Why Designate Market Makers?
Affirmative Obligations and Market Quality

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Comments Welcome

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Abstract

We study why most financial markets designate one or more agents who precommit to provide more liquidity than they would endogenously choose, and identify two reasons that such affirmative obligations can improve welfare. The first relies on the insight that the informational component of the competitive bid-ask spread represents a transfer across traders, not a social cost to completing trades. As such, this trading cost dissuades efficient trading, while a restriction on spread widths encourages efficient trading. Secondly, a restriction on spread widths encourages traders to become informed, which speeds the rate at which market prices move toward true asset values in the wake of information events. We consider the setting where competition ensures that affirmative obligations impose net trading losses on designated market makers that must be compensated by side payments, as observed on the Euronext limit order market, and also the setting where the designated market maker is allowed some advantages relative to limit order traders so that profits can be earned during tranquil periods to offset losses incurred when affirmative obligations are binding, as observed on the NYSE.

I. Introduction

Researchers have, at least since Demsetz (1968), emphasized the importance of liquidity in financial markets. Liquidity can be supplied through quotations in a dealer market or limit orders in an auction market, either of which gives liquidity demanders the option to transact up to a specified quantity at a specified price. Liquidity demanders typically pay liquidity suppliers for the right to transact quickly, in that their buy orders are on average completed at higher prices than their sell orders.

In this paper, we shed some light on the little-studied question of why most financial markets choose to designate one or more agents as market makers, who agree to take on certain affirmative obligations to provide liquidity. To be meaningful, these affirmative obligations must require designated market makers to provide liquidity beyond that which they would endogenously choose to provide, in at least some circumstances. An important distinction is that we do not ask why some agents choose to supply liquidity or why liquidity provision is valuable, but rather why it is efficient to create contracts where some agents *precommit* to provide more liquidity than they would otherwise choose.

The answer to the question we pose cannot simply be "because liquidity is valuable." Standard textbook models of a competitive industry imply that, in the absence of barriers to entry to becoming a supplier of liquidity or significant externalities, market forces will induce dealers or limit order traders to endogenously provide the socially optimal amount of liquidity, i.e. the amount where the marginal value to society of increasing liquidity equals the marginal cost to society. Nevertheless, designated market makers with affirmative obligations are often observed.[1] Perhaps the most prominent example is the New York Stock Exchange (NYSE) specialist, who is charged with maintaining a "fair and orderly market".[2] However, the NYSE is far from unique in designating market makers. In their survey of stock market structures around the world, Charitou and Panayides (2006) note that the Tokyo Stock Exchange is the only major stock market that relies entirely on the endogenous submission of limit orders for liquidity provision. Most major stock markets, including the NYSE, Nasdaq, the Toronto Stock Exchange, the London Stock Exchange, the Deutsche Borse, Euronext, and the main stock markets of Spain, Italy, Greece, Denmark, Austria, Finland, Norway, and Switzerland designate market makers with affirmative obligations to supply liquidity for at least some stocks.

We demonstrate some reasons why it can be socially efficient to specify affirmative obligations for designated market makers, focusing in particular on the obligation to maintain a quoted bid-ask spread that does not exceed a specified level. A "maximum spread rule" is by far the most common affirmative obligation noted by Charitou and Panayides (2006) in their survey of international stock markets.

We consider two scenarios. In the first, we assume that market making is fully competitive and that the designated market maker has no inherent advantage in terms of information or costs as compared to other liquidity providers. In this case competition precludes spreads from ever being set so wide as to yield a positive expected profit, yet we obligate the designated market maker to sometimes maintain spreads that are

[1] Make note that several derivative markets also use designated market makers, and some have recently introduced them.
[2] The specialist has affirmative obligations to prevent discrete price jumps (the "price continuity rule") and to commit capital to improve on the best prices in the limit order book at times when endogenous liquidity is lacking.

narrower than the competitive outcome. To entice a market maker to assume such an obligation would require a subsidy or side payment. Compensation agreements of this type are in fact observed on Euronext and some other limit order markets, whereby the listed firm makes direct payments to the designated market maker.

The second scenario explores an alternate compensation mechanism, namely endowing the market maker with some monopoly power, but restraining behavior with a maximum spread rule. The basic idea is that at times when the competitive spread would be wide, e.g. just after an information event, restrictions on the allowable spread result in market maker losses. At other times, when the competitive spread would be narrow, the monopoly power of the market maker (restrained by the spread rule) allows the liquidity provider to recoup these losses. This scenario is a simplified version of the NYSE specialist system, where the specialist's ability to observe real time conditions on the trading floor provides an informational advantage as compared to off-exchange submitters of limit orders.[3] Our analysis shows that this mechanism of compensating the liquidity provider can result in improved welfare relative to the competitive case, while still allowing the market maker to break even.[4]

To examine the effects of market maker affirmative obligations, we rely on the sequential trade framework of Glosten and Milgrom (1985, henceforth "GM"), which involves informed traders, uninformed (liquidity) traders, and market makers. Initially, we assess bid and ask quotes and trading outcomes by period for specified sets of

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[3] Ready (1997) and Harris and Panchapagesan (2005) provide empirical evidence that the specialist is able to profit from her information advantage relative to those who submit limit orders.

[4] We do not solve for the optimal compensation mechanism. Rather our goal is to illustrate the intuition of how affirmative obligations, in combination with two different methods of compensating the market maker, can improve social welfare.

parameters using the GM condition that market-making profits are zero in expectation during each trading round. This fully competitive framework provides a benchmark for assessing market performance. We then address market performance in the presence of (1) an affirmative obligation that requires a designated market-maker to maintain a quoted spread that is the lesser of the competitive spread or a stated percentage of the asset's conditional expected value, and (2) an affirmative obligation to maintain a spread that equals a stated percentage of the asset's conditional expected value, which depending on market conditions can be greater or less than the competitive spread. We refer to the former as the "maximum spread rule" and the latter as the "fixed spread rule".

When the constraint narrows the spread relative to competitive levels, the designated market maker suffers losses to informed traders. Nevertheless, social welfare can be improved by the affirmative obligation. As Glosten and Milgrom emphasize the bid-ask spread arises in this framework as an informational phenomenon, allowing the market maker to recoup from uninformed traders the losses incurred in transacting with better-informed traders. More generally, the costs incurred by a market maker include costs to society as a whole that arise because real resources must be used to complete trades, as well as expected market-maker losses that arise from informational asymmetries. However, while the latter reflects a private cost to the market maker, it is a transfer rather than a cost from the viewpoint of society as a whole. Some uninformed traders, for whom the potential gain from trade is less than the spread, are dissuaded from trading by the spread. One reason that a maximum spread rule improves social welfare is that more uninformed investors will choose to trade when the spread is narrower.

Increased trading by uninformed investors enhances efficiency as long as the spread is not constrained to be less than the social cost of completing trades.

A second social benefit attributable to a maximum spread rule can arise due to improved price discovery. In addition to facilitating transactions, an important function of financial markets is to establish through trading and other market communications the correct value of an asset. In the GM sequential trade framework the asset's true value is known (potentially with noise) to informed investors, but not to market makers or uninformed investors. While uninformed trades fluctuate randomly between buys and sells, informed trades are clustered on the buy (sell) side if the asset is under (over)-priced in the market, which pushes market prices towards value.

Rules constraining the spread affect the speed of price discovery by encouraging more trading by both informed and uninformed investors. When we hold the proportion of the trading population that is informed fixed, we find for parameters examined that increased noise due to more uninformed trading in the presence of a maximum spread rule dominates, and the rate of price discovery is slowed when a maximum spread rule is imposed. However, a maximum spread rule also improves the profitability of being informed and incentives to become informed. When we allow the percentage of the trading population that is informed to vary endogenously as a function of the spread rule in effect we find that the rate of price discovery is improved by the existence of both the maximum spread rule and the fixed spread rule.

Our analysis does not comprise a complete theory of affirmative obligations. We focus only on only one type of market maker obligation, the commitment to maintain narrow spreads. Further, since the GM framework focuses on traders who arrive sequentially in an exogenously determined order, and who transact either zero or one unit, we have not considered potential effects on trade timing, trade sizes, or repeat trading. Also, since the GM model provides a fully competitive outcome as the benchmark, we have not considered the possible role of affirmative obligations in a market that is less than perfectly competitive, e.g. due to costs of submitting limit orders. Finally, though we consider two possible compensation methods, we have not provided a formal analysis of the important question of how market makers should optimally be compensated for taking on affirmative obligations to supply liquidity. Nevertheless, we hope that our analysis provides a useful contribution toward the development of a comprehensive theory of optimal contracting for liquidity provision.

II. Related Literature

Many authors have provided models of market maker behavior.[5] Among these, Demsetz (1968) shows that market maker spreads will decline as a function of typical trading activity in the stock. Ho and Stoll (1980) provide a model of the effects of inventory accumulation on market maker quotes. Dutta and Madhavan (1997) consider the possibility of collusion among dealers, while Kandel and Marx (1997) study the effect of a discrete pricing grid on dealer quotation strategies.

However, in the literature cited above, the emphasis is on endogenous liquidity provision, i.e. on dealers' and limit order traders' optimal behavior in the absence of any externally imposed obligation to supply liquidity. Glosten (1989) provides a model of a

[5] There is also an extensive empirical literature on market maker quotations. Among these, Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) each provide empirical evidence on NYSE specialist quotes, while Bessembinder (2003) studies intermarket quotations for NYSE stocks. Christie and Schultz (1994) and Barclay, Christie, Harris, Kandel, and Shultz (1999), among others, study Nasdaq quotations.

monopolist market maker, motivated by reference to the NYSE's single specialist in each stock. As in GM, market making that is competitive in the sense that expected profits equal zero on each trade can lead to marker failure if the degree of information asymmetry between the market maker and informed traders becomes too severe. Glosten extends the GM analysis to allow for both large and small trades, and for monopolistic as well as competitive market making. His key finding is that for some parameters the monopolistic market maker is willing to incur losses on the large trades favored by informed traders, while earning profits on small trades. The monopolist structure is therefore more robust, in the sense that the market may remain open even at times when trading is dominated by informed investors, and where a fully competitive market would shut down. However, Glosten also does not consider the role of affirmative market making obligations.

Rock (1996) and Seppi (1997) extend the analysis by allowing for limit orders that compete with a single designated market maker ("specialist"). In Rock's model, risk neutral limit order traders have an advantage against risk-averse specialists, countered by an information advantage to the specialist. In the Seppi model, limit order submitters incur a cost, so that competition from the limit order book is muted, allowing the specialist a degree of monopoly power. Seppi uses this framework to assess the effect of a change in the minimum price increment, which alters relative importance of markets' price and time priority rules, on market quality. However, neither Seppi nor Rock incorporates affirmative market making obligations in their models.

Venkataraman and Weisburd (2006) provide a model quantifying the effect of a designated market maker in a periodic auction market. Their model features a finite number of investors in each auction, leading to imperfect risk sharing. The designated market maker in their model is essentially an additional trader who is present in every round of trading, leading to improved risk sharing. In contrast, by comparing to the fully competitive benchmark we implicitly assume the presence of a sufficient number of liquidity suppliers, and highlight the efficiency gains created when one or more of the existing traders take on affirmative obligations to supply more liquidity than they would endogenously choose.

A limited set of empirical researchers have focused on the question of whether designated market makers affect market quality. Anand and Weaver examine market quality on the Chicago Board Options Exchange (CBOE) during 1999, when that market began to assign "Designated Primary Market Makers" to each traded option.[6] They document decreased bid-ask spreads and increased CBOE market share after designated market makers were assigned. Venkataraman and Weisburd (2006) study the Euronext Paris equity market, where listed firms have the option to contract for the services of a designated market maker, who is required to maintain a maximum spread. The authors report that market quality is better for stocks with designated market makers as compared to matched stocks without. Even more striking, they document a positive abnormal return of nearly 5% for stocks announcing the introduction of designated market makers. Finally, Panayides (2006) provides evidence that specialists on the NYSE exhibit different behaviors during times that they are constrained by an alternate affirmative obligation, the "price continuity rule" (which is related to our maximum spread rule) imposed by the exchange. Particularly relevant for our analysis, Panayides finds that

[6] The designated market makers on the CBOE took on affirmative obligations including a continuous maximum spread rule and a requirement to execute odd lot trades. In return, the designated market maker was allowed exclusive access to the limit order book and was guaranteed a share of order flow.

market makers incur losses at times when the rule is binding, but are able to earn positive profits during periods when they are not constrained by the rule.

The paper that is most similar to ours in terms of research approach is Hollifield, Miller, Sandas, and Slive (2006), who also consider the social gains produced by trade in a security market. In particular, they compare the gains from trade actually realized in an imperfectly competitive limit order market to the maximum theoretically attainable gains from trade and to the gains that would be obtained with a monopolist market maker. We compare the gains from trade realized in a perfectly competitive market to the gains realized in a market where a maximum spread rule sometimes constrains the spread to be less than the competitive level, and compare both sets of outcomes to the maximum theoretically attainable gains from trade.

III. The Framework

Each potential trader i is endowed with cash plus one unit of the risky asset. This asset has an economic value of V, which is initially known to some traders but must be estimated by other traders and the market maker. As in Glosten and Milgrom (1985), the subjective value of the asset to each trader also depends on a preference parameter ρ_i; such that the trader's personal valuation of the asset under full information is $V + \rho_i$. Individuals with a strong saving motive will have positive subjective value while individuals with a strong consumption motive will have negative subjective values. We assume that the distribution of ρ_i across traders has a zero mean and is symmetric. Cross-sectional variation in ρ_i is the reason that trading improves social utility. Each trader's final utility is their cash balance plus the product of the number of units of the asset they hold and their personal valuation of the asset. Traders are risk neutral, and trade to maximize expected utility. For the market maker ρ is zero, i.e. the market maker derives utility only from monetary gains and losses.

Following Glosten and Milgrom (1985), potential traders arrive at the market sequentially and in random order. Upon observing the market maker's ask and bid quotes the trader can choose to buy one additional unit of the asset, sell the endowed unit of the asset, or refrain from trading. When a trade is executed the market maker incurs an out of pocket cost, c. A known proportion of the traders are informed. These traders know the economic value of the asset, V, while the remaining traders and the market maker do not know the asset value, but can form a conditional expectation of value.

Let A_i and B_i denote the ask and bid quotes in effect at the time customer i arrives at the market. The change in a customer's final utility due to the trade if she elects to purchase an additional unit of the asset is $(\rho_i + V) - A_i$, while the gain or loss to the market maker from a customer buy is $A_i - V - c$. The total social (customer plus market maker) gain due to the customer purchase is $\rho_i - c$. Similarly, the change in a customer's final utility if she elects to sell her endowed unit of the asset is $B_i - (\rho_i + V)$, while the gain to the market maker from a customer sale is $- B_i + V - c$, providing a net social gain from a customer sale of $-c - \rho_i$. If N potential traders come to market, resulting in N_B customer buys and N_S customer sales (with $N_B + N_S \leq N$), then the accumulated gains from trade can be stated as:

Total Gain to Traders (TGT) = $V(N_B - N_S) + \sum_{i=1}^{N_B} \rho_i - \sum_{j=1}^{Ns} \rho_j - \sum_{i=1}^{N_B} A_i + \sum_{j=1}^{Ns} B_j$ (1)

Total Gain to Market Maker (TGM) = $V(N_S - N_B) - (N_S + N_B)c + \sum_{i=1}^{N_B} A_i - \sum_{j=1}^{Ns} B_j$ (2)

Total Gain to Society (TGS = TGT + TGM) = $\sum_{i=1}^{N_B} \rho_i - \sum_{j=1}^{Ns} \rho_j - (N_S + N_B)c$. (3)

Note that the expression for the total gain to society from trading does not depend on the actual value of the asset, V, since the existing assets are simply moved across traders. The total gain does depend on cross-sectional variation in the subjective valuation parameter, ρ, and in particular on the extent to which the sum of the ρ for buyers exceeds the sum of the ρ for sellers, and on the real resources consumed in executing trades. Also, while the ask and bid quotes do not directly enter the expression for TGS, the total gain to society from trading depends indirectly on the quotes, as these affect decisions to trade.

Note that $dTGS/dN_S = -\rho_i - c$, implying that the social gains from trade are increased by an additional customer sale if $\rho_i < -c$. Similarly, $dTGS/dN_B = \rho_i - c$, implying that the social gains from trade are improved by an additional customer purchase if $\rho_i > c$. Social welfare is maximized if all those with $\rho_i > c$ purchase an additional unit of the asset, all those with $\rho_i < -c$ sell their endowed unit of the asset, and those with $|\rho_i| < c$ do not trade. These conditions simply reflect that welfare is maximized when the assets are transferred to those who value them most highly, except when the differential in valuations is less than the social cost of consummating the transaction. For any given cross-sectional distribution of ρ_i it is possible to compute the maximized TGS and use it as a benchmark, by comparing the actual TGS obtained from any particular market structure to the maximized TGS.

Actual trading decisions in the GM framework will differ from those that maximize TGS because the ask and bid quotes reflect the conditional expected value of the asset rather than the true value, and because the bid-ask spread includes an asymmetric information component in addition to the component that reflects the social cost of completing trades, c. In the ensuing discussion we will refer to trades that would maximize social welfare as those that traders "should" make, and to trading decisions that differ from those that would maximize social welfare as "mistakes". However, all trading decisions are rational and privately optimal, and are mistakes only when compared to the perfect, but unobtainable, benchmark. Some decisions deviate from those that would maximize social welfare because of market imperfections, including imperfect price discovery and information-based externalities.

Let Z_i denote the observable history of trades prior to trader i arriving at the market, as well as any other information known to all market participants. GM show that in their framework the competitive bid and ask quotes offered to trader i will be

$B_i = E(V \mid Sell, Z_i) - c$,

and

$A_i = E(V \mid Buy, Z_i) + c$,

where $E(V \mid Sell, Z_i)$ denotes the expected value of V conditional on Z_i and a sale by trader i and $E(V \mid Buy, Z_i)$ denotes the expected value of the asset conditional on Z_i and a purchase by trader i. The Appendix discusses in detail how we determine the GM quotes in each trading round.

If trader i is informed then she knows the asset value, V, and will buy if $\rho_i + V > A_i$, or equivalently if $\rho_i > E(V \mid Buy, Z_i) - V + c$. Similarly, informed trader i will sell if $\rho_i + V < B_i$, or equivalently if $\rho_i < E(V \mid Sell, Z_i) - V - c$. The informed trader will refrain from trading if $B_i < \rho_i + V < A_i$. As noted earlier, it is socially efficient for traders to buy if $\rho_i > c$ and to sell if $\rho_i < -c$.

Note that the informed trader on some occasions will sell when they should buy or not trade, will sometimes buy when they should sell or refrain from trading, or may fail to trade when they should do so.[7] For example an informed trader with $\rho_i < -c$ should sell to in order to maximize social gains from trade, but will elect to buy if $\rho_i - c > E(V \mid Buy, Z_i) - V$, i.e. if conditional expected value of the asset is sufficiently less than the true value. Similarly, an informed trader with $\rho_i > c$ should buy to enhance total social gains from trade, but will choose to sell instead if $\rho_i + c < E(V \mid Sell, Z_i) - V$, i.e. if the conditional expected value sufficiently exceeds the true value. The informed trader may make decisions that depart from those that maximize social welfare because securities are not priced at their full information values, and informed traders may have private incentives to capture the mispricing. However, these trades in the wrong direction are only suboptimal when compared to a world characterized by full information. In the presence of asymmetric information, trading is required to reveal the full information value of the security.

If price discovery is complete, in the sense that $E(V \mid Sell, Z_i) = E(V \mid Buy, Z_i) = V$, then the informed trader will always trade in the correct direction. This insight illuminates one reason that market rules, including the maximum spread rule, can potentially affect the total social gains from trade: if the rule improves the speed with which the market discovers the true security value, then it will also reduce the number of trades in the "wrong" direction by informed traders.

An uninformed trader who arrives at time i does not know the value of the security, but can form the conditional expectation $E(V \mid Z_i)$. The uninformed trader will

[7] Hollifield, Miller, Sandas, and Slive (2006) also note that one reason actual markets fail to realize the theoretically attainable gains from trade is that informed traders will sometimes trade in the wrong direction.

decide whether to buy, sell, or refrain from trading depending on her subjective expected value and market maker quotations. In particular, the uninformed trader will buy if ρ_i + E(V| Z_i) > A_i, or equivalently if ρ_i > E(V |Buy, Z_i) – E(V| Z_i) + c. Similarly, the uninformed trader will sell if ρ_i + E(V| Z_i) < B_i, or equivalently if ρ_i < E(V |Sell, Z_i) – E(V| Z_i) – c. The informed trader will refrain from trading if B_i < ρ_i + E(V| Z_i) < A_i.

In the GM framework E(V|Buy, Z_i) exceeds E(V| Z_i) and E(V|Sell, Z_i) is less than E(V| Z_i), reflecting the presence of traders better informed than the market maker. Hence, the uninformed trader will never make an error of commission by trading in the wrong direction. However, the uninformed trader will make errors of omission. In particular, when 0 < ρ_i – c < E(V |Buy, Z_i) - E(V| Z_i) the uninformed trader will refrain from trading even though social welfare would be enhanced by a buy, and when 0 > ρ_i + c > E(V |Sell, Z_i) - E(V| Z_i) the uninformed trader will choose to not trade even though a sale would enhance social welfare.

This discussion illustrates a second avenue by which market rules, including a maximum spread rule, can potentially improve social welfare: by encouraging uninformed traders to trade in cases where they otherwise would not. This reflects a simple externality argument. The portion of the bid-ask spread that reflects information asymmetries represents a private cost to the market maker that is passed on to customers, but does not reflect a net social cost of completing trades, leading to less trading than is socially efficient.

IV. Assessing the Potential Effects of a Maximum Spread Rule

To assess and illustrate the effects of imposing a maximum spread rule in an otherwise competitive financial market, we adopt a simulation approach. In each individual simulation, fifty potential traders come to the market sequentially and in random order. Each individual trader observes the quotations and chooses to buy one unit, sell one unit, or to refrain from trading. Several market outcomes, including informed traders' gains from trade, uninformed traders gains' from trade, market maker profit or losses in transacting with informed and uninformed traders, the number of no-trade decisions, and the number of trades that are in the "correct" direction, are recorded for each simulation. We also measure price discovery by recording for each trade the pricing error defined as the absolute deviation between $E(V| Z_i)$ and the true value, V, and also noting in which trading round of the simulation this differential is reduced to specified threshold.

Market outcomes are simulated both when spreads are set according to the GM condition that expected market making profits are zero on each trade, and in the presence of a maximum spread rule where spreads are constrained to never be wider than a specified percentage of the asset's expected value $E(V| Z_i)$ at the beginning of each trading round. The appendix describes in more detail how we determine the GM quotations, conditional asset values, and trader decisions in each trading round. The simulations are repeated 10,000 times, providing 10,000 sets of market outcomes. We focus on mean outcomes across the 10,000 simulations.

We also record means of some measures, such as the pricing error, conditional on the round of trading. Each simulation begins with an unknown asset value. In the absence of an observed trading history to aid in price discovery, the early rounds of the simulation are characterized by relatively large divergences between market prices and true asset values, and can reasonably be interpreted as representing market conditions in the wake of an information event, where it is know that informed traders have received new information regarding asset values. Conversely the later rounds of the simulations can reasonably be interpreted as representing outcomes during more tranquil market conditions.

A trader who arrives in a given trading round is informed as to the asset value with publicly known probability P_I and uninformed with probability $P_U = 1 - P_I$. The actual asset value for a given simulation is either high (V = H) or low (V = L), with equal ex ante probability, where we set H = 2 and L = 1. We also assign to each individual trader i the subjective preference parameter ρ_i, as a random draw from a zero-mean normal distribution. We consider outcomes when the cross-sectional standard deviation of ρ, denoted σ_ρ, equals either 0.2 or 0.3, with the latter representing the case traders diverge more in the intensity of their desire to trade. We set the out-of-pocket cost of executing trades, c, to zero in the simulations, implying that the socially efficient outcome is for every trader to transact. The proportion of the population that is informed is determined endogenously. Specifically, the cost of becoming informed is set to 10% of the unconditional expected value of the asset E(V) = 1.5. The number of traders that choose to become informed is set such that the expected gain per informed trader (relative to informed trader arrivals, including non-trade outcomes) is equal to the cost of acquiring information.

Prior to the first trade in each simulation the expected value of the asset based on public information is E(V) = 1.5. As in GM, the market maker sets "no regret" ask and bid quotes, and uses Bayesian learning to update $E(V| Z_i)$ after observing the trading outcome (observed buy, sell, or no trade) in each period. Our procedures for computing the GM quotes and for constraining the bid ask spread are described in detail in the appendix.

A. Simulation Outcomes With Competitive Quotes

Figure 1 displays mean spreads by trading round in the simulated GM framework, where quotes are set in each period such that expected market-making profits are zero. Each simulation allows for fifty potential traders to arrive, and we report average outcomes across 10,000 simulations. We simulate outcomes when the standard deviation of the private valuation parameter, ρ, is set to 0.3 and when it is set to 0.2. In the former case, we set the probability that a given trader is informed to be $P_I = .1896$, while in the latter case $P_I = .1703$.[8] Outcomes obtained in the GM framework serve as a benchmark against which to compare outcomes when a maximum spread rule is imposed. Two features of the figure are worth noting. First, average spreads are wide early on (in the wake of the known information event) and become narrower as information is incorporated into prices. Second, the spreads for $\sigma_\rho = 0.2$ are generally wider than those when $\sigma_\rho = 0.3$. This feature reflects the fact that informed traders on average have less subjective desires to trade when $\sigma_\rho = 0.2$, implying that they act more aggressively on their private information. Further, more uninformed traders choose to not trade when σ_ρ

[8] Recall that the proportion of the population that is informed is determined endogenously, conditional on the expected gain per informed trader (relative to informed trader arrivals, including non-trade outcomes) is equal to 10% of the unconditional expected value E(V)= 1.5.

= 0.2. These considerations worsen the adverse selection problem facing the market maker, requiring a wider spread in order for the market maker to break even.

Table 1 reports on several measures of trading activity and gains from trade. Panel A of Table 1 reports on trading activity in the GM setting. With c = 0 it is socially efficient for every trader to transact. However, due to the non-zero bid-ask spread, some traders do not. Notably, more traders choose to transact when $\sigma_\rho = 0.3$ than when $\sigma_\rho = 0.2$. This effect is larger for uninformed traders, as 86.4% transact in the former case compared to 78.6% in the latter case, while 93.7% of informed traders transact in the former case compared to 92.9% in the latter case. This reflects that greater cross-sectional variation in ρ implies that agents have a stronger desire to trade. Also, given the opportunity to trade profitably on their private information, some informed traders transact in the "wrong" direction, purchasing the asset even though their subjective valuation is negative, and vice versa. The percentage of informed traders who transact in the "correct" direction is 69.7% when $\sigma_\rho = 0.3$, and is 68.3% when $\sigma_\rho = 0.2$.

Panel B of Table 1 reports on measures of the gains from trade in the GM setting. The total gain to the market maker (TGM, as defined in expression (2)) is essentially zero, as required in the GM setting. When we compute TGM separately for trades with informed and uninformed traders, we observe that the market maker profits in trades with the uninformed trader and suffers losses in trades with the informed trader. The average profits and losses across fifty potential trades (1.70 when $\sigma_\rho = 0.3$ and 1.33 when $\sigma_\rho = 0.2$) are large relative to the unconditional mean value of the asset, which is 1.5.

Total gains to traders (TGT, as defined by expression (1)) are computed separately for informed and uninformed traders, as is the total gain to society (TGS, as defined by expression (3)) and each is reported in the indicated columns of Panel B. Each of these quantities is positive, reflecting utility gains from trading, and more so when σ_ρ is greater, reflecting stronger desires to trade. However, since some traders refrain from trading and some trade in the wrong direction, the actual gains from trade fall short of the maximum possible social gains from trade, by 8.6% when $\sigma_\rho = 0.3$ and by 13.5% when $\sigma_\rho = 0.2$.

Figure 2 displays descriptive information regarding the rate of price discovery in the GM framework. In each round of each simulation we compute the absolute value of the "pricing error", defined as $E(V| Z_i) - V$. Prior to the first round of trading this differential is always 0.5. Since informed traders are more likely to buy if the value is high and sell if the value is low, the observed pattern of buys and sells is informative, and Bayesian updating by the market maker on average decreases the differential between expected and actual value. The pricing error declines in a monotone manner with additional rounds, and the decline is more rapid when $\sigma_\rho = 0.2$ than when $\sigma_\rho = 0.3$. This last result reflects the fact that when $\sigma_\rho = 0.2$, the proportion of trading by informed traders relative to that by uninformed traders (i.e., more uninformed traders choose not to trade when $\sigma_\rho = 0.2$) is larger compared to the case when $\sigma_\rho = 0.3$. The higher proportion of informed trading leads to more rapid price discovery. The rates of price discovery displayed on Figure 2 for the GM framework comprise benchmarks for price discovery in the presence of a maximum spread rule.

B. Simulation Outcomes in the Presence of the Maximum Spread Rule

We next simulate market outcomes when the market maker is subject to a constraint on the maximum bid-ask spread, as a percentage of the current period expected value, E(V| Z_i). All parameters, including trader's subjective valuations, are the same as in the GM setting. When the constraint is not binding the bid and ask quotes are set as in GM so that expected profit conditional on a trade is zero.[9] When the constraint is binding the ask and bid quotes are adjusted toward each other in order to meet the constraint.

Quotations in the GM setting are typically not symmetric, in that the midpoint of the bid and ask quotes need not be equal to the conditional expectation of the asset value. We implement the maximum spread rule while maintaining any asymmetry that existed in the unconstrained quotes.[10] In particular, letting the superscript C denote a constrained quote and the superscript U denote an unconstrained (zero expected profit) quote, we select constrained ask and bid quotes at the arrival of trader i such that:

$$\frac{A_i^C - B_i^C}{A_i^U - B_i^U} = \frac{A_i^C - E(V \mid Z_i)}{A_i^U - E(V \mid Z_i)} = \frac{E(V \mid Z_i) - B_i^C}{E(V \mid Z_i) - B_i^U}.$$

If, for example, the constrained quote is 80% as wide as the unconstrained quote, then the constrained ask lies 80% as far above the expected value as does the unconstrained ask, and the constrained bid lies 80% as far below the expected value as does the unconstrained bid.

[9] However, the quotes in this case generally differ from those that would have prevailed in the same round in the absence of a maximum spread rule, because constraints on quotations in earlier trading rounds will generally have altered earlier trading decisions, which affects the conditional expected asset value.
[10] One alternative method of implementing the constraint is to reduce the bid and ask by the same amount, thereby ignoring any asymmetry that existed in the unconstrained quotes as:
$A_i^U - A_i^C = B_i^U - B_i^C = 0.5 \times \left[(A_i^U - B_i^U) - (A_i^C - B_i^C)\right]$. However, we find that such a constrain can result in decreased social gains relative to the GM case, reflecting that asymmetries in the GM quotations contain socially valuable information.

In Tables 2 through 5 we report on average trading activity and gains from trade across 10,000 simulations when maximum spread rules of varying tightness are in effect. GM outcomes are also reported for comparison. Tables 2 and 3 report outcomes when $\sigma_\rho = 0.3$, while Tables 4 and 5 report outcomes when $\sigma_\rho = 0.2$. For results reported on Tables 2 and 4 we fixed the proportion of traders that are informed at the same level used for the GM analysis. In contrast, for results reported on Tables 3 and 5 the proportion of traders that are informed is determined endogenously.

B.1. Outcomes with more variation in the desire to trade: $\sigma_\rho = 0.3$.

Focusing first on the trading activity results reported on Table 2, Panel A, we can observe that a maximum spread rule of 20% is never constraining, while a maximum spread of 10% constrains the market maker during about one third of the trading rounds, and a maximum spread of 5% constrains the quotes slightly more than half of the time. For comparison, we also report results for a maximum spread of zero, which constrains at all times. As would be expected, traders choose to transact more frequently when the spread is constrained. For example, informed traders transact on 93.6% of their arrivals in the GM case, as compared to 95.7% of the time when the spread is constrained to 5%. Uninformed trading grows more rapidly, from 86.4% in the GM case to 92.1% with a 5% spread.

Panel B of Table 2 reports on measures of gains from trade with and without the spread rule. The single most important observation is that the social gains from trade increase in the presence of the maximum spread rule, and more so when the spread is more constraining. The total social gain from trading increases from 10.93 when spreads are set at the zero profit level to 11.07 when the spread is constrained to zero. Note, however, that the social gains from trade remain less than the maximum possible level (by 7.4%) even with a zero spread, which reflects that some informed traders still trade in the "wrong" direction.

Implementing a maximum spread rule imposes losses on market makers, totaling 0.27 when the spread is constrained to 10%, 0.95 when the spread is constrained to 5%, and 2.35 when the spread is constrained to zero. This reflects that the maximum spread rule increases market maker losses to informed traders, and constrains the market maker's ability to recoup the losses when trading with uninformed traders. However, the increased gains from trade captured by both informed and uninformed traders in the presence of the maximum spread rule exceed the market maker losses. Clearly the market maker would need to be compensated for the losses imposed by the maximum spread rule, an issue that we address in part in the following section.

As noted in Section IV.A, the maximum spread rule may also affect the market's rate of price discovery. We report on this issue in two ways. First, Figure 3 displays the average pricing error, $|E(V| Z_i) - V|$, by round, relative to the average pricing errors obtained in the GM setting, as displayed on Figure 2. In cases where the average pricing error is larger (smaller) with the maximum spread than in the GM setting Figure 3 displays positive (negative) deviations. Second, on Table 6 we report on the average number of trading rounds required before the pricing error is reduced from its initial value of 0.5 to a level of 0.1.

The result that can be observed on Figure 3 and in column (1) of Table 6 is that, if the proportion of traders that are informed is held fixed, the maximum spread rule slows the rate of price discovery for the market setting and parameters we study. The maximum spread rule encourages more transactions by both informed and uninformed traders. Since uninformed traders transact randomly on the buy or sell sides, their trades comprise noise from the perspective of price discovery. In this setting the increased noise from greater uninformed trading more than offsets more aggressive trading by informed investors, and price discovery suffers.

Figure 3 shows that the increased pricing error averages about 0.0075, when the maximum spread rule is 10%, 0.015 when the maximum spread is 5%, and about 0.03 when the maximum spread is zero. Table 6 shows that the pricing error is reduced to a level of 0.1 after an average of 38.76 trading rounds in the GM case. This threshold is not reached until an average of 39.1 rounds when the maximum spread is 10%, 39.7 rounds if the maximum spread is 5%, and 41.0 rounds if the maximum spread is zero.

Recall, however, that we have assumed to this point that the proportion of traders who are informed is exogenously fixed at the same level as was optimal in the GM case. However, as Table 2 verifies, informed trading is more profitable with a maximum spread rule. Therefore, more traders would choose to bear any given fixed cost to become informed in the presence of the maximum spread rule.

We next assess the proportion of the trading population that would endogenously choose to bear a cost of 10% of the unconditional expected value E(V) to become informed, given the presence of an array of maximum spread rules. The optimal percentage of informed traders is determined numerically by allowing traders (selected at random) to purchase information. The equilibrium number of informed traders is determined when the average gain per informed trader across the 10,000 simulations is equal to the cost of acquiring information.

Table 3 reports results that correspond to those on Table 2, except that the number of informed traders is determined endogenously, and reflects the maximum spread rule in effect. Similarly, Figure 4 displays price discovery results relative to the GM benchmark in the case where the number of informed traders is determined endogenously that correspond to those on Figure 3 for an exogenous number of informed traders. The key result obtained from this exercise is that the maximum spread rule improves the market's rate of price discovery once the effect on the rule on the decision to become informed is also taken into account. Figure 4 shows that the improvement in price discovery after fifty trading rounds averages about 0.1 when the spread is constrained to 10% of expected value, and averages about .015 when the spread is constrained to zero. Results reported in column 2 of Table 6 confirm the more rapid price discovery, as the average pricing error is reduced to a level of 0.1 after 38.8 rounds of trade in the GM case, 37.6 rounds with a 10% maximum spread, and after 37.3 rounds with a zero spread. Finally, it can be noted by comparing results on Table 3 to those on Table 2 that the informed traders transact in the "correct" direction more frequently when the number of informed traders is endogenous. This reflects the fact that more rapid price discovery reduces incentives for informed traders to transact in the wrong direction, as noted in Section IV.A above.

B.2. Outcomes with less variation in the desire to trade: $\sigma_\rho = 0.2$.

Tables 4 and 5 report results for the case when $\sigma_\rho = 0.2$ that correspond to those reported in Tables 2 and 3 for the case when $\sigma_\rho = 0.3$. Table 4, Panel A shows that when the proportion of traders that are informed is exogenously fixed at the same level as was optimal in the GM case, the maximum spread rule is binding more frequently with σ_ρ = 0.2 compared to when σ_ρ = 0.3. For example, a maximum spread rule of 20% constrains the quotes about 14% of the trading rounds when σ_ρ = 0.2, but never constrains the quotes when σ_ρ = 0.3, while a maximum spread rule of 10% constrains the quotes about 35% of the time when σ_ρ = 0.2, but only binds about 33% of the time when σ_ρ = 0.3. Even though the maximum spread rule constrains the market maker more frequently in the case when σ_ρ = 0.2, the percentage of traders that choose to transact is actually lower than the case when σ_ρ = 0.3. For example, comparing the outcomes under a maximum spread rule of 20% in Tables 2 and 4, the uninformed traders transact on 78.1% of their arrivals when σ_ρ = 0.2 compared to 86.2% of their arrivals when σ_ρ = 0.3. The trading decisions of the informed traders are less affected by the difference in σ_ρ. Because a smaller σ_ρ means less intensity in the desire to trade, it worsens the adverse selection problems and increases the spread for the market makers to break even, thus therefore increases the times that the maximum spread is constrained. Moreover, with a smaller σ_ρ, more uninformed traders will choose not to trade (relative to informed traders) for a given spread, which also leads to a smaller total social gain of trade. As shown in Table 4, Panel B, the total social gain from trading still increases in the presence of the maximum spread rule, from 6.90 when spreads are set at the zero profit level to 7.25 when spread is constrained to zero. However, the magnitude is much smaller than that when σ_ρ = 0.3 (increasing from 10.93 to 11.07).

Consistent with the results obtained when σ_ρ = 0.3, when find when σ_ρ = 0.2 that, if the proportion of traders that are informed is exogenously fixed at the same level that was optimal in the GM case, the price discovery suffers with a maximum spread rule. As shown in Figure 5, the average pricing error is increased in the presence of the maximum spread rule relative to that observed in the GM setting, as displayed on Figure 2. Further, the degradation in price discovery is larger than was observed when $\sigma_\rho = 0.3$. Column (3) of Table 6 reports the average number of rounds required before the pricing error is reduced from 0.5 to 0.1 when $\sigma_\rho = 0.2$ and fixed number of informed traders. Consistent with the results reported for the case where $\sigma_\rho = 0.3$ as reported in Column (1) of Table 6, the pricing error is reduced to a level of 0.1 more slowly with a narrower maximum spread rule.

However, once the effect on the rule on the decision to become informed is also taken into account, the maximum spread rule also improves the market's rate of price discovery, and with $\sigma_\rho = 0.2$, the effect of the maximum spread rule is much stronger than when $\sigma_\rho = 0.3$. Figure 6 shows that the improvement in price discovery after fifty trading rounds averages about 0.02 when the spread is constrained to 10% of expected value and averages about 0.03 when the spread is constrained to 5%. These improvements are two to three times larger than corresponding results $\sigma_\rho = 0.3$. Results in column (4) in Table 6 also confirms more rapid price discovery compared to outcomes when $\sigma_\rho = 0.3$. In column (2) of Table 6, the average pricing error is reduced to a level of 0.1 after 34.6 rounds of trade in the GM case, 33.0 rounds with a 10% maximum spread and 31.7 rounds with zero spreads. The corresponding results were 38.8, 37.6, and 37.3 trading rounds, respectively, for the case with $\sigma_\rho = 0.3$.

To summarize, the maximum spread rule has more dramatic effects when cross-sectional variation in the parameter describing the subjective desire to trade, ρ, is reduced. Less variation in ρ implies that uninformed traders are more sensitive to spreads, and informed traders trade more aggressively on their private information, leading to wider competitive spreads. The maximum spread rule therefore restricts quotes more often, and further enhances the gains to being informed. The maximum spread rule therefore encourages more traders to become informed when there is less cross-sectional variation in ρ, implying a stronger effect on the rate of price discovery.

C. Simulation Outcomes Under a Constant Spread Rule

The results reported in Tables 2 through 5 show that the maximum spread rule imposes losses on market makers, and hence would require a side payment or subsidy to the market maker charged with posting the quotes that narrow the spread relative to the GM benchmark. Such side payments are indeed observed on the Euronext market, where the designated market maker has no particular advantage relative to other liquidity suppliers who compete by entering limit orders.

An alternative is to allow the market maker a degree of market power, such that she can earn profits in some market conditions to offset losses suffered when affirmative obligations imply a spread narrower than the GM spread. The NYSE trading floor allows the specialist an information advantage as compared to off-exchange suppliers of limit orders. We consider a simple version of such an arrangement, where the designated market maker is required to always post a spread that equals a specified percentage of the conditional expected value of the asset, $E(V|\ Z_i)$. This percentage is selected such that the spread is narrower than the average GM spread that would be observed for the same parameters in the early rounds of trading (i.e. in the wake of the information event), but is wider than the average GM spread in the later rounds of trading, allowing the market maker to earn profits during the tranquil period to offset losses incurred in the wake of the information event. This setting is similar to that modeled by Glosten (1997), except that he focused on profits on small trades used to subsidize losses on large trades at a point in time, while we study the intertemporal effects as profits earned during tranquil periods offset losses suffered in the wake of information events.

More specifically, we require the market maker to always set a spread equal to 7.5% of the conditional expected asset value, while setting $\sigma_\rho = 0.2$.[11] Figure 7 reproduces the average GM spread by trading round for these parameters, and also the average outcome from the constant spread specification. The constant spread is on average narrower than the GM spread for the first 25 trading rounds, but is wider for the last 25 rounds of trade.

Figure 8 displays the average market making profit by trading round given the GM spread and the constant spread. Profit under the GM spread fluctuates randomly around zero, reflecting that the zero expected profit condition holds at all times. Profit under the constant spread rule is negative in the early rounds of trading, i.e. in the wake of the information event, and positive in the later rounds of trading. Average market making losses in the early trading rounds are substantial, exceeding 0.04 *per trading round* (compared to an unconditional expected asset value of 1.5.) However, as numerical results in Table 7 verify, the market maker earns sufficient profits in the later trading rounds to break even overall. For comparison, Table 7 also reports results obtained under the GM setting and when spreads are constrained to zero.

[11] Note that the spread is constant as a percentage of the conditional asset value, but varies within and across simulations as the conditional asset value evolves.

Table 7 shows that the constant spread rule widens spreads relative to the GM benchmark more often than it narrows them (58% vs. 42%). As a consequence, and in contrast to results under the maximum spread rule, uninformed traders trade slightly less often with a constant spread rule than in the GM setting. Nevertheless, social gains from trade are higher with the constant spread rule than under the GM outcome. This reflects that a larger percentage of traders choose to become informed with the constant spread rule than in the GM setting (21.3% vs. 17.0%), and that the increase in informed traders' gains from trade more than offset the loss due to less uninformed trading.

As a consequence of more traders choosing to become informed, the constant spread rule also speeds price discovery relative to the GM benchmark, as demonstrated in Figure 9. The improvement in price discovery after fifty trading rounds with the constant spread rule averages about 0.032, which is larger than the corresponding improvements in price discovery under the maximum spread rule show on Figure 6, even when the spread is constrained to zero. This improvement in price discovery reflects the decrease in uninformed trading with the constant spread rule, relative to either the GM setting or the zero-spread outcome.

We draw two key conclusions from this analysis. First, market rules that allow the market maker to set spreads wider than the zero-profit benchmark during tranquil periods in order to offset losses imposed by a requirement to keep spreads narrow in the wake of information events can improve social welfare relative to the fully competitive benchmark. The efficiency gain in this case is attributable to an increase in the number of traders who choose to become informed, and unlike results obtained for the maximum spread rule, does not reflect increased trading by uninformed investors. Informed traders earn more with the constant spread rule because of the narrow spreads in the wake of information events, while the wider spreads during tranquil periods are of little consequence for information-based profits. Further, the constant spread rule is self-financing, and unlike the maximum spread rule does not require a side payment to the designated market maker. Of course, it does require that the designated market maker be allowed some degree of market power to set positive expected profit spreads during tranquil periods.

V. Conclusions

In this paper, we study why most financial markets choose to designate one or more agents as market makers, who agree to take on certain affirmative obligations to provide liquidity. We note that the answer to the question we pose cannot simply be "because liquidity is valuable", because profit seeking behavior should induce the provision of the socially optimal amount of liquidity, under standard assumptions.

We demonstrate two reasons it can be socially efficient to specify affirmative obligations for designated market makers, focusing in particular on the obligation to maintain a quoted bid-ask spread that does not exceed a specified level, while relying on the sequential trade framework of Glosten and Milgrom (1985) As they emphasize, the bid-ask spread is, in part, an informational phenomenon, allowing the market maker to recoup from uninformed traders the losses incurred in transacting with better-informed traders. However, the informational component of the spread is a transfer rather than a cost from the viewpoint of society as a whole. Some uninformed traders, for whom the potential gain from trade is less than the spread, are dissuaded from trading by the spread.

One reason that a maximum spread rule improves social welfare is that more uninformed investors will choose to trade when the spread is narrower. Increased trading by uninformed investors enhances efficiency as long as the spread is not constrained to be less than the social cost of completing trades.

The second social benefit attributable to a maximum spread rule can arise due to improved price discovery. In addition to facilitating transactions, an important function of financial markets is to establish through trading and other market communications the correct value of an asset. Rules constraining the spread affect the speed of price discovery by encouraging more trading by both informed and uninformed investors. Further, a maximum spread rule also improves the profitability of being informed and incentives to become informed. When we allow the percentage of the trading population that is informed to vary endogenously as a function of the spread rule in effect we find that the rate of price discovery is improved by the existence of both the maximum spread rule and the constant spread rule.

Our analysis comprises a start towards complete theory of affirmative obligations. We focus only on only one type of market maker obligation, the commitment to maintain narrow spreads. Actual markets feature additional obligations, including the NYSE's "price continuity" rule, which requires that the magnitude of successive price changes be limited. Further, since the GM framework focuses on traders who arrive sequentially in an exogenously determined order, and who transact either zero or one unit, we have not considered potential effects on trade timing, trade sizes, or repeat trading. Also, since the GM model provides a fully competitive outcome as the benchmark, we have not considered the possible role of affirmative obligations in a market that is less than perfectly competitive, e.g. due to costs of submitting limit orders. Finally, though we consider two possible compensation methods (a direct payment to designated market makers who have no inherent advantage versus limit order traders, and allowing profits during tranquil periods to offset losses after information events), we have not provided a formal analysis of the important question of how market makers should optimally be compensated for taking on affirmative obligations to supply liquidity. Each of these limitations highlights useful opportunities for future research.

Appendix: The Glosten-Milgrom Sequential Trade Market

We determine bid and ask quotes implied by the GM model and quotes as constrained by the maximum spread rule on a period by period basis, as follows. The asset value, V, during each simulation is either high (V=H) or low (V=L). Let Z_i denote the observable history of trades prior to trader i arriving at the market, as well as any other information known to all market participants. The market maker knows that the order flow is correlated with the value of the asset, and update the conditional asset value on the basis of observed order flow using Bayes' Rule. Entering round i, the market maker has a formed a conditional probability that the true value is high, $\Pr(V=H \mid Z_i)$, a conditional probability the true value is low, $\Pr(V=L \mid Z_i)$, and a conditional estimate of value as:

$$E(V \mid Z_i)=H\times \Pr(V=H \mid Z_i) + L\times \Pr(V=L \mid Z_i). \tag{A1}$$

The market maker also know that both the informed and uninformed traders' private valuations are normally distributed with standard deviation as σ_ρ, but the informed traders private valuation is centered on the true value while the uninformed traders private value is centered on $E(V \mid Z_i)$. The bid and ask quotes and the trader's decision are endogenously determined, as a lower ask implies more buy orders and a higher bid implies more sell orders.

The GM ask price at round i, denoted A_i, is determined as follows. The probability of a buy conditional on the ask quote, the arrival of an informed trader, and actual value being high is:

$$\Pr(\text{Buy} \mid I, V{=}H, A_i) = 1\text{-}F(A_i, H, \sigma_\rho)$$[12] (A2)

while the probability of a buy conditional on an informed trader and low asset value is:

$$\Pr(\text{Buy} \mid I, V{=}L, A_i) = 1\text{-}F(A_i, L, \sigma_\rho). \tag{A3}$$

If trader i is uninformed, the probability of a buy does not depend on the true value of the asset:

$$\Pr(\text{Buy} \mid U, A_i)=1\text{-}F(A_i,E(V\mid Z_i), \sigma_\rho) \tag{A4}$$

Therefore, the probability of a buy order conditional on asset value can be stated as:

$$\Pr(\text{Buy} \mid V{=}H)=PI^*\ \Pr(\text{Buy} \mid I, V{=}H, A_i) + PU^*\ \Pr(\text{Buy} \mid U, A_i) \tag{A5}$$

$$\Pr(\text{Buy} \mid V{=}L)=PI^*\ \Pr(\text{Buy} \mid I, V{=}L, A_i) + PU^*\ \Pr(\text{Buy} \mid U, A_i) \tag{A6}$$

Upon observing a buy order, the market maker uses the Bayes Rule to update the probability of the true asset value is high or low:

$$\Pr(V{=}H \mid \text{Buy}, Z_i) = \frac{\Pr(V{=}H \mid Z_i)\times\Pr(\text{Buy} \mid V=H)}{\Pr(V{=}L \mid Z_i)\times\Pr(\text{Buy} \mid V=L)+\Pr(V{=}H \mid Z_i)\times\Pr(\text{Buy} \mid V=H)} \tag{A7}$$

$$\Pr(V{=}L \mid \text{Buy}, Z_i) = \frac{\Pr(V{=}L \mid Z_i)\times\Pr(\text{Buy} \mid V=L)}{\Pr(V{=}L \mid Z_i)\times\Pr(\text{Buy} \mid V=L)+\Pr(V{=}H \mid Z_i)\times\Pr(\text{Buy} \mid V=H)} \tag{A8}$$

Conditional on Hi and the buy outcome by trader i, the market maker will update the expected value of V as the following:

$$E(V \mid \text{Buy}, Z_i) = L \times \Pr(V{=}L \mid \text{Buy}, Z_i)+H\times\Pr(V{=}H \mid \text{Buy}, Z_i) \tag{A9}$$

As in GM, the zero profit ask quote offered in round i is:

$$A_i = E(V \mid \text{Buy}, Z_i) + c \tag{A10}$$

where $E(V \mid \text{Buy}, Z_i)$ denotes the expected value of the asset conditional on Hi and

[12] F(X, mean, std) is a function that computes the normal cdf at each of the values in X using the corresponding parameters in mean and std.

a purchase by trader i and c denotes the out of pocket cost of completing trades. In our analysis, we assume c is zero.

Except under restrictive assumptions, there is no closed form solution to (A10), nor need the solutions to (A10) be unique. Following Glosten (1989), we assume that competition among market makers will lead to selection of the lowest ask price that satisfies (A10). We use numerical techniques to search for all solutions within the range $E(V|Z_i)$ to H, and select the smallest as the competitive ask price.

The GM bid price at round i, B_i is determined analogously. When value is high (or low), given B_i and that trader i is informed, the probability of a sell is:

$$\Pr(\text{Sell} \mid I, V{=}H, B_i) = F(B_i, H, \sigma_\rho) \tag{A11}$$

$$\Pr(\text{Sell} \mid I, V{=}L, B_i) = F(B_i, L, \sigma_\rho) \tag{A12}$$

Given Bi, and that trader i is uninformed, the probability of a sell is:

$$\Pr(\text{Sell} \mid U, B_i) = F(B_i, E(V|Z_i), \sigma_\rho) \tag{A13}$$

Therefore, when the true value is high (or low), probability of observing a sell outcome is:

$$\Pr(\text{Sell} \mid V{=}L) = PI^* \Pr(\text{Sell} \mid I, V{=}L, B_i) + PU^* \Pr(\text{Sell} \mid U, B_i) \tag{A14}$$

Upon observing a sell outcome, the market maker uses the Bayes Rule to update the probability that the true value is high or low as:

$$\Pr(V=H|\text{Sell},Z_i) = \frac{\Pr(V=H|Z_i)\times\Pr(\text{Sell}|V=H)}{\Pr(V=L|Z_i)\times\Pr(\text{Sell}|V=L)+\Pr(V=H|Z_i)\times\Pr(\text{Sell}|V=H)} \tag{A15}$$

$$\Pr(V=L|\text{Sell},Z_i) = \frac{\Pr(V=L|Z_i)\times\Pr(\text{Sell}|V=L)}{\Pr(V=L|Z_i)\times\Pr(\text{Sell}|V=L)+\Pr(V=H|Z_i)\times\Pr(\text{Sell}|V=H)} \tag{A16}$$

Conditional on Zi and an observed sell order by trader i, the market maker will update the expected value of V as the following:

$$E(V|Sell, Z_i)= L \times Pr(V=L|Sell, Z_i) + H \times Pr(V=H|Sell, Z_i) \tag{A17}$$

The GM bid quote offered to trader i is

$$B_i = E(V\ |Sell, Z_i) + c \tag{A18}$$

where $E(V\ |Sell, Z_i)$ denotes the expected value of the asset conditional on Zi and a sell by trader i and c denotes the social cost of completing trades.

We also select the actual bid quote by a numerical search over the range L to $E(V|Z_i)$, and select the maximum bid among the solutions to (A18) as the GM quote.

Observing the bid and ask quotes (B_i and A_i), trader i buys if her own value (for an informed trader V+ ρi, for uniformed trader $E(V|Z_i)$+ ρi) exceeds the ask, and sells if her value is below the bid. If her subjective valuation is between the bid and the ask she does not trade. Based on the outcome (buy, sell, or no trade), the market maker recalculates conditional probabilities. The new conditional probability is the market makers posterior probability of the event, and hence it incorporates the new information he has learned from observing the trade.

If there is a buy at round i,

$$Pr(V=H \mid Z_{i+1}) = Pr(V=H \mid buy, Z_i) \tag{A19}$$

$$Pr(V=L \mid Z_{i+1}) = Pr(V=L \mid buy, Z_i) \tag{A20}$$

If there is a sell at round i,

$$Pr(V=H \mid Z_{i+1}) = Pr(V=H \mid sell, Z_i) \tag{A21}$$

$$Pr(V=L \mid Z_{i+1}) = Pr(V=L \mid sell, Z_i) \tag{A22}$$

If there is no trade at round i,

$$Pr(V=H \mid Z_{i+1}) = Pr(V=H \mid No\ Trade, Z_i) \tag{A23}$$

$$Pr(V=L \mid Z_{i+1}) = Pr(V=L \mid No\ Trade, Z_i) \tag{A24}$$

Where Pr(V=H | No Trade, Z_i)= 1- Pr(V=H | buy, Z_i)- Pr(V=H | sell, Z_i) (A25)

And Pr(V=L | No Trade, Z_i)= 1- Pr(V=L | buy, Z_i)- Pr(V=L | sell, Z_i) (A26)

The posterior conditional probability from round i then becomes the market makers new prior to set the expected value $E(V|Z_{i+1})$ competitive bid B_{i+1} and ask price A_{i+1}. Trader i+1 arrives, makes her decision, and the market maker updates using Bayes' rule, and the process continues.

We incorporate a maximum spread rules as follows. All parameters, including trader's subjective valuations, are the same as in the GM setting. Letting the superscript C denote a constrained quote and the superscript U denote an unconstrained (zero expected profit) quote, we select constrained ask and bid quotes at the arrival of trader i such that:

$$\frac{A_i^C - B_i^C}{A_i^U - B_i^U} = \frac{A_i^C - E(V \mid Z_i)}{A_i^U - E(V \mid Z_i)} = \frac{E(V \mid Z_i) - B_i^C}{E(V \mid Z_i) - B_i^U} \tag{A27}$$

When the constraint is not binding the bid and ask quotes are set as in GM so that expected profit conditional on a trade is zero.[13] When the constraint is binding the ask and bid quotes are adjusted toward each other in order to meet the constraint.

[13] However, the quotes in this case generally differ from those that would have prevailed in the same round in the absence of a maximum spread rule, because constraints on quotations in earlier trading rounds will generally have altered earlier trading decisions, which affects the conditional expected asset value.

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Figure 1: The average competitive GM bid ask spread by round

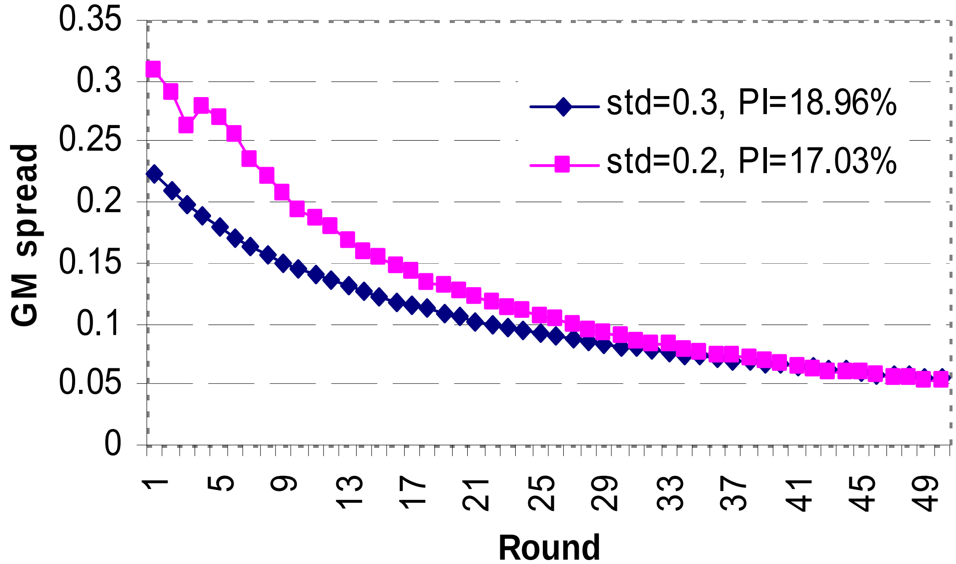

Figure 2: The rate of price discovery with the GM spread, given that the cost of becoming informed is 10% of the asset's expected value.

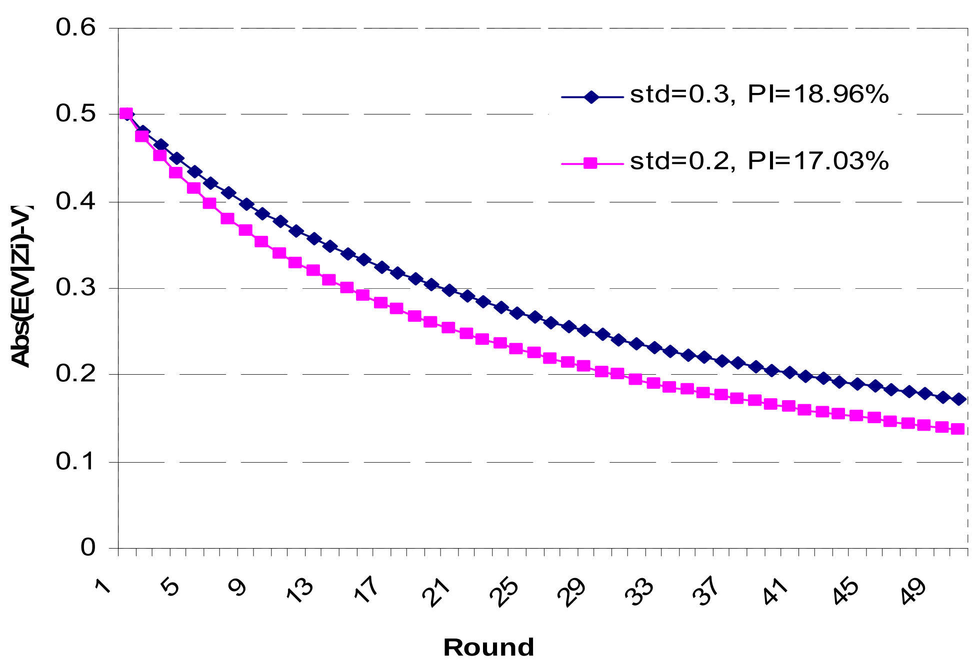

Figure 3: The effect of the maximum spread rule on the rate of price discovery, when the standard deviation of ρ is 0.3 and the proportion of traders that are informed is fixed. Each observation is the difference between the average pricing error (absolute value of trade price minus true value) with the maximum spread rule and the average pricing error observed in the GM framework. Positive values therefore indicated slower price discovery relative to the GM benchmark, while negative values indicate faster price discovery.

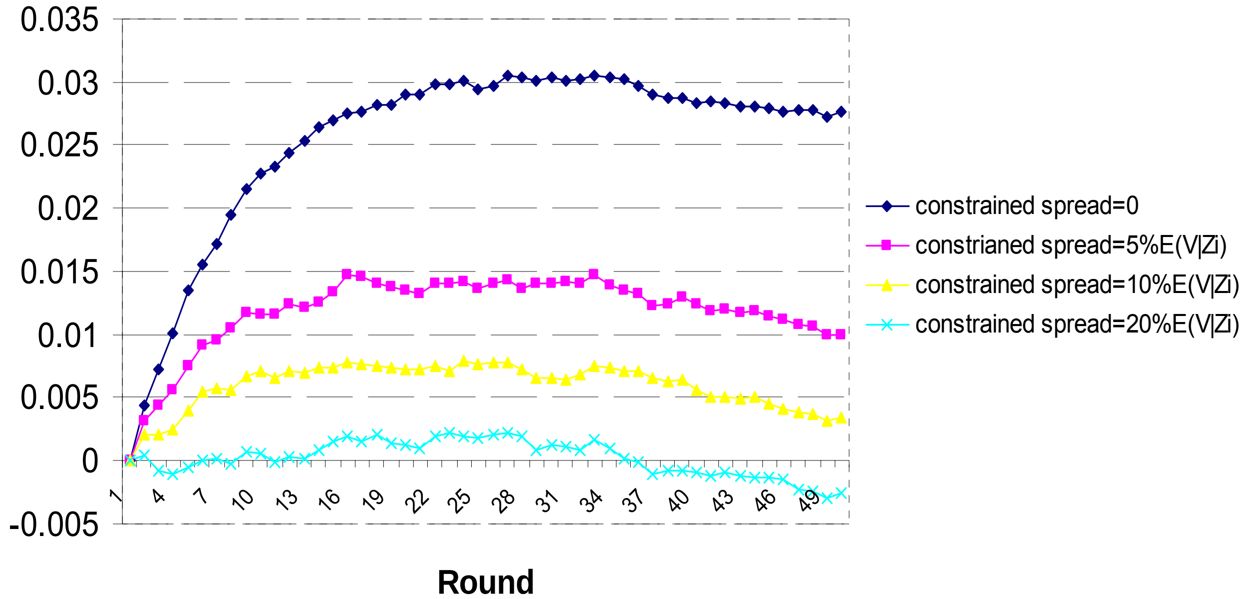

Figure 4: The effect of the maximum spread rule on the rate of price discovery, when the standard deviation of ρ is 0.3 and the proportion of traders that are informed is determined endogenously. Each observation is the difference between the average pricing error (absolute value of trade price minus true value) with the maximum spread rule and the average pricing error observed in the GM framework. Positive values therefore indicated slower price discovery relative to the GM benchmark, while negative values indicate faster price discovery.

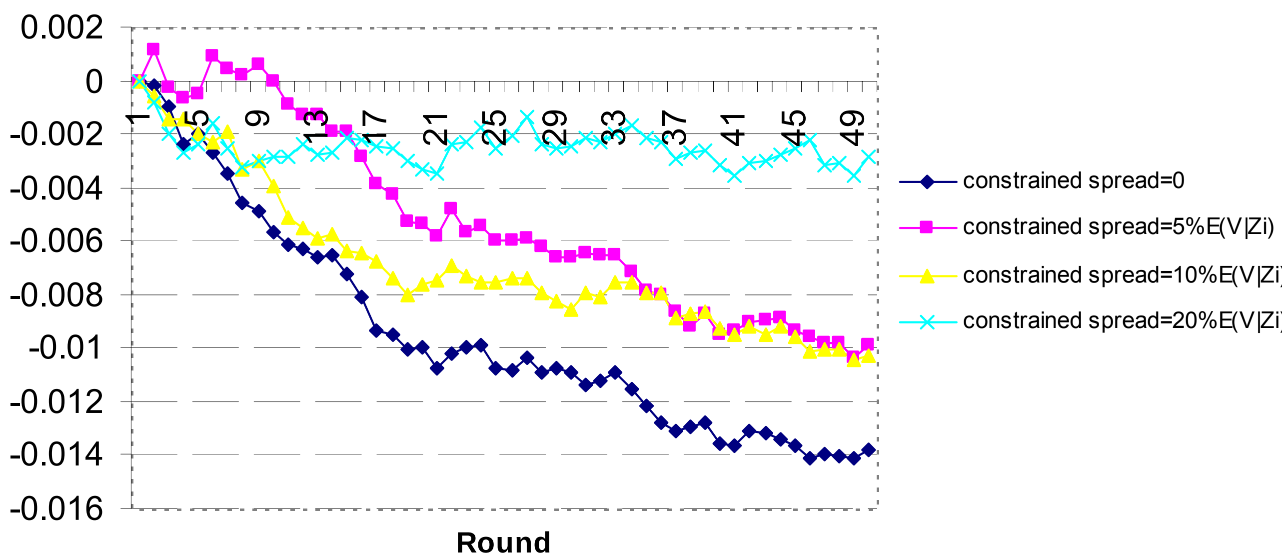

Figure 5: The effect of the maximum spread rule on the rate of price discovery, when the standard deviation of ρ is 0.2 and the proportion of traders that are informed is fixed. Each observation is the difference between the average pricing error (absolute value of trade price minus true value) with the maximum spread rule and the average pricing error observed in the GM framework. Positive values therefore indicated slower price discovery relative to the GM benchmark, while negative values indicate faster price discovery.

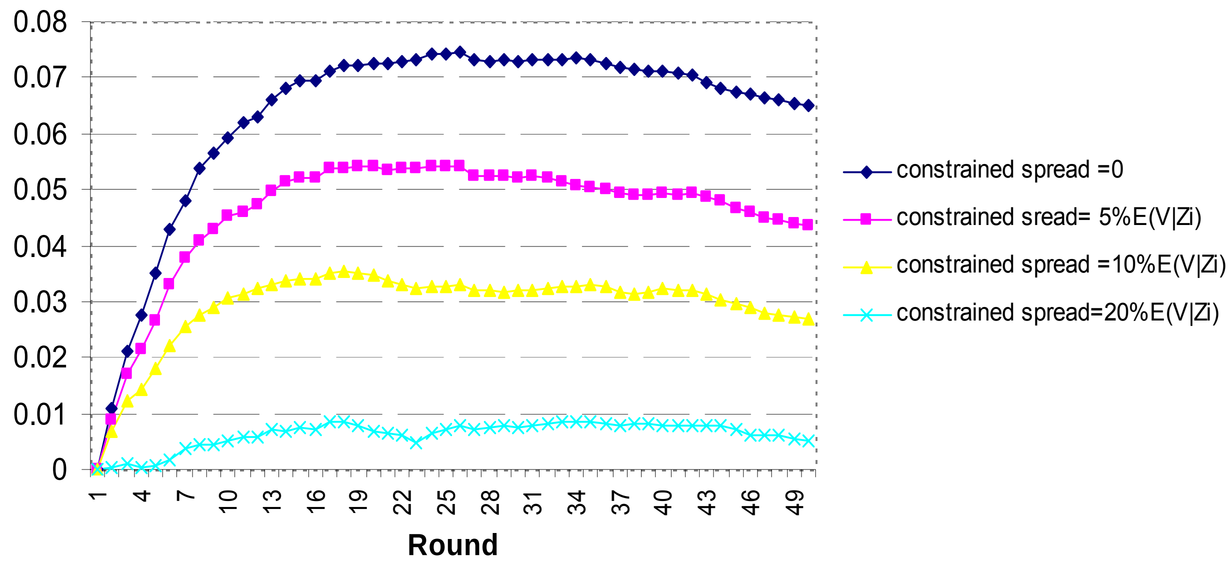

Figure 6: The effect of the maximum spread rule on the rate of price discovery, when the standard deviation of ρ is 0.2 and the proportion of traders that are informed is determined endogenously. Each observation is the difference between the average pricing error (absolute value of trade price minus true value) with the maximum spread rule and the average pricing error observed in the GM framework. Positive values therefore indicated slower price discovery relative to the GM benchmark, while negative values indicate faster price discovery.

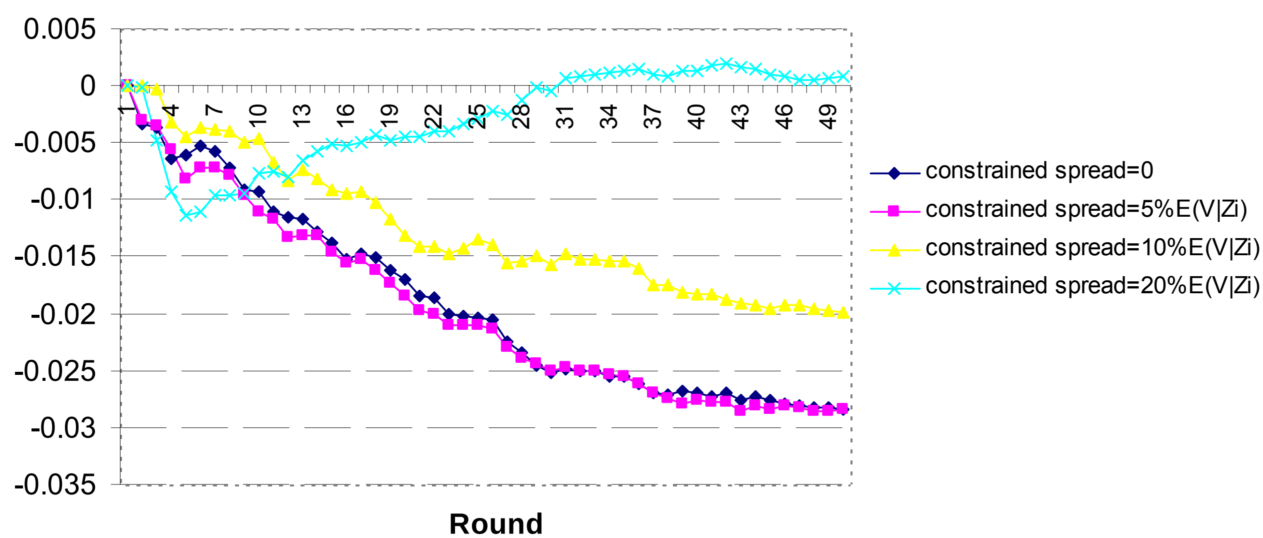

Figure 7: The average competitive GM bid ask spread and the spread constrained to be 7.5% of conditional expected asset value, by trading round.

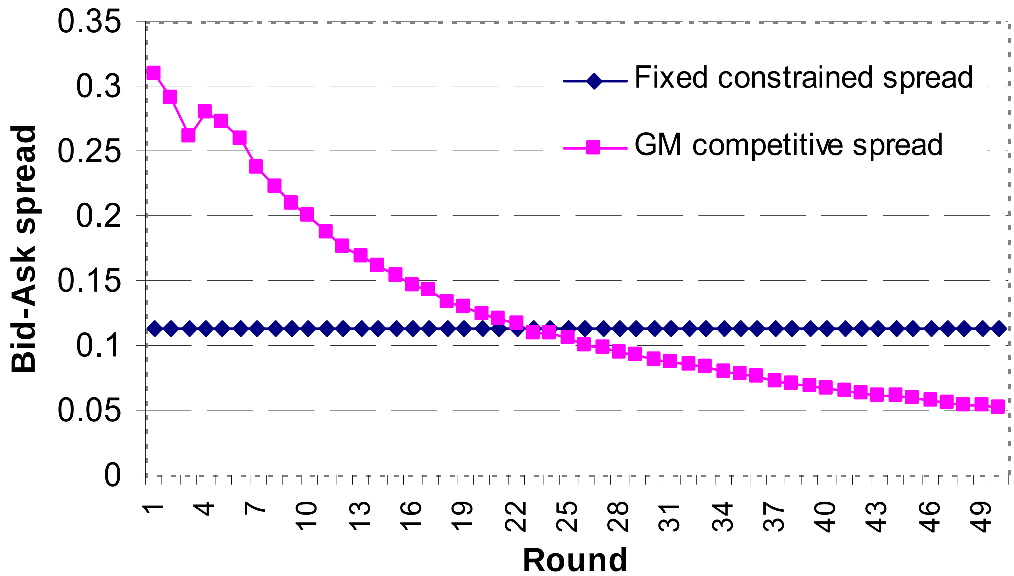

Figure 8: Average market-maker profit by trading round, with GM spreads and with spreads constrained to 7.5% of expected asset value.

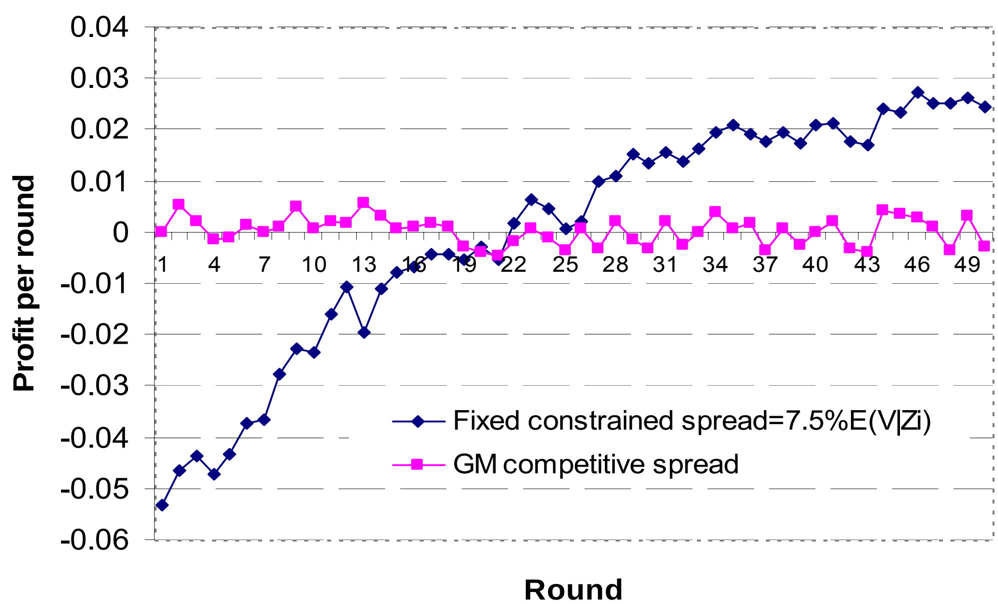

Figure 9: The effect of the fixed spread on the rate of price discovery, when the standard deviation of ρ is 0.2 and the proportion of traders that are informed is determined endogenously. Each observation is the difference between the average pricing error (absolute value of trade price minus true value) with the fixed spread rule and the average pricing error observed in the GM framework. Positive values therefore indicated slower price discovery relative to the GM benchmark, while negative values indicate faster price discovery.

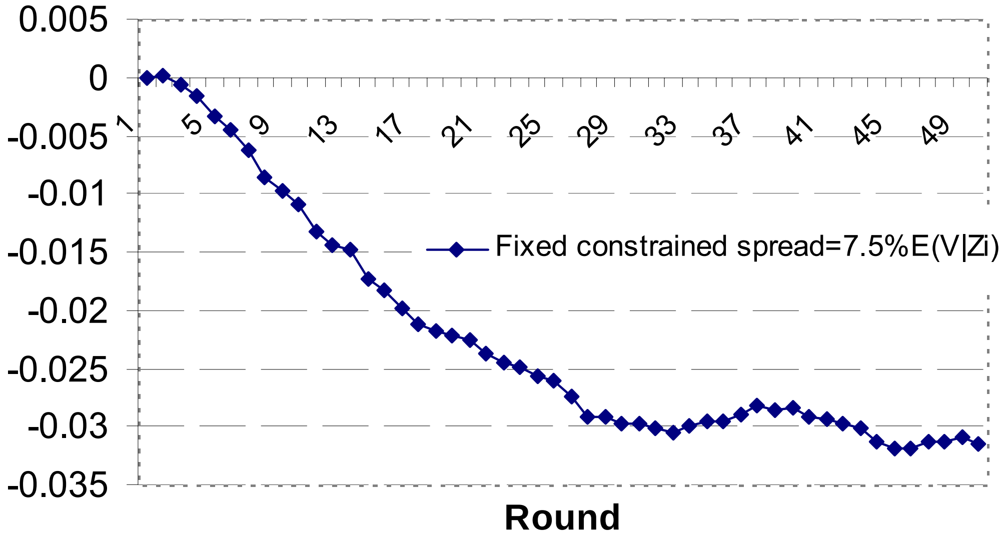

Table 1: Trading activity and gains from trade in the Glosten-Milgrom zero-profit framework, when the standard deviation of traders' private valuations (ρ) equals 0.2 and 0.3. Reported are mean outcomes across 10,000 simulations. The P-value is for a t-test of the hypothesis that the outcomes are equal across groups.

Panel A: Trading Activity					
Standard Deviation of Traders Private Valuations (ρ)	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0.3	18.96	81.04	93.65	86.36	69.68
0.2	17.03	82.97	92.89	78.60	68.30
P Value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Standard Deviation of Traders Private Valuations (ρ)	Market Maker			Informed trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0.3	1.6977	-1.6872	0.0105	3.1552	7.7643	10.9300	11.9488	-8.59%
0.2	1.3358	-1.3214	0.0144	2.1515	4.7347	6.9006	7.9659	-13.47%
P value	<0.0001	<0.0001	<0.8442	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 2: Trading activity and gains from trade with differing maximum spread rules, when the standard deviation of traders' private valuations (ρ) is 0.3 and the proportion of traders that are informed is held constant. Reported are mean outcomes across 10,000 simulations. The P-value is for a one-way analysis of variance test of the hypothesis that the outcomes are equal across groups.

Panel A: Trading Activity						
Maximum Allowable Spread	Percentage of trades where spread is constrained	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0	100.00	18.90	81.10	100.00	100.00	70.70
5%	54.92	18.94	81.06	95.67	92.10	69.21
10%	32.91	18.95	81.05	94.01	88.10	69.44
20%	0.00	19.01	80.99	93.60	86.22	69.78
No constraint (Glosten-Milgrom)	0.00	18.96	81.04	93.65	86.36	69.68
P-value	<0.0001	0.7653	0.7653	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Maximum Allowable Spread	Market Maker			Informed Trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0	0.0255	-2.3733	-2.3478	3.7435	9.6698	11.0655	11.9488	-7.44
5%	1.0598	-2.0074	-0.9476	3.4028	8.5686	11.0237	11.9488	-7.79
10%	1.5342	-1.8000	-0.2657	3.2374	8.0052	10.9769	11.9488	-8.19
20%	1.6782	-1.6921	-0.0139	3.1599	7.7790	10.9250	11.9488	-8.64
No constraint (Glosten-Milgrom)	1.6977	-1.6872	0.0105	3.1552	7.7643	10.9300	11.9488	-8.59
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	1.0000	<0.0001

Table 3: Trading activity and gains from trade with differing maximum spread rules, when the standard deviation of traders' private valuations (ρ) is 0.3 and the proportion of traders that are informed is determined endogenously. Reported are mean outcomes across 10,000 simulations. The P-value is for a one-way analysis of variance test of the hypothesis that the outcomes are equal across groups.

Panel A: Trading Activity						
Maximum Allowable Spread	Percentage of trades where spread is constrained	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0	100.00	21.98	78.02	100.00	100.00	73.78
5%	52.60	20.61	79.39	95.59	92.35	71.16
10%	32.85	19.99	80.01	94.32	88.40	70.85
20%	0.00	19.32	80.68	93.64	86.23	70.42
No constraint (Glosten-Milgrom)	0.00	18.96	81.04	93.65	86.36	69.68
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Maximum Allowable Spread	Market Maker			Informed Trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0	0.0070	-2.4080	-2.4010	4.1397	9.3101	11.0489	11.9488	-7.58
5%	1.0387	-2.0298	-0.9911	3.6268	8.3978	11.0335	11.9488	-7.70
10%	1.5008	-1.8102	-0.3094	3.3760	7.9131	10.9796	11.9488	-8.17
20%	1.7125	-1.6894	0.0231	3.2141	7.6909	10.9281	11.9488	-8.61
No constraint (Glosten-Milgrom)	1.6977	-1.6872	0.0105	3.1552	7.7643	10.9300	11.9488	-8.59
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	1.0000	<0.0001

Table 4: Trading activity and gains from trade with differing maximum spread rules, when the standard deviation of traders' private valuations (ρ) is 0.2 and the proportion of traders that are informed is held constant. Reported are mean outcomes across 10,000 simulations. The P-value is for a one-way analysis of variance test of the hypothesis that the outcomes are equal across groups.

Panel A: Trading Activity						
Maximum Allowable Spread	Percentage of trades where spread is constrained	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0	100.00	16.94	83.06	100.00	100.00	65.13
5%	55.59	16.99	83.01	95.51	88.33	64.36
10%	35.16	16.90	83.10	94.42	82.60	65.49
20%	13.85	16.96	83.04	93.51	78.91	66.90
No constraint (Glosten-Milgrom)	0.00	17.03	82.97	92.89	78.60	68.30
P-value	<0.0001	0.4462	0.4462	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Maximum Allowable Spread	Market Maker			Informed Trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0	0.0204	-2.3678	-2.3474	3.0030	6.5937	7.2493	7.9659	-9.03
5%	1.0206	-2.0152	-0.9946	2.6777	5.5002	7.1833	7.9659	-9.87
10%	1.3319	-1.7403	-0.4084	2.4543	5.0358	7.0817	7.9659	-11.18
20%	1.3189	-1.4402	-0.1213	2.2245	4.8342	6.9374	7.9659	-13.01
No constraint (Glosten-Milgrom)	1.3358	-1.3214	0.0144	2.1514	4.7347	6.9005	7.9659	-13.47
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	1.0000	<0.0001

Table 5: Trading activity and gains from trade with differing maximum spread rules, when the standard deviation of traders' private valuations (ρ) is 0.2 and the proportion of traders that are informed is determined endogenously. Reported are mean outcomes across 10,000 simulations. The P-value is for a one-way analysis of variance test of the hypothesis that the outcomes are equal across groups.

Panel A: Trading Activity						
Maximum Allowable Spread	Percentage of trades where spread is constrained	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0	100.00	24.19	75.81	100.00	100.00	73.85
5%	45.49	22.22	77.78	95.30	89.87	71.09
10%	32.29	20.08	79.92	94.26	84.32	69.67
20%	16.57	17.32	82.68	93.68	79.68	68.11
No constraint (Glosten-Milgrom)	0.00	17.03	82.97	92.89	78.60	68.30
P-value (ANOVA)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Maximum Allowable Spread	Market Maker			Informed trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0	0.0266	-2.3943	-2.3677	3.6143	6.0135	7.2601	7.9659	-8.89
5%	0.7894	-1.9785	-1.1891	3.0723	5.3209	7.2041	7.9659	-9.59
10%	1.0826	-1.7212	-0.6385	2.6938	5.0343	7.0896	7.9659	-11.05
20%	1.2014	-1.4184	-0.2170	2.2495	4.9005	6.9330	7.9659	-13.06
No constraint (Glosten-Milgrom)	1.3358	-1.3214	0.0144	2.1514	4.7347	6.9005	7.9659	-13.47
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	1.0000	<0.0001

Table 6: The trading round where the difference between the expected value and the true value becomes less than 0.1. Results are displayed when the Standard Deviation of Traders' Private Valuations (ρ) are set equal to 0.2 and 0.3, and when the proportion of traders that are informed is held fixed or is allowed to vary endogenously. The P-value is for a one-way analysis of variance test of the hypothesis that the outcomes are equal across groups. Reported are mean outcomes across 10,000 simulations.

Round				
	Column (1)	Column (2)	Column (3)	Column (4)
Maximum Allowable Spread	ρ = 0.3 and fixed number of informed traders.	ρ = 0.3 and endogenous number of informed traders.	ρ = 0.2 and fixed number of informed traders.	ρ = 0.2 and endogenous number of informed traders.
0	41.0397	37.2838	41.0039	31.6842
5%	39.6558	37.5226	38.9101	31.3809
10%	39.1263	37.5984	37.6968	33.0438
20%	38.8743	38.3531	36.2499	35.4689
No constraint (Glosten-Milgrom)	38.7636	38.7636	34.6153	34.6153
P-value	<0.0001	<0.0001	<0.0001	<0.0001

Table 7: Trading activity and gains from trade with the GM spread and with a spread fixed at 7.5% of conditional asset value, when the standard deviation of traders' private valuations (ρ) is 0.2 and the proportion of traders that are informed is determined endogenously. The P-value is for a one-way analysis of variance test of the hypothesis that all outcomes are equal. Reported are mean outcomes across 10,000 simulations.

Panel A: Trading Activity							
Maximum Allowable Spread	Percentage of trades where spread is reduced	Percentage of trades where spread is enlarged	Percentage of traders that are informed	Percentage of traders that are uninformed	Percentage of informed traders that choose to transact	Percentage of uninformed traders that choose to transact	Percentage of Informed Traders Trading in the Correct Direction
0	100.00	0.00	24.19	75.81	100.00	100.00	73.85
7.5%	42.24	57.76	21.26	78.74	86.83	77.97	64.64
No constraint (Glosten-Milgrom)	0.00	0.00	17.03	82.97	92.89	78.60	68.30
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Panel B: Gains from Trading								
Maximum Allowable Spread	Market Maker			Informed trader	Uninformed trader	Society as a Whole	Maximum Possible Social Gain	Actual Social Gain vs. Maximum Possible
	Trading with uninformed	Trading with informed	Total					
0	0.0266	-2.3943	-2.3677	3.6143	6.0135	7.2601	7.9659	-8.89
7.5%	1.6548	-1.6544	0.0004	2.6503	4.3359	6.9866	7.9659	-12.39
No constraint (Glosten-Milgrom)	1.3358	-1.3214	0.0144	2.1514	4.7347	6.9005	7.9659	-13.47
P-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	1.0000	<0.0001