Market Microstructure: A Survey of Microfoundations, Empirical Results, and Policy Implications

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Abstract

We survey the literature analyzing the price formation and trading process, and the consequences of market organization for price discovery and welfare. We offer a synthesis of the theoretical microfoundations and empirical approaches. Within this framework, we confront adverse selection, inventory costs and market power theories to the evidence on transactions costs and price impact. Building on these results, we proceed to an equilibrium analysis of policy issues. We review the extent to which market frictions can be mitigated by such features of market design as the degree of transparency, the use of call auctions, the pricing grid, and the regulation of competition between liquidity suppliers or exchanges.

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The Microstructure of Stock Markets

Mark Garman (1976) quite aptly coined the phrase "market microstructure" as the title of an article about market making and inventory costs. The phrase became a descriptive title for the investigation of the economic forces affecting trades, quotes and prices. Our review covers not only what research has had to say about the nature of transaction prices, but also the broader literature on the interrelation between institutional structure, strategic behavior, prices and welfare.

In perfect markets, Walrasian equilibrium prices reflect the competitive demand curves of all potential investors. While the determination of these fundamental equilibrium valuations is the focus of (most) asset pricing, market microstructure studies how, in the short term, transaction prices converge to (or deviate from) long–term equilibrium values. Walras himself was concerned about the convergence to equilibrium prices, through a tâtonnement process. One of the first descriptions of the microstructure of a financial market can be found in the Elements d'Economie Politique Pure (1874), where he describes the workings of the Paris Bourse. Walras's field observations contributed to the genesis of his formalization of how supply and demand are expressed and markets clear.[1] Market microstructure offers a unique opportunity to confront directly microeconomic theory with the actual workings of markets. This facilitates both tests of economic models and the development of policy prescriptions.

Short–term deviations between transaction prices and long–term fundamental values arise because of frictions reflecting order–handling costs, as well as asymmetric information or strategic behavior. A potential source of market power stems from the delegation of trade execution to financial intermediaries. Delegation arises because most potential investors cannot spend their time monitoring the market and placing and revising supply and demand curves for financial assets. Only a small subset of all economic agents become full–time traders and stand ready to accommodate the trading needs of the rest of the population. This raises the possibility that these key liquidity suppliers behave strategically. The organization of financial markets defines the rules of the game played by investors and liquidity suppliers. These rules affect the way in which prices are formed and trades determined, as well as the scope for asymmetric information or strategic

[1] Walker (1987) offers a historical perspective on this aspect of the genesis of general equilibrium theory.

behavior, and thus the frictions and transactions costs arising in the trading process.

The resources devoted to the trading process and the magnitude of transaction costs incurred by investors both illustrate the importance of market microstructure. While the cost of transacting could seem small, the volume of transactions makes the overall economic effect non-trivial. For example, in 2002 and 2003, roughly 360 billion shares traded on the NYSE alone. A transaction cost charge of only five cents implies a corresponding flow of 18 billion dollars. This represents an important friction with respect to the allocation of capital.[2] Large transaction costs increase the cost of capital for corporations and reduce the efficiency of portfolio allocation for investors, thus lowering economic efficiency and welfare.

The discussions of a number of security market issues have been markedly informed by the microstructure literature. The NASDAQ collusion case arose as a consequence of the empirical microstructure study of Christie and Schultz (1994). Its resolution involved very substantial changes in the structure of the market. This outcome resulted from a number of microstructure analyses performed on behalf of both sides of the debate. The effects of decimalization, payment for order flow, transparency, and the respective roles of specialists, floors and electronic limit order markets are additional examples of issues engaging regulators, the financial services industry and microstructure researchers.

To provide a unified perspective we survey the theoretical literature within the framework of a simple synthetic model of the market for a risky asset with N competing market makers.[3] We also discuss which theoretical predictions have been tested, and to what extent they have been rejected or found consistent with the data, and we rely on the theoretical analyses to offer an interpretation for empirical findings. We thus show how the market microstructure literature, building upon first economic principles, provides a tool to analyze traders' behavior and market design, and offers a rationale for a large array of stylized facts and empirical findings. Our endeavor to integrate the theoretical and empirical sides of the literature differs from O'Hara (1997), whose book surveys several theoretical models. Madhavan (2000) offers an interesting survey of the

[2]In particular, the volume of activity is very sensitive to the level of transactions costs, as illustrated by the dramatic increase in turnover during the last 25 years. While this increase is partly due to phenomena which are outside the scope of market microstructure, such as the development of derivative trading, it also reflects the decline in trading costs that resulted from the deregulation of commissions, improvements in trading technology, and the increase in the competitiveness and openness of exchanges.

[3]For the sake of brevity we only describe the assumptions and results, omitting the proofs. The latter are available upon request for the interested reader.

microstructure literature, building on an empirical specification in the line of Hasbrouck (1988). Our focus differs from his, as we emphasize the microfoundations of the literature, and the scope for strategic behavior. Taking this approach enables us to offer an equilibrium–based analysis of policy and market design issues. We concentrate on the portion of the literature that addresses price formation and market design, while not addressing other important issues such as the interactions between market microstructure and corporate finance or asset pricing.[4]

Section 1 surveys the first generation of the market microstructure literature, analyzing the price impact of trades and the spread, assuming competitive suppliers of liquidity. Under this assumption, the revenues of the agents supplying liquidity, corresponding to the spread, simply reflect the costs they incur: order-handling costs (Roll, 1984), adverse–selection costs (Kyle, 1985, Glosten and Milgrom, 1985, Glosten, 1994) and inventory costs (Stoll, 1978). While this literature identified these costs theoretically, it also developed empirical methodologies to analyze data on transaction prices and quantities and estimated trading costs, through the relation between trades and prices and the bid-ask spread (Roll, 1984, Glosten and Harris, 1988, and Hasbrouck, 1988). This literature has shown that trades have both a transitory and a permanent impact on prices. While the former can be traced back to order-handling and inventory costs, the latter reflects information. Furthermore, as data on inventories became available, empirical studies of specialists' or traders' inventories examined the relevance of the inventory paradigm. While this literature has shown that inventory considerations have an impact on the trades of liquidity suppliers, the empirical significance of the impact of inventories on the positioning of their quotes is less clear.[5]

In Section 2 the competitive assumption is relaxed to discuss the case in which the supply of liquidity is provided by strategic agents bidding actively in the market. Their market power can lead to a relative lack of liquidity, as shown theoretically by Kyle (1989), Bernhardt and Hughson (1997) and Biais, Martimort and Rochet (2000), and empirically by Christie and Schultz (1994) and

[4]Like a large fraction of the market microstructure literature, the present survey is devoted to the analysis of stock markets. The analysis of other markets (e.g., derivatives, foreign exchange, or energy markets), and their comparison with stock markets is an important avenue of research. Evans and Lyons (2002) and Lyons (1995) analyze the foreign exchange market, Biais and Hillion (1994) study options markets, Green, Hollifield and Schürhoff (2003) and Harris and Piwowar (2003) examine the municipal bond market and Hotchkiss and Ronen (2002) consider the corporate bond market.

[5]We also discuss how the first generation of the market microstructure literature conceptualized liquidity in financial markets as reflecting the incentives of the traders to cluster to benefit from the additional liquidity they provide to one another (Admati and Pfleiderer (1988b) and Pagano (1989)).

Christie, Harris and Schultz (1994). As the focus of the market microstructure literature shifted from competitive to strategic liquidity suppliers, empirical studies went beyond the analyses of transactions prices and quantities. We survey the insights offered by the literature on quotes and order placement strategies.

Building on the concepts and insights presented in the previous sections, as well as on recent theoretical, empirical and experimental studies, Section 3 discusses market design. The literature suggests that call auctions can facilitate gains from trade, enhance liquidity by concentrating trades at one point in time and foster price discovery; however, for large trades, empirical and theoretical analyses suggest that the continuous market also offers a useful trading venue. The literature also points to the benefits of allowing investors to compete to supply liquidity by placing limit orders, to the adverse–selection problems generated by asymmetric access to the marketplace (e.g., Rock, 1990), and to the usefulness of repeated trading relationships to mitigate adverse selection. Furthermore, empirical studies show that while market fragmentation can reduce competition within each of the market centers, it can enhance competition across exchanges. Market microstructure studies have also identified tradeoffs associated with alternative levels of market transparency and the size of the pricing grid.

Section 4 offers a brief conclusion and sketches some avenues for further research.

1 Competitive market makers and the cost of trades

In the first part of this section, we analyze, within a simple synthetic model, three sources of market frictions: order-handling costs, inventory costs, and adverse selection. In the second part of the section, we survey empirical analyses testing and estimating the models.

1.1 Theoretical analyses

Consider the market for a risky asset. Denote by π the expectation of the final (or fundamental) value, v. There are N liquidity suppliers. Denote by U_i the utility function, H_i the information set, C_i the cash endowment, and I_i the risky asset endowment of liquidity supplier i.

Even with competitive market makers, transaction prices and trading outcomes reflect fine details of the structure of the market, such as the sequencing of moves or the price formation rule. We will first consider the case in which the market order Q is placed and then equilibrium achieved in a uniform–price auction. As discussed more precisely below, this trading mechanism is

similar to the call auction used to set opening prices in electronic limit order books such as Eurex (in Frankfurt) or Euronext (in Amsterdam, Brussels and Paris). In this uniform–price auction, liquidity supplier i optimally designs her limit order schedule by choosing, for each possible price p, the quantity she offers or demands: $q_i(p)$.

$$Max_{q_i(p)} EU_i(C_i + I_i v + (v - p)q_i(p)|H_i), \forall p. \tag{1}$$

The equilibrium price is set by the market–clearing condition:

$$Q + \sum_{i=1,...,N} q_i(p) = 0. \tag{2}$$

Second, we will consider the alternative case in which limit orders are posted first, and then hit by a market order. In this context we will focus on discriminatory–price auctions. This is similar to the workings of limit order books during the trading day.

1.1.1 Order–handling costs and the bid–ask bounce

In the line of Roll (1984) suppose the N market makers are risk neutral and incur an identical cost $\frac{c}{2}q^2$ to trade q shares. This reflects order–handling costs (but not other components of the spread, reflecting inventory costs, adverse selection, or market power, analyzed below). Suppose a market order to buy Q shares has been placed by an uninformed liquidity trader. In our simple uniform–price auction model ((1) and (2)), the competitive market makers each sell $\frac{Q}{N}$ shares at the ask price:

$$A = \pi + (\frac{c}{N})Q, \tag{3}$$

reflecting their marginal cost. Similarly, if the liquidity trader had placed a sell order, the bid price would have been:

$$B = \pi - (\frac{c}{N})Q. \tag{4}$$

Correspondingly, the spread is: $2\frac{c}{N}Q$. Generalizing this simple model i) to allow the fundamental value to follow a random walk, and ii) assuming the market orders are i.i.d., there is negative serial autocorrelation in transaction price changes (or returns), due to the bouncing of transaction prices between the bid and the ask quote.

1.1.2 Inventory

Now suppose the market makers are risk averse, as first analyzed by Stoll (1978) and by Ho and Stoll (1981 and 1983). To simplify the analysis we will hereafter focus on CARA utility functions and jointly normally–distributed random variables. Denote the constant absolute risk aversion index of the market makers κ, σ^2 the variance of the final cash flow of the asset ($V(v)$), and I the average inventory position of the market makers ($I = \sum_{i=1}^{N} I_i/N$). Again applying our simple uniform–price auction model ((1) and (2)), when the liquidity trader submits a market order to buy Q shares, the ask price is set as the marginal valuation of the shares by the competitive market makers:

$$A = [\pi - \kappa\sigma^2 I] + (\frac{c + \kappa\sigma^2}{N})Q. \tag{5}$$

Symmetrically, the bid price is:

$$B = [\pi - \kappa\sigma^2 I] - (\frac{c + \kappa\sigma^2}{N})Q. \tag{6}$$

The midpoint of the spread (m) is equal to the fundamental value of the asset (π) minus a risk premium compensating the market makers for the risk of holding their initial inventory ($\kappa\sigma^2 I$). Market makers with very long positions are reluctant to add additional inventory and relatively inclined towards selling. Consequently, their ask *and* bid prices will be relatively low. Similarly, market makers with very short inventory positions will tend to post relatively higher quotes and will tend to buy. Thus, market makers' inventories will exhibit mean reversion. Because of the central role of inventory considerations in this analysis, it is often referred to as the inventory paradigm. In this model, the spread reflects the risk–bearing cost incurred by market makers building up positions to accommodate the public order flow. The price impact of trades increases in trade size, as does the risk aversion of the market makers κ and the variance of the value σ^2.

While this analysis, in the line of the work of Stoll (1978), is cast in a mean-variance framework in which the link between prices and inventory is linear, under alternative parameterizations inventory effects can be nonlinear. For example, the impact of inventory on prices could be relatively strong for extreme inventory positions. Amihud and Mendelson (1980) analyze an alternative model in which dealers are risk neutral, and yet set prices to manage their inventory positions, because they face constraints on the maximum inventory they can hold. In this dynamic model mean reversion in inventories also arises, along with a nonlinear impact of inventory on pricing.

While individuals are indeed likely to exhibit risk aversion, it is less obvious why the banks,

securities houses and other financial institutions employing dealers would be averse to diversifiable risk. To speak to this issue it could be fruitful to analyze theoretically the internal organization of these financial institutions. For example, suppose the dealers need to exert costly but unobservable effort to be efficient and take profitable inventory positions. To incentivize them to exert effort, it is necessary to compensate them based on the profits they make. In this context, even if diversifiable risk does not enter the objective function of the financial institution, it plays a role in the objective function of an individual dealer quoting bid and ask prices.

1.1.3 Adverse selection

Now consider the case in which the market order is placed by an investor trading both for liquidity and informational motives. Considering informed investors is in the line of Bagehot (1971), Grossman and Stiglitz (1980), Kyle (1985), and Glosten and Milgrom (1985). To study the consequences of adverse selection, while avoiding the unpalatable assumption of exogenous noise traders,[6] and still building on the insights of the inventory paradigm, we now extend the simple model introduced above to the asymmetric information case.[7]

Suppose the market order is placed by a strategic, risk–averse agent with CARA utility. Denote her risk aversion parameter γ, which is potentially different from the market maker's risk aversion, κ. She is endowed with L shares of the risky asset, and has observed a signal s on the final value v. Specifically, $v = \pi + s + \epsilon$, where π is a constant, $E(s) = 0, E(\epsilon) = 0$, and σ^2 now denotes the variance of ϵ. The market makers do not know exactly the inventory shock of the informed trader. From their viewpoint L is a random variable.[8]

The informed agent chooses the size of her market order Q, anticipating rationally its impact on the price. Once this order has been placed, the competitive liquidity suppliers place schedules of limit orders, taking into account the information content of the market order. This order reflects both the signal (s) and the risk–sharing need (L) of the informed agent. In our simple normal

[6]The exogenous noise trading assumption raises the issue of why there exist noise traders willing to lose money. It also makes it impossible to conduct any welfare analysis or to compare different market structures, since it prevents accounting for the impact of the market structure on noise trading. Glosten (1989) and Spiegel and Subrahmanyam (1992) endogenize liquidity trading resulting from rational risk–sharing motives.

[7]Subrahmanyam (1991) extends the analysis of Kyle (1985) to the case of risk–averse market makers posting reservation quotes.

[8]We maintain the assumption, which greatly facilitates the algebraic calculations, that s, ϵ, and L are jointly normal and independent.

distribution–exponential utility context, the information revealed by the market order is equivalent to that contained by the summary statistics: $\theta = s - \gamma\sigma^2 L$. θ reflects the valuation of the strategic informed trader for the asset, which is increasing in her private signal, and decreasing in her inventory. Denote:

$$\delta = \frac{V(s)}{V(s) + (\gamma\sigma^2)^2 V(L)}.$$

δ quantifies the relative weight of the noise and signal in the summary statistic θ. δ also measures the magnitude of the adverse-selection problem. For example, $\delta = 0$ corresponds to the case in which there is no private information.

If $\delta < \frac{1}{2}$, then, in our uniform–price auction, there exists a perfect Bayesian equilibrium where the trade of the informed agent (Q) is affine and increasing in θ and the equilibrium price (P) and the updated conditional expectation of the asset value are affine in the informed trade (Q). More precisely,

$$E(v|Q) = [\delta m + (1-\delta)\pi] + \delta(2\lambda + \gamma\sigma^2)Q, \tag{7}$$

$$Q = \frac{(\pi - m) + \theta}{2\lambda + \gamma\sigma^2}, \tag{8}$$

and:

$$P = m + \lambda Q, \tag{9}$$

where,

$$m = \pi - \frac{\kappa V(v|\theta)}{1-\delta} I, \tag{10}$$

and:

$$\lambda = \frac{\frac{c}{N} + \frac{\kappa V(v|\theta)}{N} + \gamma\sigma^2\delta}{1 - 2\delta}. \tag{11}$$

When $\delta = 0$, i.e., there is no private information, this simplifies to the above presented Roll/Ho and Stoll model. Symmetrically, in the case where market makers are risk neutral ($\kappa = 0$), and there is no order–handling cost ($c = 0$), we obtain a specification similar to Kyle (1985), where prices are equal to updated expectations of the value of the asset, conditional on the order flow. Buy orders

convey good news and drive ask prices up, while sell orders convey bad news and push bid prices down. In the general case where $\delta > 0, \gamma > 0$ and $c > 0$, the informational component of the spread is added to those reflecting risk aversion and order-handling costs. The larger the size of the order, the larger its impact on prices. The strategic insider is aware of this effect, and limits the size of the trade to limit its impact.[9] This provides a theoretical framework within which to analyze liquidity: when information asymmetries are severe, market makers have limited risk–bearing ability or when order–handling costs are large, trades have a strong impact on prices, which can be interpreted as a form of illiquidity.

Equivalence with a call auction In equilibrium, there is a one–to–one mapping between the summary statistic θ, the price p, and the informed demand Q. Hence, the game is strategically equivalent to a call auction, where the informed trader and the liquidity suppliers would move simultaneously. Since the liquidity suppliers express their demand as a function of the price, they can include the price in their information set, which is equivalent to conditioning on Q. Thus the equilibrium above is relevant to analyze prices and trades in a call auction. This trading mechanism is used to set opening prices on Euronext or Xetra, and to set closing prices on Euronext. While conditioning on Q in a sequential game was introduced by Kyle (1985) and Glosten and Milgrom (1985), conditioning on p in a simultaneous–move game was introduced by Grossman (1976) and Grossman and Stiglitz (1980).

Single arrival models versus batch arrival models The analysis presented above, similar to Glosten and Milgrom (1985), is cast in the context of a "single arrival" model, where market orders from individuals arrive at the market center individually, and the terms of trade can change for each arriving market order. Alternatively, in "batch arrival" models, as in Kyle (1985), market orders are aggregated, and the net order flow arrives at the market center. The signed quantity to be traded by one or more informed traders is linear in the signal: βs, while the noise trade is a random variable u. Thus, the aggregated net trade is $Q = \beta s + u$. As in the model above, the price associated with a signed trade of Q is given by equation (9). Equilibrium consists of a specification of β and λ. As above, the signal available to the dealers is of the form "s plus noise." In the above model the noise is the unknown hedging demand, while in Kyle (1985) it is the exogenous

[9] An additional way for informed agents to limit part of their price impact is to sell information to other investors, as analyzed by Admati and Pfleiderer (1986, 1988a, 1990), and Biais and Germain (2002).

uninformed trade.

Each type of arrival model has its own strengths and weaknesses. In a single arrival model, the market order user can see the terms of trade or correctly infer what they will be. Consequently, it is straightforward to analyze the optimal order as a function of the terms of trade. In contrast, in a batch arrival model the actual terms of trade to an individual will end up being a function of what all the other market order users do. Analyzing the trade of a risk–averse market order user thus becomes complicated. To simplify the analysis, batch arrival models typically rely on exogenous noise trades along with risk–neutral informed traders. On the other hand, batch arrival models seem to be better suited to analyzing the dynamics of quoting during a day. In actual implementation, single and batch arrival models in order–driven markets have very similar mathematical structure.

Welfare The profits of the informed agent ($Q(v-p)$) are the mirror image of the losses of the uninformed agents. From a utilitarian perspective, and with CARA utilities, this transfer has no direct impact on social welfare. Nevertheless, information asymmetries do reduce social welfare, because they reduce the risk–sharing gains from trades which can be achieved in the marketplace. This is just another form of Akerlof's (1970) lemons' problem, and is conceptually very similar to the consequences of adverse selection in insurance markets analyzed by Rothschild and Stiglitz (1976). To illustrate these points in the context of our simple model, assume liquidity suppliers are risk neutral ($\kappa = 0$) and there are no order–handling costs ($c = 0$).[10] In this case, to maximize gains from trade, the risk–averse agent should entirely trade out of his endowment shock. Denote this first–best trade $Q^* : Q^* = -L$. Because of information asymmetries and strategic behavior, however, the equilibrium trade (Q) is less responsive to inventory shocks than the first–best trade. Simple manipulations yield:

$$|\frac{\partial Q}{\partial L}| = 1 - 2\delta < |\frac{\partial Q^*}{\partial L}| = 1.$$

This lower responsiveness of trades to endowment shocks reduces trading and the associated welfare gains. The greater the magnitude of the adverse–selection problem, measured by δ, the lower the second–best welfare. In the limit, as δ goes to one half, trading goes to 0, and there is a market break–down.[11]

[10] Our simple model is amenable to welfare analysis, since there are no noise traders, and all agents are expected-utility maximizers.

[11] This discussion underscores the potential problems of the exogenous noise trading assumption. As discussed

This result, obtained in a single arrival model without a noise trader, differs from the result arising in a batch arrival model with noise traders. In the latter, the market can never close down as long as the variance of the noise trade is positive. Since the noise trade is unaffected by the terms of trade it is always possible to extract enough profit from the noise traders to offset the losses to informed traders. This is not always possible in the single arrival model.

Equilibrium multiplicity and endogenous liquidity Restricting the focus to linear strategies leads to uniqueness of the equilibrium. Yet, as is general in signalling games, equilibrium multiplicity can arise.[12] Building upon the modelling framework and insights of Glosten and Milgrom (1985), Dow (2005) shows that with rational expected-utility maximizing liquidity traders, multiple equilibria can arise, corresponding to different levels of endogenous liquidity. If it is anticipated that liquidity will be large, liquidity traders trade intensively, and the spread is tight. If low liquidity is expected, uninformed trading is reduced, the proportion of informed trades is large and the spread is wide. Hence, there are different equilibrium levels of endogenous liquidity, risk sharing and welfare. This contrasts with the analysis of Rochet and Vila (1994), which establishes equilibrium uniqueness in a variant of the Kyle (1985) model, without parametric assumptions on the distributions of the random variables, and under the assumption that the informed trader can place limit orders. Uniqueness obtains in this context because of the inelasticity of noise trader demand and hence the zero–sum property of the game played by the informed agents and the noise traders.

Equilibrium multiplicity and coordination on endogenous liquidity also arise in Admati and Pfleiderer (1988b), Pagano (1989) and Foster and Viswanathan (1990). In these models, investors choose to concentrate their trades on a single market or at a single point in time, to benefit

above, when all traders are rational, an increase in adverse selection tends to reduce trading. Models assuming noise traders can reach the opposite conclusion. For example, in Easley, Kiefer and O'Hara (1997), as the proportion of informed traders increases and adverse selection problems worsen, trading volume goes up. This result, which is at the root of the econometric approach of Easley et al (1997), is in not in line with the Akerlof (1970) logic. If instead of exogenous noise trading, Easley et al (1997) considered rational liquidity traders, in equilibrium trading volume would decrease as market makers would revise upward the probability that there is an informed trader and volume would increase as this probability is revised downward.

[12]With normal distributions Bhattacharya and Spiegel (1991) examine non–linear strategies. Biais and Rochet (1997) analyze the class of (non–linear) perfect Bayesian equilibria arising for arbitrary (bounded support) distributions, in trading games where, as in the specification above, the informed agent is risk averse and trades both to exploit his signal and to share risk. Bagnoli, Viswanathan and Holden (2001) and Noldeke and Troeger (1998) study the links between the linearity of the equilibrium and the normality of the distributions.

from the liquidity externalities generated by other traders.[13] This theory of clustering in trades offers an interpretation for the observed intraday patterns in volume, in which trading tends to be concentrated at certain points within the trading day. Yet, while empirically clustering occurs at the opening and the closing of the market, this does not follow directly from these theoretical analyses. Hong and Wang (2000) complement them by studying the case in which, while informational and non–informational shocks occur continuously over time, the market is periodically closed. This model is able to generate several stylized facts well documented by empirical studies, such as U shapes in trading volume (Jain and Joh, 1988) or in stock returns (Harris, 1986, Smirlock and Starks, 1986, and Wood, McInish and Ord, 1985).

1.1.4 Models in which the informed market order hits previously placed limit orders

We now turn to the alternative sequencing of the game, in which the first movers in the game are liquidity suppliers such as dealers or limit order traders posting prices. These orders are then hit by market orders. This corresponds to continuous trading on NASDAQ as well as in electronic limit order books, such as Euronext, Xetra and SETS in Europe, the Tokyo Stock Exchange, the Chinese stock exchanges, and ECNs such as Island in the US.

Picking off orders As noted by Copeland and Galai (1983), this sequencing offers an opportunity to an informed agent to hit standing limit orders when it is profitable to do so. Such profits opportunities can arise when the agent has private signals, or if she reacts faster than the liquidity suppliers to public information arrival. Foucault, Roëll and Sandas (2003) study the decision by dealers to review market conditions and refresh their quotes. There is a tradeoff between the cost of frequent reviews and the benefits of being picked off less frequently. In addition, there is an externality between market makers, since the frequency with which one market maker reviews his quotes has an impact on the magnitude of the adverse-selection problem faced by his competitors. In this context, the frequency of quote revisions, the size of the bid–ask spread, and the magnitude of the adverse-selection problem are jointly determined in equilibrium. When one market maker revises his quotes, if the others are informed of this (for example, by a special signal on their trading screens), they rapidly change their own quotes. This offers a theoretical interpretation for the empirical finding in Biais, Hillion and Spatt (1995) that after the best ask or bid has been cancelled, possibly because it had become out of line with the valuation of the stock, it is often

[13] Note that in Pagano (1989) there is no adverse selection.

the case that another cancellation takes place very rapidly on the same side of the book. While this interpretation corresponds to trading on the Paris Bourse, Foucault, Roëll and Sandas (2003) emphasize the consequence of quote staleness in the presence of SOES "bandits" on NASDAQ.

Discriminatory pricing When liquidity suppliers move first and place limit orders which are then hit by the informed market order, it is natural to consider discriminatory, rather than uniform pricing. To clarify the differences between these two pricing rules, it is helpful to consider a numerical example. Consider the situation in which the market order Q can be for one or two shares, with equal probabilities. For brevity focus on the ask side of the book. Suppose the best ask price in the book is \$15 for 1 share, while the second best ask price is \$15.5 for another share. Suppose these limit orders are hit by a market order to buy 2 shares. In a uniform–price auction, these 2 shares would trade at \$15.5. In contrast, with discriminatory pricing, the market order would walk up the book, and 1 share would be filled at \$15, while the other share would execute at \$15.5.

As shown by Rock (1990) and Glosten (1994), adverse selection in this discriminatory–price auction differs from adverse selection in the uniform–price auction analyzed by Kyle (1985). In the latter, the relevant conditioning variable is the total size of the trade, Q. In the above example, liquidity suppliers know that $Q = 1$ when the price is \$15, while $Q = 2$ when the price is \$15.5. In contrast, when market orders walk up (or down) the book and each limit order is filled at its own price, order execution only signals that the total size of the trade is greater than or equal to a threshold. In the above example, the liquidity suppliers know that when the best ask quote, at \$15, is filled, the total size of the trade can be 1 or 2, $Q \geq 1$. Hence, the expectation of the value of the security given that the first limit order has been executed is: $E(v|Q \geq 1) = \frac{1}{2}E(v|Q = 1) + \frac{1}{2}E(v|Q = 2)$.

More generally, while liquidity suppliers cannot condition on Q when they place their orders, they know that the limit order to sell at price p is hit when the total trade size is at least as large as the cumulated depth of the book ($q(p)$) up to that price. Consequently, the expectation of the value of the security given that this limit order has been hit is the following "upper–tail expectation":

$$E[v|Q > q(p)]. \tag{12}$$

In this context, if the liquidity suppliers are risk neutral and competitive, ask prices are equal to such "upper–tail expectations" while, symmetrically, bid prices are lower–tail expectations.

An important feature of quoted prices set in this discriminatory–pricing context is that there

is a "small–trade spread," i.e., infinitesimal trades have a discrete impact on transaction prices. This contrasts with the uniform–price mechanism analyzed above where the price impact is commensurate with the size of the trade. This small–trade spread arises because the ask price for an infinitesimal buy order impounds non–infinitesimal information content. Indeed, the conditioning set, in the upper–tail expectation: $E[v|Q > 0]$, includes the case where the total quantity is small (Q close to 0), as well as the cases where it is much greater. To see this, consider the following slight modification of the numerical example above. Suppose the market order Q can be for $\zeta < 1$ share or 2 shares, with equal probability. With competitive market makers, the best ask price in the book, for ζ shares, is equal to the corresponding upper–tail expectation: $E(v|Q \geq \zeta) = \frac{1}{2}E(v|Q = \zeta) + \frac{1}{2}E(v|Q = 2)$. As ζ goes to zero, this upper tail expectation goes to: $\frac{1}{2}E(v) + \frac{1}{2}E(v|Q = 2)$, and the half spread goes to: $\frac{1}{2}[E(v|Q = 2) - E(v)]$, which is bounded away from 0.

In this discriminatory–price auction, neither the marginal (or last) price nor the average price equal revised expectations given the actual order size. In particular, small trades are profitable to the quoters and large trades are unprofitable. Thus, small orders can lead to small revisions of expectations, but nontrivial impacts on prices.

1.2 Empirical analyses

In this subsection, we first propose an empirical counterpart to the synthetic theoretical model presented above.[14] Then, we survey empirical approaches and results in light of this synthetic framework.

1.2.1 A simple synthetic framework

The empirical counterpart of the price equation (9) is:

$$P_t = m_t + \lambda_t \, Q_t, \tag{13}$$

where P_t is the transaction price at time t, m_t is the midpoint, and λ_t can be interpreted as the effective half–spread at the time of the transaction Q_t. Typically, the index t is taken to be discrete,

[14]The reader should bear in mind the following caveats, however. For simplicity, we ignore the effects of discrete prices. Furthermore, and maybe more importantly, a fully–fledged model of the dynamics of trades and quotes in the presence of inventory and information effects can potentially give rise to rather intractable nonlinearities and non–stationarity. For simplicity, in the empirical specification presented here we ignore these difficulties and treat the time series of observations as generated by the repetition of one–period models.

and represents a clock measured in number of trades.

In the theoretical analysis above, the impact of the inventory of the market makers on the mid–quote is reflected in equation (10). Its empirical counterpart is:

$$m_t = \pi_t - bI_t, \tag{14}$$

where, reflecting the time series nature of the data, the variables m_t, π_t, and I_t are indexed by time. To study time-series data, we need to specify the dynamics of I_t. A natural candidate would be: $I_t = I_{t-1} - Q_{t-1}$. A more general formulation is:

$$I_{t+1} = aI_t - Q_t + u_{t+1} \tag{15}$$

Technically, $a < 1$ ensures that the impact of trades on inventories is not permanent. Economically this may reflect several effects: First, the set of agents supplying liquidity is not constant as agents can exit or enter the pool of market makers. Second, liquidity suppliers can unwind their trades in other markets, or hedge them in other securities or markets. If, for example, inventory is large, quotes will be low, tending to attract liquidity suppliers and hedgers, thus reducing the average inventory. u_{t+1} can be thought of as a random exogenous shock on the inventories of the market makers.

In the theoretical analysis in the previous subsection, the trade is given by equation (8). Its empirical counterpart is:

$$Q_t = A_t - d(m_t - \pi_t) + \eta_t, \tag{16}$$

where η_t is the unpredictable component of the trade, conveying noisy information about the insider signal, $d(m_t - \pi_t)$ reflects the impact of market makers' inventories on trades, and A_t reflects potential additional predictability in demand at time t. Substituting $m_t - \pi_t = -bI_t$, from equation (14), the trade equation is:

$$Q_t = A_t + bdI_t + \eta_t, \tag{17}$$

i.e., the greater the inventory of the liquidity suppliers, the more they are expected to sell, and correspondingly the more the liquidity trader is expected to buy.

In the theoretical analysis in the previous subsection, the update of the value of the asset conditional on the trade is given by equation (7). To specify its empirical counterpart note that,

since changes in expectations must not be forecastable, changes in the true price in response to trade must be a function only of the unanticipated trade. Generalizing slightly the linear equation (7), consider a quadratic polynomial in the signed trade. Also the empirical result in Jones, Kaul and Lipson (1994b), that it is the occurrence of trades rather than the size of trades which conveys information, suggests including in the regressors the discrete variable, η_{0t}, taking the value 1 for purchases and -1 for sales (as in Glosten and Harris (1988)). This leads to the following specification for the permanent response to trades:

$$\pi_{t+1} = \pi_t + z_0\eta_{0t} + z_1\eta_t + z_2\eta_t^2 + \upsilon_{t+1}, \tag{18}$$

where the error term (υ_{t+1}) is typically assumed i.i.d.[15]

1.2.2 Surveying several empirical analyses in light of our simple synthetic framework

Order-handling costs Roll's (1984) model corresponds to the case where in (13) there is a constant spread, in (14) $b = 0$, in (16) $d = A_t = 0$, η_t are i.i.d and take the value 1 or -1 with equal probability, and in (18) $z_0 = z_1 = z_2 = 0$.

As shown by Roll (1984), in this model the half–spread is equal to $\sqrt{-cov(P_{t+1} - P_t, P_t - P_{t-1})}$. Hence computing the covariance between consecutive price changes provides an estimate of the spread, even when data on bid and ask quotes or trade sizes is not available. Because the bid–ask bounce does not play a large role in the variance of returns measured at low frequency, the Roll estimator is not very well adapted for low frequency data. On the other hand, with daily or higher frequency data, the Roll estimator can prove useful, especially when bid and ask quotes are not observed. Schultz (2000) applies the Roll method to intraday data to quantify decreases in spreads on NASDAQ from 1993 to 1996, a period during which effective spreads cannot be directly measured. Over the period in which the effective spread can be estimated, Schultz (2000) shows that it is close to the Roll spread. However, the Roll estimator is implementable only if the empirical first-order autocovariance is negative. When estimating the spread using annual samples of daily return data, Roll (1984) found positive autocovariances for roughly half the stocks. Hasbrouck (2004) proposes a solution to this problem relying on Bayesian estimation of the Roll model using the Gibbs sampler. With NYSE data, Hasbrouck (2002) finds that the original Roll moment

[15] George, Kaul and Nimalendran (1991) generalize equation (18) to account for serial correlation. They show that studies failing to account for serial correlation present in the data overestimate the adverse-selection effect.

estimator does not fare very well, due to positive autocovariances for half the stocks, while its extension using the Gibbs sampler generates estimates of the spread very similar to those obtained with high frequency data.

Inventory costs In the context of the synthetic specification outlined in equations (13) to (18), the case in which inventory (and order-handling) costs influence quotes and trades but there is no adverse selection corresponds to the case in which $z_0 = z_1 = z_2 = 0$. In this context, Ho and Macris (1984) offer an empirical analysis of price and trades dynamics in options markets.

Equation (17), which specifies the dynamics of signed trades, implies they should reflect the inventories of the liquidity suppliers. Consistent with this equation, several papers have provided empirical evidence consistent with the view that market makers tend to sell (buy) when they hold long (short) positions. Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) find that there is reversion of specialist inventories towards their mean, though at a slow rate.[16] The order of magnitude of the readjustment lag is between a day and a month. Madhavan and Sofianos (1998) find that specialists participate more actively as sellers (buyers) when they hold long (short) positions. Lyons (1995) provides evidence consistent with inventory effects in the foreign exchange market. Manaster and Mann (1996) find that Chicago Mercantile Exchange (CME) market makers with relatively long (short) positions tend to sell (buy). Also in line with the inventory control theory, Reiss and Werner (1998) and Hansch, Naik and Viswanathan (1998) find that, on the London Stock Exchange, dealers with long positions tend to sell to dealers with short positions. This collection of findings suggests that the reversion of market maker inventories is a robust feature of many diverse trading mechanisms, consistent with $bd > 0$ in equation (17).

Equation (14) implies that the midquote should be decreasing in the inventory of the liquidity suppliers. The empirical evidence of this impact of inventories on prices and quotes is ambiguous, however. On the one hand, consistent with equation (14), Madhavan and Smidt (1993) find that increases in the inventory of a specialist leads to decreases in quotes. On the other hand, Madhavan and Sofianos (1998) find that specialists control their inventories through the timing of the direction of their trades rather than by adjusting quotes. Furthermore, Manaster and Mann (1996) find that, contrary to the implications of the pure inventory theory, market makers with long (short) positions

[16] Hasbrouck and Sofianos (1993) show that inventory dynamics vary across stocks. They also find little evidence that specialists are hedging their positions across stocks or with options.

tend to sell at relatively large (buy at small) prices.[17] This suggests that theories of pricing by market makers need to reflect additional features besides the pure theory of inventory control.

Adverse selection Glosten and Harris (1988) offer one of the first empirical specifications in line with the adverse-selection paradigm. Their model corresponds to the case in which there are no inventory effects so that in (14) $b = 0$ and in (16) $d = 0$ and $A_t = 0$.[18] They estimated this market microstructure model using intraday data and found that significant amounts of NYSE common stock spreads were due to asymmetric information. Several more recent studies offer empirical results consistent with the adverse-selection model.

λ in equation (13) is a measure of the depth of the market (as λ goes up, depth is reduced). As the informational motivation of trades becomes relatively more important, λ goes up. Consistent with this prediction, Lee, Mucklow and Ready (1993) find that around earnings announcements (when adverse selection is likely to be more severe) depth is reduced and spreads widen on the NYSE. This is more pronounced for announcements with larger subsequent price changes.[19] In addition, Sofianos (1995) finds that specialists on average incur positioning losses on their inventory, which are compensated by their revenues from spreads.[20] Furthermore, the adverse-selection model predicts that the informational price impact of trades should be commensurate with the private signal underlying the informed trade. Consistent with this, Seppi (1992) finds positive correlation between price changes associated with block trades and subsequent innovations in earnings announcements. Also consistent with equations (13) to (18), Huang and Stoll (1994) find that, after a large purchase occurring at a price significantly above the midquote, the midquote is expected to go up, reflecting the impact of the trade on the bid and ask prices.

Both inventory and adverse-selection theories predict that trades impact prices, but the former predicts that this impact should be transient, while the latter predicts that this impact should be permanent. This permanent impact is a manifestation of the impact of unexpected trades on expectations, modeled in equation (18) above. In the context of the pure inventory/order–

[17] Of course, the structure of the market studied by Manaster and Mann (1996) on the CME is very different than the NYSE specialist system.

[18] In addition, Glosten and Harris (1988) developed a methodology to take into account discreteness of the price grid (a feature of the data not taken into account in the empirical specification (13) to (18)).

[19] Similarly, Kavajecz (1999) finds that both specialists and limit order traders reduce depth around information events.

[20] See also the results of Naik and Yadav (1999).

handling cost paradigm, z_0, z_1 and z_2 should be 0, in contrast to the prediction of the adverse-selection paradigm. Madhavan and Smidt (1991) offer an interesting empirical analysis of inventory and information effects, using data on quotes, order flow and specialist inventory. Hasbrouck (1991) analyzes the joint process of trade and quote revisions using a VAR approach.[21] In fact, manipulating equations (13) through (18) and taking $a < 1$ in equation (15), one can obtain the VAR specification in Hasbrouck (1991). He finds that trades do have a permanent impact, inconsistent with the hypothesis that there is no information content in trades.[22] In a similar spirit, and in the line of the seminal work of Kraus and Stoll (1972) and Holthausen, Leftwich and Mayers (1990), a body of empirical literature has studied the permanent price impact of block trades, reflecting adverse selection, and their transient impact, likely to reflect inventory and liquidity considerations.[23]

1.3 Summary and avenues of further research

Table 1 offers a summary of the results surveyed in this section. The perfect market hypothesis, that trades have no impact on prices, is strongly rejected. The literature provides insights as to the causes of this rejection. The hypothesis that market makers face no inventory constraints is rejected. In addition, trades have a permanent impact on prices. That this impact is *permanent* (as shown by the work of Hasbrouck) is important because it points at information effects, while analyses restricted to the short–term impact of trades on prices could not disentangle inventory effects (as studied by Ho and Macris, 1984) from adverse selection (as studied in Glosten and Harris, 1988). Another interesting piece of evidence on the long–term impact of trades on prices stems from the foreign exchange market. While macroeconomic variables fail to explain variations in exchange rates (see e.g., Meese and Rogoff, 1983), Evans and Lyons (2002) find that signed order flow has significant explanatory power. In the same spirit, Chordia, Roll and Subrahmanyam (2002) find that stock market returns are affected by order imbalance.

While the finding that trades have a permanent impact on prices is consistent with the adverse-selection theory, further work is needed to test that paradigm. Other phenomena besides adverse

[21] This VAR specification is richer than the specification in Hasbrouck (1988), which i) analyzed the univariate process of signed trades and ii) regressed quotes changes onto trades.

[22] The impact of *public* information upon price changes is analyzed in Jones, Kaul and Lipson (1994a).

[23] All these analyses focus on the joint distribution of trades and prices. Indeed, without analyzing this joint distribution, it is very difficult to identify adverse selection effects. To the contrary, Easley et al (1997) rely crucially on parametric assumptions to estimate the adverse selection parameter without using price data.

selection, such as the reaction of traders and investors to public information, could lead to positive correlation between the direction of trades and that of price changes. An important avenue for further research is to find out the extent to which the permanent impact of trades on prices reflects private as opposed to public information. Neal and Wheatley (1998) offer intriguing results on this issue. They estimate for closed-end funds a market microstructure econometric model similar to that described in the above section. While for these assets there is very little scope for asymmetric information about the value, the estimates of the adverse-selection component are large and significant. This suggests that either adverse selection arises primarily from factors other than the current liquidation value or that the empirical models are misspecified.

Another interesting avenue of research is to study the joint process of order types, size and arrival time. Using descriptive statistics, Biais, Hillion and Spatt (1995) found that the time until the arrival of the next order is shorter (longer) when the last time interval was short (long), when the spread is large or when the last trade was large. Engle and Russell (1998) introduced the autoregressive conditional duration model to analyze these issues further. Thus Engle and Russell (1998) confirmed the finding that time intervals between trades or orders are positively serially autocorrelated and Engle and Dufour (2000) established that in volatile times trades and orders are more frequent and the price impact of trades is greater. It would be very interesting to offer a structural theoretical framework to guide further empirical analyses. Such a model could study how rational traders decide when to place orders, for informational or liquidity reasons. While such a model would be difficult to solve analytically, one could possibly use the numerical approach of Goettler, Parlour, and Rajan (2003). Quite promisingly, positive autocorrelation in the interval between orders does arise in Goettler, Parlour, and Rajan (2003).

2 Active bidding, strategic liquidity suppliers and endogenous liquidity demand

Instead of focusing on competitive market makers, the second generation of the market microstructure literature considers strategic agents, bidding proactively to exploit market conditions and possibly private information, while supplying liquidity. Competition between liquidity suppliers is similar to competition between bidders in an auction. Models based on inventory effects are similar to analyses of private–value auctions, while adverse selection–based models parallel common–value auctions. When the number of liquidity suppliers is limited, because inventory–holding and adverse–

selection costs reduce their willingness or ability to supply liquidity, strategic market makers can earn rents, reflecting their market power.

2.1 Strategic liquidity supply without adverse selection

2.1.1 Theoretical analyses

We start by revisiting the uniform–price model from the previous section, corresponding to price formation in a call auction. We now consider strategic rather than competitive liquidity suppliers. For simplicity assume there is no information asymmetry ($\delta = 0$) and no order–handling costs ($c = 0$), but the N liquidity suppliers can be risk averse ($\kappa \geq 0$). As in the previous section, given the market order Q equilibrium is determined by the optimality condition of the liquidity suppliers (1) and the market–clearing condition (2). The only difference is that, now, the liquidity suppliers choose their demand functions taking into account their impact on the market price. Adapting the approach of Klemperer and Meyer (1989) to our context, one can show that there exist multiple linear equilibria to this market game. Given Q and her rational expectation of the linear demand curves of her $N-1$ competitors, each liquidity supplier faces a linear residual supply curve. Trading off the desires to increase her market share and to minimize her impact on prices, the liquidity supplier chooses an optimal price and quantity pair. She can implement this choice with a linear demand curve. The market–clearing condition is that all liquidity suppliers choose the same price. Some of the corresponding equilibria deviate significantly from the competitive outcome and involve rents for the liquidity suppliers.

Turning to the alternative sequencing of the trading game, liquidity suppliers first post schedules of limit orders which are then hit by a market order. This sequence corresponds to continuous trading in electronic limit order books. Along with strategic considerations, the price schedules arising in equilibrium reflect the costs faced by the liquidity suppliers. As shown in Subsection 1.1.2, the marginal cost of supplying the q^{th} share is: $\pi - \kappa\sigma^2 I + \kappa\sigma^2 q/N$ (see equation (5)), which is increasing in q. Thus, when liquidity supplier i posts less than competitive prices, the extent to which her competitors can increase their market shares is limited by the corresponding increase in their costs. Hence, each liquidity supplier faces a trade–off between price and quantity and accordingly sets ask (bid) prices above marginal cost (below marginal value) (Roëll (1999), and Viswanathan and Wang (2005)).

The scope for market power is different in the two trading mechanisms, however. In the first

one, liquidity suppliers can earn rents even if they are risk neutral. In the second one, rents arise only under risk aversion, which is necessary to ensure increasing marginal costs. This reflects the different forms of competition arising in the two market environments. The uniform–price auction induces Cournot behavior, while the discriminatory–price auction induces Bertrand competition. Rents can be earned in the former case, even with constant marginal cost. In the latter, rents can be earned only if marginal cost is increasing.[24]

2.1.2 Empirical findings

These theoretical analyses are consistent with several empirical studies suggestive of strategic behavior by liquidity suppliers. Christie and Schultz (1994) and Christie, Harris and Schultz (1994) document the use of a wide pricing grid to sustain large spreads on NASDAQ.[25] As a consequence of the resulting controversy, the SEC required that public investors be allowed to supply liquidity by placing limit orders, thereby competing with NASDAQ dealers. Barclay, Christie, Harris, Kandel and Schultz (1999) study the consequences of this reform implemented in 1997. They find that quoted and effective spreads after the implementation of the reform fell substantially from their pre-reform level. Additionally, they find that an even larger decline in the spread occurred from 1994 to 1996 (i.e., before the reform) as a consequence of the adverse publicity and investigations. The impact of the controversy in reducing spreads is analogous to the reaction to the Christie and Schultz (1994) paper that is documented in Christie, Harris and Schultz (1994). Naik and Yadav (1999) analyze empirically the consequences of the reform which took place in 1997 in the London Stock Exchange, allowing the public to compete with dealers through the submission of limit orders. They find that the effective spread decreased significantly, and that this decrease is larger than that documented by Barclay et al. (1999) for NASDAQ. They also find that the cross–subsidization among trade sizes has disappeared, leading to a decline in trading costs for small trades and an increase in these costs for large trades. These results suggest that allowing all investors to place limit orders leads to a reduction in the market power of the dealers. While non–anonymity is key in supporting such collusion on large spreads in a repeated interaction environment, the anonymity prevailing in ECNs makes it less likely to emerge. This is consistent with the finding by Simaan, Weaver and Whitcomb (2003) that odd–tick avoidance is less prevalent in ECNs.

[24] Biais, Foucault and Salanié (1998) offer a comparison of the rents arising in different market structures.

[25] See also Huang and Stoll (1996) and Gibson, Singh and Yerramilli (2003).

The empirical and theoretical papers surveyed above suggest that, when the number of dealers is finite, liquidity supply is imperfect. However, dealers' entry could be expected to mitigate, or eliminate this imperfection. Indeed, Wahal (1997) shows that on NASDAQ entry and exit of market makers is a pervasive phenomenon, and entry leads to declines in spreads. However, the empirical results of Ellis, Michaely and O'Hara (2002) show that the competitive pressure exerted by such entry is limited. They find that entering market makers fail to capture a meaningful share of the market. Correspondingly, one dealer tends to dominate trading in a stock, which tends to increase spreads.

2.1.3 Dynamic order placement strategies

For tractability, our synthetic model, as well as a large part of the microstructure literature, is based on a one-period analysis. This approach does not capture the dynamic nature of liquidity provision and order placement strategies in the marketplace. Several empirical and theoretical papers offer insights into this dynamic process, however.

While in many theoretical analyses (including those surveyed above) some traders are exogenously assumed to use limit orders and others market orders, in practice, investors can choose between limit and market orders. Cohen, Maier, Schwartz and Whitcomb (1981) offer the first framework to analyze this decision. Foucault (1999) endogenizes the choice between market and limit orders in a stationary dynamic model in which the equilibrium price and order flow processes are jointly determined. He analyzes theoretically the investor's decision to hit the current quote or place a limit order as a function of the state of the order book, imposing rational expectations about the endogenous probability of execution of limit orders. Consistent with intuition, it is optimal to place limit orders when the spread is large, while it is optimal to place market orders when the spread is tight. Parallel to this theoretical analysis, Harris and Hasbrouck (1996, see Table 5) find that for stocks with a 1/4 spread (in their sample period the tick size was 1/8) the execution performance of orders placed within the quotes dominates that of market orders.[26] This is also consistent with the empirical analysis of the conditional frequencies of different strategies in the electronic limit order book in Paris by Biais, Hillion and Spatt (1995). They find that when the spread is relatively wide liquidity is often supplied (limit order suppliers beat the existing quote), while when the spread is relatively narrow, investors are more willing to accept the prevailing liq-

[26] Harris and Hasbrouck (1996, Table 3) also include some summary statistics on order frequencies and observe that in their dataset the most commonly used limit order tends to be the best performing order.

uidity, which is being offered on relatively favorable terms, and place market orders.[27] This gives rise to mean reversion in the bid–ask spread and negative serial autocorrelation in ask (bid, and midquote) price changes, as, when the ask price has moved above its equilibrium level, it is undercut by a more favorable limit order to sell.[28] Note that this reversion to the mean is not instantaneous, as it takes some time for the liquidity providers to identify these order placement opportunities. Yet, Biais, Hillion and Spatt (1995) find that order placement occurs more rapidly when the spread is large than when it's tight. This relatively fast reaction reflects the speed with which investors monitoring the market seize the opportunity to supply liquidity, when the latter is scarce and well compensated.

Parlour's (1998) theoretical analysis of dynamic order placement studies how investors trade off less attractive pricing against the improved price priority obtained by jumping ahead of the queue of limit orders and undercutting the current best quotes. Consistent with this theoretical analysis, Biais, Hillion and Spatt (1995) find that investors are more likely to place limit orders within the quotes when the depth at the quotes is large.

Goettler, Parlour and Rajan (2003) extend the analysis of Foucault (1999) to a richer setting. While this richer model is not analytically tractable, they characterize its solution numerically. This approach is interesting because it gives more flexibility to the researcher to construct models rich enough to generate patterns in line with those observed in the data. For example, Goettler, Parlour and Rajan (2003) show that order flow is persistent, as one type of order is likely to be followed by a similar order, as was empirically observed by Biais, Hillion and Spatt (1995).[29] The numerical analysis of Goettler, Parlour and Rajan (2002) underscores that order flow persistence can arise because of persistence in the state of the book to which subsequent traders react.

[27]The finding by Madhavan and Sofianos (1998) that the specialist tends to participate more in trades when the spread is large is consistent with the specialist following a similar type of liquidity supply strategy. Further insights into the role of the specialist and that of limit orders in the supply of liquidity are offered in the theoretical analysis of Seppi (1997).

[28]This is related to, but different from, the negative autocorrelation in transaction price changes generated by the bid–ask bounce, analyzed in Roll (1984).

[29]Other interesting empirical studies of order flow dynamics include Bisière and Kamionka (2000), Lo, MacKinlay and Zhang (2002), Engle and Russell (1998), Griffiths, Smith, Turnbull and White (2000) and Ellul, Holden, Jain and Jennings (2003).

2.2 Strategic liquidity supply with adverse selection

2.2.1 Uninformed liquidity suppliers

Theoretical analyses We now turn to the case of liquidity suppliers who face an informed agent. For simplicity suppose they are risk neutral. We focus on the case in which liquidity suppliers first post schedules of limit orders and the informed agent then submits a market order, corresponding to continuous trading in a limit order book. This can be thought of as a screening game, contrasting with the signalling game analyzed by Kyle (1985), where the market order is placed first and then market makers compete in price. To determine their optimal price schedules, the market makers must evaluate the cost of supplying liquidity. As explained in Subsection 1.1.4, equation (12), the cost of supplying the q^{th} share is equal to: $E(v|Q > q)$.

First consider the case where there is only one, monopolistic, liquidity supplier, as in Glosten (1989). In the line of textbook monopoly theory, the marginal selling price quoted by the monopolist for the q^{th} unit is the sum of his marginal cost and a monopolistic markup, $m_1(q)$ (where the subscript refers to the fact that there is only one liquidity supplier):

$$A(q) = E(v|Q > q) + m_1(q).$$

Similar to analyses of price discrimination, the markup of the monopolist reflects the elasticity of the demand he faces, which in turn reflects the distribution of the different types of agents:

$$m_1(q(\theta)) = \frac{1 - F(\theta)}{f(\theta)}(1 - \partial E(v|\tilde{\theta} > \theta)/\partial\theta),$$

where θ is the valuation of the informed agent for the asset (as explained in Subsection 1.1.3), $q(\theta)$ is the optimal trade size for the agent whose type is θ, and $F(\theta)$ is the c.d.f. of agents' types, while $f(\theta)$ is the corresponding density. One can draw an analogy between the results obtained by Glosten (1989) and those obtained by the analysis of monopoly pricing with information asymmetries on private values by Goldman, Leland and Sibley (1984). The distinctive feature of the analysis of Glosten (1989) is the common-value environment, where the marginal cost of supplying shares is endogenous.

Second, consider the case in which there are $N > 1$ strategic liquidity suppliers competing in limit order schedules. Bernhardt and Hughson (1997) show that when the number of liquidity suppliers is finite, there exists no equilibrium where oligopolists earn zero expected profits. Thus, the equilibrium of the screening game differs from that of the signalling game, where liquidity

suppliers earn zero–profits (Kyle, 1985). Biais, Martimort and Rochet (2000), characterize the equilibrium price schedules arising in this context. As in the monopoly case, ask and bid quotes are the sum of a cost component and a mark–up:

$$A(q) = E(v|Q > q) + m_N^A(q), B(q) = E(v|Q < q) - m_N^B(q). \tag{19}$$

The mark–up is decreasing in the number of liquidity suppliers and goes to 0 as N goes to infinity. In that limiting case the oligopolistic equilibrium converges to the competitive equilibrium analyzed by Glosten (1994). Intuitively, the logic of this equilibrium is similar to that of the private value case analyzed in the previous subsection (2.1.1). In both cases, market power arises because marginal costs are increasing. In the private value case this increase is due to risk aversion, while in the common value case it is due to adverse selection.

Empirical findings Sandas (2001) offers a structural analysis of Glosten's (1994) model of competitive liquidity supply in an electronic limit order book, testing that ask (bid) prices are equal to the upper (lower) tail expectation given above in equation (12).[30] Using the GMM overidentifying restrictions approach enables him to both estimate the deep parameters of the model and test the null hypothesis that the model is consistent with the data. In its richest parametrization, the model is rejected for about half the stocks. The model is rejected because the slope of the limit order book appears to be steeper than predicted by the theory. This could reflect market power.

Biais, Bisière and Spatt (2002) investigate this point further by analyzing limit orders placed on Island and testing whether ask and bid quotes are as given in equation (19). While the minimum tick size is extremely small on Island, it is coarser on NASDAQ, especially before decimalization. The results obtained by Biais, Bisière and Spatt (2002) are consistent with Island limit order traders earning oligopolistic rents (i.e., $m_N(q) > 0$) before decimalization, but not after. The coarse tick size prevailing on NASDAQ prevented the dealers from posting competitive quotes. Interestingly, Island limit order traders earned rents by just undercutting the NASDAQ spread rather than competing aggressively with one another. Decimalization brought NASDAQ quotes close to their competitive level, annihilating the oligopolistic profits earned by Island liquidity suppliers. This suggests that in addition to the direct effect of tick size on rents in one market, evidenced by

[30] Hollifield, Miller and Sandas (2003) also offer a structural econometric test of order placement theories. They estimate the execution probability and adverse selection risk for alternative limit order submissions.

Christie and Schultz (1994) and Christie, Harris and Schultz (1994), minimum price increments have effects across markets, due to competition for liquidity supply between market centers.

2.2.2 Informed liquidity suppliers

Liquidity suppliers can directly observe signals about the asset payoff: Kyle (1989) presents an influential model of competition between strategic informed traders in a uniform–price auction. To review some of his findings within the context of our synthetic framework, consider the uniform–price auction model presented in Subsection 2.1.1, and extend it by assuming that the strategic liquidity suppliers observe private signals, denoted $s_i, i = 1, ...N$.[31] The price is determined by the standard market–clearing condition. To simplify the analysis, Kyle (1989) considers exogenous noise trading, as opposed to endowment shocks. Each strategic trader submits limit orders (demand curves) reflecting her signal: $q_i(p, s_i)$. Kyle (1989) shows there exists an equilibrium in which the limit orders are linear both in price and information. As in the private value case presented in the previous subsection, each quoter faces a linear residual supply curve, and trades off price and quantity effects. Heterogeneous information provides an additional difficulty, as each quoter must take into account the other quoters' information conveyed by the price. As in the private value case, equilibrium has a Cournot flavor, and deviates from the competitive outcome. In the context of this uniform–price market, Kyle (1989) finds that the profits to the informed quoters do not necessarily go away as their numbers get large.

In the spirit of the auction–theoretic work of Engelbrecht, Milgrom and Weber (1983), Calcagno and Lovo (1998) offer an extension of Kyle's (1985) dynamic analysis to the case where the informed agent is not the market order trader, but one of two risk–neutral market makers. As in Kyle (1985), the market makers compete in prices for market orders. The latter stem from exogenous noise traders. At each point in time there is an auction, in which each of the market makers places one bid price and one ask price (conditional on his observation of past prices and trades), and the exogenous noise trader hits the best bid or ask. The uninformed market maker understands he faces a winner's curse, and factors it into his bidding strategy. In equilibrium he earns zero expected profits. In order to preserve his rent, the informed agent follows mixed strategies, so that his quotes are only partially revealing, except at the last round of the game. The informed agent faces a tradeoff between larger quantities (and thus larger immediate profits) and more information

[31] The original Kyle (1989) model actually analyzes the case where all traders have equal access to the market. For the sake of internal consistency, we stick to our paradigm, where one trader faces several liquidity suppliers.

revelation. This is similar to the tradeoff arising in Kyle (1985). The difference is that, in Calcagno and Lovo (1998), it is the quotes of the market makers, rather than the market order flow, which partially reveal information, and thus lead the price discovery process. It could be interesting, in future research, to test empirically the extent to which market makers, rather than their customers, possess private information.

Manaster and Mann (1996) provide empirical evidence which speaks to this issue. They find that CME market makers tend to sell at relatively high prices and to buy at relatively low prices. This is consistent with market makers taking positions based on superior information about the likely evolution of prices.[32] Such information could be gathered based on market information, such as orders or the observation of other market participants on the floor. While this private information could be the source of the profitability of market makers, there may be an alternative interpretation, emphasizing the market power of market makers, which enables them to buy at relatively cheap (bid) prices and sell at relatively expensive (ask) prices.

Liquidity suppliers can also observe pieces of market information: Vayanos (1999) offers a dynamic extension of Kyle (1989), in which strategic risk–averse agents have private information about their endowments, while information about the dividend flow is public. To share risk, agents with long positions are inclined to sell, while agents with short positions are inclined to buy. This is similar to the case analyzed in Subsection 1.1.3, where the valuation of the strategic trader for the asset (θ) was shown to be decreasing in her endowment in the stock. In this context, the equilibrium aggregate valuation is decreasing in aggregate holdings. Hence information about endowments is not only informative about private values but also about common values, since endowments affect market prices. Hence, since they reflect endowments, trades convey signals relevant for pricing the asset. Consequently, they have an impact on prices.[33] To reduce this impact the agents reduce the aggressiveness of their trades. This limits their ability to share risk and is therefore detrimental to social welfare. This distortion would not arise if endowments were public information.

[32]Interestingly, the empirical result obtained by Manaster and Mann (1996), and its theoretical counterpart based on informed market makers, go in the opposite direction from the empirical results obtained for the NYSE and London Stock Exchange, which correspond to the situation in which the market makers are uninformed and face superiorly informed traders (see Table 1).

[33]Keim and Madhavan (1997) find that institutional investors following indexing strategies incur significant price impact. This is consistent with the theoretical results of Vayanos (1999), to the extent that these investors have private information about their trading needs.

Similarly, Cao, Evans and Lyons (2003) analyze how dealers can extract from their order flow information about aggregate holdings and therefore, market pricing, and Viswanathan and Wang (2005) analyze the case of traders informed about the asset payoff, who transmit orders to dealers, who then use the information content of those orders in the interdealer market.

2.3 Conclusion and implications

The findings of the second generation of market microstructure research surveyed in this section are summarized in Table 2, Panels A and B. Overall they suggest that the assumption that liquidity providers are competitive, although convenient to simplify theoretical analyses, does not arise out of the formal treatment of realistic institutional arrangements for trade. In a variety of market structures, a very large number of liquidity suppliers is needed for the equilibrium to be approximated by a zero–profit condition. Hence, oligopolistic rents must be taken into account, along with inventory, adverse-selection and order–handling costs, to understand the sources of transactions costs. From a policy perspective, this suggests that exchange regulators and organizers must foster entry and competition for the supply of liquidity, in order to reduce market power, and consequently transactions costs.

An interesting avenue for further research is to identify the nature of private information by disentangling fundamental information about individual firms from signals inferred from the observation of the trading process. While the former can be obtained by investors and asset managers, market makers and traders have special access to the latter. This can contribute to their market power.

3 Market design

The organization of the market can be seen as the extensive form of the game played by investors and traders. It determines the way in which the private information and strategic behavior of the traders affect the market outcome. Like auction design or mechanism design, market microstructure analyzes how the rules of the game can be designed to minimize frictions and thus optimize the efficiency of the market outcome. In this section we review the body of empirical and theoretical results comparing the determination of prices and allocations within several particular market structures. At a higher level these results can be used to provide important insights about the efficient design of trading systems.

3.1 Call versus Continuous

3.1.1 Concentrating trades at one point in time can be efficient

While pure call markets are not common (and indeed, the Arizona Stock Exchange has not attracted much interest), the literature points to some benefits of periodic calls. For example, call markets can be used to concentrate liquidity when the latter is not plentiful. This raises the question of why economic agents need to be instructed to concentrate their trades, by means of such a trading mechanism.

This may be related to the public good nature of liquidity. Admati and Pfleiderer (1988b) and Pagano (1989) show that clustering of trades naturally arises, even if it is not mandated by the structure of the market. Yet, in such a context, multiple equilibria can arise, due to the strategic complementarities among liquidity supplies. Hence mandating concentration of trades and orders, by using a call market, can be seen as a device to help traders coordinate on an equilibrium, in order to minimize trading costs.

The theoretical analysis of Vayanos (1999), mentioned in the previous section, offers another reason why mandating agents to concentrate their trades, as in a call market, can be welfare improving. As discussed above, he shows that, to reduce their price impact, the strategic agents split their trades. Since this reduces their ability to trade out of their endowment shocks, it reduces the gains from trade achieved in the marketplace. Gains from trade could be improved if the trader could credibly commit to engage in a single trade. In this case, a liquidity supplier could accommodate his risk–sharing demand, at the price corresponding to his trade size, without fearing that additional trades would take place in the future, altering further the value of the stock.[34] The smaller the time interval between trading opportunities (h), the greater the ability of traders to strategically split their trades and the greater the welfare loss. This loss is maximized when h goes to 0. Batching orders at discrete points in time, as in a call market, may enhance welfare, by enhancing the ability of strategic traders to commit to a single trade.

The theoretical analysis of Copeland and Galai (1983) presented in Section 1, suggests yet another reason why call trading can be efficient. In their analysis, adverse selection stems from asymmetry in the timing of the moves—providers of liquidity must quote based on current information, while a future market order that hits that quote is based on the information available at that future time. In a call auction, providers of liquidity must quote, but they can deliver the quote

[34] This is in the same spirit as in the upstairs block market analyzed by Seppi (1990).

just before the known time of the call. Thus, if the arrival rate of information is high relative to the arrival rate of orders, as would be the case in a thinly–traded security, the call auction can minimize informational differences at the time of trade and lead to greater risk sharing. On the other hand, if the arrival rate of orders is high relative to the arrival rate of new information, the gains from periodic calls are small, and offset by the gains to traders of being able to rebalance their portfolios when they choose.

Trading halts can be viewed, at least in part, as an institutional response to these economic forces. A trading halt occurs when the arrival rate of information is high. The halt itself sends a signal to the traders who monitor their quotes relatively infrequently, giving them the opportunity to revise their limit orders. Consistent with these remarks, Corwin and Lipson (2000) find that cancellations and the placement of new limit orders are particularly frequent during trading halts and that a large proportion of the order book at the resumption of trading is composed of orders placed during the halt.

3.1.2 The informational efficiency of call auctions

Amihud and Mendelson (1987) found that on the NYSE the opening price was noisier than the closing price.[35] One possible interpretation is that the market mechanism used at the opening, similar to a uniform–price call auction, is less efficient than the mechanism used at the close, i.e., continuous trading. An alternative interpretation is that the opening price is more difficult to find than the closing price, reflecting the contrast between the uncertainty following the overnight trading period and the price discovery achieved at the end of the trading day. To differentiate across these two alternative interpretations, Amihud and Mendelson (1991) and Amihud, Mendelson and Murgia (1990) analyzed markets in which call auctions were held at other points in time than the opening. They found that prices set in such call auctions were not less efficient than comparable continuous market prices. This leads to the conclusion that the relative inefficiency of the opening call auction does not reflect the trading mechanism but the fact that the market is closed overnight.

To cope with the difficulty of the discovery of opening prices many stock exchanges have introduced tâtonnement procedures. For example during the preopening period, in the Paris Bourse, agents can place, revise or cancel orders and indicative prices reflecting aggregate supply and

[35] Ronen (1997) notes that measures of informational efficiency computed for several stocks over the same period of time are likely not to be independent, since the dynamics of the prices of these stocks are correlated. She proposes a GMM–based method, to deal with this correlation.

demand are displayed. Medrano and Vives (2001) show theoretically that in this mechanism information revelation and order flow will accelerate close to the opening. This is consistent with the empirical findings of Biais, Hillion and Spatt (1999).

These empirical findings can be interpreted in light of recent experimental studies. Schnitzlein (1996) finds that the informational efficiency of prices is not significantly different in a one-shot, uniform–price, call auction from that of a continuous market. Biais and Pouget (2000) find that, while the mere presence of an opening call auction is not sufficient to improve drastically the informational efficiency of prices, the combined effect of a preopening period and a call auction does improve the informational efficiency of the price discovery process.

3.1.3 Uniform pricing in call auctions

Another difference between call auctions and continuous trading is that in the former all trades are executed at a single uniform price, while in the latter, as orders walk up or down the book, and as the latter evolves, trades are filled at different prices. In the previous sections we reviewed the difference between equilibrium outcomes arising under uniform pricing (Kyle (1985), (1989)) and those arising with discriminatory pricing (Glosten (1994), Bernhardt and Hughson (1997), Biais, Martimort and Rochet (2000)). These analyses show that there is a small trade spread in the discriminatory–price auction, but not in the uniform–price auction. On the other hand, for large trades, transactions costs are lower in the discriminatory–price auction than in the uniform–price auction. This is consistent with the empirical results of Kehr, Krahnen and Theissen (2002) who find that, on the Frankfurt Stock Exchange, for small trades transactions costs are lower in the call market, while for large trades they are lower in the continuous market.

While the results presented in the previous section suggest that strategic behavior is common in financial markets, they also imply that the adverse consequences of this behavior are mitigated when the number of market participants increases. Which trading mechanism facilitates most this convergence to efficiency? Rustichini, Satterthwaite and Williams (1994) provide answers to this question. To translate their analysis in our framework, consider N strategic agents, trading to share risk (and assume away adverse selection on common value and order–handling costs). Half the agents own one share, and consider selling it. The other half does not own any shares, but consider buying. In addition to the differences in endowments, the agents have different risk aversion coefficients, and hence different valuations for the share. In our simple, normal distribution,

exponential utility framework, the valuation for the stock of seller i (i.e., her certainty equivalent) is: $\pi - \kappa_i \sigma^2$, and her gain from trade if she sells at price p is: $p - (\pi - \kappa_i \sigma^2)$. Symmetrically, the gain from trade of buyer j if she buys one share at price p is: $(\pi - \kappa_j \sigma^2) - p$. The socially optimal trade allocates the share to the agent with the highest valuation. Strategic behavior, however, can entail inefficiencies since some mutually profitable trades fail to take place. Rustichini, Satterthwaite and Williams (1994) consider a double auction, i.e., a call market, where sellers can place a limit order to sell one share and buyers can place a bid for one share. They show that equilibrium converges to efficiency when N goes to infinity. The maximum inefficiency is of the order of $O(\frac{1}{N^2})$. Satterthwaite and Williams (2002) prove that there is no other trading mechanism converging faster to efficiency. In that sense, the call auction is an optimal market structure.

3.1.4 Conclusion

The literature surveyed in this subsection is summarized in Table 3, Panel A. Overall it suggests that call auctions can enhance welfare, and possibly the informational efficiency of the market. Continuous markets, however, can offer a useful complement to opening call auctions. Studying the complementarity, and possibly the competition, between these two market structures is an interesting avenue for further research.

3.2 Who should supply liquidity?

Liquidity can be supplied by a variety of agents including limit-order traders, dealers, floor brokers and specialists. These parties can be subject to different priority rules, enjoy market power to different degrees and possess differing amounts of information. For example, on the NYSE, until 2002, only the specialist had access to an immediate electronic display of the limit order book beyond the best quotes, while on NASDAQ and the London Stock Exchange, until 1997, only dealers had the opportunity to post quotes. In pure limit order markets, such as the Paris Bourse, differences among liquidity suppliers are less important. A fundamental issue in the design of trading systems concerns the determination of the different rules applying to liquidity suppliers and the information to which they have access. The NYSE specialist example illustrates some important adverse selection issues that arise as a consequence of the asymmetry in the timing of trading opportunities of different liquidity suppliers.

When a marketable order arrives on the trading floor, the specialist can decide to allow the

order to be executed against the outstanding limit orders, or to fill the order himself. He can achieve that by undercutting the book or by "stopping" the order and guaranteeing execution at the posted quote or price improvement.[36] As the specialist possesses information about the potential information content of the order, based for example upon the pricing in related markets, the size of the incoming order or the identity of the potential counterparty, he can condition his decisions upon information not available to the investors when they placed limit orders in the book.[37] As shown by Rock (1990), this creates an adverse-selection problem for these investors and discourages them from providing liquidity. As stated in equation (12) in Section 1.1.4: $E(v|Q > q)$ is the cost of the q^{th} unit sold by the limit order traders, where Q is the size of the market order. The opportunistic intervention of the specialist modifies the distribution of Q, and raises the cost of the limit order traders. This reduces the extent to which they provide liquidity for the market. Rock (1990) shows that, when the specialist is risk neutral (so that there are no risk–sharing benefits from splitting the trade between him and the limit order traders), the adverse-selection problem is so extreme that the limit order book entirely dries up, and the specialist is the only liquidity provider.[38] Consistent with this analysis, Ready (1999) finds that orders that the specialist stops are more profitable to the liquidity supplier than orders which are allowed to transact against the limit order book. Of course, there have been many institutional changes since this study, such as decimalization and direct access to the limit order book. It would be interesting to examine how these changes have influenced the extent of adverse selection.

On the NYSE the specialist observes the orders that are in the book immediately prior to the opening, and can use this information to choose his own supply or demand. This raises essentially the same adverse-selection problem as in Rock (1990). In fact, the magnitude of this problem may be especially large at the opening relative to the trading day due to the large uncertainty about the valuation of the stock and the considerable private information obtained by the specialist through

[36]Sofianos (1995) has documented frequent specialists' trades inside the quoted spread, corresponding to price improvements. Note, however, that since decimalization, liquid stocks often have a one cent spread, reducing the scope for price improvement.

[37]This is consistent with the finding in Madhavan and Sofianos (1998) that specialists participate more in smaller trades.

[38]Seppi (1997) extends the analysis of Rock (1990) to compare the performance of a pure limit-order market to that of a hybrid market with a specialist and competing limit orders. He finds that a hybrid market provides better liquidity to small retail and institutional trades, while a pure limit-order market may offer better liquidity on mid-size orders. Note that, while Rock (1990) considers continuous prices, Seppi (1997) analyzes a discrete pricing grid, which mitigates market breakdown. Parlour and Seppi (2003) further analyze these issues.

the observation of the supply and demand stemming from many orders. Stoll and Whaley (1990) relate empirically the monopoly power of the specialist at the opening to the statistical properties of opening prices, namely that the open–to–open volatility is larger than the close–to–close volatility, and that the overnight innovations in returns are partially reversed during the day. Madhavan and Panchapagesan (2000) analyze empirically the limit orders in the book at the opening and the specialist's opening trade. They find that this trade tends to bring the opening price closer to the fundamental value of the asset. While they interpret this result as suggesting that the specialist enhances price discovery at the opening, we offer the alternative interpretation that the specialist buys (sells) when the price reflecting the orders in the book is undervalued (overvalued). In that interpretation, the intervention of the specialist creates an adverse selection problem.[39]

Benveniste, Marcus and Wilhelm (1992) offer an interesting counter–argument to the view that the status of the specialist enhances adverse selection. They argue that the repeated and non–anonymous interaction between the specialist and floor brokers can help to cope efficiently with information asymmetries. Consider the opposite situation, whereby investors would infrequently and anonymously interact in the marketplace. In that setting there would not be significant reputational costs to being opportunistic in the trading process. In contrast, because the brokers non–anonymously and repeatedly interact with the specialist, they would bear large reputational costs if they were to misrepresent their trading intentions to him.[40] Consistent with this argument, Venkataram (2001) finds empirically that, other things equal, the NYSE is more liquid than the Paris Bourse.

Table 3, Panel B, summarizes the theoretical and empirical analyses of the role of the specialist surveyed in this subsection. Overall these analyses suggest that, to reduce market power, and consequently transactions costs, all investors should be granted the ability to supply liquidity on equal conditions (level playing field). Indeed, most major markets (including the NYSE, NASDAQ, the London Stock Exchange, the Tokyo Stock Exchange, XETRA and the Paris Bourse) now allow for the placement of limit orders by all investors.

[39] A similar adverse selection problem can arise at the close of the NYSE. Market on close orders can be frozen and observed by the specialist and floor traders before the closing auction. This creates an opportunity to strategically undercut these orders in the last minutes of the trading day.

[40] A similar mechanism could reduce adverse selection in the upstairs market, in line with the empirical results of Booth, Lin, Martikainen and Tse (2002).

3.3 Transparency

In transparent markets abundant information is available to investors and traders about orders and quotes (ex–ante transparency) and about transactions (ex–post transparency). As this tends to equalize information across market participants, transparency reduces the magnitude of adverse-selection problems. Since these problems, as shown in Subsection 1.1.3, reduce the gains from trade, transparency can be anticipated to increase welfare. Indeed, within the context of an adverse selection–based model of the spread (in the same spirit as the synthetic model outlined in Subsection 1.1.3), Pagano and Roëll (1996) show theoretically that transparency reduces the transaction costs incurred by uninformed investors. Consistent with that analysis, Flood, Huisman, Koedjick and Mahieu (1999) find that pre–trade transparency narrows spreads in experimental financial markets. In 2002, the NYSE started disseminating electronically its limit order book. As shown by Boehmer, Saar and Yu (2004), this increased transparency enabled investors to monitor, work and cancel their limit orders. This attracted more limit orders in the book, resulting in greater displayed liquidity. As the transparency of the open limit order book reduced the informational advantage of the specialist, it reduced his participation rate.

One could argue, however, that trade disclosure can make it harder to supply liquidity to large traders. After large trades, in a transparent market, the market maker can be in a difficult bargaining position to unwind his inventory. Naik, Neuberger, and Viswanathan (1999) offer an interesting counterargument. After the risk–averse dealer has bought a block from a potentially informed trader, he seeks to unload his position. Yet to mitigate his price impact, he reduces the size of his trade, thus reducing his ability to share risk.[41] This does not arise with trade disclosure. In that case, since the market has already taken into account the information content of the trade, the dealer can unwind his inventory with little incremental price impact. Consequently, trade disclosure enhances risk sharing. The empirical evidence in Gemmill (1996) is consistent with the view that transparency at least does not reduce liquidity. Gemmill (1996) analyzes liquidity in the London Stock Exchange under three publication regimes: from 1987 to 1988 dealers had to immediately report their trades, from 1991 to 1992 they had to do so within 90 minutes, while from 1989 to 1990 they had 24 hours to do so. He finds that there is no gain in liquidity from delayed publication of block trades, as the spreads and the speed of price adjustment are not affected by the disclosure regime.

[41] This is similar to the effect analyzed in Vayanos (1999) and discussed in Subsection 2.2.2 above.

Yet, in a dynamic trading environment, transparency can have ambiguous consequences, as shown by the experimental and theoretical analyses of Bloomfield and O'Hara (1999 and 2000). If the market is opaque, only the liquidity supplier who accommodated the order is informed about it. This incentivizes liquidity suppliers initially to quote relatively tight spreads, to attract order flow and acquire private information.[42] Subsequently, the liquidity suppliers who did not participate in the initial trade face a double winner's curse problem: with respect to the informed agent, and with respect to the informed liquidity supplier. This widens their spreads. The market spread is wide also, as the informed liquidity supplier finds it optimal to undercut his competitors by just one tick. Thus, different temporal patterns emerge in the opaque and transparent markets. While in the latter, spreads may initially be relatively large, they decrease fast, as information is revealed through time. In the former, in contrast, while initial spreads are relatively tight, later spreads tend to remain relatively large. It could be interesting to test this result by comparing U-shape intraday patterns in spreads across markets with different levels of transparency.

The above results are summarized in Table 3, Panel C. The contrasting conclusions reached by the different studies reflect the facets of market liquidity on which they focus. It could be interesting to integrate these different perspectives, to identify and quantify the tradeoffs among the different aspects of transparency. This could be useful to evaluate the overall impact of transparency on welfare.

3.4 Tick Size

Early studies of the discreteness of transaction prices documented the pervasiveness of clustering on round prices (Harris, 1991) and developed econometric methodologies to bridge the gap between theoretical models with continuous prices and discrete transactions price data (Glosten and Harris (1988), Hausman, Lo and MacKinlay (1992)). The emphasis then shifted towards analyzing the consequences of price discreteness on trading strategies and market outcomes.

Coarse pricing grids can mechanically constrain liquidity suppliers and result in excessively large spreads.[43] Consider for example a discrete–price version of the Glosten (1994) model, as in Sandas (2001). Assuming that time precedence holds, and that there are a large number of

[42] This could provide an interpretation for the findings by Madhavan, Porter and Weaver (2000) that an increase in ex–ante transparency on the Toronto Stock Exchange in 1990 led to an increase in spreads.

[43] Harris (1994) develops an econometric methodology to assess the consequences on the spread of a reduction in the tick size.

potential traders, equilibrium requires that at each price the last share offered just breaks even. Under perfect competition, the marginal order placed at the best ask price, A_1, just breaks even, i.e., the quantity offered at this price is $Q_{A,1}$ such that: $A_1 = E[V|Q \geq Q_{A,1}]$. Similarly, if A_i is the i^{th} offer price, the cumulative quantity offered at A_i or lower, $Q_{A,i}$, is given by $A_i = E[V|Q \geq Q_{A,i}]$. The equilibrium limit order schedule with discrete pricing is a step function with points of upward jumps (in the case of the offer) lying on the continuous price equilibrium schedule. This model predicts that a decrease in the tick size will generally reduce the quoted spread, reduce the amount offered at each price, but leave cumulative quantity at the original set of prices unchanged. Indeed, Bessembinder (2003), and Bacidore, Battalio, Jennings and Farkas (2001) find that decimalization led to lower spreads and did not reduce execution quality. Gibson, Singh and Yerramili (2003) find that decimalization tends to bring spreads more in line with the cost of supplying liquidity.[44]

However, Goldstein and Kavajecz (2000) and Jones and Lipson (2001) provide evidence that tightening the pricing grid can reduce the overall depth of the order book. This reduction in liquidity could reflect an increase in the magnitude of the Rock (1990) adverse-selection problem, since reducing the tick size makes it less costly to undercut the book.[45] Making it less costly to undercut also undermines the value of the time priority enjoyed by limit orders, and thus discourages their placement, as noted by Harris (1994).[46] Furthermore, Cordella and Foucault (1999) show that, with relatively coarse prices, liquidity suppliers find it advantageous to rapidly quote the narrowest possible spread, to benefit from time priority at this relatively advantageous price. By making time priority less valuable, fine ticks reduce the cost of hiding orders – as the main cost of hidden orders is that they do not benefit from time priority. Consistent with this point, Harris (1998) finds that on the Toronto Stock Exchange and the Paris Bourse the fraction of orders that is hidden is relatively larger when the tick size is relatively finer.

The results presented in this subsection are summarized in Table 3, Panel D. These analyses suggest that, while tick size may a priori seem a relatively trivial issue, it can have significant consequences in the market by emphasizing the consequences of other imperfections, such as for example the Rock (1990) adverse-selection problem, or the non–competitive behavior of liquidity suppliers, as illustrated by Christie and Schultz (1994).

[44]Chordia and Subrahmanyam (1995) analyze the interplay between tick size and payment for order flow.

[45]Such undercutting could stem from human traders or computerized trading algorithms, which can very rapidly and directly transmit orders electronically to the book.

[46]See also Spatt and Srivastava (1994).

3.5 Intermarket Competition

3.5.1 The costs of fragmentation

As discussed in Subsection 1.1.3, since orders provide liquidity to one another, there is a natural tendency for trades to concentrate on one market (see Pagano (1989), Admati and Pfleiderer (1988b) and Chowdhry and Nanda (1991)). While these analyses suggest that market fragmentation should not arise in equilibrium, they are developed under the assumption that liquidity suppliers are competitive. Strategic liquidity suppliers can find it optimal to provide liquidity outside the primary market, thus inducing market fragmentation.[47] For example, they can offer "quote matching," i.e., promise to execute a maximum number of shares at the market quote determined in the primary market. This is possible when time priority is not enforced across exchanges.[48] Suppose that a quote-matching exchange promises to transact Q_0, and assume for simplicity that all small orders go to the quote matching exchange and the pricing grid is continuous. Then the market ask will be the smallest allowable price greater than $E[V|Q \geq Q_0]$, which exceeds $E[V|Q \geq 0]$. The remainder of the equilibrium limit order schedule will be unaffected. With a relatively large tick size, quote matching will have no effect on the nature of the quotes. However, as the tick size gets smaller, or the adverse-selection problem gets larger, quote matching is predicted to have more of an effect, and correspondingly market fragmentation widens the spread.[49] It should also be noted that according to this model, quote matching will be profitable at any tick size, no matter how small.

If "quote matchers" are able to capture relatively uninformed orders, the adverse selection problem faced by limit orders traders in the primary market is increased, similar to the effect of the specialist in Rock (1990). Consistent with this analysis, Easley, Kiefer and O'Hara (1996) find that there is a significant difference in the information content of orders executed in New York and Cincinnati and Hasbrouck (1995) finds that the preponderance of price discovery takes place on the NYSE.[50]

[47] Blume and Goldstein (1997) and Bessembinder and Kaufman (1997) provide empirical evidence of effective fragmentation.

[48] Deviation from time priority can arise in the U.S., as specialists on one exchange can match the National Best Bid and Offer, and thus execute orders even if they did not previously post the best bid or offer. Our analysis of the negative consequences of this feature of the National Market System is consistent with the finding in the industrial organization literature that price matching is anti–competitive.

[49] In contrast, in a private-value environment, fragmentation does not generate adverse selection, and thus does not widen the average spread, as shown by Biais (1993).

[50] On the other hand, the result that price discovery occurs mostly on the primary market, is consistent with

3.5.2 The benefits of intermarket competition

While the above arguments imply that fragmentation reduces market quality when the liquidity suppliers in the central marketplace are competitive, this result is not necessarily upheld when these liquidity suppliers enjoy market power. In that case, the presence of a second market can exert a beneficial competitive pressure on the central market. Several empirical studies actually point in that direction. Battalio, Greene and Jennings (1997) study the impact of a reform which allowed brokers to execute their customer orders themselves on the Boston and Cincinnati Stock Exchanges without respecting the time priority of other dealers on those exchanges. They find that the ability of brokers to preference their own specialist units led to a substantial diversion of executions from the NYSE to these regional markets. As this took place, the NYSE spread actually declined. Similarly, Battalio (1997) finds that NYSE spreads were reduced after Madoff Securities began purchasing order flow to attract order flow away from the NYSE. In the same spirit, the results of Lightfoot, Martin, Peterson and Sirri (1999) do not support the hypothesis that preferencing arrangements reduce the quality of financial markets. Neal (1987), Mayhew (2002), and de Fontnouvelle, Fishe and Harris (2003) find that competition among exchanges reduces spreads for options. Biais, Bisière and Spatt (2002) show that competition between two different market centers (Island and NASDAQ) is useful to complement the competition prevailing within each of these markets.

Furthermore, while fragmentation reduces the incentives to supply liquidity in the primary market, it need not imply reduced aggregate depth, as shown in Glosten (1998). Consider two competing pure limit order books, I and II, each honoring time precedence among its own quoters, but not across markets. Market order users randomly send their orders to one or the other of the exchanges. However, order–handling rules require that if an order exhausts the quantity on one exchange the remainder is sent to the other exchange for execution. Let μ be the probability that a market order is sent to exchange I. The last share at the lowest offer A on exchange I will execute if 1) the market order is sent to exchange I and it is larger than Q_I or 2) the market order is sent to exchange II and it is larger than $Q_{II} + Q_I$. Thus, the quantities Q_I and Q_{II} must satisfy:

$$\mu(A - E[V|Q > Q_I]) \Pr(Q > Q_I) + (1-\mu)(A - E[V|Q > Q_{II} + Q_I]) \Pr(Q > Q_{II} + Q_I) = 0,$$

the informed order flow hitting the NYSE first. This can give an informational advantage to the NYSE specialist, relative to the regional ones. In this context, regional specialists would be exposed to a winner's curse problem, if they undercut the NYSE quotes.

and:

$$(1-\mu)(A - E[V|Q > Q_{II}])\Pr(Q > Q_{II}) + \mu(A - E[V|Q > Q_I + Q_{II}])\Pr(Q > Q_I + Q_{II}) = 0.$$

Thus, the ask price must be greater than $E[V|Q > Q_I]$, and lower than $E[V|Q > Q_{II} + Q_I]$. Thus there is a reduced incentive to quote quantity on each exchange. However, the aggregate quantity, $Q_I + Q_{II}$, will be larger when there are two exchanges. In effect, competition between the exchanges forces the quoters to compete on the average share rather than the marginal share, thus reducing the profitability of the infra-marginal shares. As the tick size decreases, the magnitude of this effect decreases, and in the limit disappears.

3.5.3 The organization of intermarket competition affects its efficiency

While the results discussed above lead to a somewhat ambiguous conclusion, they may reflect some specific features of the architecture of U.S. markets that would not arise in other contexts. First, in a setting where time priority would be enforced across markets the above discussed negative effects of intermarket competition would not arise. Second, the profitability of attracting orders away from the NYSE may reflect the rents of those present on the floor and the corresponding transactions costs incurred by the other players. This suggests that in a context where i) time priority would be enforced across markets, and ii) no one would benefit from a privileged status, the competition between markets would not have negative effects. Note that conditions i) and ii) would hold in the case of competition between electronic limit order books, where price and time priority would be enforced across markets. The consolidation of all sources of liquidity that would arise in this context is reminiscent of the analysis of "the inevitability of an electronic limit order book" analyzed in Glosten (1994).

In addition, the coexistence of markets could be useful to reap the benefits from competition among exchanges, especially with respect to the dynamics of the market structure and the incentives to innovate in developing new trading mechanisms and technologies. For example, the modernization of European stock markets since the mid–eighties, including the switch to continuous trading and electronic markets, was spurred by the competitive pressure of London. Competition between exchanges, however, need not lead to optimal market structures, as shown by Foucault and Parlour (2004). In their model, stock exchanges choose listing fees and trading costs, which determine their attractiveness for firms interested in listing and for investors. As firms differ in the extent to which they value decreases in trading costs, and as different combinations of fees and costs can be viewed

as differentiated products, two competing exchanges can find it optimal to design different fees and costs structures, and serve two different market niches. The corresponding duopolistic equilibrium fails to maximize welfare and can lead to lower welfare than a monopolistic situation.

4 Conclusion

One conclusion emerging from this survey is that market microstructure definitely matters. The results surveyed in Sections 1 and 2 show that, because of order handling and inventory costs, adverse selection and market power, trades have an impact on prices and fully efficient allocations are in general not achieved. The results surveyed in Section 3 show that the organization of the market can emphasize or mitigate these costs and the associated inefficiencies: to mitigate market power and facilitate risk sharing, there should be free entry to supply liquidity and pricing grids should not be coarse. to minimize adverse-selection costs, markets should be transparent and the different suppliers of liquidity should be allowed to intervene on a level playing field, in terms of market information, priority and order–handling procedures.

Electronic limit order books offer an obvious vehicle to implement these desirable features of the microstructure of markets: they make it possible for many investors around the globe to observe market information and compete to supply liquidity; they make it possible to implement clear algorithms, such as call auctions or continuous double auctions, and enforce pre–defined priority rules. Indeed, in recent years, there has been a general move towards open electronic limit order books in industrialized countries (Euronext, Xetra, SETS, Island,...) as well as in developing economies (China, Africa, Brazil, ...). The NYSE relies increasingly upon its electronic limit order book, which enables automatic order execution. We expect this market model to develop further, consistent with the view that the electronic open limit order book is inevitable (as discussed in Glosten (1994)). Rather than a gigantic integrated order book, it is likely that several limit order books will coexist. Such a coexistence is desirable, since, along with the competition among liquidity suppliers within one market, the competition across markets plays an important role in curbing market power and intermediation rents. The evolution of and competition between markets will be affected by their corporate governance. Several exchanges have recently gone public, e.g., Euronext, and the London and Frankfurt Bourses. In contrast, the NYSE is not publicly held, but rather is owned by its members (specialists and brokers). It will be useful to analyze the implications of the governance and ownership of market organizations.

The next challenge facing market microstructure researchers is to translate their analyses into applicable methods. These should be useful for investors and traders in the design of their order placement strategies.[51] Major financial players are currently developing tools to measure liquidity and design trading robots, relying in part on the insights generated by the microstructure literature. This literature should also be useful for market organizers to develop and improve trading mechanisms. The application of mechanism design theory could prove useful in this context. Indeed, it has already been very useful in the analysis of auctions (e.g., in the case of spectrum auctions) or IPOs.[52] The analysis of experimental markets should also prove useful. It enables one to vary the institutional context and the structure of the market, an option which is not available for field researchers and costly for market organizers.[53] It also enables the researchers to observe important elements which are difficult to disentangle from field data: information sets, potential gains from trade, equilibrium behavior.[54] Finally, it enables measurement of the extent to which agents converge to, or deviate from, equilibrium behavior, and how this is related to the organization of the market or the psychology of participants.[55]

[51]This line of research could build on the insights into institutional trading behavior offered by Chan and Lakonishok (1995), Keim and Madhavan (1995), and Cheng and Madhavan (1997), the econometric approach developed by Lo, MacKinlay, and Zhang (2002), and the analysis of order placement strategies by Biais, Hillion and Spatt (1995) and Harris and Hasbrouck (1996).

[52]For IPOs, see, e.g., Benveniste and Spindt (1989), Benveniste and Wilhelm (1990), Spatt and Srivastava (1991), and Biais, Bossaerts and Rochet (2001). For auctions, see, e.g., the analysis of Satterthwaite and Williams (2002) discussed above in this survey. Biais and Mariotti (2003) and Biais, Martimort and Rochet (2000) apply mechanism design theory to the trading of financial securities.

[53]See, e.g., Bloomfield and O'Hara (1998, 1999, 2000), Schnitzlein (1996), and Flood et al. (1999).

[54]See, e.g., Pouget (2001).

[55]See, e.g., Biais and Pouget (2000) and Biais, Hilton, Mazurier and Pouget (2004).

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TABLE 1: COMPETITIVE MARKET MAKERS AND THE COST OF TRADES

	Theoretical implications	Empirical results
Inventory paradigm	As market makers buy (sell) & their inventory increases (decreases), they seek to sell (buy) back. Hence they lower (raise) their quotes, to control the order flow and bring their inventory back to their preferred position. (Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1981 and 1983)).	Market makers with long (short) positions tend to sell (buy) back (Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), Manaster and Mann (1996), Reiss and Werner (1998), Hansch et al (1998)). Results on the impact of inventory positions on prices are ambiguous: Increases (decreases) in the inventory of the NYSE specialist lead to decreases (increases) in quotes (Madhavan and Smidt (1993)). After price rises (decreases), where he is likely to have sold (bought), the specialist is more likely to be on the bid side of the book (Kavajecz (1999)). But, on the CME, floor brokers tend to sell at high prices and buy at low prices (Manaster and Mann (1996)).
Adverse selection paradigm	Trading with privately informed investors leads to losses for market makers. They set spreads to compensate for these losses. Hence, spreads increase with adverse selection. (Glosten and Milgrom (1985) and Kyle (1985)).	Trades have a permanent impact on prices (Hasbrouck (1991), Holthausen, Leftwich and Mayers (1990)), consistent with transactions reflecting private *or public* information (Neal and Wheatley (1998)). Block trades predict innovations in earnings (Seppi (1992)). Market makers incur positioning losses on their inventory (Sofianos (1995), Naik and Yadav (1999)). Spreads increase and depth decreases before earnings announcements (Lee et al (1993) and Kavajecz (1999)).

TABLE 2: STRATEGIC LIQUIDITY SUPPLY
Panel A: Analyses which do not rely on adverse selection

	Theoretical analyses	Empirical results
One-period analyses	When the number of liquidity suppliers is finite, equilibrium prices are non-competitive. In a uniform-price mechanism this obtains with risk averse or risk neutral dealers (Klemperer & Meyer (1989)). In a discriminatory price mechanism, this arises only if dealers are risk averse, which results in increasing marginal costs of supplying liquidity (Biais, Foucault & Salanié (1998), Roëll (1999), Viswanathan and Wang (2005)).	NASDAQ quotes before 1994 were consistent with collusion between dealers (Christie & Schultz (1994) and Christie, Harris & Schultz (1994)). For comparable stocks, Huang and Stoll (1996) find larger spreads on NASDAQ than on the NYSE. After 1997, as limit order traders were authorized to compete with dealers to supply liquidity, spreads were significantly reduced on NASDAQ (Barclay et al (1999)) and on the London Stock Exchange (Naik and Yadav (1999)).
Dynamic analyses	It is optimal to place limit orders when the spread is large and market orders when it is tight (Foucault (1999)).	On the NYSE, for stocks with ¼ spread, limit orders within the quotes outperform market orders (Harris and Hasbrouck (1996)).
	Investors trade off time priority and price when deciding where to place orders in the book (Parlour (1998)).	On the Paris Bourse, limit orders within the quotes are more frequent when the spread is large or depth at the quotes is large (Biais, Hillion and Spatt (1995)).
	Persistence in states of the order book leads to positive serial correlation in order types (Goettler, Parlour and Rajan (2003)).	Limit orders exhibit positive serial correlation (Biais, Hillion and Spatt (1995), Griffiths et al (2000), Ellul et al (2003)).

TABLE 2: STRATEGIC LIQUIDITY SUPPLY
Panel B: Analyses relying on adverse selection

	Theoretical analyses	Empirical results
Uninformed market makers	Because of adverse selection, the marginal cost of supplying liquidity is increasing (Glosten (1994)). Consequently, with a finite number of market makers, there are oligopolistic rents, increasing in the degree of adverse selection (Bernhardt and Hughson (1997) and Biais, Martimort and Rochet (2000)).	The reduction in spreads following the 1997 NASDAQ market reform was far more pronounced for small volume firms (Barclay et al (1999)), which are those for which adverse selection problems are likely to be the most severe. Sandas (2001) finds steeper limit order schedules than predicted by the Glosten (1994) competitive model. Limit orders placed on Island earned oligopolistic rents before NASDAQ decimalization (Biais, Bisière and Spatt (2002)).
Informed market makers	Informed market makers inject noise in their quotes to avoid immediate full revelation and preserve their informational edge, yet their quotes and trades reveal some information to the market (Calcagno and Lovo (1998)).	CME market makers' trades tend to be in the right direction (Manaster and Mann (1996)). .

TABLE 3: MARKET DESIGN
Panel A: Call versus continuous market

	Theoretical analyses	Empirical analyses
Efficient pricing		NYSE opening call auction prices are noisier than closing prices, but the Tokyo Stock Exchange midday call auction price is not (Amihud and Mendelson (1987 and 1991)).
	Prior to the call auction, information revelation and order flow tend to accelerate towards the end of the pre-opening period (Medrano and Vives (2001)).	Order flow and information revelation do accelerate towards the end of the preopening in the Paris Bourse (Biais, Hillion and Spatt (1999)). The preopening enhances the efficiency of the opening call in experimental markets (Biais and Pouget (2001)).
Risk Sharing	Strategic agents, with private information about their risk sharing needs, limit their trades to reduce market impact. This is stronger with continuous trading than when there is a larger time interval between trades (Vayanos (1999)). Double auctions converge fast to the optimal trading mechanism when the number of traders goes to infinity (Satterthwaite and Williams (2002)).	
Adverse selection	Limit orders are exposed to adverse selection when picked off by subsequent market orders reflecting recent information (Copeland and Galai (1983)). Simultaneous moves in a call auction circumvent this problem.	New order placements and cancellation are relatively more frequent during trading halts held prior to subsequent call auctions to resume trading (Corwin and Lipson (2000)).

TABLE 3: MARKET DESIGN
Panel B: The specialist

Due to the presence of the specialist, adverse selection can be :	Theoretical analyses	Empirical analyses
worsened …	When an order arrives on the floor the specialist can choose to undercut the book, to stop the order or to let it hit the book. This creates an adverse selection problem (Rock (1990)). A similar adverse selection problem arises at the opening of the market, since the specialist places his orders after the public (Stoll and Whaley (1990)). To the extent that small trades have a lower informational content it can be advantageous for the specialist to step up and execute these (Seppi (1997)).	Petersen and Falkowski (1994) and Sofianos (1995) document order stopping. Consistent with the analysis of Rock (1990), Ready (1999) finds that stopped orders are more profitable for liquidity suppliers than orders allowed to trade with the book. At the opening, the specialist tends to place orders to buy (sell), when the clearing price that would result from public orders is undervalued (overvalued) (Madhavan and Panchapagesan (2000)).
or mitigated.	The specialist, interacting repeatedly with brokers, can extract private information from them, thus reducing adverse selection (Benveniste et al (1992)).	Other things equal, the NYSE (a specialist market) is more liquid than the Paris Bourse (a limit order market) (Venkataram (2001)).

TABLE 3: MARKET DESIGN
Panel C: Transparency

Form of transparency	Theoretical analyses	Empirical analyses	Experimental analyses
Ex ante	Better information reduces adverse selection and hence spreads (Pagano and Roell (1996)).	An increase in ex-ante transparency attracted more limit orders in the NYSE book, resulting in greater displayed liquidity (Boehmer, Saar and Yu (2004)), but on the Toronto Stock Exchange it was followed by an increase in spreads (Madhavan, Porter and Weaver (2000)).	Pre-trade transparency narrows spreads (Flood et al. (1999)).
Ex post	Trade disclosure enhances risk sharing (Naik et al. (1999)).	In the London Stock Exchange, dealer spreads were not affected by changes in the trade disclosure regime (Gemmill (1996)).	Opening spreads are larger, but subsequent spreads tighter, when ex-post transparency is enhanced (Bloomfield and O'Hara (1999 and 2000)).

TABLE 3: MARKET DESIGN
Panel D: Tick size

Theoretical analyses	Empirical analyses
Coarse price grids can constrain spreads to be excessively wide (Harris (1994)).	Decimalization led to lower spreads without reducing execution quality (Bessembinder (2003) and Bacidore, Battalio, Jennings and Farkas (2001)) and brought spreads more in line with the cost of supplying liquidity (Gibson, Singh and Yerramili (2003)).
With a coarse grid, it can be attractive to be the first dealer to post a one tick spread. This raises the incentives to undercut wider spreads (Cordella and Foucault (1999)).	Some studies find a reduction in the cumulated depth of the NYSE book after the reduction of tick size from one eighth to one sixteenth (Goldstein and Kavajecz (2000) and Jones and Lipson (2001)).
Finer ticks can exacerbate Rock's (1990) adverse selection problem (Seppi (1997)).	