAS_{PM}$) provides further evidence of a negative relationship between stock and product market elasticities. These results show that my main findings are not specific to using data from limit-order books but instead generalize to the well-researched setting of index additions.

B. *Effect of the 1991 Gulf War on Stock Price Elasticity*

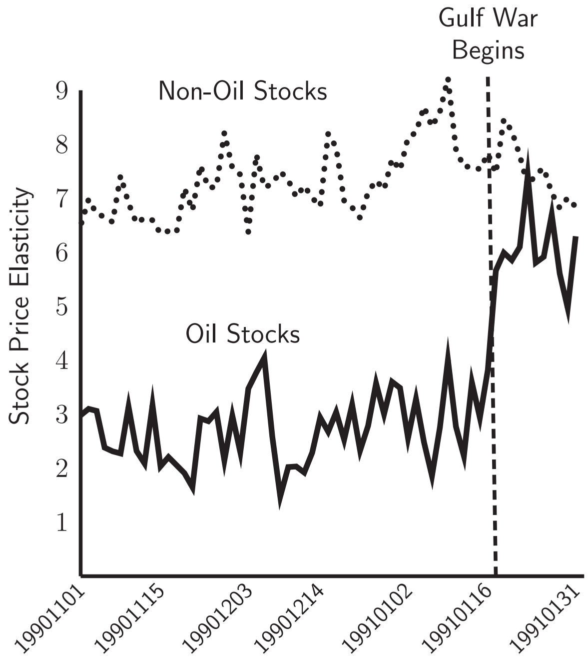
In this section, I present panel difference-in-difference tests using a large exogenous shock. On January 17, 1991, the First Gulf War began with a general U.S. military offensive against Iraq. I compare the change in elasticity following the start of the war for firms in petroleum-related industries to the change in elasticity for firms in other industries.

The war is likely to have affected petroleum-related firms more directly than other firms. Kilian (2008) shows that the 1991 Gulf War led to a negative supply shock of oil. However, the resulting price shock is not fully attributable to the supply shock. Instead, there was substantial precautionary demand pressure, which also increased prices (Barsky & Kilian, 2004). At the same time, competitive intensity was reduced as entry became more difficult. Therefore, it is likely that the short-run demand for oil-related goods became less elastic with the start of the Gulf War as a shortage of oil became more likely. If so, we would expect that the elasticity of the stocks of oil-related firms would increase relative to other firms after the start of the war. These firms will co-move

[9] I do not question this assumption in this paper, but merely wish to test my hypothesis in the same setting that has been used in prior research.

[10] Negative elasticity for index deletions is consistent with Chen, Noronha, and Singal (2004), who report asymmetric abnormal returns between additions and deletions.

FIGURE 2.—STOCK PRICE ELASTICITY OF DEMAND AND THE FIRST GULF WAR



This figure represents the daily average stock price elasticity of Exxon, Schlumberger, and Dresser Industries (oil stocks) compared to the average daily elasticity for all other stocks (nonoil stocks) over the period November 1, 1990, to December 31, 1991. The first military conflict of the Persian Gulf War was on January 17, 1991, and is indicated by the vertical dashed line.

TABLE 5.—PRICE ELASTICITY OF DEMAND FOR OIL VERSUS NONOIL STOCKS

	Prewar	War	Difference
A: Stock price elasticity			
Oil stocks	2.730	6.029	3.299***
			(< 0.001)
Nonoil stocks	7.316	7.451	0.135
			(0.481)
Difference	−4.586***	−1.422***	3.164***
	(< 0.001)	(< 0.001)	(< 0.001)
B: Daily returns			
Oil stocks	−0.043	0.112	0.155
			(0.779)
Nonoil stocks	0.272	0.510	0.238
			(0.443)
Difference	−0.315	−0.398	−0.083
	(0.097)*	(0.510)	(0.905)
C: Proportional bid-ask spread			
Oil stocks	0.585	0.529	−0.056***
			(0.001)
Nonoil stocks	2.056	1.935	−0.121***
			(0.008)
Difference	−1.471***	−1.406***	0.065
	(< 0.001)	(< 0.001)	(0.102)
D: Turnover			
Oil stocks	1.852	2.343	0.491*
			(0.078)
Nonoil stocks	2.183	2.635	0.452*
			(0.098)
Difference	−0.331**	−0.292	0.039
	(0.019)	(0.394)	(0.862)

Table entries are average price elasticity of demand, daily returns (in percentages), and the proportional bid-ask spread (in percentage) by time period and by firm industry. Oil stocks are Exxon, Schlumberger, and Dresser Industries in SIC codes 2911, 1389, and 1382. Nonoil stock are all other stocks in the TORQ database. The prewar period is November 1, 1990, to January 16, 1991. The war period is January 17, 1991, to January 31, 1991. The numbers in parentheses are p-values from a t-test assuming unequal variances across samples. Statistically significant at *10%, **5%, and ***1%.

more closely with one another since their future cash flows will all be closely related to the outcome of the war.

There are three firms in the TORQ database in industries related to oil: Exxon, Schlumberger, and Dresser Industries (SIC codes 2911, 1389, and 1382). I compute the daily average elasticity over these three firms and also for the remaining nonoil-related firms in the database. I then compute both portfolios' time-series averages for the prewar period from November 1, 1990, to January 16, 1991, and the war period from January 17, 1991, to January 31, 1991.

Figure 2 presents evidence that the start of the war had a significant impact on the elasticity of the oil stocks. Their average elasticity jumps on January 17, the day that the conflict began, and remains high through the end of the sample period, while nonoil stocks are unaffected.

The average elasticities of oil and nonoil stocks in the pre- and postwar periods are reported in table 5. In panel A, the average elasticity of the three oil stocks in the war period more than doubled after the war began. The elasticity of the nonoil stocks is unchanged between the two periods. The difference-in-difference between the two portfolios and the two time periods is statistically significant.

Panels B, C, and D of table 5, present similar analyses for changes in stock returns, bid-ask spreads, and turnover. The difference-in-difference for each of these variables is insignificant. Thus, the results presented here provide further evidence that stock price elasticity is negatively related to the elasticity of demand in the product market, using an exogenous change in industry conditions.

C. *Return Decompositions and Competitive Intensity*

To refine the connection between stock returns and product market profitability, I decompose individual stock returns into cash-flow news and expected-return news following the procedure as proposed in Campbell (1991) and refined for individual stocks in Vuolteenaho (2002). Expected-return news indicates changes in expectations about the firm's discount rate. Cash-flow news indicates changes in expectations about future cash flows.

Following Vuolteenaho (2002), I decompose stock returns for all firms in the CRSP-Compustat merged database from 1950 to 1990, using a vector autoregression (VAR) with three elements: yearly stock returns, return on equity, and book-to-market. The accounting-based VAR method requires yearly estimates, in contrast to the daily stock return comovement I estimated above. As before, for each stock, I calculate comovement of both yearly cash flow and expected-returns news with the equal-weighted industry average, at the two-digit SIC level, accounting for the three Fama-French factors. I require at least ten years of return decompositions to provide reliable estimates. Then for each industry, I record the median co-movement coefficient.

I find that firms in more competitive industries have less cash-flow news co-movement (correlation of −0.46, p-value of 0.004), consistent with the main results. I also find that expected-return news co-movement is negatively correlated with product market competition, though less so (correlation of −0.34, *p*-value of 0.036). In a regression of product market elasticity on both cash-flow and expected-return news, I find that cash-flow news is negative and significant and discount-rate news is insignificant. These results confirm the main findings using yearly return data over a long-run period and suggest that the interrelatedness of the portion of stock returns driven by cash-flow innovations is greater in less competitive industries.

D. *Industry Maturity*

Klepper and Graddy (1990) study how industries evolve over time. They report that firms in more mature industries are likely to be less heterogeneous than firms in new industries. Concentration ratios are also likely to increase as an industry matures. Fama and French (2004) argue that the decline in the survival rates of firms from the 1970s to the 1990s may be explained by a decrease in the cost of equity capital, allowing greater heterogeneity among publicly traded firms. Chun et al. (2008) show that cross-industry variation in the adoption of information technology increased heterogeneity and shortened the expected life span of firms. Thus, industry maturity may explain substitutability and stock price elasticity rather than the competitiveness of the industry. To empirically test this idea, I record each sample stock's industry maturity following Klepper and Graddy (1990). I record the number of firms listed on Compustat for each four-digit SIC code industry, from 1950 to 1990. I then identify the year with the most firms as the peak year. If the peak year is 1990, the industry is not yet mature. When I include a dummy variable for mature industries, or the peak year, in the regressions in table 4, the results are unchanged, and the maturity variables are insignificant.

V. Conclusion

This paper shows that firms in more competitive industries have less elastic demand curves for their stocks. This finding is consistent with prior theoretical and empirical results that show that product market competition increases firm-specific heterogeneity and reduces correlations between firms' performance outcomes. This implies that competition reduces the substitutability of firms, which leads to less elastic demand curves. These results are robust to controls for heterogeneous beliefs, information asymmetry, firm size, volatility, and industry fixed effects.

The main results of the paper use off-equilibrium demand schedules inferred from the limit-order book of NYSE stocks during 1990 and 1991. To provide additional evidence, I test the relation between product market competition and stock price elasticity using different data sources and exogenous shocks. First, I use S&P 500 index changes to provide exogenous demand shocks to identify elasticity. Second, I decompose yearly returns from 1950 to 1990 into cash flow and expected returns news to measure industry comovement. Third, I exploit the start of the First Gulf War in January 1991 to compare elasticity changes following an exogenous shift in the characteristics of the oil industry, compared to non-oil-related firms. In each of these robustness tests, I find consistent evidence that increased product market competition leads to less elastic demand curves for stock.

The lack of perfect substitutes for stocks violates a key assumption of standard asset pricing models. In particular, it is not costless to take a position in a mispriced stock and attempt to hedge the position with a substitute because the investor bears the risk of imperfect substitutability. The results in this paper help to explain how limits to arbitrage are affected by competitive intensity in the product market. These results may shed light on how cross-industry, cross-country, and time-varying changes in competition affect stock trading and prices.

REFERENCES

Ahern, Kenneth R., "Sample Selection and Event Study Estimation," *Journal of Empirical Finance* 16 (2009), 466–482.

Bagwell, Laurie Simon, "Dutch Auction Repurchases: An Analysis of Shareholder Heterogeneity," *Journal of Finance* 47 (1992), 71–105.

Barsky, Robert B., and Lutz Kilian, "Oil and the Macroeconomy since the 1970s," *Journal of Economic Perspectives* 18 (2004), 115–134.

Bessembinder, Hendrik, "Quote-Based Competition and Trade Execution Costs in NYSE-Listed Stocks," *Journal of Financial Economics* 70 (2003), 385–422.

Bils, Mark, and Peter J. Klenow, "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy* 112 (2004), 947–985.

Board of Governors, "Flow of Funds Accounts of the United States," Board of Governors of the Federal Reserve System discussion paper (2012).

Boehmer, Ekkehart, Gideon Saar, and Lei Yu, "Lifting the Veil: An Analysis of Pre-Trade Transparency at the NYSE," *Journal of Finance* 60 (2005), 783–815.

Brennan, Michael J., and Avanidhar Subrahmanyam, "Investment Analysis and Price Formation in Securities Markets," *Journal of Financial Economics* 38 (1995), 361–381.

Campbell, John Y., "A Variance Decomposition for Stock Returns," *Economic Journal* 101 (1991), 157–179.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance* 551 (2001), 1–43.

Chacko, George C., Jakub W. Jurek, and Erik Stafford, "The Price of Immediacy," *Journal of Finance* 63 (2008), 1253–1290.

Chen, Honghui, Greg Noronha, and Vijay Singal, "The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation," *Journal of Finance* 59 (2004), 1901–1929.

Chun, Hyunbae, Jung-Wook Kim, Randall Morck, and Bernard Yeung, "Creative Destruction and Firm-Specific Performance Heterogeneity," *Journal of Financial Economics* 89 (2008), 109–135.

Demsetz, Harold, "Why Regulate Utilities?" *Journal of Law and Economics* 11 (1968), 55–65.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, "Differences of Opinion and the Cross Section of Stock Returns," *Journal of Finance* 57 (2002), 2113–2141.

Domowitz, Ian, R. Glenn Hubbard, and Bruce C. Petersen, "Market Structure and Cyclical Fluctuations in U.S. Manufacturing," this REVIEW 70 (1988), 55–66.

Durnev, Art, Randall Morck, and Bernard Yeung, "Value-Enhancing Capital Budgeting and Firm-Specific Stock Return Variation," *Journal of Finance* 59 (2004), 65–105.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, "Factoring Information into Returns," Cornell University working paper (2004).

Fama, Eugene F., and Kenneth R. French, "The Cross-Section of Expected Stock Returns," *Journal of Finance* 47 (1992), 427–465.

——— "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33 (1993), 3–56.

——— "New Lists: Fundamentals and Survival Rates," *Journal of Financial Economics* 73 (2004), 229–269.

Foucault, Thierry, Ohad Kadan, and Eugene Kandel, "Limit Order Book as a Market for Liquidity," *Review of Financial Studies* 18 (2005), 1171–1217.

Gatev, Evan, William N. Goetzmann, and K. Geert Rouwenhorst, "Pairs Trading: Performance of a Relative-Value Arbitrage Rule," *Review of Financial Studies* 19 (2006), 797–827.

Glosten, Lawrence, and Lawrence Harris, "Estimating the Components of the Bid-Ask Spread," *Journal of Financial Economics* 21 (1988), 123–142.

Grossman, Sanford J., and Joseph E. Stiglitz, "On the Impossibility of Infomationally Efficient Markets," *American Economic Review* 70 (1980), 393–408.

Hall, Robert E., "Market Structure and Macroeconomic Fluctuations," *Brookings Papers on Economic Activity* 1986 (1986), 285–338.

——— "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy* 96 (1988), 921–947.

Harris, Milton, and Artur Raviv, "Differences of Opinion Make a Horse Race," *Review of Financial Studies* 6 (1993), 473–506.

Hasbrouck, Joel, "Using the TORQ Database," New York University working paper (1992).

Hasbrouck, Joel, George Sofianos, and Deborah Sosebee, "New York Stock Exchange Systems and Trading Procedures," NYSE working paper 93-01 (1993).

Hollifield, Burton, Robert A. Miller, and Patrik Sandås, "Empirical Analysis of Limit Order Markets," *Review of Economic Studies* 71 (2004), 1027–1063.

Hollifield, Burton, Robert A. Miller, and Joshua Slive, "Estimating the Gains from Trade in Limit-Order Markets," *Journal of Finance* 61 (2006), 2753–2804.

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, "The Effect of Large Block Transactions on Security Prices: A Cross-Sectional Analysis," *Journal of Financial Economics* 19 (1987), 237–267.

Irvine, Paul J., and Jeffrey Pontiff, "Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition," *Review of Financial Studies* 22 (2009), 1149–1177.

Jin, Li, and Stewart Myers, "R^2 around the World: New Theory and New Tests," *Journal of Financial Economics* 79 (2006), 257–292.

Kalay, Avner, Orly Sade, and Avi Wohl, "Measuring Stock Illiquidity: An Investigation of the Demand and Supply Schedules at the TASE," *Journal of Financial Economics* 74 (2004), 461–486.

Kandel, Shmuel, Oded Sarig, and Avi Wohl, "The Demand for Stocks: An Analysis of IPO Auctions," *Review of Financial Studies* 12 (1999), 227–247.

Kaul, Aditya, Vikas Mehrotra, and Randall Morck, "Demand Curves for Stocks *Do* Slope Down: New Evidence from an Index Weights Adjustment," *Journal of Finance* 55 (2000), 893–912.

Kavajecz, Kenneth A., "A Specialist's Quoted Depth and the Limit Order Book," *Journal of Finance* 54 (1999), 747–771.

Keim, Donald B., and Ananth Madhavan, "The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects," *Review of Financial Studies* 9 (1996), 1–36.

Kilian, Lutz, "Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?" this REVIEW 90 (2008), 216–240.

Kim, Jung-Wook, Jason Lee, and Randall Morck, "Heterogeneous Investors and Their Changing Demand and Supply Schedules for Individual Common Stocks," NBER working paper 10410 (2004).

Klepper, Steven, and Elizabeth Graddy, "The Evolution of New Industries and the Determinants of Market Structure," *RAND Journal of Economics* 21 (1990), 27–44.

Kyle, Albert S., "Continuous Auctions and Insider Trading," *Econometrica* 53 (1985), 1315–1335.

Lee, Charles M. C., and Balkrishna Radhakrishna, "Inferring Investor Behavior: Evidence from TORQ Data," *Journal of Financial Markets* 3 (2000), 83–111.

Loderer, Claudio, John W. Cooney, and Leonard D. Van Drunen, "The Price Elasticity of Demand for Common Stock," *Journal of Finance* 46 (1991), 621–651.

MacKay, Peter, and Gordon M. Phillips, "How Does Industry Affect Firm Financial Structure?" *Review of Financial Studies* 18 (2005), 1433–1466.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, "Why Do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks," *Review of Financial Studies* 10 (1997), 1035–1064.

Merton, Robert C., "A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance* 42 (1987), 483–510.

Miller, Edward M., "Risk, Uncertainty, and Divergence of Opinion," *Journal of Finance* 32 (1977), 1151–1168.

Morck, Randall, Bernard Yeung, and Wayne Yu, "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?" *Journal of Financial Economics* 58 (2000), 215–260.

Norrbin, Stefan C., "The Relation between Price and Marginal Cost in U.S. Industry: A Contradiction," *Journal of Political Economy* 101 (1993), 1149–1164.

Petajisto, Antti, "Why Do Demand Curves for Stocks Slope Down?" *Journal of Financial and Quantitative Analysis* 44 (2009), 1013–1044.

Raith, Michael, "Competition, Risk, and Managerial Incentives," *American Economic Review* 93 (2003), 1425–1436.

Roll, Richard, "R^2," *Journal of Finance* 43 (1988), 541–566.

Shleifer, Andrei, "Do Demand Curves for Stocks Slope Down?" *Journal of Finance* 41 (1986), 579–590.

Sofianos, George, and Ingrid M. Werner, "The Trades of NYSE Floor Brokers," *Journal of Financial Markets* 3 (2000), 139–176.

Solow, Robert M., "Technical Change and the Aggregate Production Function," this REVIEW 39 (1957), 312–320.

Vuolteenaho, Tuomo, "What Drives Firm-Level Stock Returns?" *Journal of Finance* 57 (2002), 233–264.

Wei, Steven X., and Chu Zhang, "Why Did Individual Stocks Become More Volatile?" *Journal of Business* 79 (2006), 259–292.

Wurgler, Jeffrey, "Financial Markets and the Allocation of Capital," *Journal of Financial Economics* 58 (2000), 187–214.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business* 75 (2002), 583–608.