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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, which fall markedly 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 trend, the magnitudes of individual stocks' supply and demand elasticities are negatively correlated at higher frequencies. That is, when a stocks exhibits an unusually elastic demand curve, it tends simultaneously to exhibit an unusually inelastic supply curve, and* vice versa*. This high frequency negative correlation also swells with the crisis. These findings have potential implications for modeling how information flows into and through stock markets, how investors react 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.*

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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 half an hour before the market closes. 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 observe demand and supply curves of common stocks before, during, and after the Asian financial crisis.

Because we observe entire demand and supply curves, we can gauge the elasticity of each curve separately and directly, rather than jointly and by inference from prices and quantities traded. This lets us sidestep entirely the standard simultaneity 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.

First, the absolute values of both demand and supply elasticities exhibit a common *long run* trend. Before the Asian crisis, both average around forty. That is, a one percent price change commands a forty percent change in quantity demanded or supplied. Both absolute values drop to roughly twenty 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. The direction of this shift is counterintuitive, for transparency is widely thought enhanced and transactions costs reduced (by the advent of on-line trading) in the post-crisis period.

Second, superimposed on this common long run trend, the absolute values of the two elasticities exhibit a negative correlation at higher frequencies. That is, stocks that develop unusually elastic demand curves tend simultaneously to develop unusually inelastic supply curves and *vice versa*. This correlation is more negative in 2:30 PM elasticities than in opening auction elasticities. The negative correlation in opening elasticities swells after the crisis; as does that in 2:30 PM elasticities, though mainly for larger firms.

We also find supply curves to be more elastic than demand curves on average. This differs from Kalay *et al*. (2004), who find higher local elasticities (estimated using limit orders near market prices) for demand curves in Tel Aviv data. The difference suggests that circumstances specific to sample periods or market structures may matter. We corroborate Kalay *et al*. (2004) in finding higher mean elasticities at 2:30 PM than in opening auctions, but our median elasticities do not exhibit this pattern.

Overall, our results support 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.

The remainder of the paper is organized as follows. Section 2 overviews relevant work; while section 3 discusses the data and elasticity measurement procedure. Section 4 describes our findings. Section 5 investigates possible explanations, and section 6 concludes.

2. Relation to Previous Studies

The wheel horses 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 supply and demand 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 certainty about fundamental values. All else equal, greater risk aversion and worse uncertainty 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 (1992), who assign different priors to different investors; and Harris and Raviv (1993) who model differences of opinion more generally.

The virtues of the wheel horses are elegance and simplicity; those of the Grossman and Stiglitz framework are explicit recognition of information costs and more realistic treatment of the economics of the investment industry (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 unavoidable information asymmetries and agency problems in firms in the financial sector create economically significant transactions costs to informed trading, even on free private information. These considerations allow different investors to persist in holding different beliefs about individual stocks' values, directly implying finitely elastic demand and supply curves.

A growing literature supports persistent information heterogeneity across investors, and thus the second class of models. Varian (1985, 1989) argues that normal trading volume is inconsistent with homogenous stock valuations, and implies heterogeneous investor beliefs. Barber and Odean (2000), Shleifer (2000), Grinblatt and Han (2005) attribute this heterogeneity to behavioral biases. But Varian (1985, 1989), Kandel and Pearson (1995), Fama and French (2007) all permit difference in opinion among rational investors. In either case, different investors perceive one stock as having different fundamental values. This directly implies finitely elastic demand and supply curves for that stock.

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 supply and demand elasticities for individual stocks to be very large.

But others dissent. Shleifer (1986), Harris and Gruel (1986), Jain (1987), Dhillon and Johnson (1991), Beamish and Whaley (1996), Lynch and Mendenhall (1997), Blouinet (2000), Liu (2000), and 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), and others argue that inclusion in an index conveys positive information about a stock; while Harris and Gruel (1986), Blouinet (2000), and others 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 (2003) 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.

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. 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 supply and demand elasticities for Tel Aviv stocks from limit orders adjacent to market prices. They report unambiguously finite elasticities, but caution that their estimates depend critically on their assumptions. Specifically, they estimate elasticities as percentage change in quantity divided by percentage change in price and take the former to be the quantity offered or sought divided by the 'total quantity of shares'. If this is 'total shares outstanding', the elasticities are small, but if 'total daily volume' is used instead they are much larger. Other alternatives they do not explore might include 'total public float' or a 'smoothed trading volume'. To sidestep these ambiguities, we estimate elasticity as the difference in log quantity offered or sought divided by the difference in log prices. This lets the data choose a denominator implicit in the slope of the curve being estimated.

Another factor that might distort estimated elasticities is strategic liquidity provision.[1] Hollifield *et al*. (2004, 2006) expand the framework of Grossman and Stiglitz (1980) to derive liquidity provider's optimal limit order strategy from her fundamental value estimate and on a trade-off between execution probability and 'picking off' risk – the risk of trading

[1] See Obzhaeva and Wang (2005), Hollifield et al. (2004, 2006), and references therein on optimal order submission strategy in a limit order market.

against better informed investors. Limit orders placed nearer the market price have a higher execution probability, but entail worse 'picking off' risk. Thus, the limit order book reflects inseparably confounded strategic liquidity provision and information heterogeneity (p. 2760): "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." That is, heterogeneous valuations across investors induce a distribution of limit orders across prices, and hence finitely elastic demand and supply curves, for individual stocks.

Hollifield et al. (2004, 2006) focus on expected trading revenues because they analyze risk neutral investors, and thus provide a state-of-the-art platform on which to build more complete descriptions of limit order distributions that account for different risk aversion, uncertainty as to fundamental values, signal extraction processes, or learning patterns. For example, extending their intuition to a world of risk-averse investors should presumably magnify the broadening effect 'picking off' risk on limit order distributions. Elasticities would then become smaller as risk aversion or uncertainty about fundamentals rises. Another useful theoretical extension would encompass investors' reaction functions to each others' trades. As trades execute at changing prices, limit order providers learn each others' opinions and use this information to update their estimates of fundamental value and hence their limit orders.

The last 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, flattening the demand curve. Seeing these execute, uninformed sell-side investors would presumably withdraw limit order depth near the market, steepening the supply curve.

Consistent with the intuition underlying these conjectures, Kavajecz (1999) finds specialists and limit order traders in the US reducing depths around information events; and Goldstein and Kavajec (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.

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 depend on a stock's price range – 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

[2] The Korean currency, the *won*, trades at approximately ₩1,000 per American dollar. For details on tick sizes, see www.kse.or.kr/webeng.

restricted, presumably limiting foreigners ability to take large positions in the stock of firms with large stable forign 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.

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]

[3] Before May 19, 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).

Because we seek to understand information heterogeneity, we focus on limit orders, which Table 1 shows comprise 94.78 percents of buy orders and 92.99 percent of sell orders. Excluding trades at the market price is desirable if these are entered by liquidity traders, but undesirable if informed traders buy or sell at the market to exploit uninformed investors. We therefore rerun our tests including market orders, and qualitatively similar results obtain.

We then take two snapshots per day of each stock's complete limit order book. The first is of the opening auction, and the second is at 2:30 PM – thirty minutes before trading ends.[5] Unexecuted limit orders expire at the end of the day, so one day's limit orders do not typically reappear the next day.

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 14:30 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, a large and heavily traded KSE listing.[6] These graphs are constructed by horizontally summing all limit orders that would execute at each theoretical price.[7] The sum of all buy orders that would execute at a given price P is the demand for Samsung 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

[5] 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.
[6] We randomly choose 3 other stocks from large, medium and small capitalization groups. These graphs all resemble Figure 1.
[7] In estimating the elasticity of demand and supply, we use limit orders only because market orders, by definition, do not specify prices.

all sell orders that would execute at price P is analogously the supply of Samsung shares offered at that price. Again, as the price rises in one tick increments, additional sell orders join that sum and the supply curve shifts extends increasingly far to the right at successively higher prices.

[Figure 2 about here]

The supply and demand schedules at both the opening auction and 14:30 resemble those in standard economics textbook, with the obvious proviso that the area to the left of the equilibrium price is unobservable in continuous trading. The 14:30 snapshot is chosen because this is 30 minutes before the close on most days. Figure 2 shows Samsung's supply and demand schedules at 15 minute intervals throughout the day including the opening and closing auction. The 14:30 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[8]

[1] $$d_j(p) = \sum_{b=1}^{B} n_{bj}\delta(p_{bj} \le p)$$

with *b* an index of bid limit orders, n_{bj} the number of shares sought in order *b*, and $\delta(p_{bj} \le p)$ 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.

[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.

[2] $s_j(p) = \sum_{a=1}^{A} n_{aj}\delta(p_{ajj} \le p)$

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 2:30PM each day. Note that these demand and supply schedules are observed, not estimated. Simultaneous equations estimation problems do not arise

3.4 Limit Order Book Range

Like other order driven markets, the KSE has no designated market makers. Instead, market orders are filled by private market makers, who stand ready to buy or sell at prices slightly below or above the equilibrium price. Handa and Schwartz (1996) model such private market makers' profits from trading at advantageous prices offsetting trading costs, non-execution costs, and disadvantageous fundamentals news; and propose that limit orders around market prices reflect liquidity provision. These models, despite their impressive sophistication, are not yet able quantify what precisely "around" market prices means this context. We therefore acknowledge part of the observed distribution of limit order depth doubtless reflects strategic liquidity provision.

However, we believe Ockham's razor favors the limit order books we observe reflecting genuinely heterogeneous estimates of fundamental value for several reasons. Indeed, Hollifield et al. (2004, 2006) propose a framework in which the two effects are fundamentally intertwined. Several considerations arise:

First, the price ranges at which we observe substantial limit order depth are quite broad, and so seem a priori inimical to liquidity provision as a sole, or even primary explanation. Table 2 shows substantial limit order depths beyond 5% away from the market price – these represent about 34% and 33% of total limit buy and sell orders respectively. For example, only 26% (24%) of total quantities demanded (supplied) fall within a one percent range around the market price. The daily price fluctuation of a KSE stock exceeds 5% in about 20% of days (across days when all four elasticities, demand and supply at open and 2:30PM, are measurable), so the tails of the limit order distribution, at least, point to heterogeneous investor beliefs.

[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 deter limit orders solely to provide liquidity a costly strategy, but might just spread liquidity-motivated limit orders further away from market prices.

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, one might expect them not to exceed 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 2:30PM and seven to thirteen-fold greater at open, seem superfluous. However, as noted above, current models of limit order strategies are hard to quantify, so this argument can not be pressed to far.

These arguments are all incomplete, unquantifiable, and rightly discreditable as hand-waving. Fortunately, Hollifield, Miller, Sandås, and Slive (2004, 2006) argue that heterogeneous investor beliefs and liquidity provision are best considered jointly. In their models, investors with heterogeneous beliefs place limit orders to capture their associated quasirents and thereby provide liquidity. Their estimates suggest this interaction lets traders with private information capture large fractions of its quasirents value, and thus encourages their acquisition of costly private information (Grossman and Stiglitz, 1980). The provision of liquidity is thus a by-product of heterogeneous investor information.

However, we concede that future research might alter our tentative conclusions if it shows the sorts of limit order depth distributions we observe justified by liquidity provision alone.

3.4. Elasticity Measurement Procedure

We measure elasticities by constructing analogs to Figure 1 for each stock twice each day. To measure the elasticity of demand of firm *j*'s stock at a point in time, we regress total demand at price p_k on the log of p_k,

[3] $$\ln d_j(p_k) = b_{0,j} - {}_D\eta_j \ln p_k + u_{jk}$$

The elasticity of demand, ${}_D\eta_j$, is thus the percentage increase in quantity demanded due to a one percent price rise, and so is minus one times the coefficient on $\ln p_k$ in [3].

The elasticity of supply, ${}_S\eta_j$, is the percentage decrease in quantity supplied due to a one percent price rise, and so is measured by the coefficient on the $\ln p_k$ in [4].

[4] $$\ln s_j(p_k) = a_j + {}_S\eta_j \ln p_k + v_{jk}$$

Both demand and supply elasticities are measured only when we have 5 or more observations. In the final sample, the mean number of price-quantity pairs used is 19 for both opening auction demand and supply elasticities, and 17 and 20 for 2:30 PM elasticities of demand and supply, respectively. The average R^2 numbers of regression [3] for opening and 2:30 PM are 73% and 66% and, those of [4] are 79% and 73% respectively.

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

4 Empirical Results

In this section, we first report patterns of demand and supply elasticities and then examine firm-level daily panel regression. 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. 1997 November is chosen as the onset of the crisis, following Kim and Wei (2002).[9]

[Figure 3 about here]

4.1 Magnitudes

Panel A and B of Figure 3 plot the time series of daily mean elasticity measurements against time. Table 3 reports the summary statistics of underlying firm level daily elasticities of supply and demand curves. Table 3 shows that the median elasticities of demand and supply

[9] On November, 1997, Bank of Korea stopped defending Korean Won and Korean government requested IMB bail-out.

curves are 20 and 22 respectively. A one percent increase in price thus causes roughly a 20 percent rise in demand and a 22 percent drop in supply.

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 the different methodologies used, the unique information events used in some of the studies, 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, sp 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, elasticities should rise through the day. Through our sample period, 2:30 PM mean elasticities generally exceed opening elasticities– consistent with 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 in comparing elasticities before and after the crisis using one measurement methodology. Thus, even if absolute magnitudes are not directly comparable across studies, we can make valid comparisons over time for Korea. The average elasticities of both supply and demand 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, is unsurprising.

More intriguingly, elasticities of both supply and demand are markedly lower after this interlude of instability. Table 3 shows a 41% drop, from 29.7 to 17.6, in median demand elasticity; and a 46% drop, from 35.8 to 19.6 in median supply elasticity. Similarly dramatic reductions are evident in 2:30 PM measurements, and in the means of both measurements. These differences are all statistically significant ($p < 0.0001$). Stocks valuations seem significantly more heterogeneous after the crisis than before it. If so, the crisis permanently altered both demand and supply curves. Note that even after the KSE market index reverts to pre-crisis level, elasticities of both demand and supply curves for individual stocks remain depressed. The drop-off is substantial – both persist at levels about 40% smaller after the crisis than before it and neither reverses within our observation window.

Substantial fluctuation at higher frequencies is clearly superimposed on this step function. However, no trend is evident within any of the subperiods. Higher frequency fluctuations thus appear to approximate martingales.

These regularities suggest an underlying factor common to demand and supply elasticities that follows a step function but otherwise changes little – varying little before or after the crisis, but changing substantially during it. 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 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 supply and demand curves. We return to these issues below.

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 crisis fire-sales. Kalay *et al*. (2004) find supply less locally elastic (around market prices) than demand for Tel Aviv stocks, 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 Korea than in Tel Aviv..

[Figures 4 and 5 about here]

4.2 Counterpoint at Higher Frequencies?

Figure 4 plots daily mean demand elasticities against daily mean supply elasticities for individual stocks. Negative correlations amid much scatter are visible for both opening and 2:30PM measures. To confirm these visual patterns, we calculate correlations between the two for each month. Figure 5 plots these against time, showing that they jibe roughly with the intuition evident in Figure 4. The correlation of supply elasticity with demand elasticity is usually negative in the opening auctions and is always markedly negative at 2:30PM. The correlation of a stock's demand elasticity and supply elasticity thus grows more negative during the day. Moreover, while the 2:30 PM elasticities show a consistent negative correlation throughout the sample period, the opening auction elasticities grow markedly more negatively correlated later in the observation window – after the 1997 financial crisis.

4.3 Panel Regressions

To investigate this negative correlation further, we turn to panel regressions using daily firm-level elasticities. We demean these data 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

[4] $$_S\eta_{j,t} = \alpha_j + \delta_t + \beta \cdot {}_D\eta_{j,t} + \varepsilon_{jk}$$

where the dependent variable is the supply elasticity of firm *j*'s stock on day *t* and the independent variable is its demand elasticity that day. We cluster standard errors by firm to adjust for possible autocorrelation in elasticities.

Panel A of Table 4 presents estimates of β_D in [4] for the full sample and for each sub-period. These are consistent Figures 4 and 5, in that regressions using opening auction elasticities are insignificant in the pre-crisis period. A negative coefficient appears during the crisis, and grows in magnitude for the post-crisis subsample. A significant negative coefficient is evident throughout in the 2:30PM elasticities, and no comparable trend is evident in its magnitude.

Panel B reruns the regressions in panel A, but weighting each daily pair of elasticity observations by the firm's market capitalization at that day's close. Weighting larger firms more heavily can be justified on several grounds. Larger firms have higher media profiles and might be subject to more frequent information events. Institutional investors likely hold larger firms and apply their sophisticated financial analysis tools to track changes in fundamental value. Larger firms' elasticities might be measured more accurately because their limit order books are typically deeper and broader; and these deeper and broader limit order books present more opportunity for informed traders to profit from private information without immediately moving the price.[10] Panel B replicates the negative correlations evident in Panel A, and shows the progressively deepening negative correlations more starkly. The open auction elasticities' negative correlation deepens more: the coefficient is -0.004 in the pre-crisis subsample and falls to -0.182 – about three times more negative than the analogous coefficient in Panel A. The 2:30 PM elasticities now also show deepening negative correlations – with a pre-crisis coefficient of -0.135 falling to -0.189 in the post-crisis subperiod.

Our finding that individual stocks' demand elasticities and supply elasticities are contemporaneously negatively correlated survives a range of robustness checks. We cluster standard errors by time, and obtain qualitatively similar results, by which we mean similar patterns of signs and statistical significance to those in the tables. Running regressions in first differences, rather than including firm fixed effects, controls for time-varying fixed effects and also generates qualitatively similar results.

5. Towards an Interpretation

In this section, we start with a simple specification of demand (or supply) function as discussed in Grossman and Stiglitz (1980) to guide our quest to find answers for empirical results reported in the previous section. Grossman and Stiglitz (1980) derive the demand (or supply) curve of investor *i* for a firm's stock as

$$[5] \qquad D_i = \frac{(p_i - P)}{\alpha V_i}$$

[10] One alternative to this specification is to use interaction term. Results are qualitatively the same whether we use WLS or OLS with interaction terms.

with $p_{i.}$ the expected value investor i assigns to the stock, P its current market price, α the risk aversion common to all investors, and V_i the investor's uncertainty about the stock's intrinsic value.

By assuming V_i identical across investors and investors' valuations $p_{i.}$ uniformly distributed, the slope of aggregate demand curve can be written as

[6] $$\frac{\partial D}{\partial P} = -\frac{1}{\alpha V}$$

Under these simplifying assumptions, the demand (or supply) curve becomes steeper if investors are more risk aversion or uncertainty about fundamental values, all else equal. Wurgler and Zhuravskaya (2002) use a representation of this sort, in which V is also interpreted as reflecting arbitrage risk. Absent uncertainty about fundamental value and given perfectly homogeneous expectations across all investors, V approaches zero and the curve becomes infinitely elastic. That is, all else equal, the lower the ambient risk aversion and uncertainty about the fundamental value, the larger the price sensitivity of quantity demanded or supplied.

This simple framework suggests that changes in either α or V might explain the post-crisis depression in elasticities we observe. For example, if the crisis causes investors to become more risk averse, perhaps because their wealth falls or because they become more aware of volatility always intrinsic to equity investments, they become less willing to enter large orders based on valuations differing from the market price. Thus an elevated α results in smaller limit orders at each price and steepens supply and demand curves for individual stocks, all else equal. Or, if the crisis made individual firms harder to value, perhaps by overturning investors' background assumptions or by inducing firms to pursue more idiosyncratic and risky strategies, investors again become less enthusiastic about betting huge amounts on their private valuations. Thus does greater uncertainty, a higher *V*, steepen demand and supply curves for individual stocks, all else equal.

This sort of model thus goes far in explaining the long-run step function evident in Figure 3. But to explain the negative correlation evident in Figures 4 and 5, we need to address the strategic interactions between buyers and sellers. The theory literature offers little guidance here, so we propose an intuitive framework and use it to motivate an exploratory empirical study in the hope of spurring formal theory work.

Risk aversion and uncertainty as to fundamental value might also induce and modulate the negative correlation as well. Kavajecz (1999) notes that specialists and limit order traders both reduce depth around information events – possibly because they fear trading against better informed investors. Thus, if private information that the stock is overvalued solidifies in the hands of some investors, they enter large sell orders at and just below the market price. This flattens the stock's supply curve. If investors not party to this private information observe such trades, they might mimic Kavajecz's (1999) traders and reduce their limit order depths for fear of trading at an informational disadvantage. All else equal, this behavior steepens the demand curve of the affected stock. If the new private information indicates that the stock is undervalued, the better informed investors enter large limit orders to buy at or above the market price so everything works in reverse – flattening the stock's demand curve and steepening its supply curve This sort of reaction function would induce the negative correlation between demand elasticity and supply elasticity we observe at high frequencies. Roll (1988) argues that most information enters the market in these ways – as private information gathered and interpreted by investors who trade on that information for private gain.

The flattening due to large orders by investors with private information would presumably be greater if they are less risk averse or more certain of their advantage. The reactions by uninformed traders would presumably be stronger if they were more risk averse or less sure of the validity of their valuations. A negative correlation between supply and demand elasticities should thus be greatest when informed traders are more bold and certain and uninformed traders more cautious and uncertain. Thus, a more prominent negative correlation at 2:30 than at the open might indicate more information heterogeneity later in the day, with privately informed traders growing more aggressive and uninformed traders reacting with a more sever withdrawal of limit order depth.

To explore this admittedly highly speculative thesis, we require proxies for ambient risk aversion, α, and uncertainty, V. We cannot readily gauge α from observed equity premiums in this context, for Siegel and Thaler (1997) show that a financial crisis affects both stock and bond markets, rendering the difference in average returns between them problematic as a way of inferring α. One approach is to seek proxies. Thus, we might infer changes in α from shifting patterns of investment. For example, a sudden flow of wealth from tech stocks into government bonds might signal a newly elevated α, all else equal. We lack data to track such shifts, but can construct some less direct proxy. In the following section, we discuss the construction of proxies for α and V.

5. 1 Proxies for Uncertainty regarding Fundamental Values

This section motivates, critiques, and describes a set of variables plausibly related to investors' uncertainty as to stocks' fundamental values. These are: the adverse selection component of the bid-ask spread, a mean intraday price flux, and share turnover.

5.1.1 The Adverse Selection Component of the Bid-Ask Spread

The *adverse selection component of the bid-ask spread* is a popular measure of information asymmetry between informed traders and liquidity providers in the microstructure literature. Since asymmetric information increases as the uncertainty concerning firm value increases, we conjecture that this variable to be positively related with *V*. Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987) argue that liquidity traders often sustain losses from trading with informed traders. Thus, liquidity providers include an adverse selection cost in the bid-ask spreads they post. This lets them cover their expected losses to informed traders.

The magnitude of this spread thus reflects liquidity traders' perceptions of their informational disadvantage, and thus of information heterogeneity in general. A larger bid-ask spread should thus correlate with lower elasticities and a more negative correlation between supply and demand elasticities.

To construct this measure, denoted *spread*, we decompose the observed spread – the lowest ask, a_t, minus the highest bid, b_t – into a *realized half-spread* and *adverse selection component* as in Huang and Stoll (1996). [11] The former component gauges liquidity providers' post-trade earnings and the latter their losses to informed traders. We define

$$[7] \qquad realized\ half-spread \quad = \quad \lambda_t\left(p_{t+\tau} - p_t\right)$$

with p_t the transaction price at time t, τ set to five minutes, and λ_t set to one for buy-initiated trades and minus one for sell initiated trades.[12] Because the spread depends on the tick size, which depends on the price, we scale by the mid-point of the prevailing bid and ask. Thus, we take the adverse selection component of the bid-ask spread as

[11] In an order-driven market, it is not possible to place a buy (sell) order above (below) the prevailing lowest ask (highest bid) price. As a result, the effective spread is always the same as the quoted spread.
[12] We have repeated the empirical analysis using τ = 30 minutes. This does not affect our results in any meaningful way.

$$[8] \qquad spread \equiv \frac{(a_t - b_t) - \lambda(p_t - p_{t+\tau})}{\frac{1}{2}(a_t + b_t)}.$$

5.1.2 Intraday Price Flux

Our second variable is *intra-day price volatility.* French and Roll (1986) and Roll (1988) show most variation in individual stock returns to be firm-specific and unrelated to public announcements. Roll (1988) argues that stock price movements are therefore largely caused by investors trading on private firm-specific information. Higher volatility thus reflects more active trading by informed arbitrageurs, and consequently a more heterogeneous distribution of private information across investors. This, in turn, implies higher uncertainly about the intrinsic value of firms to most investors, and thus less elastic demand and supply curves. The same situation also implies a more severe reaction of uninformed investors to informed traders, and thus a more prominent negative correlation between supply and demand elasticities.

We estimate the intraday price flux, denoted *volatility*, for each stock each trading day as the standard deviation of 5-minute price changes scaled by the mid-points of bid and ask prices.

5.1.3 Share turnover

Our third proxy is s*hare turnover.* Trading occurs when investors disagree about fundamental values (Karpoff, 1986). This presumably happens when different investors have access to different private information – or draw different conclusions from common information. Thus, trading volume measures the heterogeneity of expectations across investors, so high volumes should accompany inelastic demand and supply curves. However, high volume periods should also be periods of lower trading cost for arbitrageurs, and so of more elastic demand and supply curves. Which effect dominates become an empirical question.

We define *turnover* as shares traded divided by total shares outstanding.

5. 2 Proxies for Risk Aversion

We take the above three variables as proxies primarily reflecting the extent of information heterogeneity, and now consider variables most directly linked to risk aversion. Obviously, the first set might also be related to risk aversion. All else equal, more timorous market makers should post higher spreads. All else equal, less risk averse investors should trade more energetically on fainter information, perhaps elevating intraday flux and volume measures. The variables to which we next turn might likewise be related to information heterogeneity as well as risk aversion.

Impecunious individual investors can participate in the stock market by buying stocks on margin or selling stocks short. Both procedures amount to borrowing money from brokerage firms to trade securities, and thus increase an investor's leverage. This necessarily renders their portfolios riskier. For example, an investor who borrows money to buy a stock can be in serious trouble if the stock price drops precipitously – unable to repay the loan by selling the stock, she can face insolvency. To protect themselves from such situations, brokers in Korea and elsewhere usually call in parts of such loans immediately if a stock's price drops. Margin trading became a popular fad among individual investors in the run-up to the Asian Crisis. Deficient credit screening by brokers allowed legions of unsophisticated and relatively shallow pocketed investors to trade on margin. When the crisis hit, prices plummeted and many of these investors faced ruin. As a result, investors awareness of the risks involved in margin trading rose.

To measure investor risk aversion, we use margin purchases as a fraction of total buy limit orders and short sales as a fraction of total sell limit orders. We denote these variables *margin interest* and *short interest*, respectively.

Several caveats are in order. First, changes in the costs of margin trading and short sales might alter these measures absent any change investor risk aversion. During the crisis, the cost of margin trading rose substantially as rapidly rising missed margin calls made brokerage firms less generous with credit. In December 1997, the Korea Securities Finance Corporation stopped lending to brokerage firms.[13] This cut the hypothecated credit the brokers previously extended to investors, forcing them to hike collateral requirements from 140 percent to an average of 174 percent; and raise initial margin requirement as well. These measures unquestionably raised both margin and short sales costs.

Although changes in either risk aversion or such costs should affect investors' decisions to buy on margin and sell short, the two have different predictions in the long run. Changes due to altered tolerance for risk should persist after the crisis, whereas changes due to elevated crisis-period trading costs should not as the costs of margin trading revert to pre-crisis levels.

[Table 5 about here]

5.3 Low Frequency Results, Revisited

Elasticities of demand and supply drop markedly from the pre-crisis period to the post crisis period, and our purpose in constructing the variables described above is to find factors that display similar patterns. Table 5 presents summary statistics for each – first across the whole sample period, and then for the pre-crisis, in-crisis, and post-crisis subperiods separately.

[13] The Korea Securities Finance Corporation, established in October 1955, is the sole provider of securities finance services under the Securities and Exchange Act.

[Figures 6 and 7 about here]

The adverse selection component of the spread rises substantially, from 0.733 before the crisis to 1.182 during it, but then falls to 0.696 after the crisis – a level lower than in the pre-crisis period. This pattern, graphed in Figure 6, fails to track the step function in elasticities also reproduced in that figure. Intraday price flux and share turnover both remain elevated in the post-crisis period, though the price flux almost returns to pre-crisis levels. Share turnover remains more substantially elevated, 2.41% in the post-crisis period versus 0.78% before the crisis, and its standard deviation is about sevenfold larger in the later period. Figure 7 graphs both measures against time, and suggests share turnover as tracking elasticities more faithfully than the other potential proxies for information asymmetry. Further work is needed to assess the extent to which increased turnover reflects the reduced transaction costs attendant to online trading, introduced in late 1990s.

[Figures 8 and 9 about here]

Figures 8 and 9 graph margin and short interest against time, and demonstrate a marked and seemingly permanent drop in both during the crisis. Margin interest falls from 20.3% of buy limit orders before the crisis to only 1.3% in the post-crisis period. Short interest drops from 1.3% of sell limit orders in the pre-crisis period to zero after it. Margin lending was tightened substantially during the crisis, but most brokerage firms restored the old rules by 1999.

Margin interest nonetheless remained markedly depressed. This is consistent with an abrupt and persistent increase in risk aversion steepening both curves, though other explanations are doubtless also possible

5.4 High Frequency Results, Revisited

Next, we revisit our finding of a negative correlation between a given stock's elasticities of supply and demand in daily data. To explore this further, we modify regression [6], including interaction terms to see if the elasticities are more strongly negatively correlated when our information heterogeneity proxies are larger. Here, we expect information heterogeneity measures to dominate, since ambient risk aversion presumably changes little from day to day (unless the composition of traders changes rapidly). We also exclude short interest from this regression because it exhibits virtually no high frequency variation in the post-crisis subperiod.

Our regression is thus

[8] $${}_{S}\eta_{j,t} = \alpha + \delta_t + \beta \cdot {}_{D}\eta_{j,t} + \gamma \cdot X_{t-1} \cdot {}_{D}\eta_{j,t} + \varepsilon_{jk}$$

with X_t a vector containing the proxies for information asymmetry and risk aversion developed above. Panel A and B of Table 6 report regressions analogous to those in Table 4.

[Table 6 about here]

The table clearly shows the increased negative correlation in the post-crisis subperiod is a direct effect, not something mediated by the interaction terms. The magnitudes of β_D, the coefficient of η_D, shown in Table 6 differ little from those shown in Table 4. The interaction terms also increase adjusted R^2 very little.

Note also that the signs and significances of the interaction coefficients are quite unstable across specifications. For example, in the post-crisis subperiod, the interaction of η_D with volume attracts a negative coefficient in opening auction data, but is insignificant in 2:30PM data. The interaction with intraday flux is negative and significant in the equal-weighted specifications using opening and 2:30 PM data, but becomes insignificant if observations are weighted by market capitalization. The interaction with margin interest is negative and significant regardless of the weighting, but only in 2:30 PM data. All these results suggest an inconsistent magnification of the negative correlation between demand and supply elasticities if information heterogeneity or risk aversion has increased. The interaction with the adverse selection spread component, in contrast, attracts positive significant coefficients – though for 2:30 PM data in equal-weighed regressions only. Taken at face value, this might imply that the negative correlation is attenuated if market makers fear they are at a worse informational disadvantage. Or, the adverse selection component might capture 'general information' uncertainty that affects both curves.

We believe the following best sums up these findings. Daily variation in plausible proxies for neither information heterogeneity and risk aversion are terribly effective at explaining neither daily variation in the magnitude of the negative correlation between a stock's supply and demand elasticities, nor the substantial rise in this negative correlation in the post-crisis subperiod.

This is unsurprising as regards risk aversion, for this is a psychological parameter that is unlikely to fluctuate greatly in the short run. Indeed, the persistently larger negative correlations after the crisis suggest a link to ambient risk aversion, which plausibly also remained elevated after the crisis. As regards information heterogeneity, whether our proxies are inadequate or high frequency variation in information heterogeneity explains little of the high frequency fluctuation in the negative correlation we observe.

5. Conclusions

The asset pricing literature descended from. Harrison and Kreps (1978) and Grossman and Stiglitz (1980) posits finitely elastic demand and supply curves for individual stocks with elasticities determined by the degree of information heterogeneity and investors' risk aversion. Blough (1988), Hindy (1989), De Long et al. (1990), Kandel and Peason (1992), 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 occurs 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 or supply and demand 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 level. This is 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. However, common proxies used to reflect information heterogeneity and risk aversion are of scant use in explaining this step function in elasticities.

A stock's elasticity of demand and elasticity of supply are robustly negatively correlated 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. This negative correlation should again be larger if information heterogeneity and risk aversion are larger. But once again, temporal variation in common proxies for information heterogeneity and risk aversion is of scant use in explaining temporal variation in the magnitude of this negative correlation.

Clearly, either our proxies are seriously flawed or other factors are complicating the picture. We invite new theoretical models that might explain the robust empirical regularities we detect.

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Figure 1. Observed Supply and Demand Schedules for Samsung Stock

The *opening auction orders* graphs (dashed) reflect all buy and sell orders submitted in the 9:00 AM auction that sets the open price. The *2:30PM limit orders* graphs (solid) reflect all limit orders on the books as of 2:30PM. Data are for November 11, 2000.

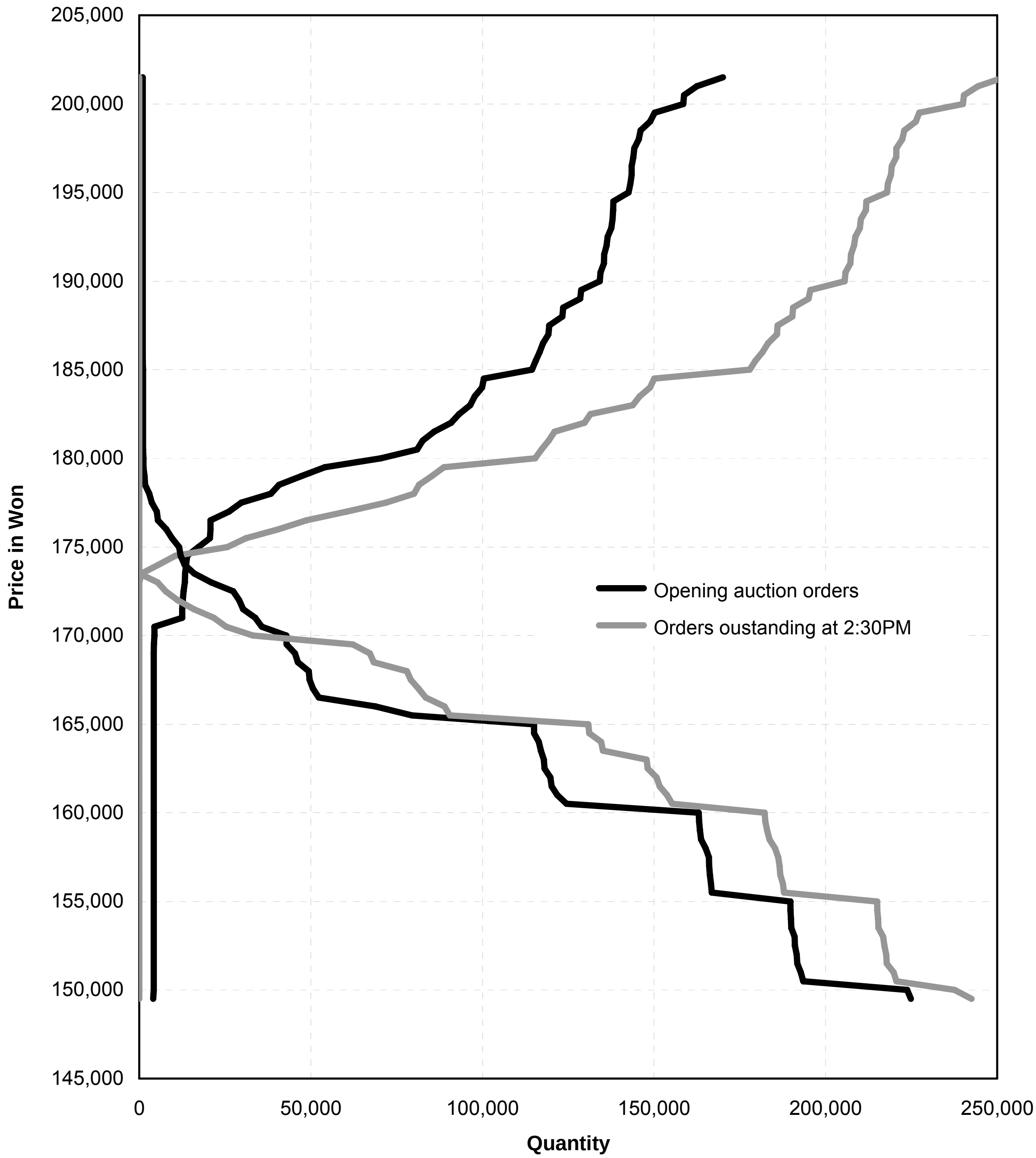


Figure 2. Supply and Demand Schedules in Real Time

Supply and demand 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. Data are for November 11, 2000.

Panel A. Supply of Samsung stock at 15 minute intervals **Panel B. Demand for Samsung stock at 15 minute intervals**

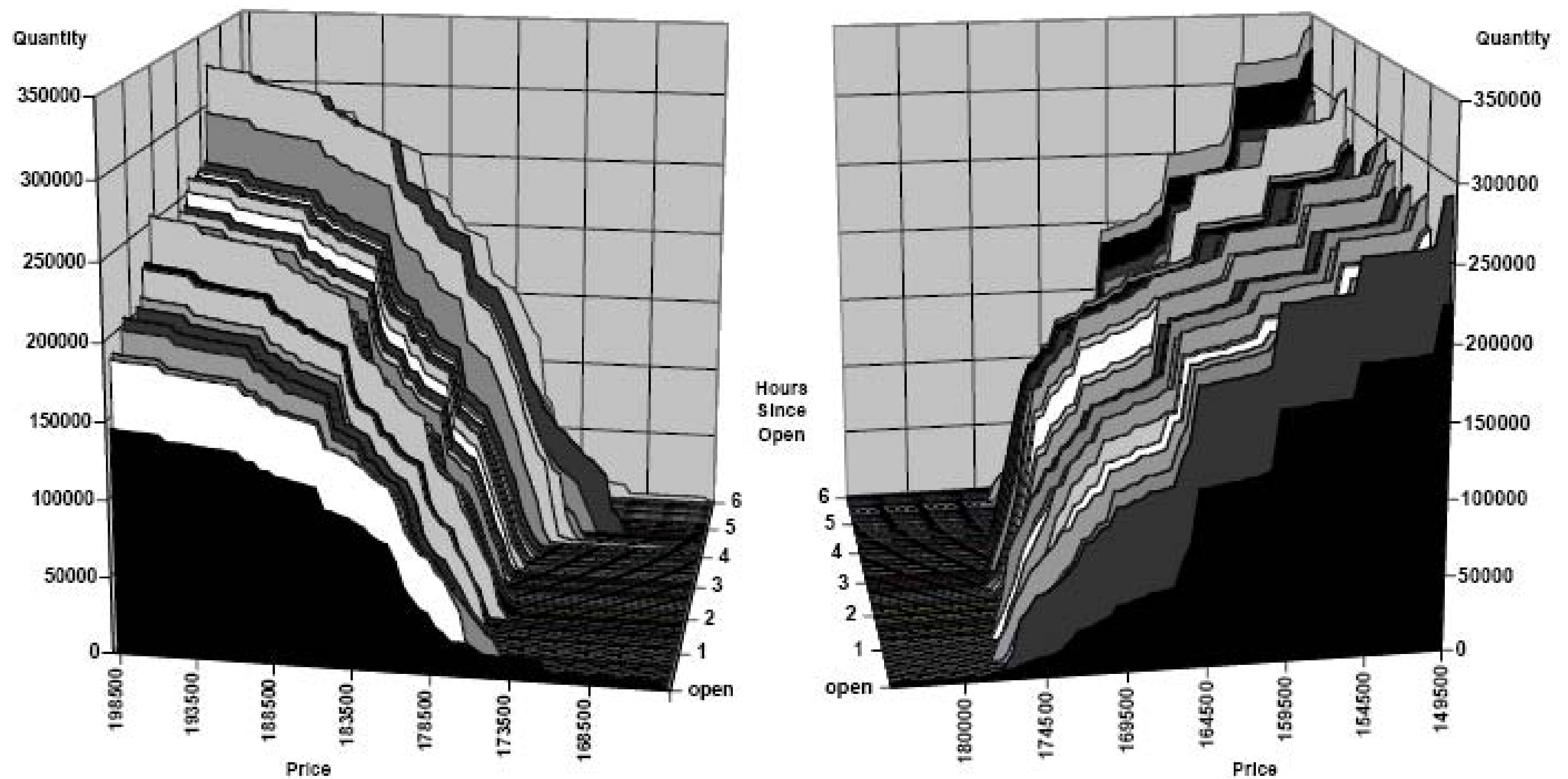


Figure 3. Mean Demand and Supply Elasticities of Individual Stocks over Time
Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand s the negative of that coefficient in an analogous regression explaining log quantity demanded. 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. Upper panel shows KSE Composite Stock Price Index over this period

KSE Index

Opening Auction Elasticities

2:30 PM Elasticities

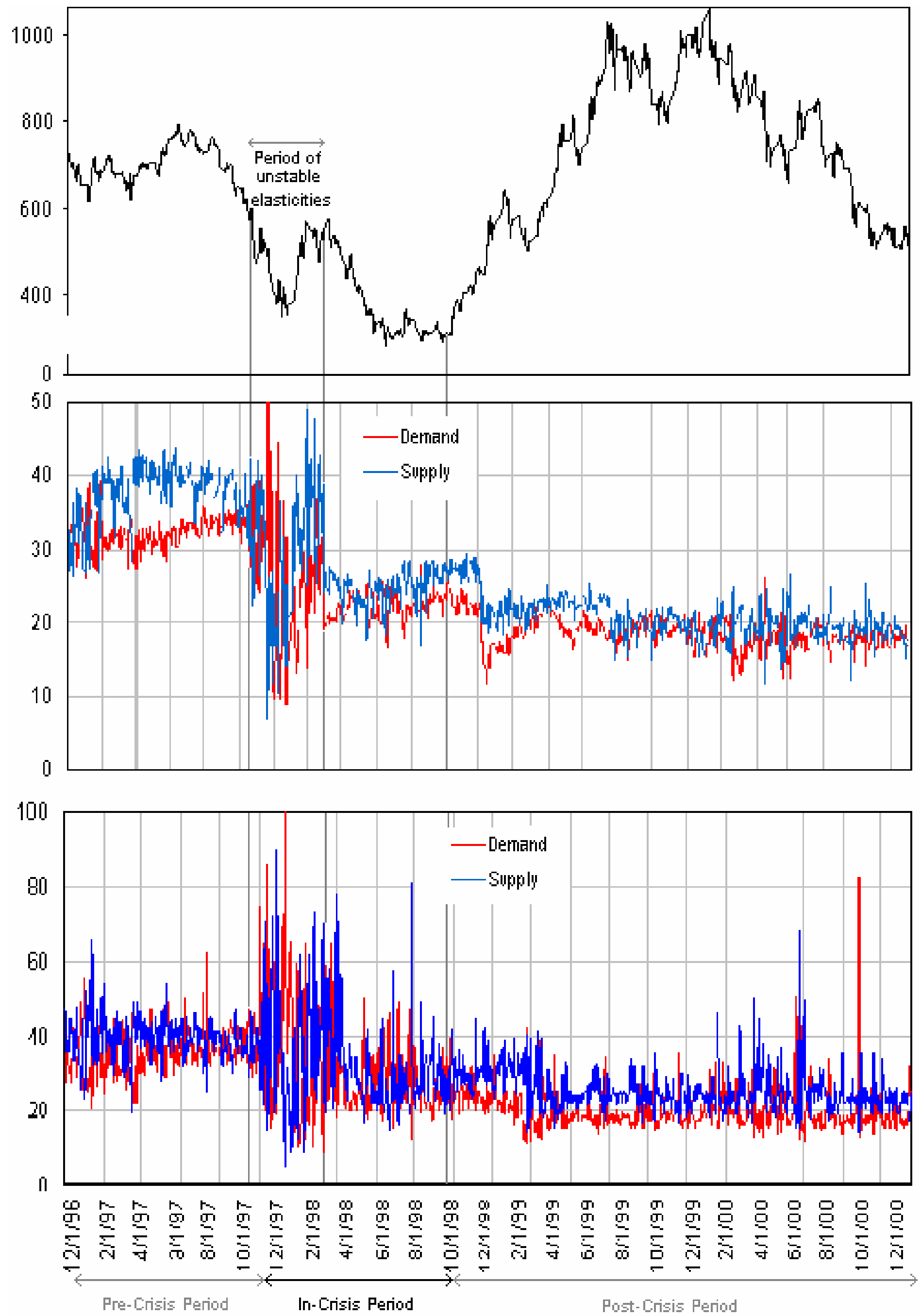
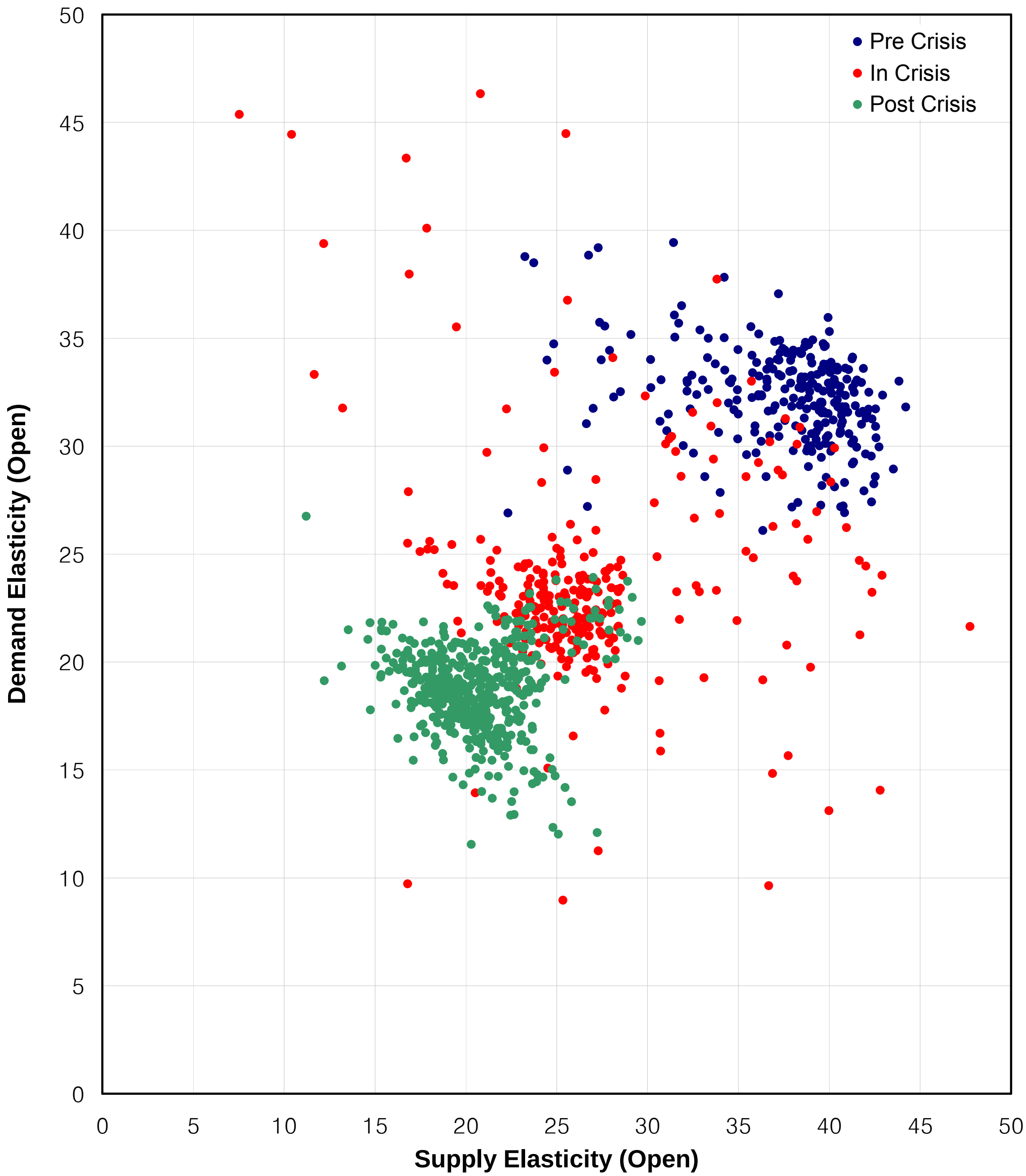


Figure 4. Mean Demand and Supply Elasticities Compared

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand s the negative of that coefficient in an analogous regression explaining log quantity demanded. 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 averages supply elasticity is plotted against its 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.

Panel A. Elasticities at Opening Auction



Panel B. Elasticities at Opening 2:30PM

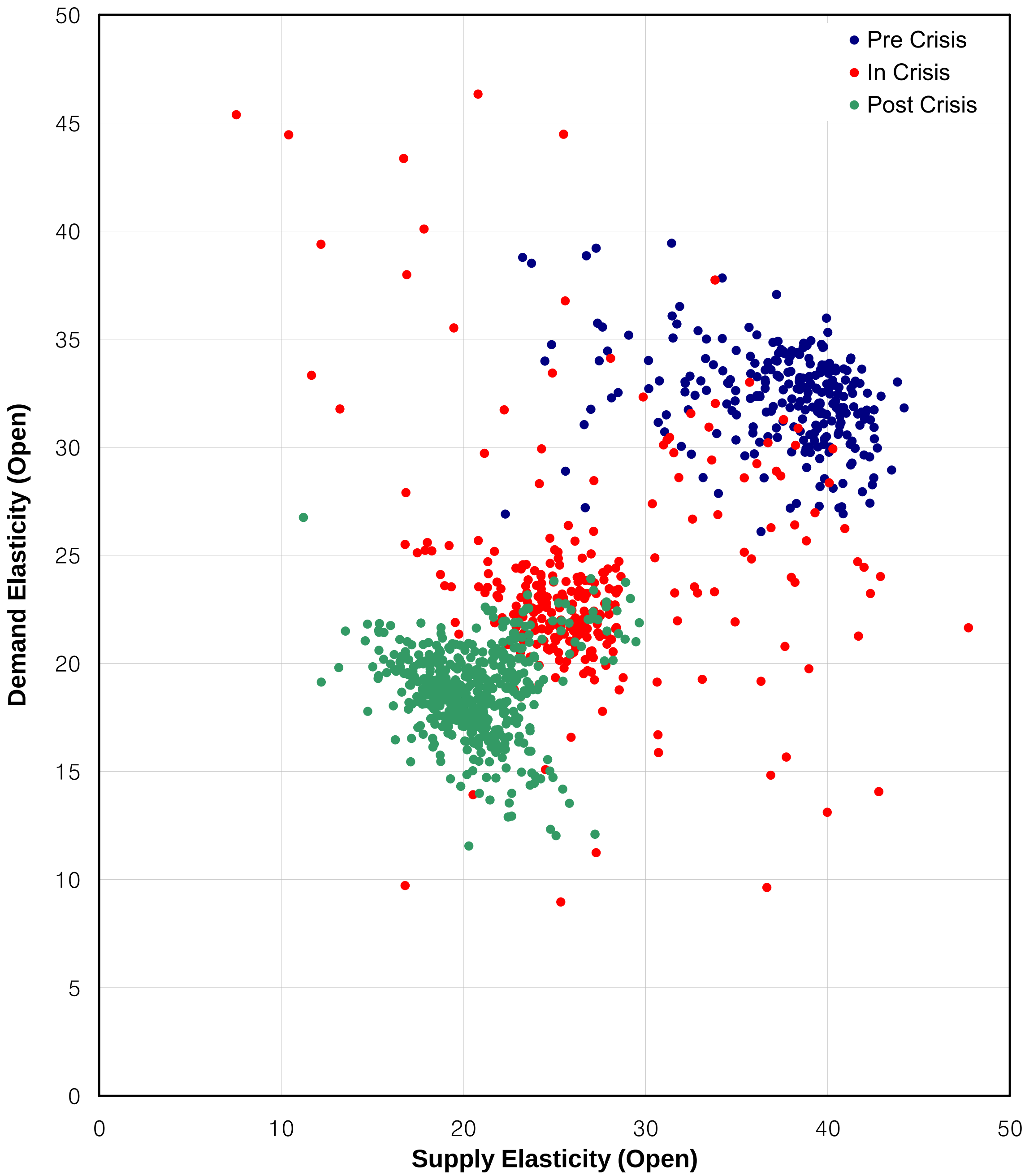


Figure 5. Correlations of Individual Stocks' Daily Average Supply and Demand Elasticities, by Month

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. 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. Correlations are of daily supply and demand elasticities, using all days in each month. Pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods are indicated.

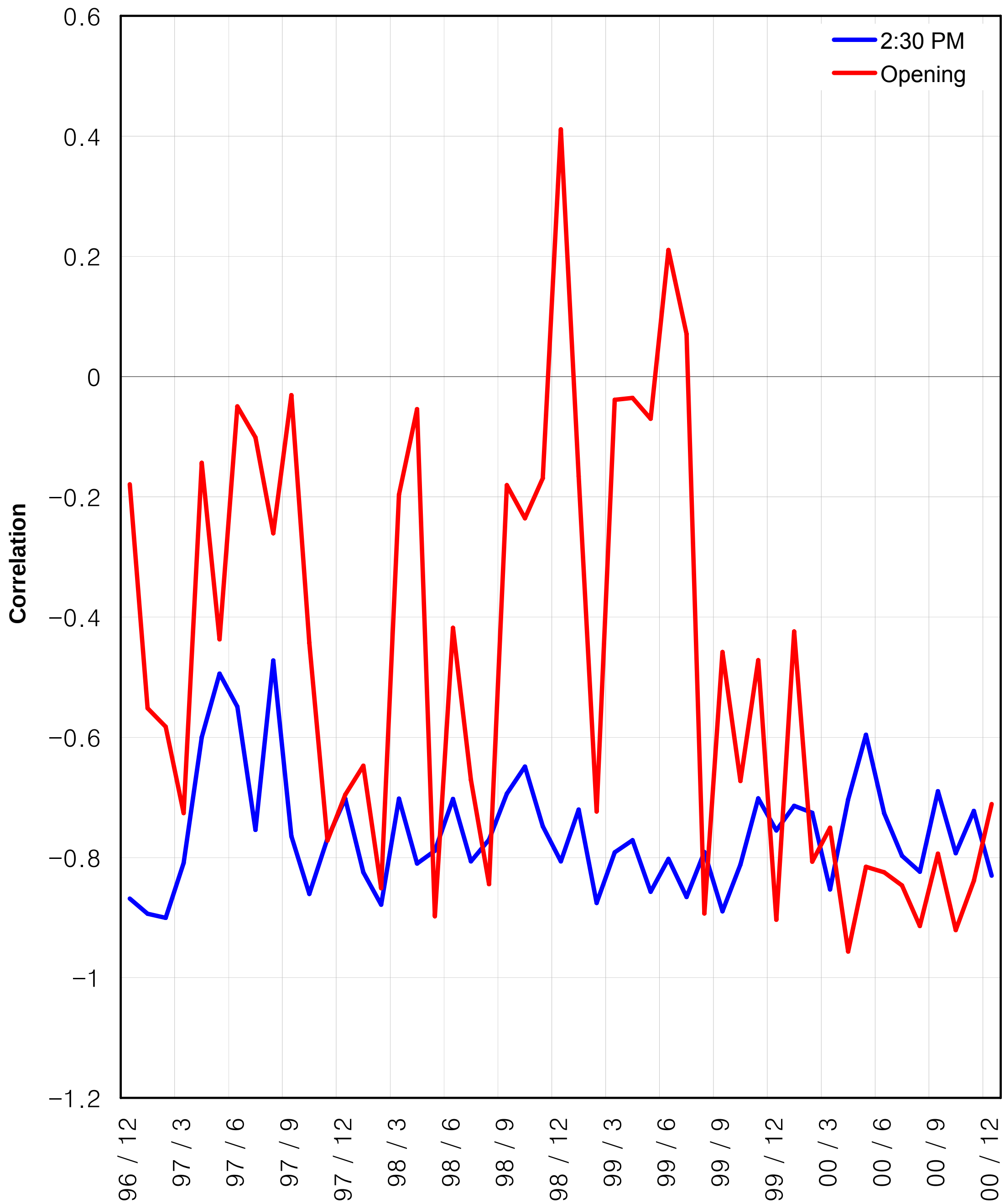


Figure 6. Elasticities and Adverse Selection in Spreads

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. Elasticities are measured daily from Dec. 1996 to Dec. 2000 in the opening auction and averaged across all stocks. Adverse selection compenents of spreads are measured separately using buy-initiated and sell-initiated transaction prices.

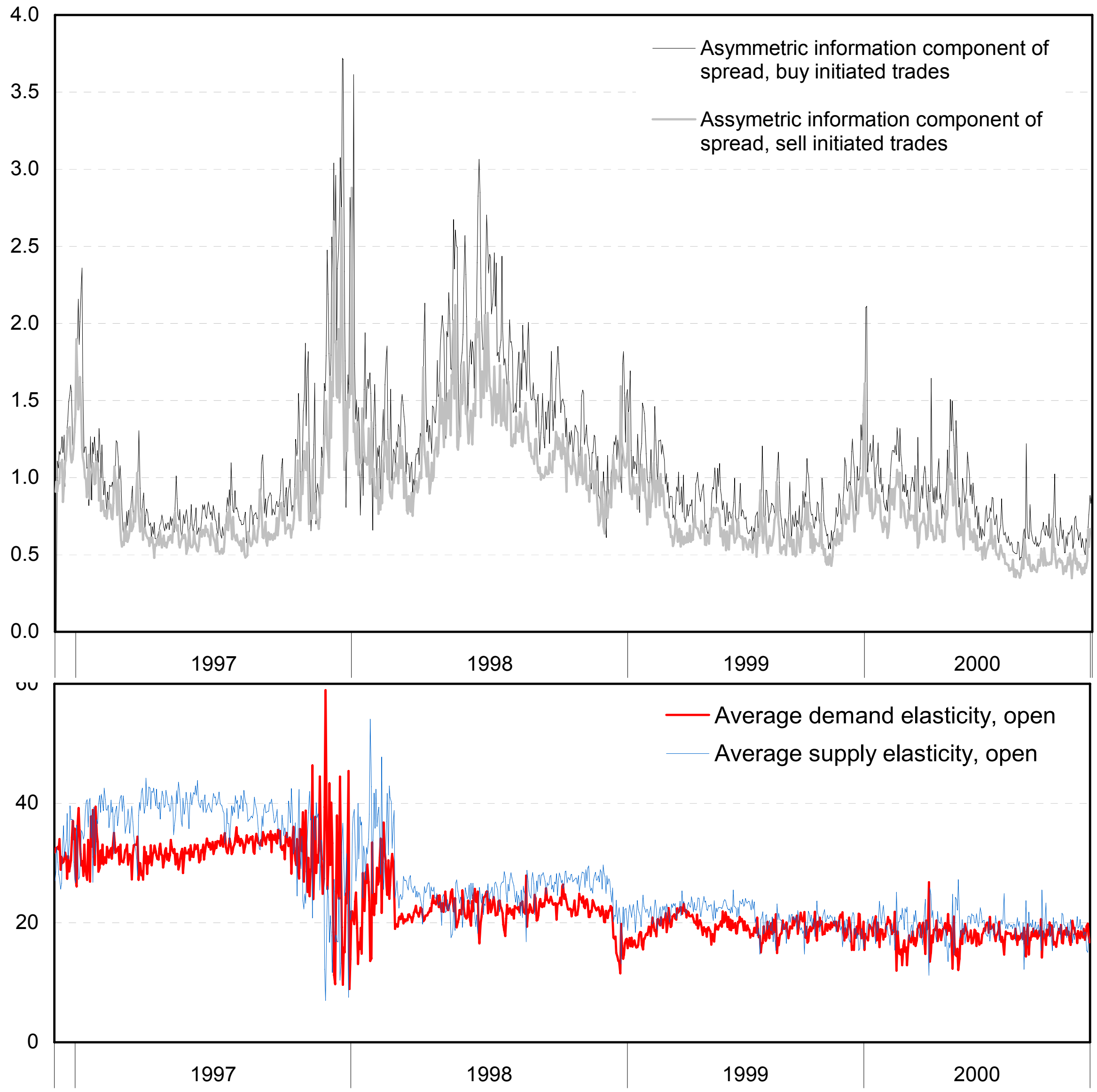


Figure 7. Elasticities, Price Flux, and Trading Activity

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. Elasticities are measured daily from Dec. 1996 to Dec. 2000 in opening auctions and averaged across all stocks. Trading activity is share turnover, the number of shares traded divided by total shares outstanding, and price flux is the standard deviation of 5-minute price changes scaled by the mid-points of bid and ask prices, measured for each stock each trading day.

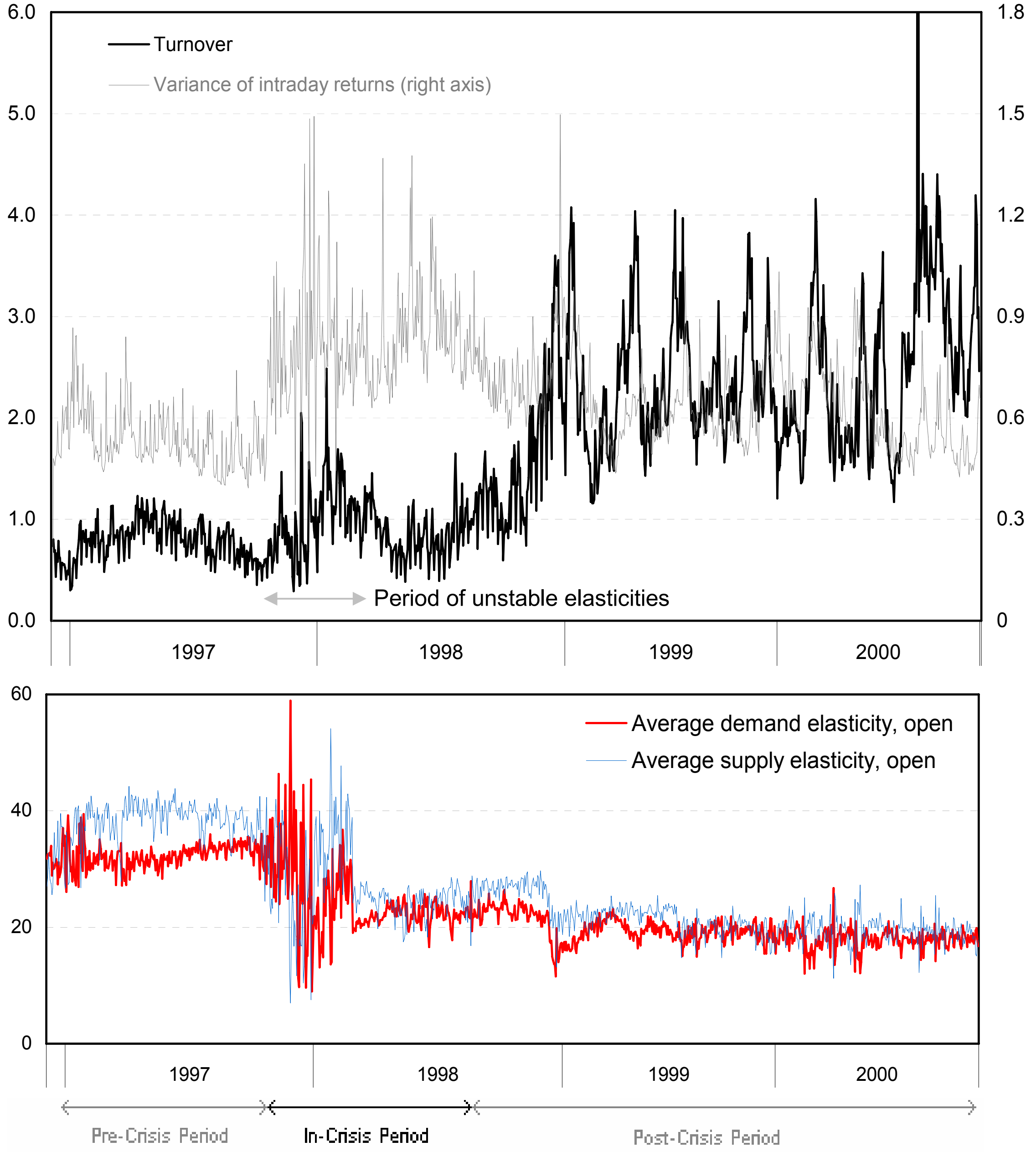


Figure 8. Elasticities and Margin Interest

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. 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 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. Upper panel shows margin buy orders as a fraction of total buy orders each day.

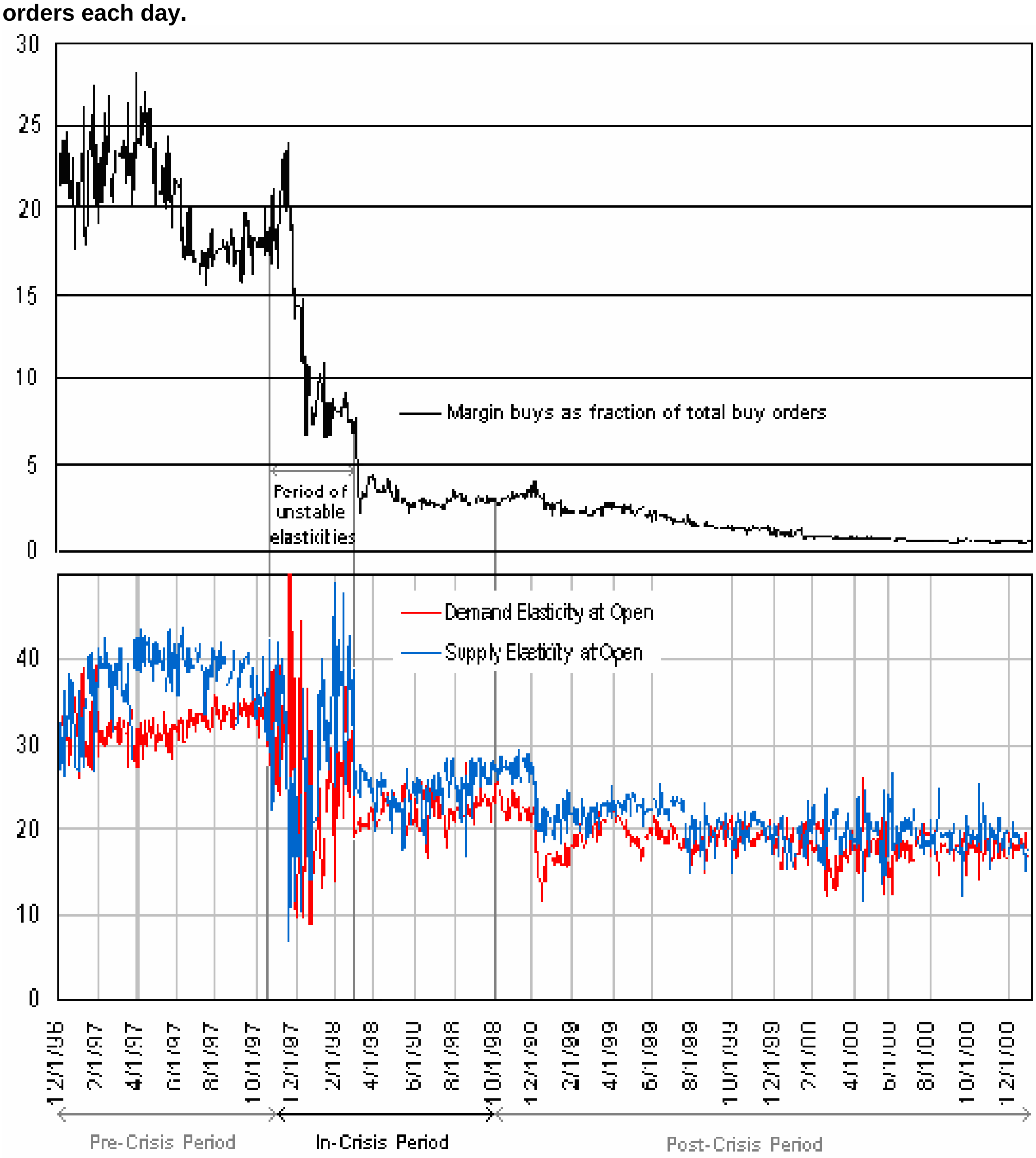


Figure 9. Elasticities and Short Interest

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. 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 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. Upper panel shows short sale orders as a fraction of total sell orders each day.

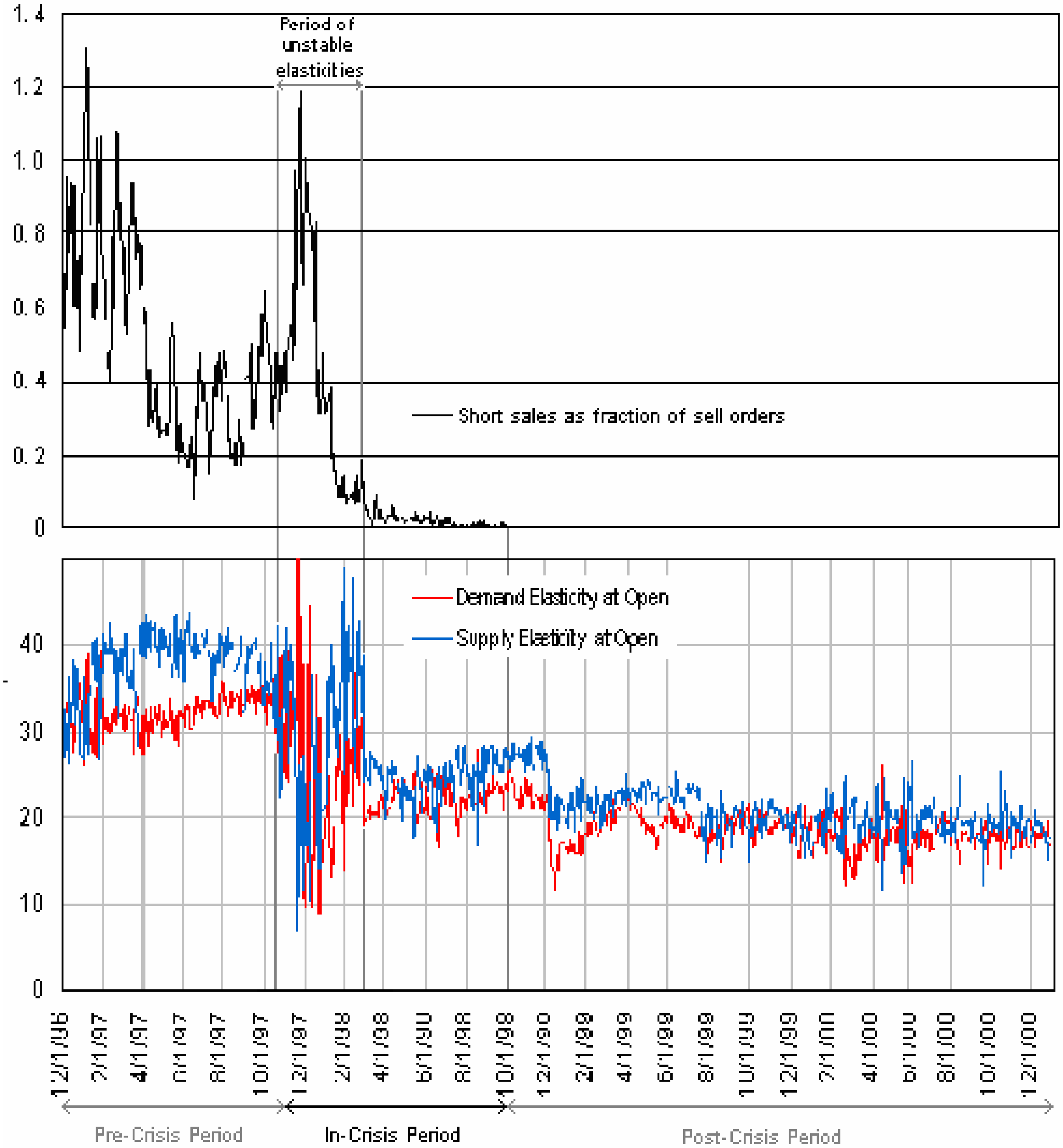


Table 1. Distribution of Orders and Trades

Buy and sell orders on the Korea Stock Exchange (KSE) from December 1996 to December 2000. Orders are flagged as buys or sells and partitioned into market and limit orders, with executed orders marked as trades. Each daily trading session is partitioned into an opening call market auction and the continuous trading during the rest of the day; with orders on the books at 14:30 each day flagged. Values in parentheses are average order sizes.

Order Type		*Entire Day*	*Opening Call Market*	*Rest of Day Continuous Market*
Buys	Market	13,938,249 (1,177.40)	3,620,127 (1,096.11)	10,318,122 (1,205.92)
	Limit	253,301,774 (1,298.60)	47,428,384 (1,251.10)	205,873,390 (1,309.54)
	Total	267,240,023 (1,292.28)	51,048,511 (1,240.11)	216,191,512 (1,304.60)
Sells	Market	19,880,406 (716.69)	6,966,032 (628.91)	12,914,374 (764.04)
	Limit	263,831,555 (1,729.71)	53,011,848 (1,254.08)	210,819,707 (1,849.31)
	Total	283,711,961 (1,658.72)	59,977,880 (1,181.47)	223,734,081 (1,786.66)

Table 2. Limit Order Book Ranges

Korea Stock Exchange limit order book quantities demanded and supplied in price ranges as percents of the close. Figures are daily averages across all stocks from December 1996 through December 2000, and each is expressed first in millions of shares and then as a percent of total limit order demand or supply.

	Demand		*Supply*	
Limit Order Price as Percent of Closing Price	***Millions of shares***	***Percent of Limit orders***	***Millions of shares***	***Percent of Limit orders***
$p < 80\%$	4,306	1.6 %	339	0.1 %
$80 \leq p < 85$	4,053	1.5	484	0.2
$85 \leq p < 90$	10,132	3.7	2,399	0.9
$90 \leq p < 95$	18,860	6.9	10,195	3.9
$95 \leq p < 99$	41,943	15.2	34,433	13.3
$99 \leq p \leq 101$	70,609	25.6	64,649	24.9
$101 < p \leq 105$	70,999	25.8	74,027	28.5
$105 < p \leq 110$	32,619	11.8	40,240	15.5
$110 < p \leq 115$	12,931	4.7	18,802	7.2
$115 < p \leq 120$	5,634	2.1	8,772	3.4
$p > 120\%$	3,384	1.2	5,217	2.0
Total	275,469	100.0 %	259,556	100.0 %
$p < 95$ or $105 < p$	91,919	33.5 %	86,448	33.2 %

Table 3. Elasticities of KSE Stocks Before, During, and After the 1997 Crisis

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. 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 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

Trading Session	*Sub-Period*	*Observations*	*Mean*	*Median*	*Standard Deviation*
Opening auction	Entire sample period	662,606	22.703	19.965	14.140
	Pre-crisis period	143,124	32.235	29.707	18.357
	In-crisis period	157,808	23.271	21.321	14.368
	Post-crisis period	361,674	18.683	17.604	9.520
2:30 PM	Entire sample period	666,563	24.810	19.143	23.947
	Pre-crisis period	147,427	35.401	29.127	29.381
	In-crisis period	157,018	26.777	21.123	26.206
	Post-crisis period	362,118	19.646	16.362	18.229

Panel B: Elasticity of Supply

Trading Session	*Sub-Period*	*Observations*	*Mean*	*Median*	*Standard Deviation*
Opening auction	Entire sample period	664,993	25.900	22.552	15.389
	Pre-crisis period	145,959	37.831	35.806	19.405
	In-crisis period	156,641	27.024	24.840	16.233
	Post-crisis period	362,393	20.609	19.564	9.118
2:30 PM	Entire sample period	682,454	29.026	23.123	25.464
	Pre-crisis period	164,763	38.275	32.497	27.495
	In-crisis period	162,425	29.426	23.928	27.240
	Post-crisis period	355,266	24.554	20.365	22.270

Table 4. Panel Regressions of Daily Observations of Stocks' Supply Elasticities on their Demand Elasticities

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and its elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. Elasticities are measured daily in opening auctions and at 14:30, 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. The dependent variable is supply elasticity. The independent variable is demand elasticity. To remove any time effects, both daily elasticities are demeaned, and firm fixed effects remove any influence of persistent firm-level characteristics. Panel A reports equal-weighted panel regressions first for opening and then for 2:30 PM elasticities for the full sample period and also for each subperiod. Panel B reports analogous results but in panel regressions weighting observations by firm market capitalization. Numbers in parentheses are probability levels adjusted for firm clustering.

Panel A: Equal-weighted panel estimation with time and firm fixed effects and firm clustered standard errors

Elasticities estimated in opening auctions

	Full window	Pre-Crisis	In-Crisis	Post-Crisis
Estimate of β_D	-0.015	-0.003	-0.020	-0.053
Prob. β_D = 0	(0.000)	(0.348)	(0.000)	(0.000)
Adjusted R^2	0.024	0.048	0.050	0.046
Observations	601,042	115,280	132,799	352,963

Elasticities estimated in continuous trading at 2:30 PM

	Full window	Pre-Crisis	In-Crisis	Post-Crisis
Estimate of β_D	-0.145	-0.150	-0.158	-0.144
Prob. β_D = 0	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.024	0.041	0.035	0.025
Observations	593,248	126,506	125,115	341,627

Panel B: Market capitalization-weighted panel estimation with time and firm fixed effects and firm clustered standard errors

Elasticities estimated in opening auctions

	Full window	Pre-Crisis	In-Crisis	Post-Crisis
Estimate of β_D	-0.048	-0.004	0.029	-0.182
Prob. β_D = 0	(0.000)	(0.733)	(0.241)	(0.000)
Adjusted R^2	0.023	0.031	0.040	0.081
Observations	597,911	114,780	132,729	350,402

Elasticities estimated in continuous trading at 2:30 PM

	Full window	Pre-Crisis	In-Crisis	Post-Crisis
Estimate of β_D	-0.148	-0.135	-0.142	-0.189
Prob. β_D = 0	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.023	0.051	0.023	0.031
Observations	589,175	125,936	124,969	338,270

Table 5. Information Heterogeneity and Risk Aversion Proxies

The *adverse selection* component of the bid-ask spread is as in Huang and Stoll (1996), using either buy- or sell-initiated transaction prices. *Intraday price flux* is the standard deviation of 5-minute returns through the trading day. *Share turnover* is daily trading volume over shares outstanding. Margin interest is margin buy orders as a fraction of total buy orders; short interest is short sale orders as a fraction of total sell orders. All variables are estimated daily across the sample period, which is partitioned into three sub-periods: (a) pre-crisis period (December 1996 – October 1997), (b) in-crisis period (November 1997 – October 1998), and (c) post-crisis period (November 1998 – December 2000).

Sample	Variable	Sample	Mean	Median	Standard Deviation
Full Sample	Adverse Selection Component of Spread	685,938	0.840	0.395	1.711
	Share Turnover	804,089	1.607	0.642	6.670
	Intraday Price Flux	776,552	0.661	0.573	0.477
	Margin Interest	798,648	7.273	1.435	11.590
	Short Interest	803,079	0.160	0.000	1.348
Pre-Crisis Period	Adverse Selection Component of Spread	169,738	0.773	0.479	1.135
	Share Turnover	201,383	0.773	0.305	1.420
	Intraday Price Flux	193,377	0.544	0.504	0.293
	Margin Interest	199,210	20.349	20.000	14.215
	Short Interest	201,064	0.480	0.000	2.313
In-Crisis Period	Adverse Selection Component of Spread	175,817	1.182	0.546	2.251
	Share Turnover	222,260	0.991	0.431	1.797
	Intraday Price Flux	205,506	0.801	0.706	0.583
	Margin Interest	219,184	5.760	2.500	8.705
	Short Interest	221,796	0.142	0.000	1.261
Post-Crisis Period	Adverse Selection Component of Spread	340,383	0.696	0.303	1.597
	Share Turnover	380,446	2.408	1.125	9.478
	Intraday Price Flux	377,669	0.644	0.555	0.469
	Margin Interest	380,254	1.294	0.417	2.441
	Short Interest	380,219	0.001	0.000	0.033

Table 6. Panel Regressions of Daily Observations of Stocks' Supply Elasticities on their Demand Elasticities and Interactions with Information Heterogeneity and Risk Aversion Proxies

Each stock's elasticity of supply is the coefficient of log price in a regression explaining log quantity supplied; and the elasticity of demand is the negative of that coefficient in an analogous regression explaining log quantity demanded. Elasticities are measured both at opening auction and at 14:30 daily, 30 minutes before the close. Until December 5, 1998, the KSE was opened Saturdays until noon, so the elasticity is estimated 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. The dependent variable is supply elasticity. Independent variables are demand elasticity and demand elasticity interacted with one-day lagged asymmetric information component of spread, intraday price flux, share turnover, and margin interest. All variables are demeaned at daily level and all regressions include firm fixed effects. Numbers in parentheses are probability levels, based on *t*-statistics adjusted for firm clustering.

Panel A: Equal-weighting of all observations.

	Elasticities at open auction				*Elasticities at 2:30 PM*			
Coefficient of	*Full Sample*	*Full Sample*	*Pre-Crisis*	*In-Crisis*	*Full Sample*	*Pre-Crisis*	*In-Crisis*	*Post-Crisis*
η_D	-0.020	-0.020	-0.005	-0.017	-0.143	-0.150	-0.155	-0.143
	(0.000)	(0.000)	(0.198)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
η_D x spread	0.006	0.006	0.000	0.002	-0.004	-0.009	-0.005	-0.002
	(0.000)	(0.000)	(0.935)	(0.450)	(0.035)	(0.039)	(0.143)	(0.450)
η_D x flux	-0.026	-0.026	0.017	-0.031	-0.046	-0.102	0.003	-0.034
	(0.001)	(0.001)	(0.221)	(0.030)	(0.001)	(0.002)	(0.833)	(0.003)
η_D x turnover	-0.005	-0.005	-0.014	-0.000	-0.001	-0.009	-0.011	0.000
	(0.000)	(0.000)	(0.000)	(0.972)	(0.272)	(0.015)	(0.000)	(0.658)
η_D x margin interest	-0.001	-0.001	-0.000	-0.002	-0.001	-0.001	0.000	-0.005
	(0.010)	(0.010)	(0.125)	(0.044)	(0.000)	(0.000)	(0.832)	(0.000)
Adjusted R^2	0.018	0.018	0.029	0.042	0.024	0.043	0.035	0.025
Observations	545,533	545,533	105,405	119,969	542,673	117,611	113,887	311,175

Panel B: Observations Weighted by Market Capitalization.

Coefficient of	*Elasticities at open auction*				*Elasticities at 2:30 PM*			
	Full Sample	***Full Sample***	***Pre-Crisis***	***In-Crisis***	***Full Sample***	***Pre-Crisis***	***In-Crisis***	***Post-Crisis***
η_D	-0.052	0.003	-0.008	-0.169	-0.162	-0.150	-0.164	-0.213
	(0.000)	(0.670)	(0.413)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
η_D x spread	-0.015	-0.024	-0.043	0.066	0.006	0.003	-0.022	0.051
	(0.446)	(0.090)	(0.087)	(0.000)	(0.400)	(0.425)	(0.061)	(0.015)
η_D x flux	-0.002	0.131	-0.060	-0.073	-0.045	-0.089	0.001	0.002
	(0.951)	(0.035)	(0.028)	(0.281)	(0.279)	(0.026)	(0.988)	(0.969)
η_D x turnover	0.004	-0.015	-0.007	-0.006	0.001	-0.010	-0.025	0.004
	(0.381)	(0.012)	(0.551)	(0.003)	(0.590)	(0.160)	(0.010)	(0.099)
η_D x margin interest	-0.001	0.000	-0.005	0.006	-0.005	-0.002	-0.002	-0.034
	(0.346)	(0.514)	(0.021)	(0.227)	(0.000)	(0.004)	(0.372)	(0.009)
Adjusted R^2	0.022	0.030	0.038	0.084	0.025	0.053	0.023	0.034
Observations	543,049	105,026	119,905	318,118	539,521	117,121	113,785	308,615