Preliminary: Comments Welcome
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Interacting Limit Order Demand and Supply Curves

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Abstract

A parsimonious model of shareholders with heterogeneous opinions about stocks' fundamental values allows limit order demand and supply elasticities to be negatively cross-correlated in the short-run, when risk aversion and information heterogeneity parameters are fixed; but positively correlated in the long-run, when these parameters can vary. Empirical analysis using complete limit order data from the Korea Stock Exchange from 1997 to 2000, which includes the 1997 Asian Financial Crisis, reveals a highly significant negative cross-correlation in the short-run, but a highly significant positive cross-correlation in the long-run. Thus, stocks tend to exhibit unusually elastic limit order demand schedules on the same days they exhibit unusually inelastic limit order supply schedules and vice versa; but stocks' monthly mean limit order demand and supply schedule elasticities co-vary positively.

KEYWORDS: limit order, elasticity, financial crisis

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1. Introduction

Despite theoretical arguments to the contrary (Aumann, 1976), recent work suggests that investors persistently "agree to disagree" about the fundamental values of financial assets as surveyed in Hong and Stein, 2007. This has implications for asset pricing and trading volume (Wang, 1994; Kandel and Pearson, 1995; Hong and Stein, 2003; Fama and French, 2007; Banerjee and Kremer, 2010), including imperfectly elastic demand and supply curves for individual stocks. In product markets, demand elasticity depends on factors such as consumer preferences; while supply elasticity depends on factors such as production technologies and market power. In contrast, at least in the short-run, stock markets resemble a pure exchange economy: buyers become sellers and vice-versa as a stock's price fluctuates relative to investors' opinions about its fundamental value, linking each stock's demand and supply schedules.[1] This paper presents a parsimonious model of this linkage, and corroborative empirical evidence from daily demand and supply schedules constructed from complete limit order book data for all Korea Stock Exchange (KSE) stocks from 1997 to 2000.

Our simple single period model incorporates three key assumptions: *(i)* competitive investors have constant relative risk-aversion; *(ii)* each trading day corresponds to an independent draw of the model's normally distributed random variables; and *(iii)* in equilibrium, investors persistently disagree about the fundamental value of the single risky asset. How aggressively an investor trades on a given day depends on her perception of how badly the asset is mispriced by the market, given a set of model parameters describing investors' risk aversion and the distribution of information across investors. This generates finitely elastic demand and supply schedules, as in Grossman and Stiglitz (1980). If the model parameters exhibit common variation across investors, the resulting demand and supply elasticities rise and fall together, and the cross-correlation is positive. For example, if all investors become more risk averse, the demand and supply schedules both steepen as investors react less aggressively to any given

[1] We take a stock's demand and supply schedules as all submitted limit orders executable at each price. Obviously, this can include orders submitted for portfolio reallocation or liquidity provision reasons, as well as orders reflecting private information.

price change. Similarly, a more transparent or homogeneous information environment flattens both curves. This positive correlation, which we dub the *symmetric market depth effect*, arises in the risk-neutral model of Admati and Pfleiderer (1988) and finds empirical support in Brennan *et al*. (2012).

Building upon these insights, we allow a second interaction between a stock's demand and supply elasticities, which we call the *asymmetric market depth effect*. On one day, the draw of random variables might leave investor *i* privately valuing the stock above its price. On such a day, she contributes nothing to the stock's market supply, but a positive amount to its market demand, thereby also contributing to the elasticity of its market demand schedule. On another day, her valuation might be below the price, so she *switches* from buying to selling. Her contribution to the market demand falls to zero, but her contribution to market supply now becomes positive, and she contributes to that schedule's elasticity. This switching induces a negative cross-correlation between demand and supply elasticities. Section 2 formally derives both market depth effects, and the circumstances under which each is likely to be predominant in empirical data.

We investigate the model's implications empirically using complete limit order books (over 550 million observations) for all Korean listed stocks from December 1996 to December 2000. The Korean Stock Exchange is a heavily limit-order driven market (limit orders constitute 94.8% of all buy orders and 93.0% of sell orders), and is thus particularly well-suited to our analysis. Unlike the NYSE or NASDAQ, it is an order driven market without specialists or designated market makers, letting us sidestep the complex interactions between various liquidity providers (Kavajecz, 1999; Hollifield *et al.*, 2004). We can *observe* (not estimate) the whole demand and supply schedules of limit orders for every listed stock at each point in time. Thus, we measure the elasticity of each schedule separately and directly. This bypasses entirely the standard identification problems associated with elasticity estimation using observed quantities traded and equilibrium prices. We can thus compare the two observed elasticities for each stock and statistically investigate the relationship between them. Our empirical results are as follows.

First, substantial limit order depth extends well away from market prices. More than a quarter of all limit orders are 10% or more away from current market price. While finitely elastic curves are possible with homogeneous expectations, but heterogeneous impatience (Parlour, 1998; Handa and Schwartz, 1996), competition between providers of immediate execution should drive limit orders towards the market price (Sandås, 2001; Kalay *et al.*, 2004).[2] Thus, our data intimate that heterogeneous impatience, though obviously important in many contexts, may not be a complete explanation here.

Second, individual stocks' demand and supply elasticities rise and fall together if observed over the long-run, consistent with our model's symmetric market depth effect. Specifically, the correlation between monthly market-level mean demand and supply elasticities exceeds 90%, and is comparable with the correlation between the monthly mean demand and supply market depth measures ("Kyle's lambdas") of Brennan *et al*. (2012). Most markedly, both demand and supply are substantially more elastic before than after the 1997 Asian Financial Crisis: A one percent price change corresponds to a 36% change in quantity demanded or supplied before the crisis, but only a 22% change after the crisis. Unlike other economic and financial indicators, which fluctuate dramatically during the crisis but then revert to near their pre-crisis levels, both elasticities persist at higher levels through December 2000, the end of our data. This persistent market depth reduction is at odds with post-crisis reforms and rising online trading, which would arguably deepen the market by enhancing transparency and reducing transactions costs, respectively (Kwak, 2007; Kim and Kim, 2008). Thus, Korean data do not echo the secular trend towards deeper markets evident in the US (Chordia *et al*. 2001), at least during our sample period. Rather, reduced market depth drops associated with the 1997 crisis persists long after real economic activity and stock market valuations recover.

Third, superimposed on this positive long-run cross-correlation, we detect a negative short-run cross-correlation. This is evident throughout the sample window, despite both mean elasticities becoming persistently lower after the 1997 crisis. These results are consistent with switching and our model's asymmetric market depth. The monthly mean cross-correlation, based on daily mean demand and supply

[2] For details, see section 3.5.

elasticities, is about -0.76, and ranges between -0.11 and -0.28 for individual stocks.[3] That is, stocks that develop unusually elastic demand schedules tend simultaneously to develop unusually inelastic supply schedules and *vice versa.* Near-zero autocorrelations are consistent with extreme values being transitory for both elasticities. Section 2 explains how negative cross-correlation caused by switching can fade away at longer time horizons, exposing a positive cross-correlation associated with long-run parameter variation.

These findings complement and extend previous empirical work in several ways. First, our direct measures of individual stocks' elasticities from complete limit order books validate studies indirectly inferring finite elasticities from share auctions (Bagwell, 1992; Kandel *et al.*, 1999; Liaw *et al.*, 2000), near-market limit orders (Sandås, 2001; Kalay *et al.*, 2004), and index revisions (Shleifer, 1986). Second, our findings of asymmetric market depths in the short-run complement prior work on the time-varying price impact of trading. For example, Kraus and Stoll (1972), Chan and Lakonishok (1993, 1995), and Gemmill (1996) report a larger price impact for buys, while Keim and Madhavan (1996) and Bikker *et al.* (2007) report a larger price impact for sells. Chiyachantana *et al.* (2004) report that the price impact of buys exceeds that of sells in the 1990s bull market; while the opposite holds in the 2001 bear market. Our model implies that, if differences of opinion are economically important, the observed price impact results from an interaction of the stock's demand and supply schedules, and that either sign can prevail. Third, our findings of symmetric market depths over the long-run are consistent with Brennan *et al.* (2012), who report a strong long-term positive cross-correlation between buy and sell price impacts, measured by Kyle's lambdas, in US data. Fourth, our model and empirical results highlight economically important channels through which stocks' demand and supply curves interact to produce symmetric and asymmetric market depth effects in the long- and short-runs, respectively, even absent liquidity trading motives (Kalay and Wohl, 2009). Finally, our empirical results provide stylized facts potentially useful in shaping more complete models of limited arbitrage and heterogeneous opinions.

[3] The larger negative point estimate for the correlation between mean demand and supply elasticities is consistent with lower standard deviations of mean elasticity estimates compared with firm-level elasticity estimates. Reported numbers for firm-level results reflect the proper use of coring as discussed in section 4.

The remainder of the paper is structured as follows. Section 2 develops a simple model to convey our economic intuition. Section 3 discusses the microstructure of the Korea Stock Exchange and our dataset, while section 4 presents our empirical results. Section 5 concludes.

2. Model and Intuition

This section develops a parsimonious one-period model of competitive risk-averse investors who have differing opinions about a stock's fundamental value. We show that this model generates finitely elastic demand and supply schedules for that stock and lets us explore how rational portfolio optimization under differing opinion affects the *depth*[4] of buy and sell limit orders across the full price range of such orders – that is, their demand and supply elasticities. Liquidity provision then emerges as a by-product of portfolio choice.

For intuitive clarity, we begin with a well-explored framework in information economics. Investors' beliefs are normally distributed, and their utility obeys a negative exponential utility function. Investors gain information solely from exogenous signals (Harrison and Kreps, 1978), however our propositions survive lettin investors gain information by observing market prices (Grossman and Stiglitz, 1980; Hellwig, 1980).[5] The important assumption we share with all three of these models is that investors' disagreement about fundamental values persists in equilibrium.

2.1 A Simple Model

We consider a one-period economy containing one risky asset with a random liquidation pay-off $v \sim N(\bar{v}, \sigma_v^2)$, with $\bar{v} > 0$ and one risk-free asset with infinitely elastic demand and supply with a return normalized to zero. The economy contains I partially informed investors. We assume each investor i has

4 Kyle (1985) takes market depth as the size of an order necessary to move the market price one unit. Consistent with this, we relate limit order depth to the steepness of demand or supply schedule, with a flatter schedule implying greater depth.

5 Derivation is available from the authors upon request.

a preference for final wealth, W_i, described by a CARA utility function

[1] $u_i(W_i) = -e^{-\gamma_i W_i}$.

The model's focus, as in Harrison and Kreps (1978) and Hong and Stein (2007), is differences in opinion. Each investor i has an opinion, $v_i = E_i(v)$, about the risky asset's payoff v. We take these opinions to be Normally distributed and unbiased, and investors' forecast errors (i.e., the difference between their opinion and the unobservable true pay-off), $v_i - v$, to be jointly independent. Each investor has a different level of confidence in her opinion, characterized by a subjective variance $\sigma_i^2 = Var(v|v_i)$. Thus, unlike Hellwig (1980), we can let each investor have a unique level of risk aversion and signal precision. Each investor $i \in \{1, \dots, I\}$ submits limit orders represented by a net demand schedule $x_i(p; v_i)$ for the risky asset across all possible prices, p as defined in [2].

[2] $x_i(p; v_i) = \frac{1}{\gamma_i \sigma_i^2}(v_i - p) = k_i(v_i - p)$

This schedule maximizes her expected utility [1] given her private opinion of the asset's payoff, v_i,. Each investor's $k_i = \frac{1}{\gamma_i \sigma_i^2}$ measures how aggressively she trades in response to her perception of the asset's mispricing (i.e., the difference between investor *i*'s opinion and the market price), $v_i - p$, and is thus the slope of her individual demand schedule.

We can allow (but need not require) the total net supply of the asset to be subject to random shocks from liquidity traders who supply a total of $z \sim N(0, \sigma_z^2)$ shares of the risky asset. If liquidity traders submit z' shares (i.e., a realization of *z)* in the market, then the market clearing condition can be defined as in [3].

[3] $\sum_{i=1}^{I} x_i(p; v_i) = z'$.

Because individual investors' demand functions $x_i(p; v_i)$ are optimal for any price, *p*, the risky asset's market clearing price, p^*, is a weighted average of all individual investors' opinions about its fundamental value

[4] $$p^* = \sum_{i=1}^{I} \frac{k_i}{K} v_i - \frac{z'}{K},$$

where $K = \sum_{i=1}^{I} k_i$.[6] Because the value of z' does not alter the key results below, we can abstract from liquidity trader effects by setting $z' = 0$ and, rewrite [4] as $p^* = \sum_{i=1}^{I} \frac{k_i}{K} v_i$.

2.2 Fixed model parameters and negative cross-correlation

In this section, we take as constants the number of investors, *I,* as well as each investors' risk aversion, $\{\gamma_i\}_{i=1,\dots,I}$, and confidence in her private valuation opinion, $\{\sigma_i^{-2}\}_{i=1,\dots,I}$. We interpret this assumption as characterizing the short-run. We then show that this leads to a negative cross-correlation between demand and supply elasticities. That is, in the short-run, whenever one elasticity is high, the other tends to be low.

To see this, consider a pure exchange market for the risky asset. Investor i is a supplier if her individual demand for the risky asset is negative – that is, if $x_i(p; v_i) < 0$. This means her net demand can be conceptualized as a demand component, D_i, minus a supply component, S_i, and can be written as

[5] $$x_i(p; v_i) = D_i(p; v_i) - S_i(p; v_i),$$

Her demand equals her net demand if the market price is below her private valuation, but zero otherwise

[6] $$D_i(p; v_i) = \begin{cases} x_i(p; v_i) = k_i(v_i - p) & \text{if } v_i > p \\ 0 & \text{if } v_i \leq p \end{cases}$$

6 Equation [4] captures Demsetz's (1968) intuition that, if some buyers demand immediate liquidity ($z' < 0$), the ensuing order imbalance can be absorbed by other traders who place sell orders at higher prices. Chacko *et al.* (2008) examine a similar issue in a model with a monopolistic market maker. We intentionally abstract from strategic liquidity provision (e.g., Handa and Schwartz, 1996; Parlour, 1998; Hollifield *et al.*, 2004; Foucault *et al., 2005*, Goettler *et al.*, 2005; Hollifield *et al.*, 2006; Goettler *et al.*, 2009; Roşu, 2009; Buti and Rindi, 2013) for parsimony and because our central focus is heterogeneity.

Similarly, her supply is minus one times her net demand if the market price is above her private valuation, but is zero otherwise:

[7] $$S_i(p; v_i) = \begin{cases} -x_i(p; v_i) = k_i(p - v_i) & \text{if } v_i < p \\ 0 & \text{if } v_i \geq p \end{cases}$$

The slope of investor i's limit order demand schedule is then[7]

[8] $$\frac{\partial D_i(p;v_i)}{\partial p} = \begin{cases} k_i = \frac{\partial}{\partial p} x_i(p; v_i) & \text{if } v_i > p \\ 0 & \text{if } v_i < p \end{cases}$$

and the slope of her limit order supply schedule is

[9] $$\frac{\partial S_i(p;v_i)}{\partial p} = \begin{cases} k_i = -\frac{\partial}{\partial p} x_i(p; v_i) & \text{if } v_i < p \\ 0 & \text{if } v_i > p \end{cases}.$$

The market demand and supply schedules are then the sums of all individual investors' demand and supply schedules, respectively.

If investor i's private valuation, v_i, is above the market price, p, her net demand of $k_i(v_i - p) > 0$ contributes to the total depth of market demand. The market demand schedule is thus the sum of the individual demand schedules of all the individual investors who find themselves in this situation

[10] $$D\big(p;\ v_{i, i=1,\dots I}\big) = \sum_{i=1}^{I} k_i(v_i - p)\delta_{v_i>p}$$

with $\delta_{v_i>p}$ an indicator set to 1 if $v_i > p$ and 0 otherwise.

Similarly, if an investor's private valuation, v_i, is below the market price, p, she wishes to sell, and contributes $k_i(p - v_i) > 0$ to market supply. The market supply is then

[11] $$S\big(p;\ v_{i, i=1,\dots I}\big) = \sum_{i=1}^{I} k_i(p - v_i)\delta_{v_i<p}$$

[7] Recall that the derivative is not defined at price p since the demand schedule has a kinked point at p. Because the set of discontinuities is finite and thus of measure zero, adding extra notation to define upper and lower limits does not affect any conclusions in the paper.

with $\delta_{v_i<p}$ an indicator set to 1 if $v_i < p$ and 0 otherwise.

The slopes of market demand and supply observable in limit orders are likewise the sums of the slopes of the individual demand and supply schedules. All investors with $v_i > p$ contribute to market demand, so the slope of the market demand schedule is

[12] $$\frac{\partial D(p; v_{i,\, i=1,\dots I})}{\partial p} = -\sum_i^I k_i \delta_{v_i>p}$$

The slope of market supply of limit orders is, similarly,

[13] $$\frac{\partial S(p; v_{i,\, i=1,\dots I})}{\partial p} = \sum_i^I k_i \delta_{v_i<p}$$

We define the market elasticity of demand to be $D^\varepsilon \equiv -\partial D/\partial p$ and the market elasticity of supply to be $S^\varepsilon \equiv \partial S/\partial p$. Both D^ε and S^ε thus depend not just on the price level, p, but also on individual investors' private valuations, $\{v_i\}_{i=1,\dots,I}$. [12] and [13] also show that both include as parameters the number of initial investors, *I,* their risk aversion parameters, $\{\gamma_i\}_{i=1,\dots,I}$, and the precisions of their private valuations of the risky asset, $\{\sigma_i^{-2}\}_{i=1,\dots,I}$, all of which we take to be constant in the short-run.

The model makes predictions about absolute values of slopes, but these can be interpreted as elasticities for several reasons. First, not scaling by *p* is defensible because the exponential form of investors' utility functions precludes wealth effects. Thus, investors' individual demand and supply schedules remain unchanged if we replace $(p, v_1, \dots, v_n)$ with $(p + c, v_1 + c, \dots, v_n + c)$. Thus, scaling by p is irrelevant. Second, using dollar changes in models, but percentage changes in empirical tests of those models in now well-established in the literature (e.g. Campbell *et al*. 1993; Llorente *et al*. 2002). Finally, these quantities behave like elasticities. For example, even one investor on each side of the limit order book with either perfect certainty, $\sigma_i^2 = 0$, or risk neutrality, $\gamma_i = 0$, collapses the model into *reductio ad absurdum* horizontal demand and supply curves. This is because such an investor must have

$k_i = \frac{1}{\gamma_i \sigma_i^2} = \infty$, which implies that $S^{\varepsilon} = \sum_i^I k_i \delta_{v_i<p} = \infty$ and $S^{\varepsilon} = \sum_i^I k_i \delta_{v_i>p} = \infty$.

We are now ready to formalize the model's first major implication, which we dub the *asymmetric market depth effect.*

Proposition 1. *If all the assumptions in our model hold and all parameters,* $\{(\gamma_i, \sigma_i^2)_{i=1,\dots,I}\}$, *are fixed, then the sum of demand and supply elasticities is constant and the demand and supply elasticities are perfectly negatively cross-correlated – that is,* $\rho(D^{\varepsilon}, S^{\varepsilon}) = -1$.

Proof: From [12] and [13], we have

$$D^{\varepsilon} + S^{\varepsilon} = \sum_{i=1}^{I} k_i\, \delta_{v_i<p} + \sum_{i=1}^{I} k_i\, \delta_{v_i>p} = \sum_{i=1}^{I} k_i = K.$$

Therefore,

$$cov(D^{\varepsilon}, S^{\varepsilon}) = cov(D^{\varepsilon}, K - D^{\varepsilon}) = -\,var(D^{\varepsilon}) < 0,$$

and, similarly,

$$cov(D^{\varepsilon}, S^{\varepsilon}) = cov(K - S^{\varepsilon}, S^{\varepsilon}) = -\,var(S^{\varepsilon}) < 0.$$

Because of this symmetry, $var(S^{\varepsilon}) = var(D^{\varepsilon})$. Combining these results immediately implies a perfect negative correlation between the market elasticities of demand and supply

$$\rho(D^{\varepsilon}, S^{\varepsilon}) \equiv \frac{cov(D^{\varepsilon}, S^{\varepsilon})}{\sqrt{var(D^{\varepsilon})}\sqrt{var(S^{\varepsilon})}} = -\frac{var(D^{\varepsilon})}{var(D^{\varepsilon})} = -1.$$

The intuition behind Proposition 1 is readily explained. If the market clearing price, p^*, is less than investor i's private valuation of the asset, v_i, she is a buyer, and thus contributes $k_i(v_i - p^*) > 0$ to the depth of market demand, $D(p^*; \ldots)$, but nothing to the depth of supply, $S(p^*; \ldots)$. Because the slope of her individual demand schedule is $\frac{\partial D_i(p;v_i)}{\partial p} = -k_i < 0$, she contributes a negative quantity to the slope of the market demand schedule, but nothing to that of the market supply schedule. However, if a different set of private valuation signals leave's investor i's private valuation, v_i, below the ensuing market clearing price, p^*, she investor *switches* from being a buyer to being a seller. As a seller, she now contributes $k_i(p^* - v_i) > 0$ to the depth of market supply and the positive quantity $\frac{\partial S(p;v_i)}{\partial p} = k_i > 0$ to the slope of the market supply schedule. However, as a buyer, she now contributes nothing to either the level or the slope of the market demand schedule.

Thus, the elasticity of market demand, D^{ε}, rises if and only if the elasticity of market supply, S^{ε}, falls by an equal amount.[8] In this way, investors' switching between being sellers and buyers induces a negative correlation between the slopes of the aggregate demand and supply curves. Whether an investor switches or not depends on the realization of her private valuation, v_i, but also on the realizations of all the other investors' valuations, $\{v_{i'}\}_{i' \neq i}$, and the ensuing market clearing price, p^*. As noted above, without loss of generality we can add to this list the realization of a liquidity demand shock, z.

Obviously, our model is a simplification, and misses many possible complications. For example, non-linear individual demand and supply schedules might arise from wealth effects and risky labor income streams, correlated with the risky asset's fundamental value, might further complicate the model. Second, short sale constraints, transaction costs, or other frictions might hinder investors from switching their position. Third, investors might have three options: buy, sell, or withdraw from the market. Such frictions could readily lift the negative "asymmetric market depth" effect, $\rho(D^{\varepsilon}, S^{\varepsilon})$, above minus one. Nonetheless, the gist of Proposition 1 is merely that investors' switching back and forth between the demand and supply sides of the limit order book readily works to render the cross-correlation close to minus one. These considerations suggest the data might show $\rho(S^{\varepsilon}, D^{\varepsilon}) \lesssim -1$, rather than the precise

[8] Note that this follows not just at the market clearing price, but also across the entire range of limit order prices. For any given price, every investor is either a buyer or a seller. This suffices to generate the negative cross-correlation of Proposition 1.

$\rho(S^{\varepsilon}, D^{\varepsilon}) = -1$ conclusion of Proposition 1.

2.4 Random model parameters and a positive cross-correlation

In this section, we relax the assumption of Proposition 1 and explore the implications of allowing investors' risk aversion parameters and the precisions of their private valuation signals to be random. We interpret these changes as characterizing the *long-run*.[9]

For simplicity, we nest the model in section 2.3 within draws of the model parameters. That is, a *regime*, ω, is first drawn to determine investors' risk aversion and confidence parameters, $\omega = \{\gamma_{\omega,i}, \sigma^2_{\omega,i}\}_{i=1,\ldots,I}$. Second, taking these parameters as constants, each day under a regime can be interpreted as a new iteration of the single period model of section 4.1. The investors draw their private valuations, $\{v_i\}_{i=1,\ldots,I}$, solve the static optimization problem, and submit their individual limit order schedules. These generate the day's market demand and supply schedules, with elasticities and market clearing price defined as in section 4.2. Finally, trades are executed and profits are realized and consumed, and the next day begins anew. After a succession of such days, a new state of the world, ω', is drawn and a second succession of trading days ensues under its parameters.[10] We refer to the switch from ω and ω' as a *regime change*.

To tie this section back to the preceding sections, we assume that once any state of the world ω is realized, all investors know its parameters $\{\gamma_{\omega,i}, \sigma^2_{\omega,i}\}_{i=1,\ldots,I}$ with certainty and presume them permanent. By *permanent*, we mean no investor contemplates the possibility of another set of parameters displacing these in solving her optimization problem. For parsimony, we also preclude trading before a state of the

[9] We could also randomly draw a new number of investors (I) for each new regime. For notational simplicity, we take I as constant. However all this section's results survive if a new I is drawn for each regime.

[10] Regime changes might include financial crises or major institutional changes. Our model is a static one, in which investors know their own parameters and solve their optimization problem anew each trading day, without considering the future at all. Thus, for modeling simplicity, we assume that investors do not anticipate changes in the state of the world. Rather, regime changes are both unexpected *ex ante* and perceived as permanent *ex post*.

world realization.

These assumptions imply a positive cross-correlation between the population mean elasticities of demand and population mean elasticities of supply, where a *population* is the set of observations within a given a regime. That is, in the long-run, when the population mean of one of the elasticities is higher, that of the other tends to higher too.

The added complication that leads to this result is that the k_i and their sum, $K = \sum_{i=1}^{I} k_i$, are now random variables that take fixed values, henceforth denoted $k_{i,\omega}$ and K_ω, only within a given state of the world ω. To see how this plays out, consider two draws of the model parameters. The first draw generates state of the world, $H = \{\gamma_{H,i}, \sigma_{H,i}^2\}_{i=1,\ldots,I}$, in which K has the value $K_H = \sum_{i=1}^{I} \left(\frac{1}{\gamma_{H,i}\,\sigma_{H,i}^2}\right)$. Investors then draw a succession of daily private valuations, solve the model, and submit their individual limit order schedules. After a long succession of such trading days, a new state of the world draw yields the set of parameters, $L = \{\gamma_{L,i}, \sigma_{L,i}^2\}_{i=1,\ldots,I}$, in which K takes the value $K_L = \sum_{i=1}^{I} \left(\frac{1}{\gamma_{L,i}\,\sigma_{L,i}^2}\right)$. Another succession of trading days occurs given these parameters.

Given enough trading days within each state of the world, the Law of Large Numbers ensures that the sample means of the demand and supply elasticities within each state of the world approximate their population means, defined as $D_\omega^\varepsilon \equiv E[D^\varepsilon|\omega\,]$ and $S_\omega^\varepsilon \equiv E[S^\varepsilon|\omega\,]$, respectively. We are now ready to state our second identity result and its implication that D_ω^ε and S_ω^ε, observed over multiple states of the world, are positively correlated.

Proposition 2. *If multiple states of the world exist, indexed by ω and each characterized by set of values for individual investors' risk aversion and private information confidence parameters,* $\omega = \{\gamma_{\omega,i}, \sigma_{\omega,i}^2\}_{i=1,\ldots,I}$, *then the population means within each state of the world of the demand and supply* *elasticities, denoted* $D_\omega^\epsilon \equiv E[D^\varepsilon|\,\omega]$ *and* $S_\omega^\epsilon \equiv E[S^\varepsilon|\,\omega]$*, respectively, are perfectly positively correlated; that is,* $\rho(D_\omega^\epsilon,\ S_\omega^\epsilon) = +1$.

Proof: Consider a state of the world ω, containing T trading days. Investors' private valuations are unbiased and Normally distributed, so they fall symmetrically around the market clearing price, p^*, each day. Moreover, all investors' private valuations each day are serially independent, so each contributes to the buy and sell side limit order books on roughly half of all trading days. Recalling that $\delta_{v_{i,t}>p_t^*}$ is an indicator set to one if investor *i*'s private valuation exceeds the market price on a given day, causing her to contribute to demand rather than supply, we have that the indicator's population mean within any state of the world ω must be $E\left(\delta_{v_{i,t}>p_t^*}|\omega\right) = \frac{1}{2}$. Given this, the population mean of the elasticity of demand is

$$D_\omega^\varepsilon = E(D^\varepsilon|\omega) = \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{I}\delta_{v_{i,t}>p_t^*}k_{i,\omega} = \sum_{i=1}^{I}k_{i,\omega}\lim_{T\to\infty}\frac{1}{T}\sum_{i=1}^{I}\delta_{v_{i,t}>p_t^*} = \frac{1}{2}\sum_{i=1}^{I}k_{i,\omega} = \frac{K_\omega}{2}$$

Recall from Proposition that $D^\varepsilon + S^\varepsilon = K$. Therefore, $D_\omega^\varepsilon + S_\omega^\varepsilon = K_\omega$ also holds for population means within state of the world ω. Substituting this into the expression derived above shows that $S_\omega^\varepsilon = K_\omega - D_\omega^\varepsilon = \frac{1}{2}K_\omega$ as well. Thus, we obtain is our second identity result: for each state of the world ω, $D_\omega^\varepsilon = S_\omega^\varepsilon = \frac{1}{2}K_\omega$. This identity immediately implies that D_ω^ε and S_ω^ε rise and fall together across different states of the world with $\rho(D_\omega^\varepsilon, S_\omega^\varepsilon) = +1$.

Proposition 2 shows that, given enough daily observations for each set of parameters, the correlation between the sample means under each parameter set will be arbitrarily close to +1.[11] Returning to the example above, suppose population mean elasticities of $D_H^\varepsilon = S_H^\varepsilon = \frac{1}{2}K_H = 35$ prevail under state *H*.

[11] This accords with the model of Admati and Pfleiderer (1988), which also implies a plus one correlation between buy and sell side market depths (the inverses of Kyle's lambdas) as model parameters shift. However, their risk-neutral model deals with market orders only.

Suppose further that a major event, such as a financial crisis, occurs and leads to a new state of the world, L, in which all investors are more risk-averse $\left(\forall i, \gamma_{L,i} > \gamma_{H,i}\right)$, less confident about their private valuations $\left(\forall i, \sigma^2_{L,i} > \sigma^2_{H,i}\right)$, or both. This implies that $k_{H,i} = \frac{1}{\gamma_{H,i}\sigma^2_{H,i}} > \frac{1}{\gamma_{L,i}\sigma^2_{L,i}} = k_{L,i}\ \forall i$, so the new state has lower elasticities, perhaps $D^\varepsilon_L = S^\varepsilon_L = \frac{1}{2}K_L = 20$. The key insight of Proposition 2 is that both population mean elasticities are higher or lower together as the economy shifts from one state of the world to another.

As with Proposition 1, market frictions and more realistic model assumptions would surely render actual demand and supply elasticities unequal. The importance of Proposition 2 is not the precise point estimate of +1, but the general intuition that the mean demand elasticity and the mean supply elasticity will be positively cross-correlated if observed across multiple regimes of the world – that is, over the long-run. Thus the data might show $\rho(S^\varepsilon, D^\varepsilon) \lesssim +1$, rather than the precise $\rho(S^\varepsilon, D^\varepsilon) = +1$ conclusion of Proposition 2.

Together, Proposition 1 and Proposition 2 suggest a reversal of signs. If investors' risk aversion and confidence in their private valuations are constant in the short term, we should observe a negative empirical cross-correlation in the short run (within a regime) in accordance with Proposition 1. But if different states of the world are realized over the longer run, infrequently sampled data from very long observation windows might let Proposition 2 dominate, producing a positive empirical cross correlation in long-run data.

3. Data and Elasticity Measurement

This section describes how we measure elasticities of limit order demand and supply schedules of individual stocks. It first describes the trading system of the Korea Stock Exchange (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 shapes of those schedules as elasticities.

3.1 Market Microstructure

The KSE is an order driven market; it has no designated market makers or specialists. It thus differs from the NYSE or NASDAQ in that liquidity providers are not obviously distinct from other investors, obviating the need to model potentially complex interactions between different avenues of liquidity provision.[12] 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 begins in 1997 with fees of 0.5%, matching standard brokerage fees at the time. But lower online fees prevail after June 1998, when 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. 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 is already substantially foreign-owned. After May 1998, all such restrictions disappear.

Trading opens at 9:00 AM 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.[13] In our data, 19.10 percent of buy orders and 21.14 percent of sell orders are submitted to opening auctions. Subsequent prices, until 10 minutes before the 3:00 PM close, are set in *continuous trading*.[14] In the last 10 minutes, another auction 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.[15] The

[12] See, for instance, Kavajecz (1999), Golstein and Kavajecz (2004), and Hollifield *et al.* (2004).

[13] Unexecuted orders from the previous trading day do not appear automatically at the opening auction. Thus, our empirical results are not driven by stale orders.

[14] Before May 22, 2000, the KSE held separate morning (9:00 AM to 12:00 AM) and afternoon (1:00 PM to 3:00 PM) sessions, each commencing with a call market.

[15] For additional detail, see e.g. Choe *et al.* (1999).

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 include only transactions involving common shares, so that each firm is represented by only one listed security.

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

[Table 1 about here]

In constructing demand and supply schedules, we focus on limit orders because market orders, by definition, do not specify prices.[16] Also, market orders are a very small fraction of total orders on the KSE. Table 1 shows limit orders comprising 94.78% of buy orders and 92.99% of sell orders. The rarity of market orders likely reflects their novelty. Market orders were introduced by the KSE on November 25th 1996, only a few days before our sample period begins, and remained little used.[17]

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.

[16] Bloomfield *et al.* (2005) and Kaniel and Liu (2006) argue that informed investors prefer limit orders to market orders. Thus, limit orders are likely more useful for gauging information heterogeneity across investors.

[17] We hope to explore this issue in future work. A financial analyst we asked about this proposed a starkly behavioral motive, resonant of a "default option" bias (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 limit order demand and supply schedules of each individual stock – first at the opening auction and then amid continuous trading, thirty minutes before the close. This second snapshot is thus at 2:30 PM each weekday, but at 11:30 AM in Saturday sessions, which the KSE held until December 5, 1998. For simplicity, we refer to the first as the o*pening snapshot* and the second as the *2:30 PM snapshot*.

These plots are constructed precisely as in economics principles textbooks, and are best explained with an example.

[Figure 1 about here]

Figure 1 graphs limit order demand and supply schedules on November 11th 2000 for Samsung Electronics, a large and heavily traded KSE listing.[18] These schedules 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 schedule 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. 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.

Using this technique, we take snapshots of the limit order demand and supply schedules 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 at that price to obtain

[18] We randomly choose three other stocks from the large, medium and small capitalization groups. Their graphs all resemble Figure 1.

demand[19]

$$[14] \qquad d_j(p) = \sum_{b=1}^{B} n_{bj}\delta_{p_{bj} \geq p}$$

with b an index of all bid limit orders, $\{1, \ldots, B\}$; n_{bj} the number of shares in stock j 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 all ask limit orders, indexed by $a \in \{1, \ldots, A\}$, as

$$[15] \qquad s_j(p) = \sum_{a=1}^{A} n_{aj}\delta_{p_{aj} \leq p}.$$

For each stock, at each 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.

3.4 Measuring Elasticities

In our model, price sensitivity of aggregate demand and supply curves for a stock are gauged by their elasticities, D^{ε} and S^{ε}, respectively. Because we wish to meaningfully compare the price sensitivities of stocks with different price levels and quantities, we require a normalization procedure for our price elasticities. We therefore take $D^{\varepsilon}$and S^{ε} to be log differences in quantities offered or sought, divided by log differences in prices. As noted above, absolute changes in a CARA utility model are intuitively equivalent to log changes in the data (see e.g., Campbell *et al.,* 1993*;* Llorente *et al.* 2002). This approach is especially useful in this context because it also lets the data choose a denominator, albeit at the cost of imposing a constant elasticity assumption across the whole of each side of the limit order book.[20] This

[19] Cancellations and revisions are tracked in real time. That is, orders cancelled during the day are included until cancelled and orders revised during the day trigger immediate price and quantity adjustments upon their revisions.

[20] Our model does not predict constant elasticity along the whole limit order curve. In fact, [10] and [12] suggest that elasticities increase as we move further away from the market price.

assumption is clearly restrictive, but parsimoniously characterizes the valuation heterogeneity across the broad price ranges that we observe in the data. Subsequent sections examine the validity of this log-linear specification using subsets of the limit order books.[21]

To measure the elasticity of demand in limit orders for firm *j*'s stock at time *t* (either at the opening auction or at 2:30PM for each trading day), we thus regress $\ln[d_{j,t}(p_k)]$, the logarithm of total demand at time *t* and limit order price p_k, on the logarithm of that limit order price, p_k, where *k* indexes successively higher limit order prices, by tick size, through the relevant price range in the limit order book for that stock that day. That is, we approximate the stock's elasticity of demand as the coefficient on ln [p_k] in the regression

[16] $$\ln[d_{j,t}(p_k)] = a_{j,t} - D^{\varepsilon}_{j,t} \ln[p_k] + u_{j,t,k}.$$

The elasticity of demand at time *t* is thus $D^{\varepsilon}_{j,t}$, the percentage decrease in the quantity of stock *j* sought given a one percent rise in its price.

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

[17] $$\ln[s_{j,t}(p_k)] = b_{j,t} + S^{\varepsilon}_{j,t} \ln[p_k] + v_{j,t,k}.$$

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 opening auction demand elasticities and 17 (12) for opening auction supply elasticities, and 17 (14) and 21 (16) for 2:30 PM demand and supply elasticities, respectively. The mean (median) regression R^2 of [16] at the opening

[21] Other examples include Kalay *et al*. (2004) who measure point elasticities at market clearing prices to investigate liquidity provision.

auction and at 2:30 PM are 74% (76%) and 64% (65%), respectively; and, those of [17] are 80% (82%) and 72% (74%), respectively, suggesting that the log-on-log specification indeed parsimoniously summarizes the data.

Finally, although [16] and [17] use regression coefficients as elasticity measurements, no simultaneity bias arises. This is because we do not jointly estimate demand and supply elasticities from the same data. Rather, we plot out observed demand and supply schedules precisely and then apply [16] and [17] to measure the slope of each side of the limit order book. Our elasticities are estimates not because of endogeneity bias, but because of measurement error – for example, we cannot include latent limit orders that investors would place if their probability of execution rose.

[Table 2 about here]

3.5 Limit Order Book Range and Liquidity Provision

Panels A and B of Table 2 show substantial limit order depths well away from the market price. In the typical open auction, about 31% of buy limit orders and 25% of sell limit orders are more than 10% away from the market price. At 2:30 PM, some 32% of buy orders and 27% of sell orders are over 10% away from the market price. Note that this dispersion is not due to stale limit orders, as all unexecuted limit orders expire at the end of the trading day.

If investors had relatively homogeneous valuations, limit orders should be concentrated around the market price. The substantial far out-of-the-money limit order depth we observe is thus suggestive of substantial differences in opinion across investors, and even professional analysts, and thus supports prior work along these lines (Hong and Stein, 2007).[22] In our model, an investor who believes an asset is

[22] Strictly speaking, models such as ours create a theoretical limit order book that spans the entire range of possible stock prices. By economically meaningful variation, we mean a range of price values for which some investors would decide to become demanders (suppliers) of the asset who would not do so for prices closer to the current market price.

overvalued by 10% would place a buy order with a limit of 10% or more below current market price.

However, inelastic demand or supply curves can also be modeled in the absence of differences in opinion if investors exhibit a substantial variation in patience (e.g., Handa and Schwarz, 1996; Parlour, 1998; Foucault *et al.*, 2005). In these models, patient investors gain by placing limit orders above and below a stock's fundamental value, providing immediate execution to impatient investors. However, these models most plausibly explain limit orders nearer the market price (Sandås, 2001; Kalay *et al.*, 2004), because competition between providers of immediate execution should push their limit orders towards the market price.[23] Thus, spreads in a U.S. market such as the NYSE are thought to reflect strategic liquidity provision by large specialists (Kavajecz, 1999). Huang and Stoll (1996) report mean quoted spreads on the NYSE of 1.2% and mean effective spreads of 0.7%. In contrast, Table 2 shows only 10.5% of buy limit orders and 9.1% of sell limit orders falling within 1% of the market price at the opening auction. At 2:30 PM, only 10.2% of buy limit orders and 6.6% of sell limit orders lie within 1% of the market price. Even if we take 3% as an acceptable price for immediate execution under normal market conditions, as much as 69 to 75% of all limit orders are too far away from the market prices in the opening auction and at 2:30 PM, respectively, to be plausibly explained by this reasoning.

Given such substantial width in limit order distributions, we see Ockham's razor favoring substantial heterogeneity in investors' private valuations. We concur with Hollifield *et al.* (2004, 2006) that valuation heterogeneity and patience heterogeneity are both important and merit full investigation. [24] However, our results suggest that differences in patience, however important, are unlikely be the whole story behind such a wide dispersion in limit order prices.

[23] The KSE lets any traders help make the market in any stocks.

[24] Hollifield *et al.* (2004) and Hollifield *et al.* (2006) model impatience and information heterogeneity in concert, and conclude that the two are inseparably confounded and must be considered jointly. They emphasize the role of valuation heterogeneity in the following quote: "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" (Hollifield *et al.,* 2006, p. 2760). Intuitively, investors with private information provide strategic liquidity at better prices than other potential providers, making actual strategic liquidity provision a by-product of heterogeneous valuations. This prediction is confirmed experimentally (Bloomfield *et al.*, 2005).

3.6. Whole and Cored Elasticities

To further abate the effects of (possibly strategic) liquidity provision in the absence of differences in opinion in, we revisit our tests using what we call *cored elasticities*: elasticity measures estimated excluding limit orders near the market price, where limit orders unassociated with valuation heterogeneity are most likely to be found.

We define *near-market* limit orders as those priced in the open interval ($p_m(1 - k)$, $p_m(1 + k)$), centered at the market price, p_m, with k set to one, two, and then three percent. By dropping price-quantity pairs with prices in these successively larger near-market open intervals, we obtain *cored* demand and supply schedules, so-named because of the holes around the market prices at their centers. At all non-near-market prices, these demand and supply schedules are identical to those described above.

Thus, given a supply schedule of price-quantity pairs $\{(p, s(p))\}$, we denote the corresponding cored supply schedules, $C_s(k)$, for k = one, two, or three percent, as

$$[18] \qquad C_s(k) \equiv \{(p, s(p)) \mid p \in (0, p_m(1-\mathrm{k})] \cup [\, p_m(1+\mathrm{k}), +\infty)\}.$$

Cored demand schedules are analogously defined.

We then run [16] and [17] on these cored demand and supply schedules to obtain *cored elasticities* of demand or supply. This approach exploits our dataset by focusing on the parts of limit order books that heretofore have received relatively little: far out-of-the-money limit orders.

4. Empirical Results

This section first reports summary statistics and results for our demand and supply elasticities. Using dates ascertained by Kim and Wei (2002), we partition our sample period into three “state of the world” 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.[25]

[Figure 2 about here]

4.1 Magnitudes

Panels A and B of Figure 2 plot daily mean elasticities, averaged across all firms, against time. Panel C plots the KSE index over the same period. Table 3 reports summary statistics for the underlying firm-level daily elasticities of demand and supply schedules. The table shows the median demand elasticities of about 20 both in opening auctions and at 2:30 PM; and median supply elasticities of 24 in opening auctions and 23 at 2:30 PM. The inverses of the elasticities are all statistically significantly greater than 0 ($p < 0.0001$), confirming finite elasticities. A one percent increase in price thus induces roughly a 20 percent drop in demand and a 23 percent rise in supply.[26]

[Table 3 about here]

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) estimate of 2.91 (2.47) by Kandel *et al.* (1999) from IPO data. Our estimates lie 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 during our sample period, whereas investors in other stock markets generally have less information.

[25] In November, 1997, the Bank of Korea stopped defending Korean Won and the Korean government requested an IMF bailout.
[26] Cored elasticities generate similar patterns. Section 4.2 discusses this issue in detail.

In our sample, supply is generally more elastic than demand. The difference in means is highly significant ($p < 0.0001$) throughout all three sub-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 the Tel Aviv Stock Exchange (TASE), 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 in the post-crisis period. Thus, our relatively high supply elasticities are not readily explained by more intense short sale activities in the KSE than in the TASE.

We may expect higher elasticities at 2:30PM than at the opening auction if information propagates throughout the day. However, the evidence is mixed. For the whole sample period, the 2:30 PM mean elasticity of each curve significantly exceeds its mean opening auction elasticity. However, the median elasticities show the opposite pattern though by much smaller margins.

4.2 Positively Correlated Demand and Supply Elasticities in the Long-Run

Because we have a long time series that includes a crisis, we can compare the magnitudes of elasticities before and after the crisis using one measurement methodology. This sidesteps the problem of absolute magnitudes not being readily comparable across studies that use different estimation methods, and permits meaningful comparisons over time as the KSE trading environment changes. The mean elasticities of both demand and supply fluctuate far more during the last months of 1997 and the first months of 1998 than either before or after (Figure 2). This period of instability begins at the onset of the 1997 Asian financial crisis, clearly evident in the KSE index in Panel C of Figure 2.

Elasticities of both demand and supply are markedly lower after this interlude of instability, implying more heterogeneous limit order pricing across investors in the post-crisis period. Table 3 shows a 39% drop, from 30.0 to 18.3, in the median opening auction demand elasticity; and a 41% drop, from

36.9 to 21.9 in the median opening auction 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 schedules remain depressed through the remainder of our sample period.

This is consistent with the crisis permanently altering both D^{ε} and S^{ε}, reflecting a permanently reduced trading aggressiveness, k_i, for the average investor, consistent with our analysis in section 2.5. Simultaneous increases or decreases in the k_i's between two different regimes generate a positive cross-correlation between the sample mean elasticities of demand and supply as shown in proposition 2.

Our model permits several possible explanations for such a shift in the unconditional means of D^{ε} and S^{ε} and the k_i. Specifically, such a decrease can be caused by any of the following; *(i)* An increase in the degree of risk aversion, i.e. a higher γ_i, for the typical investor, *(ii)* A decrease in investor confidence in their private opinion, i.e. a higher σ_i^2, for the typical investor, (*iii)* A change in the number (I in the model)[27] or composition of investors submitting limit orders. Each story provides a plausible explanation. Campbell and Cochrane (1999) show how the advent of a recession or crisis can elevate risk aversion for the average investor. Investor confidence in their beliefs or valuation models may be shaken by a crisis, thus increasing σ_i^2. Some investors may leave the market after the crisis, decreasing market depth.

The persistent decreases in observed elasticities, potentially associated with the above factors, run counter to major institutional changes in the KSE after the crisis that aimed to increase market depth.[28] Korea's post-crisis institutional reforms increased transparency (Solomon *et al*. 2002), which should

[27] Even when $k_i = k$ for all i, a lower number of investors, I, reduces the demand and supply elasticities because $D^{\varepsilon} + S^{\varepsilon} = \sum_{i=1}^{I} k_i = kI$.

[28] One notable exception is the stricter restrictions on margin purchase, including higher collateral requirements and initial margins, imposed during the crisis period. Because margin buying was exclusively used by domestic individual investors before the crisis, these restrictions could have impeded aggressive limit order placement by those investors in the post-crisis period, reducing market depth. Indeed, margin purchases, some 20% of buy orders in the pre-crisis period, constitute only about 1% of post-crisis buys. However, an analogous argument cannot explain the similar drop in market depth for sell orders because short sales were rarely used even in either period, constituting less than 0.5% of sell orders in the pre-crisis period and nearly vanishing in the post-crisis period.

decrease information heterogeneity, leaving both schedules more elastic. The June 1998 advent of low-cost online trading also reduces arbitrage costs, and thus should also have flattened demand and supply schedules. Another major reform, the removal of foreign ownership caps in May 1998, was introduced to reinvigorate the stock market, reflecting the hope that foreign investors might contribute information, or liquidity, and thus elevate market depths. However, its impact on limit order elasticities is *a priori* ambiguous. Were foreign investors' valuations more heterogeneous, their presence could permanently reduce the elasticities, explaining the step function pattern we observe. Because our data distinguish limit orders by domestic individuals, domestic institutions, and foreigners, we can test this. First, we confirm that restricting the sample to stocks where all three types are present does not change the results reported in Table 3. We then construct three demand and supply schedules, one for each investor type, each day for each stock, and compare their mean elasticities before and after the crisis period. Foreigners' elasticities decline significantly less, and have significantly higher post-crisis means, than the elasticities of domestic investors.[29] Thus, the removal of the cap on foreign ownership is also an unlikely suspect for reducing elasticities in the post-crisis period.

In fact, Figure 2 shows both demand and supply elasticities settling into their lower post-crisis ranges in March 1998, substantially before any of the aforementioned reforms. All of these observations, taken together, suggest that the seemingly permanently lower post-crisis elasticities we observe might mainly reflect (*i)* lasting increases in risk aversion, or *(ii)* decreases in investors' confidence in their private valuation opinions, or *(iii)* shifts in intangible characteristics and the number of investors, or some combination of all three. A more complete model might show how these factors might impede arbitrage, and thereby steepen both the market demand and market supply curves.

A possible alternative explanation of our findings might be provided by recent work linking long-

[29] After the crisis, the mean demand elasticity drops by 48%, from 29.9 to 15.4, for domestic individuals ($p < 0.01$) and by 46%, from 55.8 to 30.0, for domestic institutions ($p < 0.01$); but only by 16%, from 42.0 to 35.3, for foreigners ($p < 0.10$). The mean supply elasticity drops by 45%, from 40.2 to 22.1, for domestic individuals ($p < 0.01$) and by 33%, from 51.6 to 34.5, for domestic institutions ($p < 0.01$); but only by 24%, from 45.9 to 35.1, for foreigners ($p < 0.05$). The post-crisis mean demand elasticity for foreigners significantly exceeds ($p < 0.01$) those for domestic individuals and domestic institutions. The post-crisis mean supply elasticity for foreigners significantly exceeds ($p < 0.01$) that for domestic individuals only.

lasting changes in risk aversion to life experiences of traumatic insecurity, such as the Great Depression (Graham and Narasimhan, 2004; Graham *et al*., 2011; Schoar and Zuo 2011; Malmendier and Nagel, 2011; Malmendier *et al*., 2011). That living through episodes of extreme stress, such as an earthquake, violent crime, or war, can alter brain physiology in ways that potentially and permanently reduce baseline tolerance for stress is also well-established in the neurosciences (Yehuda, 2002). Given these insights, we posit that our findings might be consisting with the Crisis of 1997 having increased Korean investors' risk aversion or, equivalently in our model, decreased their confidence in their private opinions, and with this introducing a post-crisis regime of less trading aggressiveness that persists through the end of our sample window.

The finding of the symmetric market depth effect in the long-run is not new. It is predicted in the risk-neutral model of Admati-Pfleiderer (1988) and demonstrated empirically by Brennan *et al*. (2012), who report a cross-correlation of 0.998 between monthly buy and sell price impact measures (Kyle's lambda) estimated from 1983 to 2008. Estimating the daily cross-correlation in our data over our whole sample, rather than by month, generates point estimates of +0.67 using opening auction elasticities and +0.23 using 2:30PM elasticities. These values, though smaller than the estimate of Brennan *et al*. (2012), are both significantly positive and thus indicate the predominance of a common long-term trend. To facilitate comparison with Brennan *et al*. (2012)'s cross-correlation between monthly buy and sell Kyle's lambdas, we estimate a second set of cross-correlation coefficients using 49 monthly means of daily mean elasticities for each curve. The cross-correlation point estimates are 0.921 for opening auction elasticities and 0.904 for 2:30 PM elasticities – far closer to Brennan *et al*. (2012)'s 0.998 estimate, despite using an entirely different methodology and data.

The novelty of this finding is the direction of the trend. Chordia *et al*. (2001) and Brennan *et al*. (2012) report a secular trend towards *increasing* market depth (smaller price impacts) in the U.S., consistent with the conventional view that, over time, trading frictions decline. Korea does not economies share this trend time, at least during our sample period, so the US finding may not generalize. The Korean data associate a substantial recession of market depth with the 1997 crisis, and our model suggests that a general elevation in investor risk aversion or a general loss of confidence in investors' private valuation signals or both might underlie this state of the world change. This term seems appropriate because the reduction in market depth persists long after real economic activity and stock market valuations recover, indeed through the end of our observation window.

[Figure 3 about here]

To see if our results are driven by orders near market prices (see section 3.6), we repeat the exercise using cored elasticities. Figure 3 shows the permanent decrease in mean elasticities to be robust to dropping limit orders priced within one, two, and three percent of the market price. Similar patterns are evident using median elasticities.[30] Thus, the significant drop in elasticities we observe is not driven by orders near market prices, and is thus not likely due to changes in strategic liquidity provision or investor impatience alone, as these effects would be concentrated near stocks' market prices.

[Figure 4 about here]

4.3 Negatively Correlated Elasticities of Demand and Supply in the Short-Run

The results above provide evidence consistent with the symmetric market depth effect that Proposition 2 predicts over the long-run. However, despite the apparent long-run common trend between mean demand and supply elasticities, a closer look at Panels A and B of Figure 2 reveals days when the magnitudes of the two elasticities differ markedly. To explore this further, we calculate scaled elasticity differences, defined as the demand elasticity minus the supply elasticity divided by their average, for each trading day. Panels A and B of Figure 4 plot the daily time-series of these scaled differences measured at the opening auction and at 2:30 PM, respectively. The mean scaled difference for the whole sample is about 8% for

[30] Within each sub-period, mean elasticities become slightly larger with cored elasticities. This may be due to non-log linear portion of the data. However, the difference is not very big.

opening auction elasticities and about 6.5% for 2:30 PM elasticities. The standard deviations of the scaled differences are large: About 10% for opening auction elasticities and as high as 18% for 2:30 PM elasticities. As a result, Panels A and B of Figure 4 show scaled differences fluctuating widely throughout the sample period, highlighting that on many trading days one side of the market is very elastic while the other is relatively inelastic. This section develops these observations into tests for the short-run asymmetric market depth effect that Proposition 1 derives from investors switching between the sell and buy side of the limit order book as the market price rises above or falls below their private valuations.

[Figure 5 about here]

Figure 5 plots individual stocks' daily mean demand elasticities against daily mean supply elasticities, first using opening auction as well as 2:30 PM elasticities, and using elasticities measured across the whole limit order book as well as cored elasticities.[31] In each case, a clear negative relationship is evident in the 2:30 PM elasticities, indicating that the result is unlikely to be driven by changes in the shapes of the schedules near the market prices.

A clear negative cross-correlation becomes apparent in the opening auction elasticities after dropping limit orders around the market price to generate cored elasticities. This is consistent with Figure 1, which shows the demand and supply schedules at the opening auction 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 price 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 price, and so are, in effect, transformed into market orders. Consequently, deleting them by using the cored elasticities is warranted.

[Table 4 and Figure 6 about here]

[31] To save space, we report 1% and 3% cored elasticities in the figure.

Panel A of Table 4 displays the cross-correlation of daily mean demand elasticities with daily mean supply elasticities each month. The cross-correlation between 2:30 PM elasticities is significantly negative and ranges between -0.67 and -0.82 across whole and cored elasticities and over the whole sample and sub-periods.[32] For opening auction elasticities, similar robust negative correlations of comparable magnitudes are evident for cored elasticities, but again less apparent for whole elasticities, as above. Panel A of Figure 6 reveals a stable negative cross-correlation within each of the pre-crisis, in-crisis, and post-crisis subperiods. This is consistent with our model because the short-run negative contribution to the cross-correlation is driven by the switching effect. New draws of investors' private valuations, the $\{v_i\}_{i=1,\ldots,I}$, induce them to switch from being buyers to being sellers and vice-versa, while the long-run positive contribution is driven by shifts in investors' aggressiveness in trading on those private valuations, the $\{k_i\}_{i=1,\ldots,I}$. Regardless of the mean value of the $k_{\omega,i}$, and thus the sub-period population mean elasticities $D_\omega^\varepsilon = S_\omega^\varepsilon = \frac{1}{2}\sum_{i=1}^{I} k_{\omega,i} = \frac{1}{2}K_\omega$, when switching moves investor i from the demand side to the supply side of the limit order book, the elasticity of demand loses her contribution $k_{\omega,i}$ and the elasticity of supply gains precisely the same amount $k_{\omega,i}$. The effect generating the negative correlation in Proposition 1 is essentially unchanged. Thus, the model can explain how a highly negative cross-correlation can be observed in regimes with markedly different mean elasticities.

Our model and empirical findings also may help reconcile seemingly contentious findings about the price impact of trades. The price impact of trades is known to be asymmetric in unconditional means. Much of the literature on block trades and institutional trades finds the price impact of a buy to be significantly larger than that of a comparable sell (Kraus and Stoll, 1972; Chan and Lakonishok, 1993, 1995; and Gemill, 1996). Saar's (2001) model explains this by stressing short sale constraints: investors can only readily sell the shares they own, but can buy any number of shares. In contrast, Keim and Madhavan (1996) find that the price impact of sells in the upstairs market (privately negotiated off-

[32] We also check the negative cross-correlation in firm-level panel regression set-up with clustered standard errors as shown in section 4.4.

exchange block trades) to be larger than that of buys. Bikker *et al.* (2007) also report a higher price impact of sells in a sample of institutional trades. Michayluk and Neuhauser (2008) report ask depth exceeding bid depth in a sample of 100 technology stocks, and effective spreads larger for sells than buys.

Our focus is not the differences in unconditional means, but the time variation in buy and sell limit order depth if heterogeneity in investors' opinions, rather than demand for immediate execution, is paramount. If differences of opinion are economically important, our model shows that observed price impacts can result from an interaction of the stock's demand and supply schedules, and that either sign can prevail. Our model thus offers a plausible reconciliation of seemingly conflicting previous results that sample the data at different frequencies or over windows of different lengths. Similarly, the finding of Chiyachantana *et al*. (2004) that the price impact of institutional buys is higher than that of institutional sells in the 1990s bull market, while the opposite is true in the 2001 bear market, might be explained in our framework under suitable assumptions of correlated opinions or liquidity demands over the business cycle.

Finally, the auto-correlations of daily mean demand and supply elasticities (not reported for brevity) are positive, though their magnitudes are small. The auto-correlation in daily 2:30 PM demand elasticities is about 0.1 whether measured across the whole sample or for the three sub-periods separately, while that in daily supply elasticities is about 0.12. The strong negative cross-correlation and small positive auto-correlation, together, imply that episodes of high asymmetric variation in depth are transitory. Section 4.4 finds similar patterns at firm-level elasticities.

4.4 Firm-Level Analyses

The cross-correlations analyzed above are of the mean demand and supply elasticities across all stocks, and thus reveal *systematic* patterns in limit order depth. However, patterns in means or in aggregate variables may not be observed in firm-level variables. For example, excess volatility observed at the index-level (Campbell and Shiller, 1988a, 1988b) is not observed at the firm-level (Vuolteenaho, 2002); and the positive contemporaneous relationship between earnings and stock returns detectable at the firm-level is not found at the index-level (Kothari *et al.*, 2006; Hirshleifer *et al.*, 2009). We therefore examine the cross-correlations of individual stocks' elasticities of limit order demand and supply in three ways.

The first approach uses daily snapshots of the demand and supply schedules for each stock to estimate the cross-correlation of its elasticity of demand and elasticity of supply each month. Panel B of Table 4 shows the means of these cross-correlations. Like the cross-correlation of the means in Panel A, the mean of the firm-level cross-correlations is significantly negative, though the point estimate is smaller. Using 2:30 PM snapshots, it ranges between -0.20 and -0.28 across the whole and variously cored elasticities and over the whole sample and various sub-periods. These lower point estimates likely reflect the larger standard deviations of our firm level elasticity estimates. For the opening auction, the mean of the cross-correlations of cored elasticities falls within a similar range – from -0.111 to -0.153. However, the means of the cross-correlations of whole elasticities are much smaller in absolute value and fall between -0.02 and -0.04. As with the mean elasticities, cored elasticities exhibit stronger negative cross-correlations than whole elasticities since whole elasticities at the opening auction are calculated including above-market buy orders and below-market sell orders as discussed in section 4.3. Panel B of Figure 5 plots the time-series of the mean of the firm-level cross-correlations through the sample period.

For both opening auction and 2:30PM, the means of the autocorrelations at the individual firm level (not reported in Table 4) are near zero and range between - –0.063 and +0.048 across the whole and variously cored elasticities and over the whole sample and various sub-periods. Such small autocorrelation point estimates are small, consistent with extreme elasticities being transitory phenomena.

[Table 5 about here]

The second approach estimates firm-month panel regressions, allowing for heteroscedasticity and firm-level clustering, of the form

[20] $$S^{\varepsilon}_{j,t} = \sum_t \alpha_t \delta_t + \sum_j \alpha_j \delta_j + \beta D^{\varepsilon}_{j,t} + \varepsilon_{j,t},$$

where the δ_t and δ_j are time and firm fixed-effects. The coefficient β gauges how the deviation of a stock's supply-side limit order elasticity from its time-series mean relates to the deviation of its supply-side elasticity from its mean value the same month. Table 5 presents estimates of β, with the $\{D^{\varepsilon}_{j,t}, S^{\varepsilon}_{j,t}\}$ being either whole elasticities or the cored elasticities described in [18], from the regressions [20] using alternatively the full sample period or the pre-crisis, in-crisis, and post-crisis sub-periods. Consistent with Table 4 and Panel B of Figure 6, highly significant negative coefficients arise in the whole sample and in each sub-period for the 2:30 PM elasticities, regardless of using whole elasticities or cored elasticities. For opening auction elasticities, highly significant negative coefficients arise in cored elasticities in the whole sample and in each sub-period. However, we obtain much smaller coefficients in absolute values and sometimes even with wrong signs for whole elasticities. These results are driven by noise generated by above-market buy orders and below-market sell orders only present at the opening auction as in Table 4 and section 4.3.

[Figure 7 about here]

The third approach examines the two elasticities around days when one is *abnormally inelastic*, We define *abnormal elasticity* as calculated elasticity minus the pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), or post-crisis (November 1998 – December 2000) sub-period mean, whichever is relevant. We define an *extreme abnormal inelasticity* to be an observation in the bottom quintile of the distribution of abnormal elasticities. Because we wish to examine the persistence of asymmetric market depth, we drop firm-day observations with missing demand or supply elasticities in any of the ten subsequent trading days.

Panels A and B of Figure 7 report results based on whole elasticities. For 2:30 PM elasticities, Panel A of Figure 6 shows that days with abnormally low demand elasticities (mean abnormal elasticity of -11.38) correspond to days with abnormally high supply elasticities (mean abnormal elasticity of +6.35). For opening auction whole elasticities, we have weaker asymmetry. While the mean abnormal open demand elasticity is -10.08, the corresponding abnormal supply elasticity is 0.39. However, consistent with previous results, when we use cored elasticities (1% or 3%) for opening auction, stronger asymmetry is restored: While the mean abnormal open demand elasticity (cored at 1%) is -12.23, corresponding abnormal supply elasticity is +1.13. Panel B of Figure 6 repeats the exercise for trading days with extreme abnormal supply inelasticities, and shows a similar asymmetric effect.

Panels A and B of Figure 7 thus reveal extreme limit order depth to be markedly asymmetric. The extension of the plots over the subsequent trading days again exposes the transitory nature of this asymmetry, with virtually complete subsidence evident within one to two trading days. This indicates a very low auto-correlation in elasticities at the firm-level, as in the daily mean elasticities across firms.

5. Conclusions

A parsimonious model shows limit order placements to depend on persistent differences in opinion across investors and on investors' trading aggressiveness, which in turn depends on their risk aversion and confidence in their private information. This extends the framework of standard models, such as Admati and Pfleiderer (1988), to predict a negative cross-correlation between a stock's elasticity of supply and elasticity of demand in the short-run and a positive correlation between its mean elasticity of supply and mean elasticity of demand over the long-run.

The negative cross-correlation between the elasticities of supply and demand, which we dub the *asymmetric market effect*, arises because new private information causes investors, previously offering to sell, to switch to offering to buy and vice versa. When an investor switches from one side of the market to the other, so does the contribution of her trading aggressiveness to the slope of that side's limit order schedule. Switching thus adds to the slope of one side of the limit order book while subtracting from the slop of the other side. Because we envision new private information arriving frequently, the model predicts this effect dominating in short-run data.

The positive cross-correlation effect, or the *symmetric market depth effect*, arises because macro events, such as financial crises, can cause investors' risk aversion and confidence in their private information to co-vary. Such events leave the aggressiveness of investors on both sides of the limit order book similarly changed, and thus both the demand and supply elasticities similarly increased or decreased. Because we envision investors' risk aversion and confidence in their private information shifting only infrequently, the model predicts this effect to be most evident in long-run data.

Complete limit order books from the Korean Stock Exchange reveal the persistent importance of far out-of-the-money buy and sell limit orders, consistent with economically significant different opinion across investors about asset values. Real time data on all limit orders allow the direct measurement of limit order demand and supply elasticities, sidestepping the identification problems normally encountered in estimating demand and supply curves from market prices and quantities traded.

Consistent with the model, a positive cross-correlation between Korean limit order demand and supply elasticities is evident in long-run data. Both become markedly less elastic after the 1997 Asian financial crisis. The model suggests that this could reflect either increased risk aversion or decreased confidence in private information reducing the aggressiveness of heterogeneously informed investors' information-based trading. Such changes, by affecting all (or most) investors in the same way at the same time, induce a common drop in limit order demand and supply elasticities. Thus, although Chordia *et al.* (2001) and Brennan *et al.* (2012) report a secular trend towards *increasing* market depth (smaller price impacts) in the U.S., we demonstrate that there can be interruptions in this trend in the sense that a major financial crisis can *reduce* market depth for a sustained period of time; and that this reduction can persist long after real economic activity and stock market valuations regain their pre-crisis levels.

In contrast, but again consistent with the model, short-run data reveal a strong negative cross-correlation between the elasticity of demand and elasticity of supply. That is, a stock tends to have an abnormally steep limit order demand schedule on days when its limit order supply schedule is unusually flat, and vice-versa. Our model can also explain the highly negative cross-correlation observed throughout the pre-, in-, and post-crisis period of our sample, despite large changes in both mean elasticities and market conditions associated with the 1997 financial crisis.

Thus, our model and empirical results highlight economically important channels through which stocks' demand and supply curves interact. This interaction produces a symmetric market depth in the long-run and an asymmetric market depth effects in the short-runs, respectively, even absent liquidity trading motives (Kalay and Wohl 2009).

Our model complements the literature on strategic liquidity provision (e.g., Handa and Schwartz, 1996; Parlour, 1998; Hollifield *et al.*, 2004; Foucault *et al., 2005*, Goettler *et al*., 2005; Hollifield *et al.*, 2006; Goettler *et al*., 2009; Roşu, 2009; Buti and Rindi, 2013). We believe both approaches to be important in understanding financial markets, and see considerable scope for future research elaborating and combining the two modeling strategies.

Our empirical results provide stylized facts that might assist modelers in these efforts. Moreover, the finding that the sign of the cross-correlation between the elasticities of supply and demand flips depending on the sampling frequency offers considerable scope for reconciling seemingly inconsistent prior empirical findings. Also, our model and empirical findings underscore the need for future work exploring the information diffusion process in financial markets, whereby informed trading capitalizes private information into stock prices (Grossman and Stiglitz 1980) and possible interaction between order flow, stock prices, and limit order book depth (Biais *et al*., 1995; Ahn *et al*., 2001).

Finally, our findings are consistent with recent work linking long-lasting changes in risk aversion to life experiences of traumatic insecurity, such as the Great Depression (Graham and Narasimhan, 2004; Graham *et al*., 2011; Schoar and Zuo 2011; Malmendier and Nagel, 2011; Malmendier *et al*., 2011). That living through episodes of extreme stress, such as an earthquake, violent crime, or war, can alter brain physiology in ways that potentially and permanently reduce baseline tolerance for stress is also well-established in the neurosciences (Yehuda, 2002). Given these insights, we posit that our findings might be consisting with the Crisis of 1997 having increased Korean investors' risk aversion or, equivalently in our model, decreased their confidence in their private opinions, and with this introducing a post-crisis regime of less trading aggressiveness that persists through the end of our sample window.

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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 opening price. The *2:30 PM limit orders* graphs (gray) reflect all outstanding limit orders as of 2:30 PM.

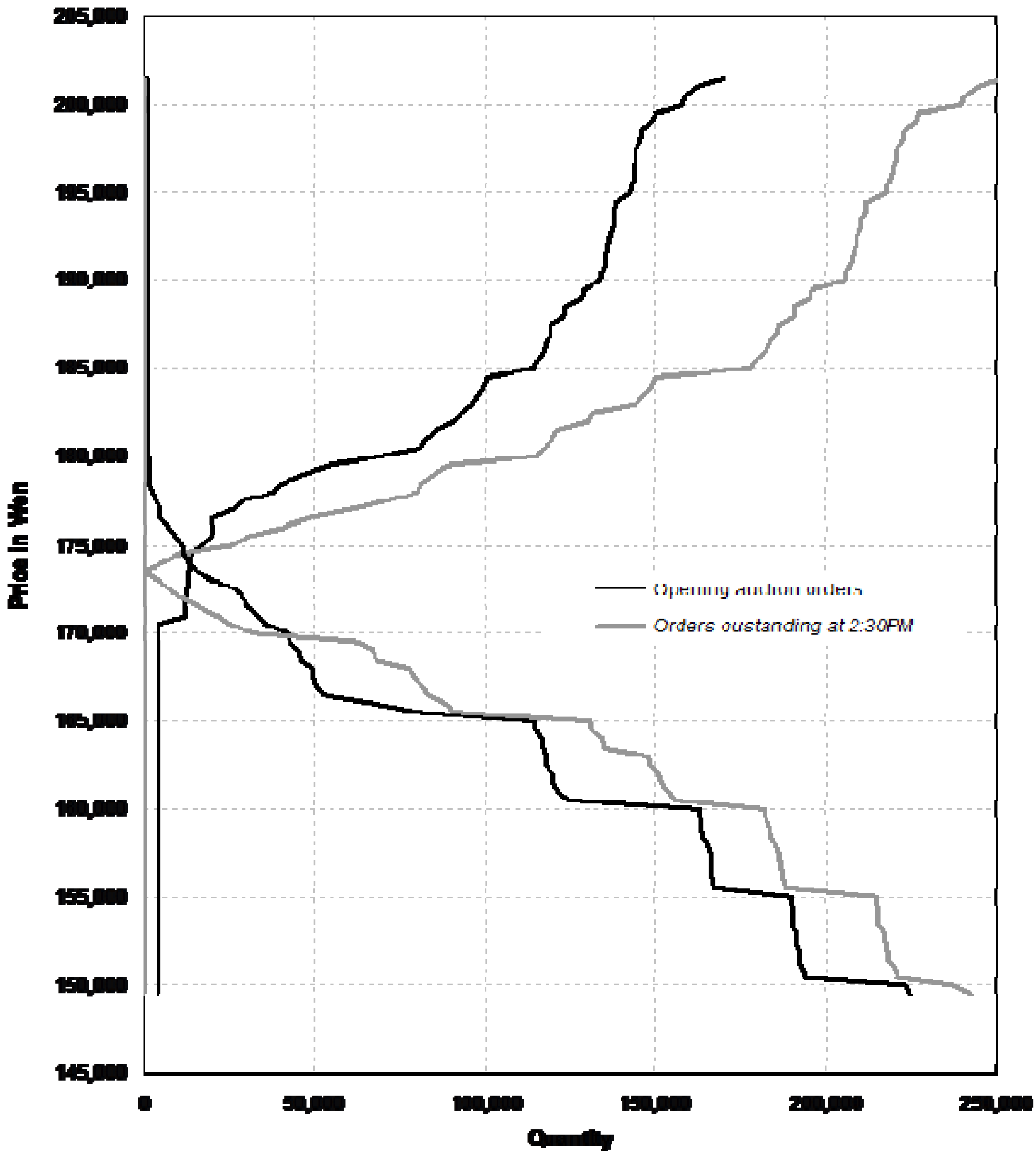
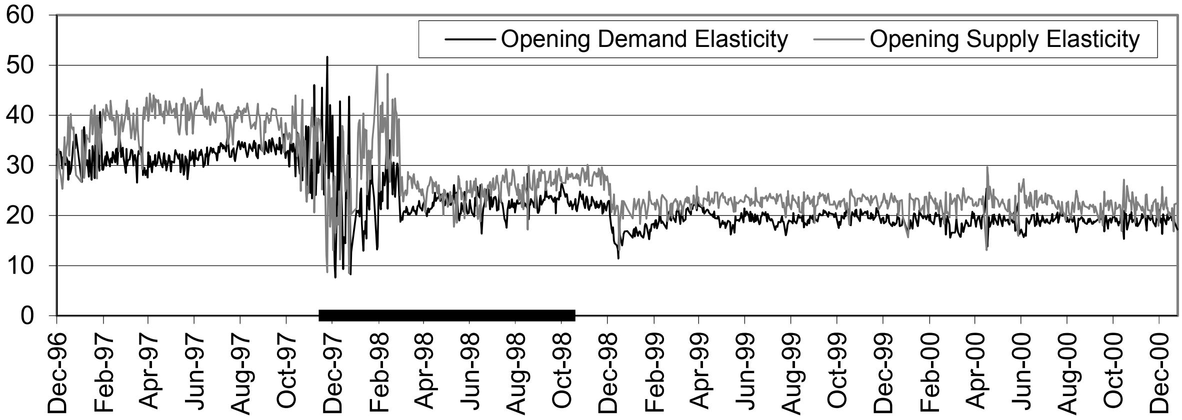


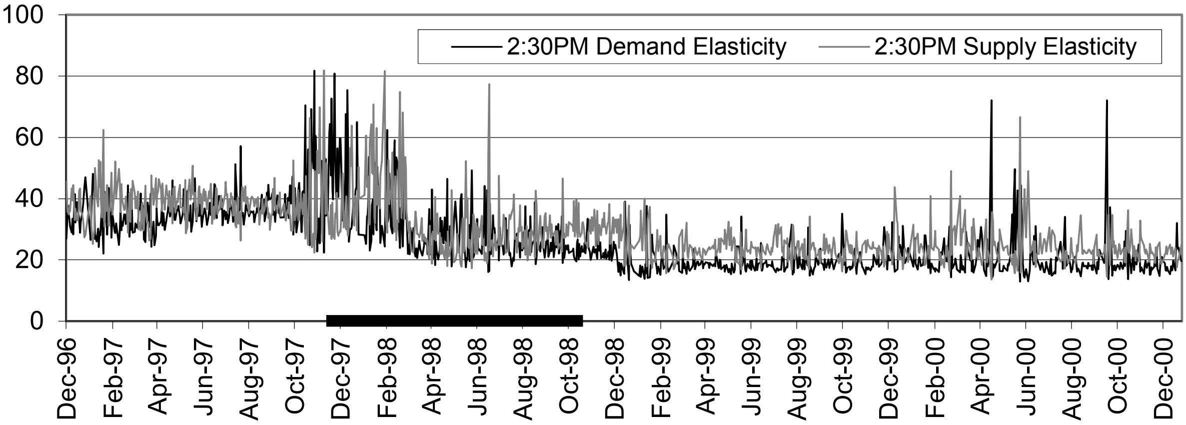
Figure 2. Mean Demand and Supply Elasticities of Individual Stocks over Time

Each stock's elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded at that price in the stock's limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated whenever the stock's relevant limit order schedule contains over five price-quantity pairs. 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 this mean is 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

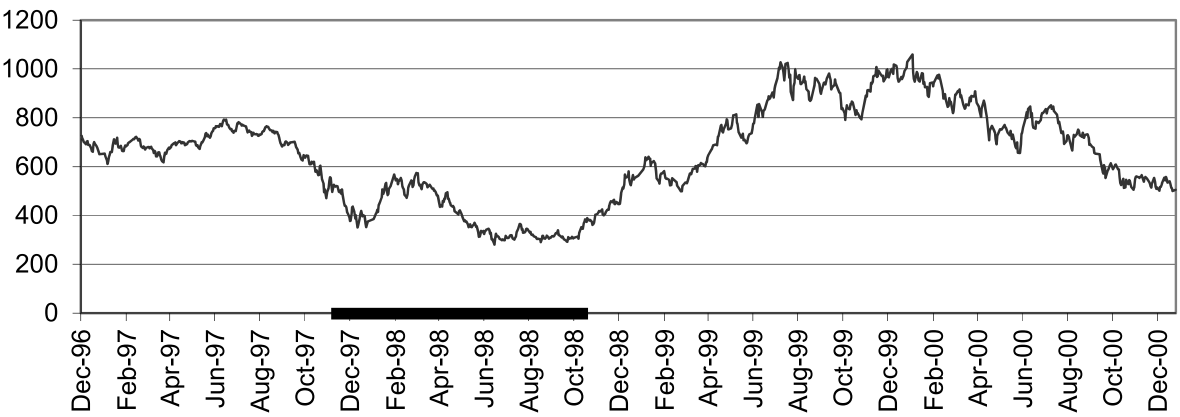
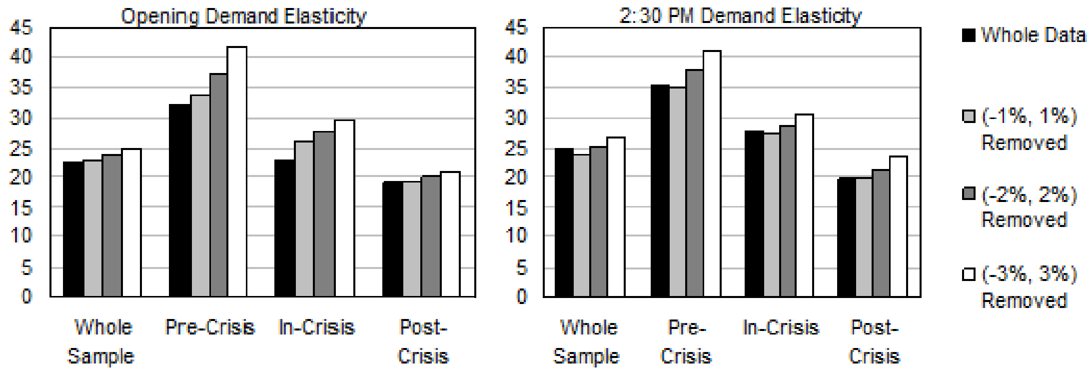


Figure 3. Mean Elasticities for the Whole Sample and Subsamples Dropping Limit Orders Priced within One, Two, or Three Percent of the Market Price.

Each stock's elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded at that price in the stock's limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated whenever the stock's relevant limit order schedule contains over five price-quantity pairs, 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 December 1996 to December 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 the Opening Auction and at 2:30 PM



Panel B: Supply Elasticities at the Opening Auction and at 2:30 PM

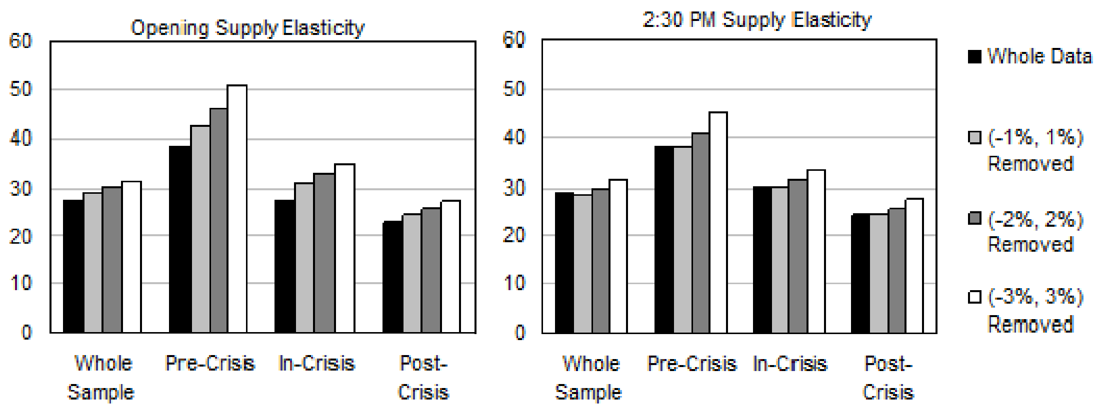
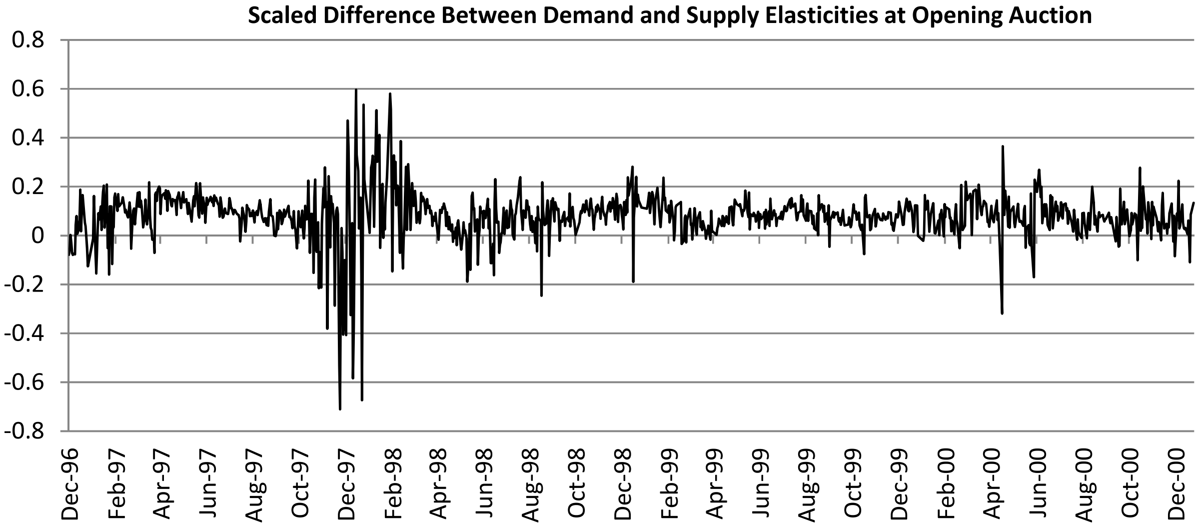


Figure 4. The Scaled Difference Between Demand and Supply Elasticities

Each stock's elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded at that price in the stock's limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated whenever the stock's relevant limit order schedule contains over five price-quantity pairs. 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. For each day, we subtract supply elasticity from demand elasticity and then scale the difference by the average of demand and supply elasticity. This scaled difference is graphed against time. The East Asian Financial Crisis period is the time 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 presents results for the market opening, whereas panel B depicts the corresponding results for 2:30 PM.

Panel A: Scaled Difference Between Demand and Supply Elasticities at the Opening Auction



Panel B: Scaled Difference Between Demand and Supply Elasticities at 2:30 PM

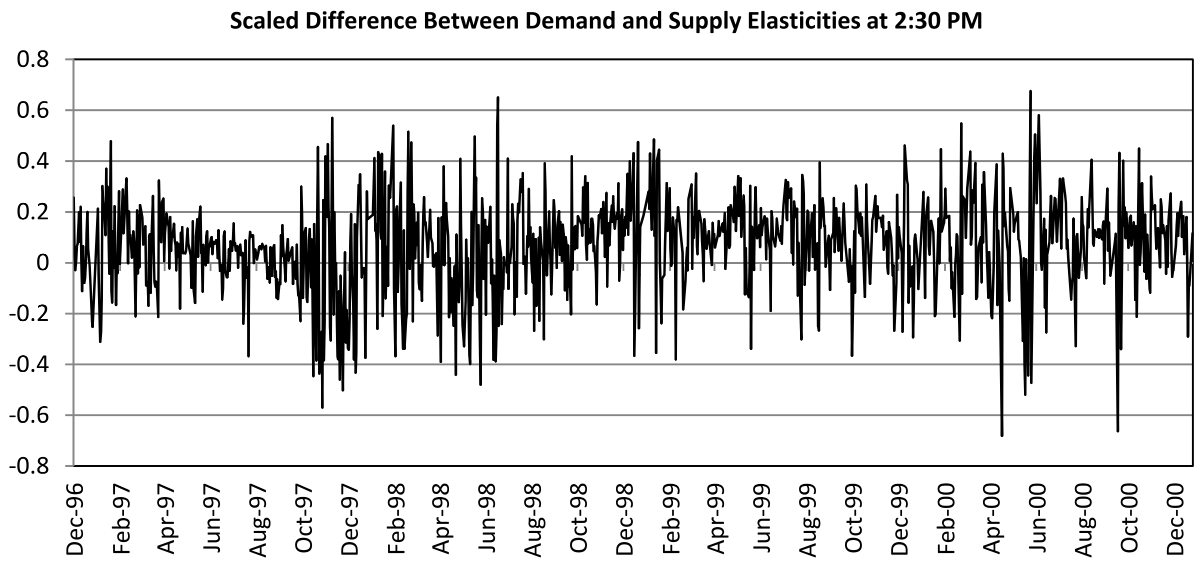
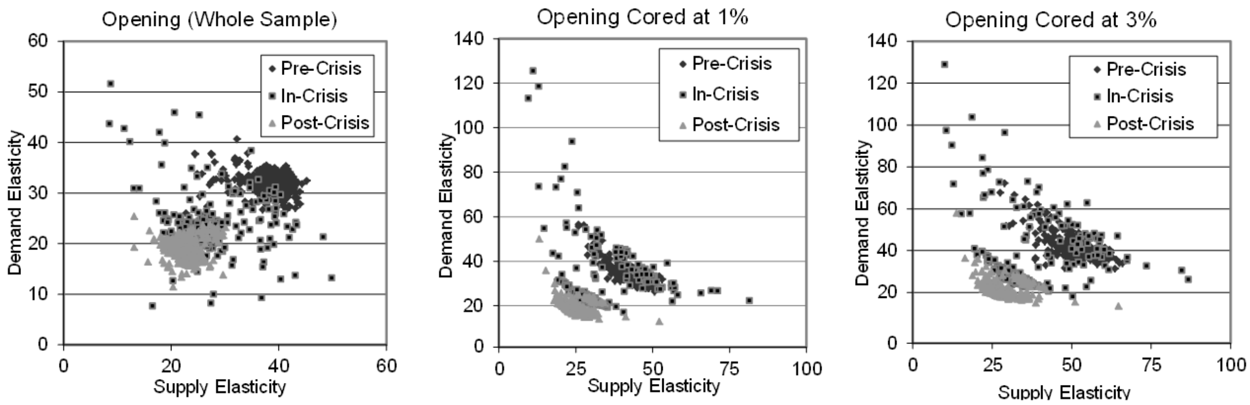


Figure 5. Relationship Between Daily Mean demand and Supply Elasticities

Daily mean demand elasticity is plotted against daily mean supply 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 at that price in the stock's limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are estimated whenever the stock's relevant limit order schedule contains over five price-quantity pairs; for the whole sample and subsamples dropping observations within one, two, or three percent of market prices. Elasticities are measured twice each day from December 1996 to December 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 the Opening Auction



Panel B: Elasticities at 2:30 PM

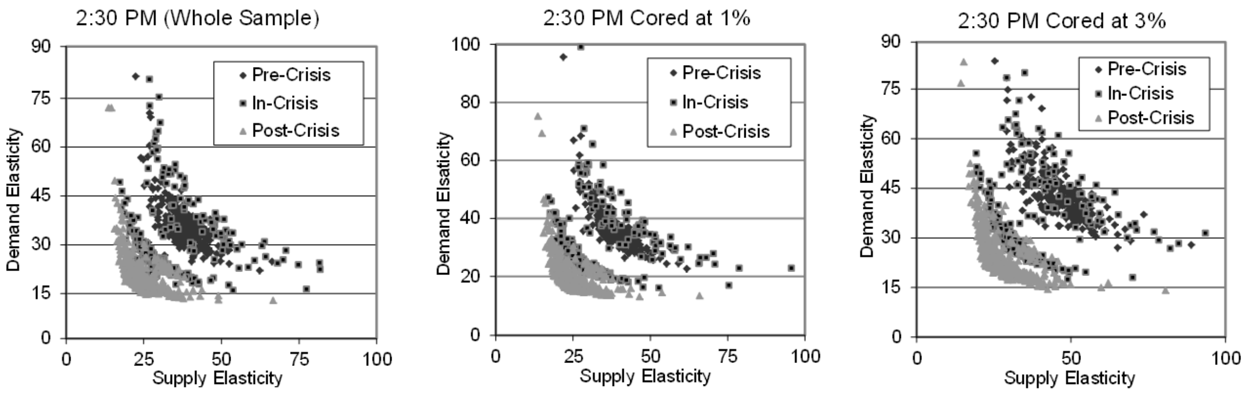
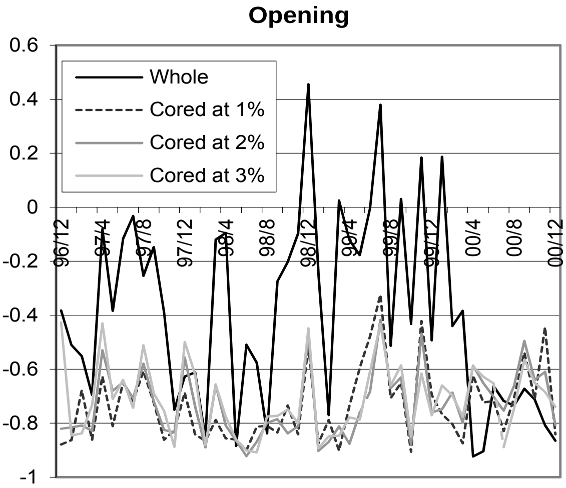
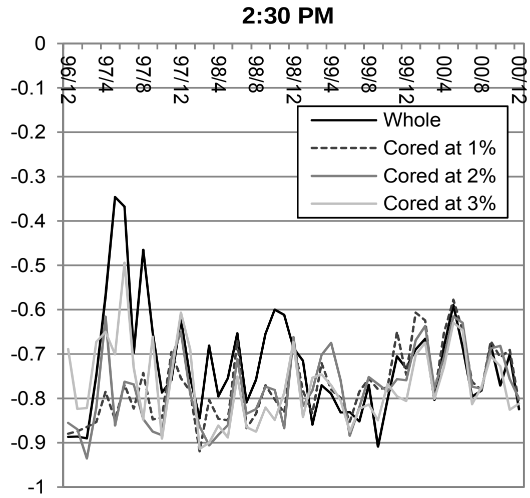


Figure 6. Correlations of Demand and Supply Elasticities

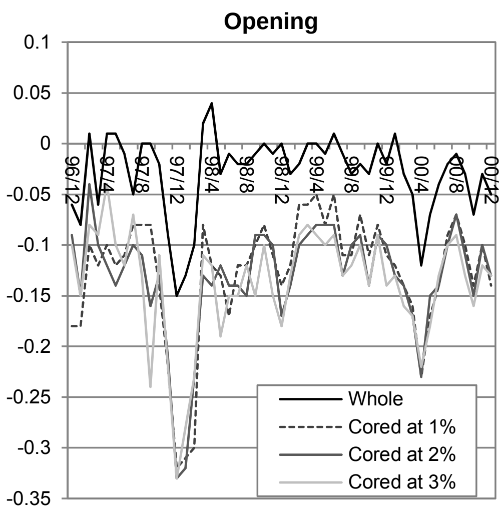
Each stock's elasticity of demand is the negative of the coefficient of log price in a regression explaining log quantity demanded at that price in the stock's limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are measured from December 1996 through December 2000 at the opening auction and at 2:30 PM whenever the stock's relevant limit order 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 11:30 AM. For Panel A, each day, we calculate the average of daily supply and demand elasticities for all firms. We then calculate the correlation between aggregate demand and supply elasticities using all days in each month. For Panel B, correlations are calculated at the individual firm level and then averaged over all the firms within the month.

Panel A: Correlations of Daily Mean Demand and Supply Elasticities Across all Stocks





Panel B: Mean Correlations of Individual Stock's Daily Demand and Supply Elasticities



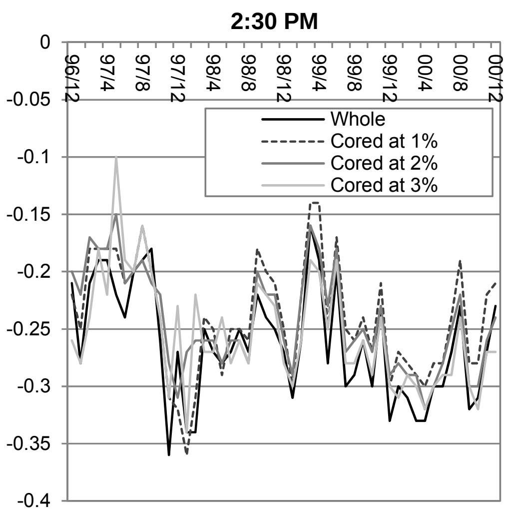
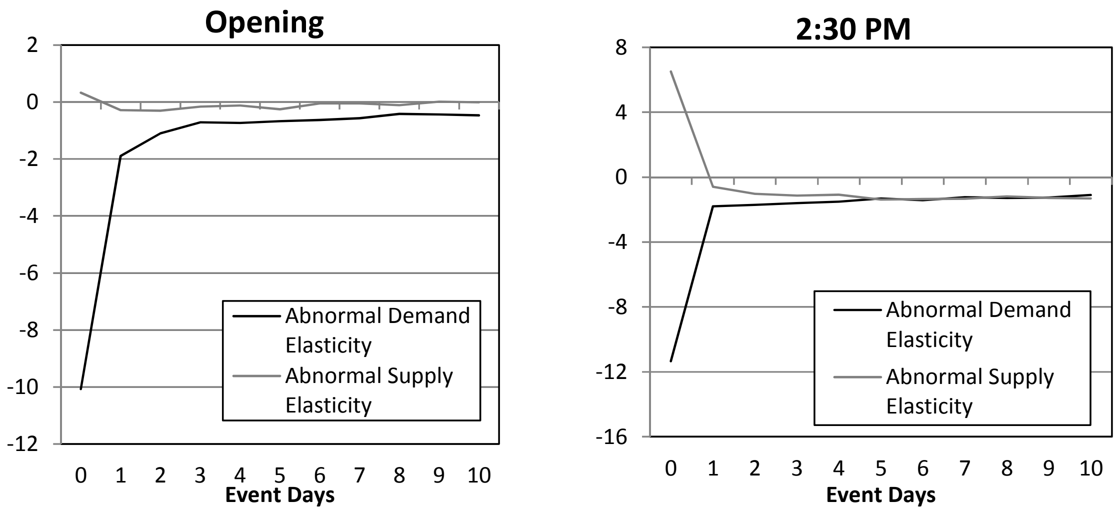


Figure 7. Days with Very Inelastic Demand and Supply Curves

The sample period is partitioned into pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods. For each period, we estimate the average values of demand and supply elasticities for each firm. We calculate the mean-adjusted values using the average values for each period. Finally, we select firm-day observations that have estimates of demand and supply elasticities for 10 subsequent trading days. Days with very inelastic demand curves are those where the abnormal demand elasticity is at 20 percentile or below for each firm. Days with very inelastic supply curves are those where the abnormal supply elasticity is at 20 percentile or below for each firm. 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 whenever a schedule has more than 5 price-quantity pairs. Elasticities are measured twice on each trading day: 1) at the opening auction and 2) 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 AM those days. The sample includes firm-day observations that have elasticities both demand and supply at either the opening auction or at 2:30 PM. We exclude the last 10 trading days.

Panel A: Days with Very Inelastic Demand Curves (Whole Curves)



Panel B: Days with Very Inelastic Supply Curves (Whole Curves)

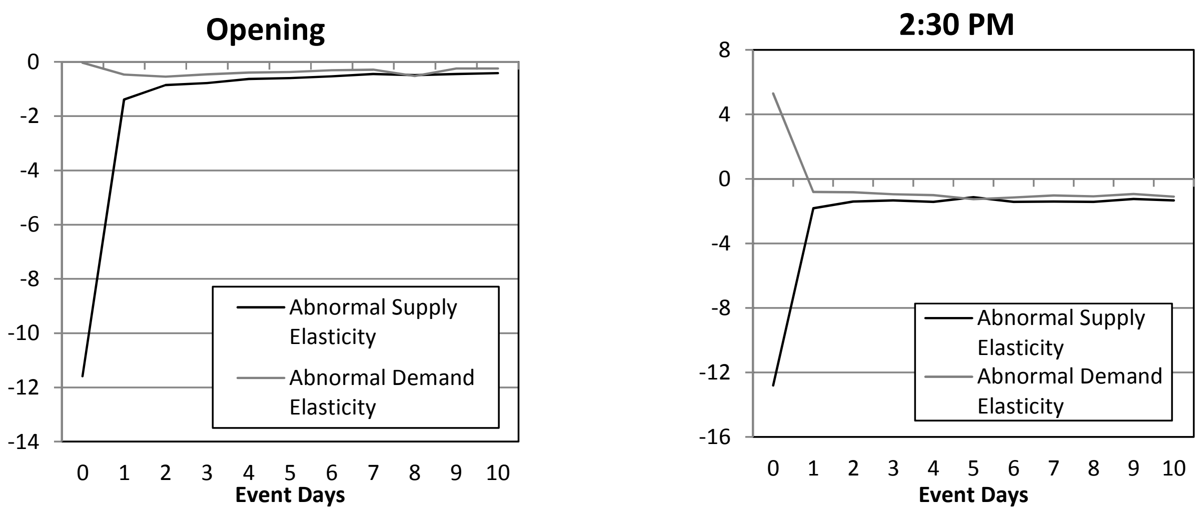


Table 1. Distribution of Orders and Trades

Orders can be limit or market orders, and can be submitted in an opening auction or in continuous trading throughout the day. Data are for common stocks trading on the Korea Stock Exchange (KSE) from December 1996 to December 2000. Each daily trading session is partitioned into an opening auction and the continuous trading during the rest of the day. Values in parentheses are average order sizes.

Order Type		Entire Day	Opening Auction	Rest of Day Continuous Market
Buys	Market	13,938,249 (1,177.4)	3,620,127 (1,096.11)	10,318,122 (1,205.92)
	Limit	253,301,774 (1,298.6)	47,428,384 (1,251.1)	205,873,390 (1,309.54)
	Total	267,240,023 (1,292.28)	51,048,511 (1,240.11)	216,191,512 (1,304.6)
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

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

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

Panel B: 2:30 PM

Limit Order Price as Percent of the Bid-Ask Mid-Point	Demand		Supply	
	Quantity	Percent of Total Quantity	Quantity	Percent of Total Quantity
Price < 85%	6,044	13.80%		
85% ≤ Price < 90%	7,984	18.2		
90% ≤ Price < 95%	10,053	22.9		
95% ≤ Price < 97%	6,359	14.5		
97% ≤ Price < 98%	4,102	9.3		
98% ≤ Price < 99%	4,907	11.2		
99% ≤ Price < 100%	4,476	10.2		
100% ≤ Price < 101%			3,321	6.60%
101% ≤ Price < 102%			4,521	9
102% ≤ Price < 103%			4,610	9.2
103% ≤ Price < 105%			8,651	17.2
105% ≤ Price < 110%			15,438	30.8
110% ≤ Price < 115%			8,563	17.1
115% ≤ Price			5,088	10.1
Total	43,925	100.00%	50,193	100.00%

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 at that price in its limit order book; while its elasticity of supply is the coefficient in an analogous regression explaining log quantity supplied. Elasticities are measured twice each day from December 1996 to December 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

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

Panel B: Elasticity of Supply

Trading Session	Sub-Period	Observations	Mean	Median	Std. Dev.
Opening auction	Entire sample period	608,952	27.048	24.409	14.341
	Pre-crisis period	125,565	38.594	36.88	18.215
	In-crisis period	136,922	27.535	25.626	14.862
	Post-crisis period	346,465	22.671	21.895	9.293
2:30 PM	Entire sample period	632,702	28.822	23.368	22.257
	Pre-crisis period	147,261	38.096	32.885	24.297
	In-crisis period	139,688	30.372	25.039	23.174
	Post-crisis period	345,753	24.246	20.402	19.482

Table 4. Monthly Cross-Correlations: Daily Mean Elasticities and Firm-Level Elasticities

In Panel A, for each trading day, we calculate the cross-sectional average values of demand and supply elasticities. Then, using these average values, we estimate the cross-correlation between demand and supply elasticities for each 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 estimated whenever a schedule has more than 5 price-quantity pairs. Whole elasticities are estimated using whole demand or supply limit order schedules, cored elasticities use all parts of the schedules except intervals within one or three percent around market prices. Elasticities are measured twice on each trading day: 1) at the opening auction and 2) 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 AM those days. The sample is partitioned into pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods. Panel B is constructed similarly, but here we first calculate the cross-sectional correlation between demand and supply elasticities for each stock for each month, and then compute the average value for the firm level cross-correlation across all firms and all months in the sample period.

Panel A: Monthly Mean Cross-Correlations (Market Level)

		Opening Auction				2:30PM			
		Entire Sample	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**	**Entire Sample**	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**
Whole Sample	Mean	-0.388	-0.343	-0.517	-0.348	-0.732	-0.668	-0.726	-0.763
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Cored at 1%	Mean	-0.750	-0.760	-0.818	-0.714	-0.778	-0.833	-0.800	-0.744
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Cored at 3%	Mean	-0.716	-0.661	-0.778	-0.711	-0.773	-0.730	-0.818	-0.771
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Panel B: Monthly Individual Cross-Correlations (Firm Level)

		Opening Auction				2:30PM			
		Entire Sample	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**	**Entire Sample**	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**
Whole Sample	Mean	-0.026	-0.020	-0.036	-0.025	-0.263	-0.215	-0.280	-0.274
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	# Obs.	36,764	7,297	7,611	21,856	37,822	7,876	7,743	22,203
Cored at 1%	Mean	-0.119	-0.111	-0.153	-0.111	-0.239	-0.200	-0.260	-0.243
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	# Obs.	32,882	5,459	6,309	21,114	36,927	7,338	7,485	22,104
Cored at 3%	Mean	-0.132	-0.114	-0.152	-0.129	-0.263	-0.210	-0.257	-0.272
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	# Obs.	26,889	1,841	4,804	20,244	30,642	2,959	6,081	21,602

Table 5. Firm-Level Panel Regressions of Supply on Demand Elasticities

Firm-level daily panel regressions are of $\tilde{\eta}^{S}_{j,t} = \alpha_j + \beta \tilde{\eta}^{D}_{j,t} + \varepsilon_{j,t}$, with $\tilde{\eta}^{S}_{j,t}$ and $\tilde{\eta}^{D}_{j,t}$ stock *j*'s market-adjusted limit order supply and demand elasticities on day *t* and the α_j are 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 whenever a schedule has more than 5 price-quantity pairs. Whole elasticities are estimated using whole demand or supply limit order schedules, cored elasticities use all parts of the schedules except intervals within one, two, or three percent around market prices. we report separate regressions using elasticities at the opening auction and using elasticity snapshots or limit order books 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 AM those days. The sample is partitioned into pre-crisis (December 1996 – October 1997), in-crisis (November 1997 – October 1998), and post-crisis (November 1998 – December 2000) periods. Probability levels (p-values) are based on *t*-statistics adjusted for firm clustering.

		Opening Auction				2:30PM			
		Entire Sample	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**	**Entire Sample**	**Pre-Crisis**	**In-Crisis**	**Post-Crisis**
Whole Sample	Mean	0.006	-0.006	-0.016	0.007	-0.178	-0.187	-0.206	-0.167
	p-value	0.016	0.166	<0.001	0.008	<0.001	<0.001	<0.001	<0.001
	adj. R^2	0.027	0.046	0.044	0.049	0.030	0.045	0.044	0.029
	# Obs.	530,405	89,321	110,910	330,174	544,224	102,645	111,088	330,491
Cored at 1%	Mean	-0.107	-0.129	-0.146	-0.083	-0.156	-0.176	-0.194	-0.143
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	adj. R^2	0.019	0.042	0.027	0.020	0.024	0.045	0.037	0.023
	# Obs.	423,593	45,162	78,700	299,731	491,918	70,914	99,680	321,324
Cored at 3%	Mean	-0.106	-0.182	-0.131	-0.119	-0.164	-0.252	-0.176	-0.181
	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	adj. R^2	0.021	0.039	0.022	0.022	0.026	0.053	0.033	0.027
	# Obs.	321,442	10,324	50,022	261,096	351,460	14,539	59,708	277,213