Characteristics of Observed Demand and Supply Schedules for Individual Stocks

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Abstract

Using complete limit order books from the Korea Stock Exchange for a three-year period including the 1998 Asian financial crisis, we observe (not estimate) demand and supply curves for individual stocks. Both curves have demonstrably finite elasticities. These fall markedly by about 40% with the crisis and remain depressed long after other economic and financial variables revert to pre-crisis norms. Although they share this common long-term modulation, the magnitudes of individual stocks’ supply and demand elasticities are negatively correlated at high frequencies. That is, when a stock exhibits an unusually elastic demand curve, it tends simultaneously to exhibit an unusually inelastic supply curve, and vice versa. These findings have potential implications for modeling how information flows into and through stock markets, how investors react or interact to information flows, and how new information is capitalized into stock prices. We advance speculative hypotheses, and invite further work – including theory papers – to explain these findings and their implications.

JEL classification: G10; G14

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1. Introduction

A complete dataset of all orders, each flagged as a buy or sell, for all Korean listed stocks from Dec. 1996 to Dec. 2000 lets us observe the whole demand and supply curves of limit orders for each individual listed stock at any instant in time. We do this twice each day – once at the beginning of trading and again at 2:30PM, half an hour before the market’s close.\(^1\) Since the market opens with a call auction session but then switches to continuous trading, this lets us explore demand and supply under the two microstructure alternatives. Since our sample period includes 1998, we also compare demand and supply curves of common stocks before, during, and after the Asian financial crisis.

Because we observe entire demand and supply curves, we measure the elasticity of each curve separately and directly, rather than jointly and by inference from prices and quantities traded. This sidesteps entirely the standard identification problems associated with elasticity estimation. Moreover, it also lets us compare the two elasticities and investigate the relationship between them. To the best of our knowledge, this is the first study to investigate these issues.

Our main results are as follows.

First, individual stocks’ supply and demand elasticities are significantly less than infinity, in that their reciprocals differ significantly from zero. This supports theories of information capitalization, derived from Harrison and Kreps (1978), Grossman and Stiglitz (1980), and others; in which market prices arise from the intersection of finitely elastic demand and supply curves for each stock. Asset pricing models that postulate infinitely elastic demand and supply for individual stocks may be useful approximations under some circumstances, but these require clarification.

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\(^1\) The KSE was open Saturday mornings until December 5, 1998, so on Saturdays during that period the second elasticity is estimated at 11:30 AM instead of 2:30 PM. Dropping these observations does not qualitatively change any of our results.
Second, the absolute values of both demand and supply elasticities exhibit a common long run modulation. Before the Asian crisis, both average around 36. That is, a one percent price change commands a 36 percent change in quantity demanded or supplied. Both absolute values drop to roughly 22 after the crisis. Unlike many other economic and financial indicators, which fluctuate dramatically around the crisis before reverting to their pre-crisis levels, individual stocks’ elasticities remain at these new average levels – apparently permanently. If investors have homogeneous valuations, elasticities should be very large, becoming infinite as valuations converge fully. The permanently reduced elasticities of demand and supply curves we observe after the crisis imply a permanently elevated heterogeneity of investors’ valuations of Korean firms. The direction of this shift is intriguing, for post-crisis reforms are thought to have enhanced transparency and the advent of online trading is thought to have reduced transactions costs.

Third, superimposed on this common long run modulation, the absolute values of the two elasticities exhibit a negative correlation at high frequencies. That is, stocks that develop unusually elastic demand curves tend simultaneously to develop unusually inelastic supply curves and vice versa. This high frequency correlation is more negative in 2:30 PM elasticities than in opening auction elasticities.

This high frequency interaction of supply and demand elasticities raises the possibility of a feedback. For example, demand elasticity might fall as buy-side limit order book depth evaporates in response to aggressive sell-side orders that flatten the stock’s supply curve. This sort of feedback reinforces the importance of selecting relatively information-free changes in quantities demanded or sought when estimating individual stocks’ demand or supply elasticities (Shleifer, 1986; Wurgler and Zhuravskaya, 2002). Such feedback is also consistent with the conclusions of French and Roll (1986), Roll (1988), and others regarding
information propagation in financial markets: most new information to be uncovered by private investors and revealed sequentially through their trading.

Because limit orders greatly preponder market orders in Korea, and because Korean limit order books retain considerable depth well away from market prices, we can measure elasticities across broad price ranges, consistent with fundamental valuation heterogeneity across limit order providers. This complements previous work using strategic limit order placement near the market to gauge local elasticities (Kalay et al., 2004).

The remainder of the paper is organized as follows. Section 2 discusses other relevant research. Section 3 discusses the data and elasticity measurement procedure. Section 4 describes our findings, and Section 5 concludes.

2. Relation to Previous Studies

The wheelhorses of asset pricing (Markowitz, 1952; Tobin, 1958; Sharpe, 1964; Lintner, 1965) postulate that individual stocks have infinitely many perfect substitutes in other stocks or portfolios, and so have horizontal demand and supply curves. In contrast, asset prices given costly information or incomplete arbitrage are determined by finitely elastic demand and supply curves for individual stocks, as in Grossman and Stiglitz (1980). Basic models of this ilk posit demand and supply elasticities as functions of investor risk aversion and uncertainty about fundamental values. All else equal, either greater risk aversion or greater uncertainty can imply more heterogeneous fundamental value estimates, and hence less elastic demand and supply curves. Subsequent elaborations include Blough (1988), who models heterogeneous information; Hindy (1989), who has different investors using different models to process common information; De Long et al. (1990), who model noise traders formally; Kandel and Peason (1995), who assign different priors to different investors; Harris and Raviv (1993) who model differences of opinion more generally, and others.
The virtues of the wheelhorses are elegance and simplicity; those of the Grossman and Stiglitz (1980) framework are explicit recognition of information costs and the microeconomics of the investment business (Shleifer and Vishny, 1997). The latter advantages are nontrivial, for Varian (1985, 1989), Shleifer and Vishny (1997), Shleifer (2000), Shiller (2002), and many others argue that information per se is costly. Shleifer and Vishny (1997) go further, arguing that inescapable information asymmetries and agency problems in finance sector firms create economically significant transactions costs to informed trading, even on free private information. These considerations allow different investors to persist in different beliefs about individual stocks’ values, directly implying finitely elastic demand and supply curves.


Scholes (1972) thus rightly stresses the importance of gauging these elasticities. Unable to observe these curves directly, he examines stock price drops upon secondary offerings announcements and concludes that these reflect negative information conveyed by firms’ decisions to issue shares, not finite elasticities. Mikkelson and Partch (1985) revisit the issue, concluding demand and supply elasticities for individual stocks to be very large.

others report share price increases when stocks are added to widely followed indexes. Shleifer attributes this to finitely elastic demand curves shifted right by index funds’ share purchases. But Jain (1987), Dhillon and Johnson (1991), Denis et al. (2003) and others argue that inclusion in an index conveys positive information about a stock; while Harris and Gruel (1986) argue for a temporary price pressure effect, whereby index fund purchases elevate prices only until arbitrageurs’ trades reverse the effect. Kaul et al. (2000) examine the reweighting of a widely tracked Canadian index, and find permanent price elevations for stocks whose weights rise and permanent price decreases for those whose weights fall. Since no stocks are added to the index and the reweighting is announced months in advance, an information effect is excluded. Since the effects do not reverse, price pressure is also untenable. In contrast, Greenwood (2005) examines a similar reweighting in Japan, and finds a complete reversal.

Thus, despite much work, generalizations about elasticities of supply and demand for individual common stocks remain elusive. Furthermore, simultaneity problems persist wherever elasticities are inferred indirectly from the price impacts of certain events. If factors that affect demand also affect supply, identification problems arise and biases ensue. In goods markets, these can be mitigated if appropriate strong instruments are available to distinguish, e.g. technology from preference shocks. But the stock market is a pure exchange market, whose traders are all plausibly affected by similar factors simultaneously.

This obliges alternative approaches of directly estimating elasticities given demand or supply curves. Thus, Bagwell (1992) examine stock repurchases; while Kandel et al. (1999) and Liaw et al. (2000) study IPOs auctions. All find finite elasticities, but also all pertain to special corporate events, not normal trading days.

Kalay et al. (2004) measure demand and supply elasticities for stocks traded on the Tel Aviv Stock Exchange from limit orders adjacent to market prices. They report
unambiguously finite elasticities, but caution that their estimates depend critically on their assumptions about the shareholder base. Specifically, they measure elasticities as percentage changes in quantities divided by percentage change in prices and take the former to be the quantity offered or sought divided by the ‘total quantity of shares’. If this denominator is shares outstanding, all shares are assumed to be for sale and their elasticities are very small: 0.083 and 0.009 for mean local demand and supply elasticities, respectively. If they scale instead by opening volume, only shareholders active at that time are assumed to be willing to trade and their elasticities are large: 415.4 and 63.6 demand and supply elasticities, respectively. Scaling by total shares in the order book at open, or by mean daily volume, yields only slightly less extreme point estimates. All of these scaling methods are defensible, as are others – such as the public float, or a smoothed trading volume.

This issue affects the estimation of any demand and supply elasticities in any markets – for example, the potential total quantity of oil might be current inventories, “proven” reserves, “possible” reserves, or all geological deposits. While accepting the validity of this issue, we follow the conventional econometrics textbook approach (e.g. Greene, 1993) and estimate elasticities as log differences in quantities offered, or sought, divided by log differences in price. This lets the data choose a denominator at the cost of imposing a constant elasticity assumption across the whole length of each curve. This assumption is clearly restrictive, but parsimoniously characterizes valuation heterogeneity across the broad price ranges we observe in the data. Since measuring this heterogeneity is our primary interest, the log on log specification is defensible. However, alternative assumptions may well be preferable in other contexts. Subsequent sections therefore examine the robustness of our results to modifying this assumption and estimating elasticities using subsets of limit order books.
Directly measuring supply and demand elasticities from observed quantities offered and sought at various prices escapes the sins of misidentification that can afflict simultaneous equations estimation using market prices and quantities traded. Moreover, since we directly observe both demand and supply elasticities, we can test also for relationships between them.

A formal model is beyond the scope of this paper, but the logic can be laid out readily. Assume the information propagation framework proposed by French and Roll (1986) and Roll (1988) is correct: a specific subset of investors are the first to learn of new information, and others only learn of it by watching for unusual trading patterns that signal new private information. As trades execute at changing prices, limit order providers observe the valuations of other investors, and use this information to update their own fundamental value estimates and the uncertainty they attach to those estimates; and hence also their limit orders. This point seems especially important given Roll (1988), who shows that stock price fluctuations usually do not correspond to public information events. From this, he infers that stock price changes are typically caused by investors seeking to gain from private information they acquire. This suggests that traders on one side of the limit order book may often be at an information advantage to those on the other side. For example, if a subset of investors learns a stock is underpriced, they should enter large buy orders at or just above the market price, flattening the demand curve. Seeing these executed, uninformed sell-side investors would presumably withdraw limit order depth near the market price, steepening the supply curve.

Consistent with the intuition underlying these conjectures, Kavajecz (1999) finds specialists and limit order traders in the U.S. reducing depths around information events, thereby reducing their exposure to adverse selection (Hollifield et al., 2004, 2006). Also consistent with this intuition, Goldstein and Kavajecz (2004) report limit order traders
remaining inactive or even withdrawing when the plummeting Dow Jones Industrial Average triggered circuit breakers that halted all trading on October 27, 1997.

Limit orders away from the market price provide liquidity, and so arise even in the absence of valuation heterogeneity – especially in limit order driven market like the KSE. Unlike the New York Stock Exchange, the KSE lacks designated market makers charged with providing liquidity to maintain orderly market. Rather, private investors submit limit orders anticipating profits from providing immediate liquidity to the market (Handa and Schwartz, 1996). Thus, limit orders placed around market prices can reflect heterogeneous patience across investors, rather than heterogeneous valuations. Patient investors place limit orders far from the market price; while less patient investors, preferring faster execution, place orders or at or near the market.

Thus, Foucault et al. (2005) model strategic liquidity providers with heterogeneous impatience in the absence of private information. In this model, the placement of limit orders is mainly determined by the extent of patience heterogeneity and the order arrival rate. For example, as their patient traders reduce liquidity related demand, or as the order arrival rate decreases, liquidity suppliers submit more aggressive limit orders to reduce execution time. A distribution of limit orders around market prices is thus possible absent any information heterogeneity or private information whatsoever. Given this reasoning, our observed elasticities may reflect strategic liquidity provision, rather than genuine valuation heterogeneity among investors. 

Hollifield et al. (2004, 2006) develop this reasoning further by incorporating strategic liquidity provision into a Grossman and Stiglitz (1980) information heterogeneity framework. Their model describes a liquidity provider’s optimal limit order strategy as a function of her fundamental value estimate and a trade-off between execution probability and an adverse selection risk – the risk of losing money trading against better informed investors. Limit
orders nearer the market price have a higher execution probability, but entail worse adverse selection problems. Thus, Hollifield et al. (2006) write: “traders with high private values submit buy orders with high execution probabilities. Traders with low private values submit sell orders with high execution probabilities. Traders with intermediate private values either submit no orders, or submit buy or sell orders with low execution probabilities”. Because of this, Hollifield et al. (2004, 2006) conclude that heterogeneous investor beliefs and liquidity provision are inseparably confounded, and thus best considered jointly. For example, investors place limit orders away from the market price not just because they are patient but also because their valuations are different from those who place more aggressive orders. That is, investors whose private valuations differ from the market price are also those who provide liquidity. Their models suggest this lets such traders capture larger quasirents, and thus encourages their acquisition of more and costlier private information (Grossman and Stiglitz, 1980). The provision of liquidity is thus a by-product of heterogeneous investor valuations.

Still, we must accept that distinguishing limit orders driven by heterogeneous valuation from those driven by heterogeneous impatience is impracticable. The framework of Hollifield et al. (2004, 2006) thus indicates that our elasticity estimates capture investor heterogeneity; but allow that this might be valuation heterogeneity, impatience heterogeneity, or some combination of the two. We therefore proceed with this ambiguity unresolved, and revisit this issue in section 3.5 and 3.6, where further evidence on this point is presented.

3. Measuring Elasticities

This section describes how we measure elasticities of demand and supply of individual stocks. It first describes the trading system of the KSE and the raw trade and quote data it generates, then how we construct demand and supply schedules for each stock twice a day, and finally how we summarize the shape of those curves into elasticities.
3.1. Market Microstructure

The KSE is an order driven market, in that it has no designated market makers or specialists. Any investor is free to make a market in any stock, however this entails certain costs. All investors, including brokers, pay a 0.3% stamp tax on executed sales. Online trading started in 1997 with fees of 0.5%, matching standard brokerage fees at the time. But online fees fell sharply after June 1998 as competition began in earnest. Tick sizes range from 0.1% to 0.5% depending on a stock’s price range. For example, a ₩5,000 stock is priced in ₩5 increments, while a ₩50,000 stock is priced in ₩50 ticks.² Bid-ask spreads are thus not entirely endogenous.

The investor base also changes with time. Before May 1998, foreign ownership was capped, limiting foreigners’ ability to buy aggressively if the firm already had large foreign blockholdings. After May 1998, all such restrictions disappeared.

Trading begins at 09:00 with a call market – an auction in which accumulated bids and offers, taken as simultaneous, are matched to generate one opening price for each stock. In our data, 19.10 percent of buy orders and 21.14 percent of sell orders are submitted to opening sessions.

Subsequent prices, until 10 minutes before the closing time at 15:00 are set in continuous trading.³ In the last 10 minutes, another auction market session determines prices. Orders not fully filled in the opening auction pass into continuous trading unless cancelled or revised. An automatic trading system records all outstanding limit orders and automatically crosses new market and limit orders with these, or with opposite market orders.⁴ The computerized order-routing system prioritizes by price and then time.

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² All prices are in Korean won, a floating currency trading at roughly ₩1,000 per US dollar during most of our sample period.
³ Before May 22, 2000, the KSE held separate morning (9:00 to 12:00) and afternoon (13:00 to 15:00) sessions, each commencing with a call market.
⁴ For additional detail, see e.g. Choe, Kho, and Stulz (1999).
3.2. **Trade and Quote Records Data**

Our Korean Stock Exchange Trade and Quote (KSETAQ) data are computer records from this system. They include all KSE transactions and limit orders – filled and unfilled. Each record gives a ticker symbol, a date and precise time; a flag for buy versus sell orders; and, for limit orders, the price.

We can also separate data used in the opening auctions from continuous trading data. Margin and short sale orders are also specially flagged. Our sample contains complete data from Dec. 1st 1996 to Dec 31st 2000, and Table 1 summarizes its composition.

![Table 1 about here](image)

In constructing demand and supply schedules, we focus on limit orders because market orders, by definition, do not specify prices.\(^5\) Also, market orders are a very small fraction of total orders on the KSE. Table 1 shows limit orders comprising 94.78 percents of buy orders and 92.99 percent of sell orders. The rarity of market orders likely reflects their novelty. Market orders were introduced by the KSE on November 25\(^{th}\) 1996, only a few days before our sample window begins, and remained little used.\(^6\) We hope to explore this event and its implications in future work.

We then take two snapshots per day of each stock’s complete limit order book. The first is at the opening auction, and the second is at 2:30 PM – thirty minutes before trading ends. Unexecuted limit orders expire at the end of the day, so one day’s limit orders do not typically reappear the next day.

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\(^5\) Bloomfield et al. (2005) and Kaniel and Liu (2006) argue that informed investors should prefer limit orders to market orders. Thus, limit orders are likely more useful for gauging information heterogeneity among investors.

\(^6\) One financial analyst we asked about this proposed a starkly behavioral motive, resonant of the “default option” bias explained in Thaler and Sunstein (2008): the standard electronic form for entering orders has a blank for price, so most investors enter one.
3.3. Demand and Supply Schedules

To gauge elasticities, we first plot out the demand and supply schedules of each individual stock – first in the opening call auction and then at 2:30 PM amid continuous trading. This is done precisely as in economics principles textbooks, and is best illustrated with an example.

[Figure 1 about here]

Figure 1 graphs the demand and supply schedules on November 11th 2000 of Samsung Electronics, a large and heavily traded KSE listing. These graphs are constructed by horizontally summing all limit orders that would execute at each theoretical price. The sum of all buy orders that would execute at a given price $p$ is the demand for Samsung Electronics at that price. As the price is decreased, tick by tick, successively more buy limit orders join the executable list so the demand curve reaches further to the right at lower prices. The sum of all sell orders that would execute at price $p$ is analogously the supply of Samsung Electronics shares offered at that price. Again, as the price rises in one tick increment, additional sell orders join that sum and the supply curve extends increasingly far to the right at successively higher prices.

[Figure 2 about here]

The demand and supply schedules at both the opening auction and 2:30 PM resemble those in standard economics textbooks, with the obvious proviso that the area to the left of the market price is unobservable in continuous trading. Figure 2 shows Samsung Electronics’ demand and supply schedules at 15-minute intervals throughout the day.

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7 We randomly choose 3 other stocks from large, medium and small capitalization groups. These graphs all resemble Figure 1.
including the opening and closing auction. The 2:30 PM snapshots are typical. Graphs on other dates and for other stocks look similar to those shown in the figures.

Using this technique, we construct supply and demand curves for each listed stock twice each day, precisely as in Figure 1. We begin by constructing analogs of Figure 1 for each stock $j$. For each bid price $p$, we sum the bid orders that would execute to obtain demand:

$$d_j(p) = \sum_{b} n_{bj} \delta(p_{bj} \geq p)$$

with $b$ an index of bid limit orders, $n_{bj}$ the number of shares sought in order $b$, and $\delta(p_{bj} \geq p)$ an indicator set to one if order $b$ executes at price $p$ and to zero otherwise. The supply of stock $j$ at $p$ is analogously defined over ask limit orders, indexed by $a$, as follows.

$$s_j(p) = \sum_{a} n_{aj} \delta(p_{aj} \leq p)$$

For each stock, at any point in time, we thus map price $p$ into a total quantity of stock $j$ demanded, $d_j(p)$, and a total quantity supplied, $s_j(p)$. This technique reveals demand and supply schedules for each stock at each day’s opening auction and again at 2:30 PM. Note that these demand and supply schedules are observed, not estimated. Simultaneous equations identification problems do not arise.

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8 When an order is submitted but subsequently cancelled, we exclude it in constructing the demand and supply schedules. Similarly, for any revised order, we use the revised price and/or quantity.
3.4. Elasticity Measurement Procedure

To measure the elasticity of demand of firm $j$’s stock at time $t$, we regress the logarithm of total demand at that time at price $p_k$, $\ln d_{j,t}(p_k)$, on the logarithm of $p_k$,

$$\ln d_{j,t}(p_k) = a_{j,t} - \eta_{j,t}^D \ln p_k + u_{j,t,k}$$  \[3\]

The elasticity of demand at time $t$, $\eta_{j,t}^D$, the percentage decrease in the quantity of stock $j$ sought given a one percent price rise, is thus minus one times the coefficient of $\ln p_k$ in [3].

The elasticity of supply at time $t$, $\eta_{j,t}^S$, is the percentage increase in the quantity of stock offered given a one percent price rise, and so is measured by the coefficient on the $\ln p_k$ in [4].

$$\ln s_{j,t}(p_k) = b_{j,t} + \eta_{j,t}^S \ln p_k + v_{j,t,k}$$  \[4\]

Both demand and supply elasticities are each measured only when we have over five price-quantity pairs. In the final sample, the mean (median) number of pairs used is 17 (13) for open demand elasticities and 17 (12) for open supply elasticities, and 17 (14) and 21 (16) for 2:30 PM demand and supply elasticities, respectively. The mean (median) regression $R^2$ of [3] at the open and at 2:30 PM are 74% (76%) and 64% (65%) respectively; and, those of [4] are 80% (82%) and 72% (74%) respectively, suggesting that the log on log specification parsimoniously summarizes the data.

Finally, although [3] and [4] use regression coefficients as elasticity measurements, no simultaneity bias arises. This is because we are not jointly estimating demand and supply
curves from the same data. Rather, we are plotting out observed demand and supply curves precisely and then using [3] and [4] to measure the slope of each curve.

3.5. Limit Order Book Range

As noted above, the elasticities of stocks demand and supply schedules reflect investors’ information heterogeneity, patience heterogeneity, or some combination of the two. This is because investors who provide immediate liquidity to impatient investors must be compensated for their trouble. As noted above, the KSE lacks designated market makers. Instead, new orders are matched against outstanding orders. But private traders can act as *de facto* market makers by standing ready to buy or sell at prices slightly below or above the market price. Handa and Schwartz (1996), and Foucault *et al.* (2005) model such private market makers’ profits from trading at advantageous prices offsetting trading costs, non-execution costs, and disadvantageous fundamentals news; and suggest that limit orders around market prices may be associated with virtual market making rather than with genuine heterogeneous valuation.

Hollifield *et al.* (2004, 2006) argue that those investors with private information, whose private valuations deviate from the market price, are also those who provide liquidity as *de facto* market makers. These *de facto* market makers maximize their quasirents by concentrating their limit orders just above or just below the market price, where execution is most likely. Consequently, if impatience heterogeneity is large relative to information heterogeneity, limit orders should be highly concentrated in close proximity to the market price. However, if limit orders are scattered farther away from the market price, information heterogeneity is more plausibly also economically important.
We therefore examine the distribution of prices in limit order books. We believe Ockham’s razor favors these limit order books reflecting genuinely heterogeneous fundamental value estimates for several reasons:

First, the price ranges at which we observe substantial limit order depth are quite broad, and so seem a priori inimical to de facto market making as a sole, or even primary explanation. Panels A and B of Table 2 show substantial limit order depths beyond 3% away from the observed market price – open prices in morning auctions or bid-ask midpoints at 2:30 PM for each schedule. This is equivalent to a 6% spread in a specialist market. These limit orders represent about 71% and 74.1% of total limit buy and sell orders for opening auction and 69.4% and 75.2% for 2:30 PM respectively. Only 10.5% (9.1%) of total quantities demanded (supplied) fall within a one percent range around the market price at the opening auction and only 10.2% (6.6%) at 2:30 PM. Such a substantial width in the limit order distribution seems consistent with heterogeneous investor beliefs, or at least, liquidity provision by investors with heterogeneous valuations as in Holliefield et al. (2004, 2006).

[Table 2 about here]

Second, Korea levies a 0.3% Tobin tax on all stock sales, even by brokers trading on their own accounts. Public shareholders serving as liquidity providers confront even higher transactions costs, for in 2000, brokerage fees ranged from 0.35% to 0.5%, though online trading costs fell sharply after June 1998, and now range between 0.025% and 0.1%. Such costs could render limit orders solely to provide liquidity more costly.

Third, Table 1 shows market orders comprising only 5.22% of shares sought and 7.01% of shares offered. If limit orders existed primarily to provide liquidity around market prices, they ought not to preponder market orders greatly, for the latter ought to include
much of the demand for quick execution. Aggregated limit order magnitudes, roughly sixteen to twenty-fold greater than market orders at 2:30 PM and seven to thirteen-fold greater at open, seem superfluous.

This evidence is admittedly circumstantial, so Section 3.6 pursues this issue further by estimating elasticities excluding price and quantity pairs proximate to market prices, where liquidity provision absent valuation heterogeneity is most plausible.

3.6. Whole and Cored Elasticities

Equations [3] and [4] assume constant elasticity across all prices. This assumption injects noise if the true elasticity varies across prices, but becomes even more problematic if Hollifield et al. (2004, 2006) does not apply; and limit orders near the market reflect competitive market making by liquidity providers with no genuinely divergent valuations. We can mitigate, and evaluate, these concerns by estimating elasticities after removing observations near the market price, where competitive market makings unassociated with valuation heterogeneity is most likely.

We define near-market limit orders as those priced in the interval \((p_m(1 - k), p_m(1 + k))\), centered around the market price, \(p_m\), with \(k\) set to one, two, and then three percent of the market price. By dropping price-quantity pairs with prices in these successively larger near-market intervals, we obtain cored supply and demand schedules, so-named because of the holes around their market prices. At all non-near-market prices, these demand and supply schedules are identical to those described above. That is, given a supply schedule of price-quantity pairs \(\{(p, s(p))\}\), we denote the corresponding cored supply schedules, \(C_s(k)\), for \(k = 1, 2,\) or three percent, as

\[
C_s(k) \equiv \{ (p, s(p)) \mid p \in (-\infty, p_m(1 - k)] \cup [ p_m(1 + k), +\infty) \}.
\]
We then run [3] and [4] on these cored demand and supply schedules to obtain cored elasticities of demand or supply.

4. **Empirical Results**

This section first reports summary statistics of demand and supply elasticities; and then presents firm-level daily panel regressions. We divide our sample period into three sub-periods; a pre-crisis period of December 1996 through October 1997, an in-crisis period of November 1997 to October 1998, and a post-crisis period of November 1998 to December 2000. This division of the sample period into three sub-periods follows the definition in Kim and Wei (2002).  

4.1. **Magnitudes**

Panels A and B of Figure 3 plot the time series of daily mean elasticities against time; Panel C of Figure 3 plots the KSE index for the same period. Table 3 reports the summary statistics of underlying firm level daily elasticities of demand and supply curves. Table 3 shows the median demand elasticities to be about 20 both in opening auctions, and at 2:30PM; while the median supply elasticities is 24 in opening auctions and 23 at 2:30 PM. A one percent increase in price thus induces roughly a 20 percent drop in demand and a 23 percent rise in supply.  

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10 Cored elasticities generate similar patterns. Section 4.2 discusses this issue in detail.
All of the elasticity estimates in Panel A of Table 3 are significantly below infinity; in the sense that their reciprocals significantly differ from zero. Regardless of the measurement technique used to estimate $\eta^D$ and $\eta^S$, standard t-tests and rank tests show the means and medians, respectively, of both $1/\eta^D$ and $1/\eta^S$ to differ significantly from zero ($p < 0.0001$).

Our elasticity measurements generally exceed the 10.50 figure imputed by Kaul et al. (2000), the 7.89 estimate obtained by Wurgler and Zhuravskaya (2002), the mean (median) elasticity of 0.68 (1.05) reported by Bagwell (1992) from Dutch auction share repurchases, and the mean (median) estimates of 2.91 (2.47) by Kandel et al. (1999) from IPO data. However, our estimate lies between the lower and upper bounds determined by Kalay et al. (2004).

These differences might reflect different methodologies, unique information events used in some of the studies, or different institutional arrangements in different countries or time periods. For example, KSE investors observe quantities demanded and supplied at the five best prices, whereas investors in other stock markets have less information, so higher average KSE elasticities are not entirely surprising.

We also check the differences between elasticities observed in opening auctions and those observed at 2:30 PM. If uncertainty regarding private information were appreciably resolved by trading, as proposed by Glosten and Milgrom (1985), elasticities should rise through the day. Through our sample period, 2:30 PM mean elasticities generally exceed mean opening elasticities – consistent with the findings of Kalay et al. (2004). However, our analogous median measurements show no discernable intraday pattern.

4.2. Harmony at Low Frequencies

One advantage of a long time series that includes a crisis is that it allows a comparison of the
magnitudes of elasticities before and after the crisis using one measurement methodology. Thus, even if absolute magnitudes are not directly comparable across studies that use different estimation methods, we can make valid comparisons over time for KSE stocks. The average elasticities of both demand and supply fluctuate far more during the last months of 1997 and first months of 1998 than either before or after. This period of instability corresponding to the onset of the 1997 Asian financial crisis, evident in the KSE index in Panel A of Figure 3, is unsurprising.

More intriguingly, elasticities of both demand and supply are markedly lower after this interlude of instability. Table 3 shows a 39% drop, from 30.0 to 18.3, in the median opening demand elasticity; and a 41% drop, from 36.9 to 21.9 in the median opening supply elasticity. Similarly dramatic reductions are evident in 2:30 PM measurements; and in the means as well. These differences are all statistically significant ($p < 0.0001$). Note that even after the KSE market index reverts to the pre-crisis level, elasticities of both demand and supply curves for individual stocks remain depressed through the remainder of our observation window. This suggests that the crisis permanently altered both demand and supply curves, to reflect permanently elevated heterogeneity across investors in firm valuations.

Substantial fluctuation at higher frequencies is clearly superimposed on this step function. However, elasticities fluctuate around stable averages in both the pre- and post-crisis periods, and no trend in the magnitude of these higher frequency fluctuations is immediately evident for each sub-period. These regularities suggest an underlying factor, common to demand and supply elasticities, which follows a step function; but otherwise changes little before or after the crisis. Possible candidates would be several institutional reforms that have permanent impact. However, we can exclude them because many of post-crisis reforms arguably rendered the country’s equity markets more transparent and thus
lowered arbitrage costs. Greater transparency should decrease information heterogeneity, leaving both curves more elastic, all else equal. The advent of low-cost online trading after June 1998, at first blush at least, should have reduced arbitrage costs and flattened demand and supply curves as well.

In our sample, supply is generally more elastic than demand. The difference in means is highly significant ($p < 0.0001$) throughout all three periods. Thus higher supply elasticities are not artifacts of fire-sales during the crisis period. Kalay et al. (2004) find supply less locally elastic (around market prices) than demand for stocks traded in Tel Aviv Stock Exchange, and posit short sale constraints as an explanation. Short sales are uncommon on the KSE, comprising only about 0.5% of pre-crisis sell orders and an essentially negligible fraction post-crisis. Our relatively high supply elasticities are thus not readily explained by more intense short sale activity in KSE than in TASE.

[Figure 4 about here]

To see if our results are driven by orders near market prices, we repeat the exercise using cored elasticities. Figure 4 shows the permanent decrease in mean elasticity is robust to dropping limit orders priced within one, two and three percent of the market price. Similar patterns are evident using median elasticities instead. Thus, the significant drop in elasticities we observe is not driven by orders near market prices.

Within each sub-period, mean elasticities appear larger if based on orders farther from the market price, though this difference attenuates in the post crisis period.¹¹ Higher elasticities for limit orders farther from the market price in the pre-crisis period are perhaps

---

¹¹ The slightly higher elasticities generated by dropping limit orders within three percent of the market may reflect a reduced sample, since we require more than five price-quantity pairs to estimate elasticities. Stocks with scant limit order depth away from the market price thus fall out of the sample, and these may be either thinly traded or subject to little valuation heterogeneity. However, the same pattern is evident using recalculated mean and median elasticities based on the whole demand or supply schedules and on the various cored schedules defined in [5], but using only those firm-day observations for which three percent cored schedules are measurable.
consistent with investors’ valuations being more homogeneous before the crisis than after it. This is because investors whose fundamental valuations are farther from the market might attach less certainty to their valuations, just as all investors in the post-crisis period might have become less sure of their private valuations. Investors less sure of their private valuations would presumably, all else equal, submit smaller limit orders, thereby rendering the stock’s demand and supply schedules less horizontal at any given price.

The finite elasticities evident in Panels A and B of Figure 4 throughout our sample period, even after excluding orders near market prices, are consistent with the persistence of economically important information heterogeneity, and thus reinforce the clues in Table 2. Since the KSE lets any trader help make the market in any stock, competitive pressure on de facto market makers lacking any private information would induce large limit orders near the market where execution probability is large. Although extreme demand for liquidity might occasionally invite such orders farther from the market, a persistent high density in the tails of the limit order distribution presents at least a strong circumstantial case for information heterogeneity. That is, investors would enter such orders only if they genuinely expected the price to move to a new range. For example, investors holding a stock they believe undervalued might enter high sell orders in anticipation of an upward correction. Investors expecting an overvalued stock to fall might enter low buy limit orders for analogous reasons.

[Figure 5 about here]

4.3. Counterpoint at Higher Frequencies?

Figure 5 plots daily mean demand elasticities against daily mean supply elasticities for individual stocks using first open and then 2:30PM snapshots, and using first the whole elasticities and then our various cored elasticities. A clear negative relationship is evident in
the 2:30 PM elasticities. A similar negative relationship becomes apparent in the opening auction elasticities after dropping limit orders within one percent of the market, and persists with the other cored elasticities as well.

[Figure 6 about here]

To verify these visual patterns, we estimate the simple correlation of daily mean demand elasticities with daily mean supply elasticities each month. Figure 6 plots these against time, showing that they jibe roughly with the patterns apparent in Figure 5. The correlation is strongly negative for elasticities based on the 2:30 snapshots, regardless of whether we use whole elasticities or cored elasticities, from which we drop limit orders priced near the market. A similarly robust negative correlation of a similar magnitude is evident using cored elasticities, but less apparent in using whole elasticities at the opening auctions.

The crystallization of a clear negative correlation, after dropping limit orders within one percent of the market price at the open, may be explained by Figure 1. This shows the demand and supply curves at the open intersecting to the right of the price axis. The opening auction includes above-market buy orders and below-market sell orders because investors cannot observe the market price until the auction is completed. In contrast, investors observe the market at 2:30 PM, precluding above-market buy limit orders and below-market sell limit orders. The orders entered at such disadvantageous prices in the opening auction actually execute at the market, and so are automatically transformed into market orders. Consequently, deleting them by using the cored elasticities is clearly warranted.
4.4. Panel Regressions

To investigate this contemporaneous negative high frequency correlation further, we turn to panel regressions using daily firm-level elasticities. We demean these data using cross-section means to remove any temporal fixed effects, and also include firm fixed effects to control for any firm characteristics that might affect elasticities. Thus, we run

\[ \bar{\eta}_{j,t}^S = \alpha_j + \beta \bar{\eta}_{j,t}^D + \varepsilon_{j,t}, \]

where stock \( j \)’s market-adjusted elasticities of supply and demand at time \( t \) are \( \bar{\eta}_{j,t}^S = \eta_{j,t}^S - \bar{\eta}_S \)
and \( \bar{\eta}_{j,t}^D = \eta_{j,t}^D - \bar{\eta}_D \), respectively, with \( \bar{\eta}_S \) and \( \bar{\eta}_D \) the mean elasticities of supply and demand, respectively, across all stocks at time \( t \); and the \( \alpha_j \) are stock-level fixed effects. We also cluster standard errors by stock to adjust for any autocorrelation in the elasticities.

[Table 4 about here]

Table 4 presents estimates of \( \beta \) from [6] using whole elasticities and the cored elasticities described in [5], as well as for our whole time window and for the pre-crisis, in-crisis, and post-crisis subperiods. Highly significant negative coefficients arise in every case for the 2:30 elasticities, and in every case for the open elasticities of cored demand and supply schedules. The sole exception is open elasticities of whole demand and supply schedule. We conclude that the stock-level panel regressions in Table 4 confirm the patterns apparent in Figures 5 and 6.
4.5. **Robustness Checks**

A variety of robustness checks generate qualitatively similar results, by which we mean similar patterns of signs and statistical significance to those in Table 4.

We cluster standard errors by stock. Clustering by time generates qualitatively similar results.

We measure fewer stocks’ elasticities when we use cored elasticities, for which we exclude the section of the demand or supply schedule near the market price. This is because we require more than five price-quantity points to take a measurement. The smallest sample arises for elasticities defined using C(0.03) which encompasses only demand or supply schedule points more than three percent above or below the market. Rerunning regressions using this smaller set of stocks but using elasticities based on the whole schedules and the other cored schedules, occluding limit orders within only one and two percent of the market, also yields qualitatively similar results. That is, except for opening auction elasticities based on whole schedules, all the coefficients are highly significantly negative.

We rerun the regressions in panels A and B of Table 4 weighting each pair of elasticities by the firm’s market capitalization at the previous day’s close. This is to see if our results differ across larger or smaller firms, which might inhabit different information environments for many reasons. Again, qualitatively similar results to those in Table 4 ensue.

4.6 **Clinching the Case for Information Heterogeneity**

A negative contemporaneous correlation between the elasticities of a stock’s supply and demand schedules is difficult to explain if finite elasticities reflect only liquidity provision, and not information heterogeneity. Absent heterogeneous private valuations, buy-side liquidity provision should not evaporate wherever sell-side liquidity provision deepens, and *vice versa*. 
However, this high frequency negative correlation of supply with demand elasticities is entirely consistent with some traders acquiring private information, as in French and Roll (1986) and Roll (1988), and with other investors inferring that information by observing trading patterns, as in Glosten and Milgrom (1985). We speculate that aggressive limit order placement by privately informed traders would increase the elasticity on their side of the market; and that investors on the other side of the market, observing this and fearing they are at an informational disadvantage, would withdraw limit orders depth lowering the elasticity on their side of the market. For example, an eruption of large buy orders would flatten the demand curve, but signal sell side limit order providers that private information is afoot. Fearing adverse selection, sell side limit order providers would reduce their exposure by withdrawing limit order depth, rendering the supply curve more elastic.

This sort of feedback raises interesting possibilities for extending models of information heterogeneity and liquidity provision, such as Hollifield et al. (2004, 2006), to include the reactions of uninformed traders and the process by which private information propagates through the market and becomes public.

5. Conclusions
The asset pricing literature descended from Harrison and Kreps (1978) and Grossman and Stiglitz (1980) posits finitely elastic demand an supply curves for individual stocks with elasticities determined by investors’ risk aversion, information heterogeneity, and uncertainty regarding fundamental valuations. Blough (1988), Hindy (1989), De Long et al. (1990), Kandel and Peason (1995), Harris and Raviv (1993), Varian (1985, 1989), Shleifer and Vishny (1997), and others all elaborate theories along these lines, which in one way or another, all preserve the assumption of finite elasticities.
We observe (not estimate) elasticities of the demand and supply curves of individual stocks on the Korea Stock Exchange and find that these are unambiguously finite. Our results thus validate the approach to asset pricing set forth in this literature.

The Asian financial crisis, which occurred midway through our sample window, upset conventional frameworks for understanding the Korean economy, and induced dramatic changes in the business strategies of many Korean firms. Such factors may have increased the heterogeneity of investors’ beliefs about fundamental values. The crisis also reduced the wealth of many investors, and arguably also heightened their perceptions of the risks inherent in equity – factors most readily interpreted as raising risk aversion among investors. Information heterogeneity and investor risk aversion are both plausible determinants of the elasticities of demand and supply curves for individual stocks in models permitting heterogeneous investor perceptions of fundamental values.

Elasticities of both supply and demand are about 40% lower in the post-crisis period, and do not revert within our observation window – although other financial and economic indicators do return to their pre-crisis levels. This pattern seems consistent with elevated valuation heterogeneity and uncertainty, with elevated risk aversion, or with both. This pattern is also consistent with investors possessing private information being less likely to enter large orders based on that information, and with liquidity providers fearing trading against better informed investors and therefore being more cautious about providing limit order depth.

A stock’s elasticity of demand and elasticity of supply typically exhibit a contemporaneous negative correlation in high frequency (daily) data. We speculate as to how informed investors entering one side of the market with large orders would flatten one of the two curves, and how uninformed investors on the other side, reacting to this, would withdraw limit order depth, steepening the other curve.
The patterns we detect in the observed (not estimated) elasticities of demand and supply of individual common stocks call for further theoretical work to ascertain the interactions between changing information heterogeneity, valuation uncertainty, and risk aversion. We especially encourage new models of the strategic interactions of risk-averse buyers and sellers of financial assets in markets with heterogeneous information; and of how rational traders infer new private information and react upon detecting it. Of course, we also welcome further empirical and theoretical work to qualify our findings, geographically or temporally, or to advance alternative explanations of the robust empirical regularities described above.
References


Blough, S., 1988, Differences of opinion and the information value of prices, working paper, The Johns Hopkins University.


Hindy, A., 1989, An equilibrium model of futures markets dynamics, working paper, MIT.


Liaw, Gwohorng, Yu-Jane Liu, and K.C. John Wei, 2000, On the demand elasticity of initial public offerings: An analysis of discriminatory auctions, working paper, Hong Kong University of Science and Technology.


Figure 1. Observed Demand and Supply Schedules for Samsung Electronics on November 11, 2000

The opening auction orders graphs (black) reflect all buy and sell orders submitted for the opening auction that sets the open price. The 2:30 PM limit orders graphs (gray) reflect all outstanding limit orders as of 2:30 PM.
Figure 2. Demand and Supply Schedules in Real Time for Samsung Electronics on November 11, 2000
Demand and supply schedules for Samsung stock from the opening auction orders through the end of trading constructed from snapshots of complete limit order books taken every 15 minutes.

Panel A. Supply of Samsung stock at 15 minute intervals

Panel B. Demand for Samsung stock at 15 minute intervals
Figure 3. Mean Demand and Supply Elasticities of Individual Stocks over Time

Each stock’s elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated when there are more than 5 price-quantity pairs for each firm, each day. Elasticities are measured twice each day from Dec. 1996 to Dec. 2000: first in the opening auction and again at 2:30 PM. Until December 5, 1998, the KSE was opened Saturday mornings, and the second elasticity is estimated at 11:30 AM on Saturdays. Daily elasticities are averaged across all stocks and graphed against time. The East Asian Financial Crisis period is the widened time axis segment from Nov. 1997 to Oct. 1998. The pre-crisis, and post crisis periods are Dec. 1996 to Oct. 1997, and Nov. 1998 to Dec. 2000, respectively.

Panel A: Opening Auction Elasticities

Panel B: 2:30 PM Elasticities

Panel C: KSE Index
Figure 4. Mean Elasticities for the Whole Sample and Subsamples Dropping Limit Orders Priced within One, Two, or Three Percent of the Market Price.
Each stock’s elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated when there are more than 5 price-quantity pairs for each firm, each day, for the whole sample and subsamples where observations within \([-k\%, k\%]\) range around market prices are removed for \(k=1, 2,\) or 3. Elasticities are measured twice each day from Dec. 1996 to Dec. 2000: first in the opening auction and again at 2:30 PM. Until December 5, 1998, the KSE was opened Saturday mornings, and the second elasticity is estimated at 11:30 AM on Saturdays. Daily elasticities are averaged across all stocks and then across days in specified periods: the entire sample, pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods.

Panel A. Demand Elasticities at Opening Auction and at 2:30 PM

Panel B. Supply Elasticities at Opening Auction and at 2:30 PM
Figure 5. Relationship Between Daily Average Demand and Supply Elasticities

Daily average supply elasticity is plotted against daily average demand elasticity, with observations color coded for pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods. Each stock’s elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated when there are more than 5 price-quantity pairs for each firm, each day, for the whole sample and subsamples dropping observations within one, two, or three percent of market prices. Elasticities are measured twice each day from Dec. 1996 to Dec. 2000: first in the opening auction and again at 2:30 PM. Until December 5, 1998, the KSE was opened Saturday mornings, and the second elasticity is estimated at 11:30 AM on Saturdays.

Panel A. Elasticities at Opening Auction
Panel B. Elasticities at Opening 2:30 PM

2:30 PM (Whole Sample)

2:30 pm (-1%,1%) Removed

2:30 PM (-2%,2%) Removed

2:30 PM (-3%,3%) Removed
Figure 6. Correlations of Individual Stocks’ Daily Mean Demand and Supply Elasticities, by Month

Each stock’s elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are measured from Dec. 1996 through Dec. 2000 at the open and at 2:30PM if the stock’s relevant schedule contains over five price-quantity pairs. Plots include correlations using the elasticities based on all limit orders, as well as those based on subsamples dropping limit orders within one, two, and three percent of the market prices. Until December 5, 1998, the KSE operated Saturday mornings, so the second elasticity on those days is estimated at 11:30AM. Correlations are of daily supply and demand elasticities, using all days in each month.

Panel A. Correlations of Daily Mean Demand and Supply Elasticities Measured at Opening Auctions

Panel B: Correlations of Daily Mean Demand and Supply Elasticities Measured at 2:30 PM
Table 1. Distribution of Orders and Trades

Trades can be limit or market orders, and can be submitted in an open call market or in continuous trading throughout the day. A second call market at the close typically has very thin trading. Data are for the Korea Stock Exchange (KSE) from December 1996 to December 2000. Each daily trading session is partitioned into an opening call market auction and the continuous trading during the rest of the day. Values in parentheses are average order sizes.

<table>
<thead>
<tr>
<th>Order Type</th>
<th>Entire Day</th>
<th>Opening Call Market</th>
<th>Rest of Day Continuous Market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Buys</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market</td>
<td>13,938,249</td>
<td>3,620,127</td>
<td>10,318,122</td>
</tr>
<tr>
<td></td>
<td>(1,177.40)</td>
<td>(1,096.11)</td>
<td>(1,205.92)</td>
</tr>
<tr>
<td>Limit</td>
<td>253,301,774</td>
<td>47,428,384</td>
<td>205,873,390</td>
</tr>
<tr>
<td></td>
<td>(1,298.60)</td>
<td>(1,251.10)</td>
<td>(1,309.54)</td>
</tr>
<tr>
<td>Total</td>
<td>267,240,023</td>
<td>51,048,511</td>
<td>216,191,512</td>
</tr>
<tr>
<td></td>
<td>(1,292.28)</td>
<td>(1,240.11)</td>
<td>(1,304.60)</td>
</tr>
<tr>
<td><strong>Sells</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market</td>
<td>19,880,406</td>
<td>6,966,032</td>
<td>12,914,374</td>
</tr>
<tr>
<td></td>
<td>(716.69)</td>
<td>(628.91)</td>
<td>(764.04)</td>
</tr>
<tr>
<td>Limit</td>
<td>263,831,555</td>
<td>53,011,848</td>
<td>210,819,707</td>
</tr>
<tr>
<td></td>
<td>(1,729.71)</td>
<td>(1,254.08)</td>
<td>(1,849.31)</td>
</tr>
<tr>
<td>Total</td>
<td>283,711,961</td>
<td>59,977,880</td>
<td>223,734,081</td>
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<tr>
<td></td>
<td>(1,658.72)</td>
<td>(1,181.47)</td>
<td>(1,786.66)</td>
</tr>
</tbody>
</table>
Table 2. Limit Order Book Ranges
On each trading day, the limit order book prices for the opening auction are normalized by the opening price while the limit order book prices at 2:30 PM are normalized by the bid-ask mid-point. Then, quantities (in millions of shares) demanded and supplied in each price range are accumulated over the sample period of December 1996 to December 2000.

Panel A: Opening Auction

<table>
<thead>
<tr>
<th>Limit Order Price as Percent of Opening Price</th>
<th>Demand Quantity</th>
<th>Demand Percent of Total Quantity</th>
<th>Supply Quantity</th>
<th>Supply Percent of Total Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price &lt; 85%</td>
<td>4,987</td>
<td>14.00%</td>
<td>64</td>
<td>0.20%</td>
</tr>
<tr>
<td>85% ≤ Price &lt; 90%</td>
<td>5,945</td>
<td>16.7</td>
<td>121</td>
<td>0.4</td>
</tr>
<tr>
<td>90% ≤ Price &lt; 95%</td>
<td>8,206</td>
<td>23</td>
<td>315</td>
<td>1</td>
</tr>
<tr>
<td>95% ≤ Price &lt; 97%</td>
<td>5,077</td>
<td>14.2</td>
<td>350</td>
<td>1.2</td>
</tr>
<tr>
<td>97% ≤ Price &lt; 98%</td>
<td>2,790</td>
<td>7.8</td>
<td>314</td>
<td>1</td>
</tr>
<tr>
<td>98% ≤ Price &lt; 99%</td>
<td>2,793</td>
<td>7.8</td>
<td>515</td>
<td>1.7</td>
</tr>
<tr>
<td>99% ≤ Price &lt; 100%</td>
<td>2,712</td>
<td>7.6</td>
<td>757</td>
<td>2.5</td>
</tr>
<tr>
<td>100% ≤ Price &lt; 101%</td>
<td>1,052</td>
<td>2.9</td>
<td>2,011</td>
<td>6.6</td>
</tr>
<tr>
<td>101% ≤ Price &lt; 102%</td>
<td>631</td>
<td>1.8</td>
<td>2,069</td>
<td>6.8</td>
</tr>
<tr>
<td>102% ≤ Price &lt; 103%</td>
<td>384</td>
<td>1.1</td>
<td>2,238</td>
<td>7.4</td>
</tr>
<tr>
<td>103% ≤ Price &lt; 105%</td>
<td>415</td>
<td>1.2</td>
<td>4,715</td>
<td>15.5</td>
</tr>
<tr>
<td>105% ≤ Price &lt; 110%</td>
<td>413</td>
<td>1.2</td>
<td>9,454</td>
<td>31.1</td>
</tr>
<tr>
<td>110% ≤ Price &lt; 115%</td>
<td>160</td>
<td>0.4</td>
<td>5,564</td>
<td>18.3</td>
</tr>
<tr>
<td>115% ≤ Price</td>
<td>95</td>
<td>0.3</td>
<td>1,938</td>
<td>6.4</td>
</tr>
<tr>
<td>Total</td>
<td>35,659</td>
<td>100.00%</td>
<td>30,423</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Panel B: 2:30 PM

<table>
<thead>
<tr>
<th>Limit Order Price as Percent of the Bid-Ask Mid-Point</th>
<th>Demand Quantity</th>
<th>Demand Percent of Total Quantity</th>
<th>Supply Quantity</th>
<th>Supply Percent of Total Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price &lt; 85%</td>
<td>6,044</td>
<td>13.80%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>85% ≤ Price &lt; 90%</td>
<td>7,984</td>
<td>18.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>90% ≤ Price &lt; 95%</td>
<td>10,053</td>
<td>22.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>95% ≤ Price &lt; 97%</td>
<td>6,359</td>
<td>14.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>97% ≤ Price &lt; 98%</td>
<td>4,102</td>
<td>9.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>98% ≤ Price &lt; 99%</td>
<td>4,907</td>
<td>11.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>99% ≤ Price &lt; 100%</td>
<td>4,476</td>
<td>10.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>100% ≤ Price &lt; 101%</td>
<td></td>
<td></td>
<td>3,321</td>
<td>6.60%</td>
</tr>
<tr>
<td>101% ≤ Price &lt; 102%</td>
<td></td>
<td></td>
<td>4,521</td>
<td>9.00%</td>
</tr>
<tr>
<td>102% ≤ Price &lt; 103%</td>
<td></td>
<td></td>
<td>4,610</td>
<td>9.20%</td>
</tr>
<tr>
<td>103% ≤ Price &lt; 105%</td>
<td></td>
<td></td>
<td>8,651</td>
<td>17.2</td>
</tr>
<tr>
<td>105% ≤ Price &lt; 110%</td>
<td></td>
<td></td>
<td>15,438</td>
<td>30.8</td>
</tr>
<tr>
<td>110% ≤ Price &lt; 115%</td>
<td></td>
<td></td>
<td>8,563</td>
<td>17.1</td>
</tr>
<tr>
<td>115% ≤ Price</td>
<td></td>
<td></td>
<td>5,088</td>
<td>10.1</td>
</tr>
<tr>
<td>Total</td>
<td>43,925</td>
<td>100.00%</td>
<td>50,193</td>
<td>100.00%</td>
</tr>
</tbody>
</table>
Table 3. Elasticities of KSE Stocks Before, During, and After the 1997 Crisis
Each stock's elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are measured twice each day from Dec. 1996 to Dec. 2000: first in the opening auction and again at 2:30 PM. Elasticities are estimated if over five price-quantity pairs exist for each firm, each day. All means and medians are significantly below infinity; that is, t-tests and rank tests, respectively, reject the null hypotheses of their reciprocals being zero at probability levels better than one percent. Until December 5, 1998, the KSE was opened Saturday mornings, and the second elasticity is estimated at 11:30 AM on Saturdays. Daily elasticities are averaged across all stocks and then observed across all days in the specified time periods: the entire sample, pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods.

### Panel A: Elasticity of Demand

<table>
<thead>
<tr>
<th>Trading Session</th>
<th>Sub-Period</th>
<th>Observations</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opening auction</td>
<td>Entire sample period</td>
<td>605,407</td>
<td>22.690</td>
<td>20.320</td>
<td>12.772</td>
</tr>
<tr>
<td></td>
<td>Pre-crisis period</td>
<td>120,588</td>
<td>32.078</td>
<td>30.015</td>
<td>16.765</td>
</tr>
<tr>
<td></td>
<td>In-crisis period</td>
<td>139,188</td>
<td>23.102</td>
<td>21.484</td>
<td>12.777</td>
</tr>
<tr>
<td></td>
<td>Post-crisis period</td>
<td>345,631</td>
<td>19.249</td>
<td>18.26</td>
<td>8.903</td>
</tr>
<tr>
<td>2:30 PM</td>
<td>Entire sample period</td>
<td>591,996</td>
<td>24.791</td>
<td>19.597</td>
<td>20.259</td>
</tr>
<tr>
<td></td>
<td>Pre-crisis period</td>
<td>122,214</td>
<td>35.189</td>
<td>29.652</td>
<td>24.322</td>
</tr>
<tr>
<td></td>
<td>In-crisis period</td>
<td>128,252</td>
<td>27.908</td>
<td>22.5</td>
<td>22.027</td>
</tr>
<tr>
<td></td>
<td>Post-crisis period</td>
<td>341,530</td>
<td>19.899</td>
<td>16.674</td>
<td>15.851</td>
</tr>
</tbody>
</table>

### Panel B: Elasticity of Supply

<table>
<thead>
<tr>
<th>Trading Session</th>
<th>Sub-Period</th>
<th>Observations</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opening auction</td>
<td>Entire sample period</td>
<td>608,952</td>
<td>27.048</td>
<td>24.409</td>
<td>14.341</td>
</tr>
<tr>
<td></td>
<td>Pre-crisis period</td>
<td>125,565</td>
<td>38.594</td>
<td>36.88</td>
<td>18.215</td>
</tr>
<tr>
<td></td>
<td>In-crisis period</td>
<td>136,922</td>
<td>27.535</td>
<td>25.626</td>
<td>14.862</td>
</tr>
<tr>
<td>2:30 PM</td>
<td>Entire sample period</td>
<td>632,702</td>
<td>28.822</td>
<td>23.368</td>
<td>22.257</td>
</tr>
<tr>
<td></td>
<td>Pre-crisis period</td>
<td>147,261</td>
<td>38.096</td>
<td>32.885</td>
<td>24.297</td>
</tr>
<tr>
<td></td>
<td>In-crisis period</td>
<td>139,688</td>
<td>30.372</td>
<td>25.039</td>
<td>23.174</td>
</tr>
<tr>
<td></td>
<td>Post-crisis period</td>
<td>345,753</td>
<td>24.246</td>
<td>20.402</td>
<td>19.482</td>
</tr>
</tbody>
</table>
Table 4. Panel Regressions of Supply Elasticities on their Demand Elasticities

Firm-level daily panel regressions are of \( \tilde{\eta}_{jt} = \alpha_j + \beta \tilde{\eta}_{jt} + \epsilon_{jt} \), with \( \tilde{\eta}_{jt} \) and \( \tilde{\eta}_{jt} \) stock \( j \)'s market-adjusted supply and demand elasticities on day \( t \) and \( q_j \) firm fixed-effects. We obtain market-adjusted elasticities of firm \( j \) by subtracting the day \( t \)'s cross-sectional mean supply or demand elasticity across all firms from firm \( j \)'s supply or demand elasticities. Each stock’s elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated when a schedule has more than 5 price-quantity pairs. Whole elasticities are estimated using whole demand or supply schedules, cored elasticities use all parts of the schedules except intervals within one, two, or three percent around market prices. Panel A uses elasticities at the open and Panel B uses elasticity snapshots at 2:30 PM, 30 minutes before the close. Until December 5, 1998, the KSE was opened Saturdays until noon, so the second elasticity is measured at 11:30 those days. The sample is partitioned into pre-crisis (Dec. 1996 – Oct. 1997), in-crisis (Nov. 1997 – Oct. 1998), and post-crisis (Nov. 1998 – Dec. 2000) periods. Probability levels (p-values) are based on \( t \)-statistics adjusted for stock clustering.

Panel A: Panel regression of supply on demand elasticity at open, with day and stock fixed effects and stock-clustered standard errors.

<table>
<thead>
<tr>
<th>Elasticity Measure</th>
<th>Entire Sample</th>
<th>Pre-Crisis Period</th>
<th>In-Crisis Period</th>
<th>Post-Crisis Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>whole Estimate of ( \beta )</td>
<td>0.006</td>
<td>-0.006</td>
<td>-0.016</td>
<td>0.007</td>
</tr>
<tr>
<td>p-value</td>
<td>0.016</td>
<td>0.166</td>
<td>0.000</td>
<td>0.008</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.027</td>
<td>0.046</td>
<td>0.044</td>
<td>0.049</td>
</tr>
<tr>
<td>Observations</td>
<td>530,405</td>
<td>89,321</td>
<td>110,910</td>
<td>330,174</td>
</tr>
<tr>
<td>cored at 1% Estimate of ( \beta )</td>
<td>-0.107</td>
<td>-0.129</td>
<td>-0.146</td>
<td>-0.083</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.019</td>
<td>0.042</td>
<td>0.027</td>
<td>0.020</td>
</tr>
<tr>
<td>Observations</td>
<td>423,593</td>
<td>45,162</td>
<td>78,700</td>
<td>299,731</td>
</tr>
<tr>
<td>cored at 2% Estimate of ( \beta )</td>
<td>-0.113</td>
<td>-0.166</td>
<td>-0.150</td>
<td>-0.098</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.022</td>
<td>0.050</td>
<td>0.030</td>
<td>0.021</td>
</tr>
<tr>
<td>Observations</td>
<td>372,210</td>
<td>24,547</td>
<td>64,633</td>
<td>283,030</td>
</tr>
<tr>
<td>cored at 3% Estimate of ( \beta )</td>
<td>-0.106</td>
<td>-0.182</td>
<td>-0.131</td>
<td>-0.119</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.021</td>
<td>0.039</td>
<td>0.022</td>
<td>0.022</td>
</tr>
<tr>
<td>Observations</td>
<td>321,442</td>
<td>10,324</td>
<td>50,022</td>
<td>261,096</td>
</tr>
</tbody>
</table>
Panel B: Panel regression of supply on demand elasticity at 2:30PM, with day and stock fixed effects and stock-clustered standard errors.

<table>
<thead>
<tr>
<th>Elasticity Measure</th>
<th>Entire Sample</th>
<th>Pre-Crisis Period</th>
<th>In-Crisis Period</th>
<th>Post-Crisis Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>whole</td>
<td>Estimate of β</td>
<td>-0.178</td>
<td>-0.187</td>
<td>-0.206</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Adjusted $R^2$</td>
<td>0.030</td>
<td>0.045</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>544,224</td>
<td>102,645</td>
<td>111,088</td>
</tr>
<tr>
<td>cored at 1%</td>
<td>Estimate of β</td>
<td>-0.156</td>
<td>-0.176</td>
<td>-0.194</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Adjusted $R^2$</td>
<td>0.024</td>
<td>0.045</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>491,918</td>
<td>70,914</td>
<td>99,680</td>
</tr>
<tr>
<td>cored at 2%</td>
<td>Estimate of β</td>
<td>-0.161</td>
<td>-0.217</td>
<td>-0.187</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Adjusted $R^2$</td>
<td>0.024</td>
<td>0.049</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>420,849</td>
<td>36,908</td>
<td>80,716</td>
</tr>
<tr>
<td>cored at 3%</td>
<td>Estimate of β</td>
<td>-0.164</td>
<td>-0.252</td>
<td>-0.176</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Adjusted $R^2$</td>
<td>0.026</td>
<td>0.053</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>351,460</td>
<td>14,539</td>
<td>59,708</td>
</tr>
</tbody>
</table>