Do Dark Pools Harm Price Discovery?*

Haoxiang Zhu
Graduate School of Business, Stanford University
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Abstract

Dark pools are equity trading systems that do not publicly display orders. Orders in dark pools are matched within the exchange bid-ask spread without a guarantee of execution. Informed traders are more likely to cluster on the heavy side of the market and therefore face a lower execution probability in the dark pool, relative to uninformed traders. Consequently, exchanges are more attractive to informed traders, whereas dark pools are more attractive to uninformed traders. Under natural conditions, adding a dark pool alongside an exchange concentrates price-relevant information into the exchange and improves price discovery.

Keywords: dark pools, price discovery, liquidity, fragmentation, equity market structure

JEL Classifications: G12, G14, G18

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1 Introduction

Dark pools are equity trading systems that do not publicly display orders. Some dark pools passively match buyers and sellers at exchange prices, such as the midpoint of the exchange bid and offer. Other dark pools essentially operate as nondisplayed limit order books that execute orders by price and time priority.

In this paper, I investigate the impact of dark pools on price discovery. Contrary to misgivings expressed by some regulators and market participants, I find that under natural conditions, adding a dark pool improves price discovery on the exchange.

According to the Securities and Exchange Commission (SEC; 2010), as of September 2009, 32 dark pools in the United States accounted for 7.9% of total equity trading volume. As of mid-2011, industry estimates from the Tabb Group, a consultancy, and Rosenblatt Securities, a broker, attribute about 12% of U.S. equity trading volume to dark pools. The market shares of dark pools in Europe, Canada, and Asia are smaller but quickly growing (International Organization of Securities Commissions, 2010).

Dark pools have raised regulatory concerns in that they may harm price discovery. The European Commission (2010), for example, remarks that “[a]n increased use of dark pools . . . raise[s] regulatory concerns as it may ultimately affect the quality of the price discovery mechanism on the ‘lit’ markets.” The International Organization of Securities Commissions (2011) similarly worries that “the development of dark pools and use of dark orders could inhibit price discovery if orders that otherwise might have been publicly displayed become dark.” According to a recent survey conducted by the CFA Institute (2009), 71% of respondents believe that the operations of dark pools are “somewhat” or “very” problematic for price discovery. The Securities and Exchange Commission (2010), too, considers “the effect of undisplayed liquidity on public price discovery” an important regulatory question. Speaking of nondisplayed liquidity, SEC Commissioner Elisse Walter commented that “[t]here could be some truth to the criticism that every share that is crossed in the dark is a share that doesn’t assist the market in determining an accurate price.”

My inquiry into dark pools builds on a simple model of strategic venue selection by informed and liquidity traders. Informed traders hope to profit from proprietary information regarding the value of the traded asset, whereas liquidity traders wish to meet their idiosyncratic liquidity needs. Both types of traders optimally choose between an exchange and a dark pool. The exchange displays a bid and an ask and executes all submitted orders at the bid or the ask. The dark pool free-rides on exchange prices.
by matching orders within the exchange’s bid and ask. Unlike the exchange, the dark pool has no market makers through which to absorb excess order flow and thus cannot guarantee execution. Sending an order to the dark pool therefore involves a trade-off between potential price improvement and the risk of no execution.

Execution risk in the dark pool drives my results. Because matching in the dark pool depends on the availability of counterparties, some orders on the “heavier” side of the market—the side with more orders—will fail to be executed. These unexecuted orders may suffer costly delays. Because informed orders are positively correlated with the value of the asset and therefore with each other, informed orders are more likely to cluster on the heavy side of the market and suffer lower execution probabilities in the dark pool. By contrast, liquidity orders are less correlated with each other and less likely to cluster on the heavy side of the market; therefore, liquidity orders have higher execution probabilities in the dark pool. This difference in execution risk pushes relatively more informed traders into the exchange and relatively more uninformed traders into the dark pool. Under natural conditions, this self selection lowers the noisiness of demand and supply on the exchange and improves price discovery.

The main intuition underlying my results does not hinge on the specific trading mechanisms used by a dark pool. For example, a dark pool may execute orders at the midpoint of the exchange bid and ask or operate as a nondisplayed limit order book. As I show, with both of these mechanisms, traders face a trade-off between potential price improvement and execution risk. Dark pools that operate as limit order books are, however, relatively more attractive to informed traders because limit orders can be used to gain execution priority and thus reduce execution risk.

Dark pools do not always improve price discovery. For example, in the unlikely event that liquidity traders push the net order flow far opposite of the informed traders, the presence of a dark pool can exacerbate the misleading inference regarding the asset value. Moreover, better price discovery needs not coincide with higher liquidity or welfare. For example, more informative orders often lead to better price discovery but also tend to worsen adverse selection on the exchange, which results in wider spreads and higher price impacts. The welfare implications of dark pools could naturally depend on elements outside the setting of my model, such as how price information is used for production decisions, asset allocation, and capital formation. Finally, for analytical tractability I have abstracted from some of the trading practices that are applied in dark pools, such as “pinging,” order routing, and “indication of interest” (IOI). These and

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*“Pinging” orders are marketable orders that seek to interact with displayed or nondisplayed liquidity. Pinging is sometimes used to learn about the presence of large hidden orders. Order routing means sending orders from venue to venue, typically by algorithms. For example, if a dark pool cannot execute an order because there is no*
other procedures used by some dark pools may well contribute to concerns regarding their impact on price discovery. This is distinct from the implications of execution risk, which I focus on in this paper.

An objective of this paper is to understand how selective fragmentation of trading across transparent exchanges and dark pools can arise and affect price discovery. The price-discovery effect of dark pools differs from their “size discovery” function, by which large institutional orders are executed without being revealed to the broad market.\(^3\)

My results further suggest that informed traders have even stronger incentives to trade on the exchange under a “trade-at” rule, which requires that trading venues that do not quote the best price either to route incoming orders to venues quoting the best price or to provide incoming orders with a sufficiently large price improvement over the prevailing best price. The impact of a trade-at rule on price discovery complements previous fairness-motivated arguments that displayed orders—which contribute to pre-trade transparency—should have strictly higher priority than do nondisplayed orders at the same price.\(^4\)

To the best of my knowledge, this paper is the first to show that the addition of a dark pool can improve price discovery. My finding stands in contrast to that of Ye (2010a), who studies the venue choice of a large informed trader in the Kyle (1985) framework and concludes that the addition of a dark pool harms price discovery on the exchange. Ye (2010a), however, assumes exogenous choices of trading venues by liquidity traders, whereas the endogenous venue choices of liquidity traders are critical to my results. Most other existing models of dark pools either exogenously fix the strategies of informed traders, as in Hendershott and Mendelson (2000), or do not consider the role of asymmetric information regarding the asset value, as in Degryse, Van Achter, and Wuyts (2009) and Buti, Rindi, and Werner (2010b). Going beyond the midpoint-matching mechanism, my study additionally reveals that dark pools with more discretion in execution prices are more attractive to informed traders.

The focus of this paper—i.e., on the fragmentation of order flow between an ex-

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3See, for example, Securities and Exchange Commission (2010) and Ready (2010) for discussions of the size-discovery function of dark pools.

4For example, the Joint CFTC-SEC Advisory Committee (2011) has noted: “Under current Regulation NMS routing rules, venues cannot ‘trade through’ a better price displayed on another market. Rather than route the order to the better price, however, a venue can retain and execute the order by matching the current best price even if it has not displayed a publicly accessible quote order at that price. While such a routing regime provides order execution at the current best displayed price, it does so at the expense of the limit order posting a best price which need not receive execution.”
change and a dark pool—differs from the focus of prior studies on competition among multiple markets. In exchange markets, for example, informed traders and liquidity traders tend to cluster by time (Admati and Pfleiderer, 1988) or by location (Pagano, 1989; Chowdhry and Nanda, 1991). However, as modeled here, informed traders cluster less with liquidity traders in the dark pool than on the exchange because informed traders face higher execution risk in the dark pool. Related to the effect captured by my model, Easley, Keifer, and O’Hara (1996) suggest that the purchase of retail order flows (“cream-skimming”) by regional exchanges results in higher order informativeness on the NYSE. In contrast with the mechanism studied in their paper, in my model dark pools rely on self selection, rather than intermediaries, to separate, at least partially, informed traders from liquidity traders.

My results have several empirical implications. For example, the model predicts that higher order imbalances tend to cause lower dark pool activity; higher volumes of dark trading lead to wider spreads and higher price impacts on exchanges; volume correlation across stocks is higher on exchanges than in dark pools; and informed traders more actively participate in dark pools when asymmetric information is more severe or when the dark pool allows more discretion in execution prices. Section 6 discusses these implications, as well as discussing recent, related empirical evidence documented by Ready (2010), Buti, Rindi, and Werner (2010a), Ye (2010b), Ray (2010), Nimalendran and Ray (2011), Degryse, de Jong, and van Kervel (2011), O’Hara and Ye (2011), and Weaver (2011), among others.

2 An Overview of Dark Pools

This section provides an overview of dark pools. I discuss why dark pools exist, how they operate, and what distinguishes them from each other. For concreteness, I tailor this discussion for the market structure and regulatory framework of the United States. Dark pools in Europe, Canada, and Asia operate similarly.

Before 2005, dark pools had low market share. Early dark pools were primarily used by institutions to trade large blocks of shares without revealing their intentions to the broad market, in order to avoid being front-run. A watershed event for the U.S. equity market was the adoption in 2005 of Regulation National Market System, or Reg NMS (Securities and Exchange Commission, 2005), which abolished rules that had protected the manual quotation systems of incumbent exchanges. In doing so, Reg NMS encouraged newer and faster electronic trading centers to compete with the

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5Predatory trading is modeled by Brunnermeier and Pedersen (2005) and Carlin, Lobo, and Viswanathan (2007).
Figure 1: U.S. equity trading volume and the market share of dark pools. The left axis plots the daily consolidated equity trading volume in the United States, estimated by Tabb Group. The right axis plots the market shares of dark pools as a percentage of the total consolidated volume, estimated by Tabb Group and Rosenblatt Securities.

incumbents. Since Reg NMS came into effect, a wide variety of trading centers have been established. As of September 2009, the United States had about 10 exchanges, 5 electronic communication networks (ECNs), 32 dark pools, and over 200 broker-dealers (Securities and Exchange Commission, 2010). Exchanges and ECNs are referred to as transparent, or “lit,” venues; dark pools and broker-dealer internalization are considered opaque, or “dark,” venues. In Europe, the adoption in 2007 of the Markets in Financial Instruments Directive (MiFID) similarly led to increased competition and a fast expansion of equity trading centers.6

Figure 1 shows the consolidated volume of U.S. equity markets from July 2008 to June 2011, as well as the market share of dark pools during the same periods, estimated by Tabb Group and Rosenblatt Securities. According to their data, the market share of dark pools roughly doubled from about 6.5% in 2008 to about 12% in 2011, whereas consolidated equity volume dropped persistently from about 10 billion shares per day in 2008 to about 7 billion shares per day in 2011. A notable exception to the decline in consolidated volume occurred around the “Flash Crash” of May 2010.

Dark pools have gained market share for reasons that go beyond recent regulations designed to encourage competition. Certain investors, such as institutions, simply need

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6For example, according to CFA Institute (2009), European equity market had 92 regulated markets (exchanges), 129 “multilateral trading facilities” (MTFs), and 13 “systematic internalizers” as of September 2010. For more discussion of MiFID and European equity market structure, see European Commission (2010).
nondisplayed venues to trade large blocks of shares without alarming the broad market. This need has increased in recent years as the order sizes and depths on exchanges have declined dramatically (Chordia, Roll, and Subrahmanyam, 2011). Further, dark pools attract investors by offering potential price improvements relative to the best prevailing bid and offer on exchanges. Finally, broker-dealers handling customer orders have strong incentives to set up their own dark pools, where they can better match customer orders internally, and therefore save trading fees that would otherwise be paid to exchanges and other trading centers.

At least two factors contribute to the lack of precise official data on dark pool transactions in the United States. First, U.S. dark pool trades are reported to “trade reporting facilities,” or TRFs, which aggregate trades executed by all off-exchange venues—including dark pools, ECNs, and broker-dealer internalization—into a single category. Thus, it is generally not possible to assign a TRF trade to a specific off-exchange venue that executes the trade.7 Second, dark pools often do not have their own identification numbers (MPID) for trade reporting. For example, a broker-dealer may report customer-to-customer trades in its dark pool together with the broker’s own over-the-counter trades with institutions, all under the same MPID. Similarly, trades in an exchange-owned dark pool can be reported together with trades conducted on the exchange’s open limit order book, all under the exchange’s MPID. Because different trading mechanisms share the same MPID, knowing the MPID that executes a trade is insufficient to determine whether that trade occurred in a dark pool.8

Dark pools differ from each other in many ways. We can categorize them, roughly, into the three groups shown in the top panel of Table 1.

Dark pools in the first group match customer orders by acting as agents (as opposed to trading on their own accounts). In this group, transaction prices are typically derived from lit venues. These derived prices include the midpoint of the national best bid and offer (NBBO) and the volume-weighted average price (VWAP). Dark pools in this group include three block-crossing dark pools: ITG Posit, Liquidnet, and Pipeline.9 Posit crosses orders a few times a day at scheduled clock times (up to some randomization), although in recent years it has also offered continuous crossing. Liquidnet is integrated into the order-management systems of institutional investors and alerts potential counterparties when a potential match is found. Pipeline maintains

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7The Securities and Exchange Commission (2009) has recently proposed a rule requiring that alternative trading systems (ATS), including dark pools, provide real-time disclosure of their identities on their trade reports.

8For example, Ye (2010b) finds that only eight U.S. dark pools can be uniquely identified by MPIDs from their Rule 605 reports to the SEC. The majority of dark pools cannot.

9See also Ready (2010) for a discussion of these three dark pools.
a flashboard of stock names in colors that change when serious trading interests are present. In addition to those three, Instinet is another agency broker that operates scheduled and continuous dark pools. Because Group-1 dark pools rely on lit venues to determine execution prices, they typically do not provide direct price discovery.

Within the second group, dark pools operate as continuous nondisplayed limit order books, accepting market, limit, or “pegged” orders. This group includes many of the dark pools owned by major broker-dealers, including Credit Suisse Crossfinder, Goldman Sachs Sigma X, Citi Match, Barclays LX, Morgan Stanley MS Pool, and UBS PIN. Unlike Group-1 dark pools that execute orders at the market midpoint or VWAP, Group-2 dark pools derive their own execution prices from the limit prices of submitted orders. Price discovery can therefore take place. Another difference is that Group-2 dark pools may contain proprietary order flows from the broker-dealers that operate them. In this sense, these dark pools are not necessarily “agency only.”

Dark pools in the third group act like fast electronic market makers that immediately accept or reject incoming orders. Examples include Getco and Knight. Like the second group, transaction prices on these platforms are not necessarily calculated from the national best bid and offer using a transparent rule. In contrast with dark pools in Groups 1 and 2, Group-3 dark pools typically trade on their own accounts as principals (as opposed to agents or marketplaces).

This three-way classification is similar to that of Tabb Group (2011), which classifies dark pools into block-cross platforms, continuous-cross platforms, and liquidity-provider platforms. The main features of these three groups are summarized in the middle panel of Table 1. Their respective market shares are plotted in Figure 2. As we can see, the market share of block-cross dark pools has declined from nearly 20% in 2008 to just above 10% in 2011. Continuous-cross dark pools have gained market share during the same period, from around 50% to around 70%. The market share of liquidity-providing dark pools increased to about 40% around 2009, but then declined to about 20% in mid 2011. Tabb Group’s data, however, do not cover the entire universe of dark pools, and the components of each category can vary over time. For this reason, these statistics are noisy and should be interpreted with caution.

Dark pools are also commonly classified by their crossing frequencies and by how they find matching counterparties, as illustrated in the bottom panel of Table 1. Aside from mechanisms such as midpoint-matching and limit order books, advertisement is

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10 Pegged orders are limit orders with the limit price set relative to an observable market price, such as the bid, the offer, or the midpoint. As the market moves, the limit price of a pegged order moves accordingly. For example, a midpoint-pegged order has a limit price equal to the midpoint of the prevailing NBBO. A buy order pegged at the offer minus one cent has a limit price equal to the prevailing best offer minus one cent.
Table 1: Dark pools by crossing mechanism. The top panel shows a classification by price discovery and order composition. The middle panel shows the classification of Tabb Group. The bottom panel shows another classification by the crossing frequencies and the methods of finding counterparties.

### Classification 1

<table>
<thead>
<tr>
<th>Types</th>
<th>Examples</th>
<th>Typical features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching at exchange prices</td>
<td>ITG Posit, Liquidnet, Pipeline, Instinet</td>
<td>Mostly owned by agency brokers and exchanges; typically execute orders at midpoint or VWAP, and customer-to-customer</td>
</tr>
<tr>
<td>Nondisplayed limit order books</td>
<td>Credit Suisse Crossfinder, Goldman Sachs, Sigma X, Citi Match, Barclays LX, Morgan Stanley MS Pool, UBS PIN</td>
<td>Most broker-dealer dark pools; may offer some price discovery and contain proprietary order flow</td>
</tr>
<tr>
<td>Electronic market makers</td>
<td>Getco and Knight</td>
<td>High-speed systems handling immediate-or-cancel orders; typically trade as principal</td>
</tr>
</tbody>
</table>

### Classification 2

<table>
<thead>
<tr>
<th>Types</th>
<th>Examples</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block cross</td>
<td>Liquidnet, BIDS, Instinet Cross</td>
<td>Similar to the first group of the top panel</td>
</tr>
<tr>
<td>Continuous cross</td>
<td>Credit Suisse Crossfinder, Goldman Sachs, Sigma X, Barclays LX, Morgan Stanley MS Pool, LeveL, Deutsche Bank SuperX</td>
<td>Similar to the second group of the top panel; LeveL is owned by a consortium of broker-dealers</td>
</tr>
<tr>
<td>Liquidity provider</td>
<td>Getco and Knight</td>
<td>Same as the third group of the top panel</td>
</tr>
</tbody>
</table>

### Classification 3

<table>
<thead>
<tr>
<th>Types</th>
<th>Examples</th>
<th>Typical features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheduled</td>
<td>ITG POSIT Match, Instinet US Crossing</td>
<td>Cross at fixed clock times, with some randomization</td>
</tr>
<tr>
<td>Matching</td>
<td>ITG POSIT Now, Instinet CBX, Direct Edge, MidPoint Match</td>
<td></td>
</tr>
<tr>
<td>Advertized</td>
<td>Pipeline, POSIT Alert, Liquidnet</td>
<td>Electronic messages sent to potential matched counterparties</td>
</tr>
<tr>
<td>Negotiated</td>
<td>Liquidnet</td>
<td></td>
</tr>
<tr>
<td>Internal</td>
<td>Credit Suisse Crossfinder, Goldman Sachs, Sigma X, Knight Link, Getco</td>
<td>Owned by broker-dealers, run as nondisplayed limit order books or electronic market makers</td>
</tr>
</tbody>
</table>
Figure 2: Market shares of three types of U.S. dark pools as fractions of total U.S. dark pool volume, estimated by Tabb Group. The three types are summarized in the middle panel of Table 1.

sometimes used to send selected information about orders resting in the dark pool to potential counterparties, in order to facilitate a match. In addition to the classifications summarized in Table 1, dark pools can be distinguished by their ownership structure. Today, most dark pools are owned by broker-dealers (with or without proprietary order flows). A small fraction is owned by consortiums of broker-dealers or exchanges. Dark pools also differ by their average trade size. According to Rosenblatt Securities (2011), two block-size dark pools (Liquidnet and Pipeline) have an order size of around 50,000 shares, which is larger than that of Posit (around 6,000 shares per order) and much larger than those of other broker dark pools (about 300 shares per order). This sharp contrast in order sizes can be attributed to the use of algorithms that split “parent” orders into smaller “children” orders, as observed by the Securities and Exchange Commission (2010).

Finally, there are two sources of nondisplayed liquidity that are usually not referred to as dark pools. One is broker-dealer internalization, by which a broker-dealer handles customer orders as a principal or an agent (Securities and Exchange Commission, 2010). A crude way of distinguishing dark pools from broker-dealer internalization is that the former are often marketplaces that allow direct customer-to-customer trades, whereas the latter typically involves broker-dealers as intermediaries.\textsuperscript{11} The other source of

\textsuperscript{11} There are exceptions. For example, dark pools acting like electronic market makers (like Getco and Knight) also provide liquidity by trading on their own accounts. Nonetheless, they are highly automated systems and rely less on human intervention than, say, dealers arranging trades over the telephone.
nondisplayed liquidity is the use of hidden orders on exchanges. Examples include reserve ("iceberg") orders and pegged orders, which are limit orders that are partially or fully hidden from the public view.\textsuperscript{12} For example, Nasdaq reports that more than 15\% of its order flow is nondisplayed.\textsuperscript{13} In particular, midpoint-pegged orders on exchanges are similar to dark pool orders waiting to be matched at the midpoint. Further discussion of dark pools and nondisplayed liquidity is provided by Johnson (2010), Butler (2007), Carrie (2008), Securities and Exchange Commission (2010), European Commission (2010), CSA/IIROC (2009), and International Organization of Securities Commissions (2011).

3 Modeling the Exchange and Dark Pool

This section presents a two-period model of trading-venue selection. Each trader chooses whether to trade on a transparent exchange or in a dark pool. The dark pool modeled in this section passively matches orders at the midpoint of the exchange’s bid and ask. Section 4 models a dark pool that operates as a nondisplayed limit order book. The order-book setting provides additional insights regarding the effect of the dark pool crossing mechanism for price discovery. A dynamic equilibrium with sequential arrival of traders is characterized in Section 5. A glossary of key model variables can be found in Appendix C.

3.1 Markets and traders

There are two trading periods, denoted by $t = 1, 2$. At the end of period 2, an asset pays an uncertain dividend $v$ that is equally likely to be $+\sigma$ or $-\sigma$. Thus, $\sigma > 0$ is the volatility of the asset value. The asset value $v$ is publicly revealed at the beginning of period 2.

Two trading venues operate in parallel: a lit exchange and a dark pool. The exchange is open in periods 1 and 2. On the exchange, a risk-neutral market maker sets competitive bid and ask prices. Market orders sent to the exchange arrive simultaneously. Exchange buy orders are executed at the ask; exchange sell orders are executed at the bid. The exchange here is thus similar to that modeled by Glosten and Milgrom\textsuperscript{12}A reserve order consists of a displayed part, say 200 shares, and a hidden part, say 1,800 shares. Once the displayed part is executed, the same amount, taken from the hidden part, becomes displayed, until the entire order is executed or canceled. Pegged orders are often fully hidden. Typically, pegged orders and hidden portions of reserve orders have lower execution priority than displayed orders with the same limit price.\textsuperscript{13}See http://www.nasdaqtrader.com/Trader.aspx?id=DarkLiquidity
After period-1 orders are executed, the market maker announces the volume $V_b$ of exchange buy orders and the volume $V_s$ of exchange sell orders. The market maker also announces the exchange “closing price” $P_1$, which is the expected asset value conditional on $V_b$ and $V_s$. A key objective of this section is to analyze price discovery, that is, the informativeness of these announcements for the fundamental value $v$ of the asset.

The dark pool executes (or “crosses”) orders in period 1 and is closed in period 2. Closing the dark pool in period 2 is without loss of generality because once the dividend $v$ is announced in period 2, exchange trading is costless. An order submitted to the dark pool is not observable to anyone but the order submitter. The execution price of dark pool trades is the midpoint of the exchange bid and ask, also known simply as the “midpoint” or “mid-market” price. In the dark pool, orders on the “heavier side”—the buyers’ side if buy orders exceed sell orders, and the sellers’ side if sell orders exceed buy orders—are randomly selected for matching with those on the “lighter” side. For example, if the dark pool receives $Q_B$ buy orders and $Q_S < Q_B$ sell orders, all of the same size, then $Q_S$ of the $Q_B$ buy orders are randomly selected, equally likely, to be executed against the $Q_S$ sell orders at the mid-market price. Unmatched orders are returned to the order submitter at the end of period 1. As described in Section 2, this midpoint execution method is common in dark pools operated by agency brokers and exchanges. An alternative dark pool mechanism, a nondisplayed limit order book, is modeled in Section 4.

For-profit traders and liquidity traders, all risk-neutral, arrive at the beginning of period 1. There is a continuum of each type. Each trader is “infinitesimal” and can trade either one unit or zero unit of the asset. The mass of for-profit traders is a constant $\bar{\mu} > 0$. For-profit traders can acquire, at a cost, perfect information about $v$, and thus become informed traders. These information-acquisition costs are pairwise-independent, with the cumulative distribution function $F : [0, \infty) \rightarrow [0, 1]$. After observing $v$, informed traders submit buy orders (in either venue) if $v = +\sigma$ and submit sell orders if $v = -\sigma$. For-profit traders who do not acquire the information do not trade. I let $\mu_I$ be the mass of informed traders; their signed trading interest is therefore $Y = \text{sign}(v) \cdot \mu_I$.

Liquidity buyers and liquidity sellers arrive at the market separately (not as netted). Each liquidity buyer already holds an undesired short position of one unit; each liquidity

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14 As I describe shortly, the model of this section is not exactly the same as that of Glosten and Milgrom (1985) because orders here arrive in batches, instead of sequentially. Sequential arrival of orders is considered in Section 5.

15 Pairwise-independence here is in the “essential” sense of Sun (2006), who gives technical conditions for the exact law of large numbers on which I rely throughout.
seller already holds an undesired long position of one unit. These undesired positions could, for example, be old hedges that have become useless. The mass $Z^+$ of liquidity buyers and the mass $Z^-$ of liquidity sellers are modeled as

$$\begin{align*}
(Z^+, Z^-) &= \begin{cases} 
(Z_0 + Z, Z_0), & \text{if } Z \geq 0, \\
(Z_0, Z_0 + |Z|), & \text{if } Z < 0,
\end{cases}
\end{align*}$$

(1)

where $Z_0$ is the “balanced” part of the liquidity trading interests and $Z$ is the “imbalanced” part. We assume that $Z_0$ and $|Z|$ have finite means, that $Z^+$ and $Z^-$ have differentiable cumulative distribution functions, and that $Z$ is distributed symmetrically with respect to zero. The symmetric distribution of $Z$ guarantees that $Z^+$ and $Z^-$ are identically distributed. The total expected mass of liquidity traders is

$$\mu_z \equiv 2\mathbb{E}(Z_0) + \mathbb{E}(|Z|).$$

(2)

Liquidity traders must hold collateral to support their undesired risky positions. For each liquidity trader, the minimum collateral requirement is the expected loss, conditional on a loss, of her undesired position. For example, a liquidity buyer who is already short one unit of the asset has a loss of $\sigma$ if $v = \sigma$, and a gain of $\sigma$ if $v = -\sigma$. The collateral requirement in this case is $\sigma$. For trader $i$, each unit of collateral has a funding cost of $\gamma_i$ per period. A delay in trade is therefore costly. These funding costs $\{\gamma_i\}$ are pairwise-independently distributed across traders, with a twice-differentiable cumulative distribution function $G : [0, \Gamma) \to [0, 1]$, for some $\Gamma \in (1, \infty]$. Failing to trade in period 1, liquidity buyer $i$ thus incurs a delay cost of

$$c_i = \gamma_i \mathbb{E}[\max(v, 0) | v > 0] = \gamma_i \sigma.$$  

(3)

A like delay cost applies to liquidity sellers. We could alternatively interpret this delay cost as stemming from risk aversion or illiquidity. The key is that liquidity traders differ in their desires for immediacy, captured by the delay cost $c_i = \gamma_i \sigma$. The delay costs of informed traders, by contrast, stem from the loss of profitable trading opportunities after $v$ is revealed in period 2.

Finally, random variables $v$, $Z_0$, $Z$, and the costs of information-acquisition and delay are all independent, and their probability distributions are common knowledge. Realizations of $Y$, $Z^+$ and $Z^-$ are unobservable, with the exception that informed traders observe $v$, and hence know $Y$. Informed and liquidity traders cannot post limit orders on the exchange; they can trade only with the exchange market maker or by
Figure 3: Time line of the two-period model.

3.2 Equilibrium

An equilibrium consists of the quoting strategy of the exchange market maker, the market participation strategies of for-profit traders, and the trading strategies of informed and liquidity traders. In equilibrium, the competitive market maker breaks even in expectation and all traders maximize their expected net profits.

Specifically, I let \( \alpha_e \) and \( \alpha_d \) be candidates for the equilibrium fractions of liquidity traders who, in period 1, send orders to the exchange and to the dark pool, respectively. The remainder, \( \alpha_0 = 1 - \alpha_e - \alpha_d \), choose not to submit orders in period 1 and delay trade to period 2. We let \( \beta \) be the period-1 fraction of informed traders who send orders to the dark pool. The remaining fraction \( 1 - \beta \) of informed traders trade on the exchange. (Obviously, informed traders never delay their trades as they will have lost their informational advantage by period 2.) Once the asset value \( v \) is revealed in period 2, all traders who have not traded in period 1—including those who deferred trading and those who failed to execute their orders in the dark pool—trade with the market maker at the unique period-2 equilibrium price of \( v \).

I first derive the equilibrium exchange bid and ask, assuming equilibrium participation fractions \((\beta, \alpha_d, \alpha_e)\). Because of symmetry and the fact that the unconditional mean of \( v \) is zero, the midpoint of the market maker’s bid and ask is zero. Therefore, the exchange ask is some \( S > 0 \), and the exchange bid is \(-S\), where \( S \) is the exchange’s effective spread, the absolute difference between the exchange transaction price and the midpoint. For simplicity, I refer to \( S \) as the “exchange spread.” As in Glosten and Milgrom (1985), the exchange bid and ask are set before exchange orders
arrive. Given the participation fractions \((\beta, \alpha_d, \alpha_e)\), the mass of informed traders on the exchange is \((1 - \beta)\mu_I\), and the expected mass of liquidity traders on the exchange is \(\alpha_e \mathbb{E}(Z^+ + Z^-) = \alpha_e \mu_z\). Because the market maker breaks even in expectation, we have that

\[
0 = -(1 - \beta)\mu_I(\sigma - S) + \alpha_e \mu_z S, \tag{4}
\]

which implies that

\[
S = \frac{(1 - \beta)\mu_I}{(1 - \beta)\mu_I + \alpha_e \mu_z} \sigma. \tag{5}
\]

The dark pool crosses orders at the mid-market price of zero.

Next, I derive the equilibrium mass \(\mu_I\) of informed traders. Given the value \(\sigma\) of information and the exchange spread \(S\), the net profit of an informed trader is \(\sigma - S\). The information-acquisition cost of the marginal for-profit trader, who is indifferent between paying for information or not, is also \(\sigma - S\). Because all for-profit traders with lower information-acquisition costs become informed, the mass of informed traders in equilibrium is \(\bar{\mu} F(\sigma - S)\), by the exact law of large numbers (Sun, 2006). We thus have

\[
\mu_I = \bar{\mu} F(\sigma - S) = \bar{\mu} F \left( \frac{\alpha_e \mu_z}{(1 - \beta)\mu_I + \alpha_e \mu_z} \sigma \right). \tag{6}
\]

For any fixed \(\beta \geq 0\) and \(\alpha_e > 0\), (6) has a unique solution \(\mu_I \in (0, \bar{\mu})\).

Finally, I turn to the equilibrium trading strategies. Without loss of generality, I focus on the strategies of buyers. In the main solution step, I calculate the expected payoffs of an informed buyer and a liquidity buyer, on the exchange and in the dark pool. The equilibrium is then naturally determined by conditions characterizing marginal traders who are indifferent between trading on the exchange and in the dark pool.

Suppose that \(\alpha_d > 0\). Because informed buyers trade in the same direction, they have the dark pool crossing probability of

\[
r^- = \mathbb{E} \left[ \min \left( 1, \frac{\alpha_d Z^-}{\alpha_d Z^+ + \beta \mu_I} \right) \right], \tag{7}
\]

where the denominator and the numerator in the fraction above are the masses of buyers and sellers in the dark pool, respectively. Liquidity buyers, on the other hand, do not observe \(v\). If informed traders are buyers, then liquidity buyers have the crossing probability \(r^-\) in the dark pool. If, however, informed traders are sellers, then liquidity
buyers have the crossing probability
\[ r^+ = \mathbb{E} \left[ \min \left( 1, \frac{\alpha_d Z^- + \beta \mu_I}{\alpha_d Z^+} \right) \right]. \] (8)

Obviously, for all \( \beta > 0 \), we have
\[ 1 > r^+ > r^- > 0. \] (9)

Because liquidity buyers assign equal probabilities to the two events \( \{v = +\sigma\} \) and \( \{v = -\sigma\} \), their dark pool crossing probability \( (r^+ + r^-)/2 \) is greater than informed traders’ crossing probability \( r^- \). In other words, correlated informed orders have a lower execution probability in the dark pool than relatively uncorrelated liquidity orders.

If the dark pool contains only liquidity orders (that is, \( \beta = 0 \)), then any dark pool buy order has the execution probability
\[ \bar{r} = \mathbb{E} \left[ \min \left( 1, \frac{Z^-}{Z^+} \right) \right]. \] (10)

For our purposes, \( \bar{r} \) measures the degree to which liquidity orders are balanced. Perfectly balanced liquidity orders correspond to \( \bar{r} = 1 \). For \( \alpha_d = 0 \), I define \( r^+ = r^- = 0 \).

The expected profits of an informed buyer on the exchange and in the dark pool are, respectively,
\[ W_e = \sigma - S, \] (11)
\[ W_d = r^- \sigma. \] (12)

I denote by \( c \) the delay cost of a generic liquidity buyer. This buyer’s net payoffs of deferring trade, trading on the exchange, and trading in the dark pool are, respectively,
\[ X_0(c) = -c, \] (13)
\[ X_e = -S, \] (14)
\[ X_d(c) = -\frac{r^+ - r^-}{2} \sigma - c \left( 1 - \frac{r^+ + r^-}{2} \right). \] (15)

The terms on the right-hand side of (15) are the liquidity trader’s adverse selection cost and delay cost in the dark pool, respectively. For \( \beta > 0 \), crossing in the dark pool implies a positive adverse selection cost because execution is more likely if a liquidity trader is on the side of the market opposite to that of informed traders. For \( \beta = 0 \),
this adverse-selection cost is zero.

From (11) and (14), \( W_e - X_e = \sigma \). For all delay cost \( c \leq \sigma \),

\[
W_d - X_d(c) = \frac{r^+ + r^-}{2} \sigma + c \left(1 - \frac{r^+ + r^-}{2}\right) \leq \sigma = W_e - X_e. \tag{16}
\]

That is, provided \( c \leq \sigma \), the dark pool is more attractive to liquidity traders than to informed traders, relative to the exchange. In particular, (16) implies that a liquidity trader with a delay cost of \( \sigma \) (or a funding cost of \( \gamma = 1 \)) behaves in the same way as an informed trader. In addition,

\[
X_d(c) - X_0(c) = -\frac{r^+ - r^-}{2} \sigma + \frac{r^+ + r^-}{2} c. \tag{17}
\]

So a liquidity trader with a funding cost of \( \gamma = (r^+ - r^-)/(r^+ + r^-) \) is indifferent between deferring trade and trading in the dark pool.

To simplify the description of the equilibria, I further define \( \hat{\mu}_I : [0, \infty) \rightarrow [0, \tilde{\mu}] \) by

\[
\hat{\mu}_I(s) = \tilde{\mu} F \left( \frac{(1 - G(1)) \mu_z}{\hat{\mu}_I(s) + (1 - G(1)) \mu_z} s \right). \tag{18}
\]

Given the value \( \sigma \) of information, \( \hat{\mu}_I(\sigma) \) is the unique “knife-edge” mass of informed traders with the property that all informed traders and a fraction \( 1 - G(1) \) of liquidity traders send orders to the exchange.

**Proposition 1.** The following results hold.

1. If

\[
\bar{r} \leq 1 - \frac{\hat{\mu}_I(\sigma)}{\hat{\mu}_I(\sigma) + (1 - G(1)) \mu_z}, \tag{19}
\]

then there exists an equilibrium \((\beta = 0, \alpha_d = \alpha_d^*, \alpha_e = 1 - \alpha_e^*), \) where \( \alpha_d^* \in (0, G(1)] \) and \( \mu_I^* \) solve

\[
G^{-1}(\alpha_d)(1 - \bar{r}) = \frac{\mu_I}{\mu_I + (1 - \alpha_d) \mu_z}, \tag{20}
\]

\[
\mu_I = \tilde{\mu} F \left( \frac{(1 - \alpha_d) \mu_z}{\mu_I + (1 - \alpha_d) \mu_z} \sigma \right). \tag{21}
\]

2. If and only if

\[
\bar{r} > 1 - \frac{\hat{\mu}_I(\sigma)}{\hat{\mu}_I(\sigma) + (1 - G(1)) \mu_z}, \tag{22}
\]

there exists an equilibrium \((\beta = \beta^*, \alpha_d = \alpha_d^*, \alpha_e = 1 - G(1)), \) where \( \beta^*, \alpha_d^* \in \)
\( (0, G(1)] \), and \( \mu^*_I \) solve

\[
\begin{align*}
    r^- &= 1 - \frac{(1 - \beta)\mu_I}{(1 - \beta)\mu_I + (1 - G(1))\mu_z}, \\
    \alpha_d &= G(1) - G \left( \frac{r^+ - r^-}{r^+ + r^-} \right), \\
    \mu_I &= \bar{\mu} F \left( \frac{(1 - G(1))\mu_z}{(1 - \beta)\mu_I + (1 - G(1))\mu_z} \right). 
\end{align*}
\]

The proof of Proposition 1 is provided in Appendix B, but we outline its main intuition here. On one hand, for informed traders to avoid the dark pool \( (\beta = 0) \), the dark pool execution probability \( \bar{r} \) must be lower than the profit of informed traders on the exchange, as implied by (19). In this case, the marginal liquidity trader is indifferent between trading on the exchange and trading in the dark pool. The marginal for-profit trader is indifferent about whether to acquire the information.

On the other hand, for informed traders to participate in the dark pool, the maximum dark pool execution probability \( \bar{r} \) must be sufficiently high, as shown in (22). In this case, the equilibrium is determined by three indifference conditions. First, informed traders must be indifferent between trading in either venue, captured by (23). (If they all trade in the dark pool, then the exchange spread becomes 0.) By (16), a liquidity trader with a delay cost of \( \sigma \) is also indifferent between the two venues. Thus, \( \alpha_0 + \alpha_d = G(1) \) and \( \alpha_e = 1 - G(1) \). The second indifference condition (24) then follows from (17). Here, the fraction \( \alpha_0 \) of liquidity traders who delay trade must be strictly positive because informed traders introduce adverse selection into the dark pool. The third condition (25) says that the marginal for-profit trader is indifferent about whether to acquire the information.

Similarly, we can characterize an equilibrium for a market structure in which only the exchange is operating and the dark pool is absent. This exchange-only equilibrium, solved below, may also be interpreted as one in which a dark pool is open but no trader uses it.

Corollary 1. With only an exchange and no dark pool, there exists an equilibrium in which \( \beta^* = \alpha_d^* = 0 \), and \( \mu^*_I \) and \( \alpha_e^* \in (1 - G(1), 1) \) solve

\[
\begin{align*}
    \frac{\mu_I}{\mu_I + \alpha_e \mu_z} &= G^{-1}(1 - \alpha_e), \\
    \mu_I &= \bar{\mu} F \left( \frac{\alpha_e \mu_z}{\mu_I + \alpha_e \mu_z \sigma} \right). 
\end{align*}
\]
Equilibrium selection

The equilibria characterized in Proposition 1 need not be unique among all equilibria solving (20)-(21) and (23)-(25). For example, under the condition (19), both sides of (20) strictly increase in $\alpha_d$. Similarly, both sides of (24) strictly increase in $\alpha_d$, and both sides of (26) strictly decrease in $\alpha_e$. Thus, given the absence of a single-crossing property, multiple equilibria may arise.\(^{16}\)

I use stability as an equilibrium selection criterion, which allows me to compute the comparative statics of the selected equilibria. Among the equilibria characterized by Case 1 of Proposition 1, I select that with the smallest liquidity participation $\alpha^*_d$ in the dark pool among those with the property that, as $\alpha_d$ varies in the neighborhood of $\alpha^*_d$, the left-hand side of (20) crosses the right-hand side from below.\(^{17}\) Under the conditions of Proposition 1, this equilibrium exists and is robust to small perturbations. If, for example, $\alpha^*_d$ is perturbed to $\alpha^*_d + \epsilon$ for sufficiently small $\epsilon > 0$, then the marginal liquidity trader has a higher cost in the dark pool than on the exchange, and therefore migrates out of the dark pool. Thus, $\alpha_d$ is “pushed back” to $\alpha^*_d$, and the equilibrium is restored. There is a symmetric argument for a small downward perturbation to $\alpha^*_d - \epsilon$.

By contrast, if there is an equilibrium in which, as $\alpha_d$ varies, the left-hand side of (20) crosses the right-hand side from above, this equilibrium would not be stable to local perturbations. Moreover, once $\alpha_d$ is determined in equilibrium, $\mu_I$ and $\beta$ are uniquely determined, too, as shown in the proof of Proposition 1.

Similarly, among equilibria characterized by Case 2 of Proposition 1, I select the one with the smallest liquidity participation $\alpha^*_d$ in the dark pool among those with the property that, as $\alpha_d$ varies in the neighborhood of $\alpha^*_d$, the left-hand side of (24) crosses the right-hand side from below. In a market without a dark pool (Corollary 1), I select the equilibrium with the largest liquidity participation $\alpha^*_e$ on the exchange among those with the property that, as $\alpha_e$ varies in the neighborhood of $\alpha^*_e$, the left-hand side of (26) crosses the right-hand side from below. By the argument given for Case 1 of Proposition 1, these selected equilibria exist and are stable.

---

\(^{16}\)One special condition that guarantees the uniqueness of the equilibrium in Case 1 of Proposition 1 is that the distribution function $G$ of delay costs is linear. With a linear $G$, the condition (19) is also necessary for the existence of solutions to (20)-(21).

\(^{17}\)Selecting the stable equilibrium corresponding to the smallest $\alpha^*_d$ is arbitrary but without loss of generality. As long as the selected equilibrium is stable, comparative statics calculated later follow through.
3.3 Market characteristics and comparative statics

I now investigate properties of the equilibria characterized by Proposition 1. I aim to answer two questions:

1. In a market with a dark pool and an exchange, how do market characteristics vary with the value \( \sigma \) of private information?
2. Given a fixed value \( \sigma \) of private information, how does adding a dark pool affect market behavior?

Key to these questions are the equilibrium participation rates \((\beta, \alpha_d, \alpha_e)\) of informed and liquidity traders. The market characteristics that I analyze are exchange spread, non-execution probability, price discovery, trading volume, and the payoffs of each group of traders. As we will see, these are closely related to each other. For example, better price discovery is naturally associated with a wider bid-ask spread, which in turn is associated with lower profits for informed traders and a lower total trading volume. The results presented below may also help interpret recent empirical evidence on dark pools and market fragmentation, as we discuss in Section 6.

By (18), increasing the value \( \sigma \) of information raises the knife-edge mass \( \hat{\mu}(\sigma) \) of informed traders, which in turn tightens the condition (19) under which informed traders avoid the dark pool. Thus, there exists some unique volatility threshold \( \bar{\sigma} \) at which (19) holds with an equality. For \( \sigma \leq \bar{\sigma} \), I analyze the equilibrium in Case 1 of Proposition 1. For \( \sigma > \bar{\sigma} \), I analyze the equilibrium in Case 2.

**Proposition 2.** In the equilibrium of Proposition 1:

1. For \( \sigma \leq \bar{\sigma} \), the dark pool participation rate \( \alpha_d \) of liquidity traders, the total mass \( \mu_I \) of informed traders, and the scaled exchange spread \( S/\sigma \) are strictly increasing in \( \sigma \). The exchange participation rate \( \alpha_e = 1 - \alpha_d \) of liquidity traders is strictly decreasing in \( \sigma \). Moreover, \( \alpha_d, \mu_I, \) and \( S \) are continuous and differentiable in \( \sigma \).

2. For \( \sigma > \bar{\sigma} \), all of \( \mu_I, \beta\mu_I, r^+ \), and \( S/\sigma \) are strictly increasing in \( \sigma \), whereas \( \alpha_d \) and \( r^- \) are strictly decreasing in \( \sigma \). Moreover, \( \beta, \alpha_d, \mu_I, S, r^+ \), and \( r^- \) are continuous and differentiable in \( \sigma \).

In the equilibrium of Corollary 1, \( \mu_I \) and \( S/\sigma \) are strictly increasing in \( \sigma \), whereas \( \alpha_e \) is strictly decreasing in \( \sigma \). Moreover, \( \alpha_e, \mu_I, \) and \( S \) are continuous and differentiable in \( \sigma \).

**Proof.** See Appendix B.

We can also compare the two equilibria of Proposition 1 and Corollary 1.
Proposition 3. In the equilibria of Proposition 1 and Corollary 1:

1. For $\sigma \leq \bar{\sigma}$, adding a dark pool strictly reduces the exchange participation rate $\alpha_e$ of liquidity traders and the total mass $\mu_I$ of informed traders. Adding a dark pool strictly increases the exchange spread $S$ and the total participation rate $\alpha_e + \alpha_d$ of liquidity traders in either venue.

2. For $\sigma > \bar{\sigma}$, adding a dark pool strictly reduces $\alpha_e$. Moreover, adding a dark pool strictly increases the exchange spread $S$ if and only if, in the equilibrium of Proposition 1,

$$r^- < 1 - \frac{\mu_I}{\mu_I + (1 - G(1 - r^-))\mu_z}. \quad (28)$$

It is sufficient (but not necessary) for (28) that either

$$G''(\gamma) \leq 0 \text{ for all } 1 - \bar{r} \leq \gamma \leq 1 \text{ and } F(c) \to 1 \text{ for all } c > 0, \quad (29)$$

or

$$\bar{r} < 1 - \frac{\bar{\mu}}{\bar{\mu} + (1 - G(1))\mu_z}. \quad (30)$$

Proof. See Appendix B. \qed

We now discuss the intuition and implications of Proposition 2 and Proposition 3 through numerical examples.

3.3.1 Participation, spread, and non-execution risk

Figure 4 shows the equilibrium participation rates in the two venues. The top-left plot illustrates the participation rates in the dark pool. For a small value of information, specifically if $\sigma \leq \bar{\sigma}$, informed traders trade exclusively on the exchange because the exchange spread is smaller than the cost of non-execution risk in the dark pool. An increase in $\sigma$ widens the exchange spread, encouraging more liquidity traders to migrate into the dark pool. For $\sigma > \bar{\sigma}$, informed traders use both venues. We observe that informed dark pool participation rate $\beta$ first increases in volatility $\sigma$ and then decreases. The intuition for this non-monotonicity is as follows. Consider an increase in the value of information from $\sigma$ to $\sigma + \epsilon$, for some $\epsilon > 0$. This higher value of information attracts additional informed traders. For a low $\beta$, the dark pool execution risk stays relatively low, and these additional informed traders prefer to trade in the dark pool, raising $\beta$. For sufficiently high $\beta$, however, informed orders cluster on one side
Figure 4: Participation on the exchange and in the dark pool. The top left plot shows the equilibrium participation rates $(\beta, \alpha_d, \alpha_e)$ in a market with a dark pool. The top right plot shows the equilibrium mass $\mu_I$ of informed traders, with or without a dark pool. The bottom left plot shows the equilibrium participation of liquidity traders on the exchange, with or without a dark pool. The bottom right plot shows the equilibrium participation of liquidity traders in either venue, with or without a dark pool. In all plots, the vertical dotted line indicates the threshold volatility $\bar{\sigma}$ at which the equilibrium of Proposition 1 changes from Case 1 to Case 2. Model parameters: $Z_0$ is uniformly distributed on the interval $[0,4]$, $Z$ is normally distributed with mean 0 and standard deviation $\sigma_z = 5$, $\mu = 8$, $G(s) = s/2$ for $s \in [0,2]$, and $F(s) = 1 - e^{-s/2}$ for $s \in [0,\infty)$.

of the dark pool and significantly reduce their execution probability. Thus, these additional informed traders send orders to the exchange, reducing $\beta$. Nonetheless, the total quantity $\beta \mu_I$ of informed traders in the dark pool is strictly increasing in $\sigma$. Finally, because informed participation in the dark pool introduces adverse selection, liquidity traders with low delay costs migrate out of the dark pool, leading to a decline in their dark pool participation rate $\alpha_d$.

The remaining three plots of Figure 4 show the comparative statics of $\mu_I$, $\alpha_e$, and
\( \alpha_e + \alpha_d \) with respect to \( \sigma \). For \( \sigma \leq \bar{\sigma} \), adding a dark pool reduces the exchange participation rate \( \alpha_e \) of liquidity traders, shown in the bottom-left plot, but increases their total participation rate \( \alpha_e + \alpha_d \) to the highest level, 1, shown in the bottom-right plot. Intuitively, the dark pool offers a lower-cost trading service for those liquidity traders who consider the exchange spread “too expensive.” These “latent” liquidity traders—traders who would never pay the exchange spread anyway—send their orders to the dark pool. With this “seed liquidity,” the dark pool diverts additional liquidity traders off the exchange, widening the exchange spread. Consequently, a smaller mass \( \mu_I \) of for-profit traders become informed, as shown in the top-right plot. For \( \sigma \geq \bar{\sigma} \), \( \alpha_e \) stays at a constant, \( 1 - G(1) \), which is smaller than the exchange participation rate of liquidity traders in a market without a dark pool. In this example, adding a dark pool widens the scaled exchange spread \( S/\sigma \) and reduces the informed trading interest \( \mu_I \).

Figure 5 plots the scaled exchange spread \( S/\sigma \) (shown on the left) and the dark pool execution probabilities (shown on the right). Because a higher value \( \sigma \) of information encourages more for-profit traders to become informed, the scaled exchange spread \( S/\sigma \) increases in \( \sigma \), whether a dark pool is present or not. For \( \sigma \leq \bar{\sigma} \), adding a dark pool raises \( S/\sigma \) by diverting some liquidity traders, but none of the informed traders, off the exchange. Non-execution risk is unaffected. For \( \sigma > \bar{\sigma} \), adding a dark pool in this example also increases the scaled spread \( S/\sigma \) because the dark pool diverts more liquidity traders than informed traders. The dark pool execution probability \( (r^+ + r^-)/2 \) for liquidity traders is not monotone in \( \sigma \). This non-monotonicity is natural because the crossing probabilities \( r^+ \) and \( r^- \) are non-linear in \( \beta, \mu_I, \) and \( \alpha_d \).

### 3.3.2 Price discovery

Now I turn to price discovery, by which I mean the extent to which the period-1 announcements \( (P_1, V_b, V_s) \) are informative of the fundamental asset value \( v \). Since the market maker observes the volume \( (V_b, V_s) \), the closing price \( P_1 \) is

\[
P_1 = \mathbb{E}[v \mid V_b, V_s].
\]

(31)

Because \( v \) is binomially distributed, its conditional distribution after period-1 trading is completely determined by its conditional expectation

\[
\mathbb{E}[v \mid P_1, V_b, V_s] = \mathbb{E}[\mathbb{E}[v \mid V_b, V_s] \mid P_1] = P_1.
\]

(32)
That is, all period-1 public information that is relevant for the asset value $v$ is conveyed by the closing price $P_1$. As we will make precise shortly, the “closer” is $P_1$ to $v$, the better is price discovery.

To explicitly calculate $P_1$, distribution assumptions are necessary. I suppose that the imbalance $Z$ of liquidity traders has a probability density $f_Z$ that is normal with mean zero and standard deviation $\sigma_z$. I suppose that the “balanced part” $Z_0$ of liquidity traders is uniformly distributed on $[0,C_0]$ for some $C_0 > 0$, with the associated density $f_{Z_0}$.

In equilibrium, the volume $V_b$ of exchange buy orders and the volume $V_s$ of exchange sell orders are

$$V_b = \begin{cases} 
(1 - \beta)\mu_I + \alpha_e Z^+, & \text{if } v = +\sigma, \\
\alpha_e Z^+, & \text{if } v = -\sigma 
\end{cases} \quad (33)$$

and

$$V_s = \begin{cases} 
\alpha_e Z^-, & \text{if } v = +\sigma, \\
(1 - \beta)\mu_I + \alpha_e Z^-, & \text{if } v = -\sigma 
\end{cases} \quad (34)$$
respectively. In the event that \( v = +\sigma \), we have

\[
Z = Z^+ - Z^- = \frac{V_b - V_s - (1 - \beta)\mu_I}{\alpha_e},
\]

\[
Z_0 = \min(Z^+, Z^-) = \frac{1}{\alpha_e} \min(V_b - (1 - \beta)\mu_I, V_s).
\]

Clearly, conditional on \( v = +\sigma \), \( V_b \) and \( V_s \) completely determine \( Z \) and \( Z_0 \), and vice versa. Because \( Z \) and \( Z_0 \) are independent, their joint probability density is

\[
f_Z \left( \frac{V_b - V_s - (1 - \beta)\mu_I}{\alpha_e} \right) \cdot \frac{1}{C_0}.
\]

Similarly, in the event that \( v = -\sigma \), the joint probability density of \((Z, Z_0)\) is

\[
f_Z \left( \frac{V_b - V_s + (1 - \beta)\mu_I}{\alpha_e} \right) \cdot \frac{1}{C_0}.
\]

Thus, given \( V_b \) and \( V_s \), the market maker’s log likelihood ratio is

\[
R_1 = \log \frac{\mathbb{P}(v = +\sigma \mid V_b, V_s)}{\mathbb{P}(v = -\sigma \mid V_b, V_s)} = \log \frac{f_Z \left( \frac{V_b - V_s - (1 - \beta)\mu_I}{\alpha_e} \right) \cdot \frac{1}{C_0}}{f_Z \left( \frac{V_b - V_s + (1 - \beta)\mu_I}{\alpha_e} \right) \cdot \frac{1}{C_0}},
\]

where we have used Bayes’ rule and the prior belief that \( \mathbb{P}(v = +\sigma) = \mathbb{P}(v = -\sigma) = 0.5 \).

Without loss of generality, I condition on \( v = +\sigma \) and consider price discovery to be unambiguously “improved” if the probability distribution of \( R_1 \) is “increased,” in the sense of first-order stochastic dominance. Complete revelation of \( v = +\sigma \) corresponds to \( R_1 = \infty \) almost surely.

Because \( Z \) is normally distributed and \( v = +\sigma \), we have

\[
R_1 = \frac{2(1 - \beta)\mu_I}{\alpha_e^2\sigma_z^2} (V_b - V_s) = \frac{2(1 - \beta)\mu_I}{\alpha_e^2\sigma_z^2} [(1 - \beta)\mu_I + \alpha_e Z] = \frac{2(1 - \beta)\mu_I}{\alpha_e^2\sigma_z^2} Z.
\]

Thus, \( R_1 \) is also normally distributed. Specially,

\[
R_1 \sim N \left( 2 \left( \frac{(1 - \beta)\mu_I}{\alpha_e\sigma_z} \right)^2, 4 \left( \frac{(1 - \beta)\mu_I}{\alpha_e\sigma_z} \right)^2 \right) \sim N \left( 2I(\beta, \alpha_e)^2, 4I(\beta, \alpha_e)^2 \right),
\]

where

\[
I(\beta, \alpha_e) \equiv \frac{(1 - \beta)\mu_I}{\alpha_e\sigma_z}
\]

is the “signal-to-noise” ratio, which is the mass of informed orders on the exchange.
Figure 6: Distribution functions of $R_1$, with and without a dark pool. The true dividend is the threshold value $+\bar{\sigma}$ and other parameters are those of Figure 4.

\begin{align*}
\text{Probability density} & \quad \text{Cumulative distribution} \\
\begin{array}{c}
\text{Lit only} \\
\text{Lit + Dark}
\end{array} & \begin{array}{c}
\begin{array}{c}
\text{Lit only} \\
\text{Lit + Dark}
\end{array} \\
\begin{array}{c}
\text{Lit only} \\
\text{Lit + Dark}
\end{array}
\end{array}
\end{align*}

(“signal”) divided by the standard deviation of the imbalance of liquidity orders on the exchange (“noise”). Naturally, $I(\beta, \alpha_e)$ is increasing in the scaled exchange spread $S/\sigma$. A higher exchange spread corresponds not only to a higher mean of the log likelihood ratio $R_1$ but also to a higher variance.

Finally, given $R_1$, the market maker sets the period-1 closing price

\[ P_1 = \frac{e^{R_1} - 1}{e^{R_1} + 1} \sigma. \]  

(43)

Conditional on $P_1$, a non-trader assigns the probability

\[ Q_1 \equiv \mathbb{P}(v = +\sigma \mid V_b, V_s) = \frac{e^{R_1}}{e^{R_1} + 1} = \frac{1}{2} \left( \frac{P_1}{\sigma} + 1 \right) \]  

(44)

that the asset value is high. Because we have conditioned on $v = +\sigma$, a higher distribution of $Q_1$ corresponds to better price discovery.

Figure 6 plots the distribution function of $R_1$, with and without a dark pool. The value $\sigma$ of information is set to be the threshold value $\bar{\sigma}$, so that $\beta = 0$ in the equilibria with a dark pool as well as the equilibria without a dark pool. By Proposition 3, adding a dark pool strictly increases the scaled spread $S/\sigma$ and hence the signal-to-noise ratio $I(\beta, \alpha_e)$. With a dark pool, the conditional distribution of $R_1$ has a higher mean, but also a higher variance. For most realizations of $R_1$, and on average, adding a dark pool decreases the cumulative distribution of $R_1$ and leads to more precise inference of $v$. Nonetheless, adding a dark pool may increase the cumulative distribution of $R_1$, thus harming price discovery, when the realization of $R_1$ is sufficiently low.
The price-discovery effect of the dark pool is further illustrated in Figure 7. The left-hand plot of Figure 7 shows the probability density function of $Q_1$, with and without a dark pool. As in Figure 6, adding a dark pool shifts the probability density function of $Q_1$ to the right, improving price discovery on average.\footnote{We can show that the expectation $\mathbb{E}[Q_1]$ is increasing in the signal-to-noise ratio $I(\beta, \alpha_e)$.} Nonetheless, the dark pool increases the probability of extremely low realizations of $Q_1$, harming price discovery in these unlikely events. The right-hand plot of Figure 7 shows how $Q_1$ depends on the imbalance $Z$ of liquidity traders. Again, for most realizations of $Z$, adding the dark pool increases $Q_1$, improving price discovery. For unlikely low realizations of $Z$, adding the dark pool reduces $Q_1$, thus harming price discovery. That is, when the trading interests of liquidity traders are sufficiently large and opposite in direction to the informed, adding the dark pool can exacerbate the “misleading” inference regarding the asset value. Because liquidity trading interests are balanced in expectation, such misleading events are rare, and the dark pool is normally beneficial for price discovery.

### 3.3.3 Volume and dark pool market share

I now calculate the trading volume handled by the exchange and the dark pool. The trading volume and the market share of the dark pool are direct empirical measures of dark pool activity. I assume that once the dividend $v$ is announced in period 2, informed traders who have not yet traded leave the market, because they will not be able to trade profitably. When calculating the exchange volume, I also include the transactions of liquidity traders in period 2. Thus, the expected trading volumes in the
dark pool, on the exchange, and in both venues are, respectively,

\[ V_d = \beta \mu_I r^- + \alpha_d \mu_z \frac{r^+ + r^-}{2}, \]  
(45)

\[ V_e = (1 - \beta) \mu_I + \alpha_e \mu_z + \alpha_d \mu_z \left(1 - \frac{r^+ + r^-}{2}\right) + \alpha_0 \mu_z, \]  
(46)

\[ V = V_e + V_d = \mu_z + \mu_I (1 - \beta + \beta r^-). \]  
(47)

By Proposition 2, these volumes are differentiable in the volatility \( \sigma \) in each of the two intervals \([0, \bar{\sigma}]\) and \((\bar{\sigma}, \infty)\).

For \( \sigma \leq \bar{\sigma} \), the dark pool volume, \( V_d = \alpha_d \mu_z \bar{r} \), is increasing in the volatility \( \sigma \), by Proposition 2. In particular, as \( \sigma \to 0 \), the dark pool participation rate \( \alpha_d \) of liquidity traders and the dark pool market share \( V_d/V \) converge to zero. For a sufficiently small \( \sigma < \bar{\sigma} \), therefore,

\[ \frac{d(V_d/V)}{d\sigma} = \frac{d}{d\sigma} \left(\frac{\alpha_d \mu_z \bar{r}}{\mu_z + \mu_I}\right) = \frac{\mu_z \bar{r}}{\mu_z + \mu_I} \frac{d\alpha_d}{d\sigma} - \frac{\alpha_d \mu_z \bar{r}}{(\mu_z + \mu_I)^2} \frac{d\mu_I}{d\sigma} > 0, \]

where the inequality follows from the fact that \( \lim_{\sigma \to 0} d\alpha_d/d\sigma > 0 \) (shown in the proof of Proposition 2). That is, if volatility \( \sigma \) is low, the dark pool market share \( V_d/V \) is also low, and is increasing in \( \sigma \). For \( \sigma \leq \bar{\sigma} \), because the total volume \( V = \mu_z + \mu_I \) is increasing in \( \sigma \), the dark pool market share is increasing in the total volume, as illustrated in the left-hand plot of Figure 8.

Figure 8 further suggests that, as the volatility \( \sigma \) increases beyond \( \bar{\sigma} \), the exchange volume \( V_e \) can increase substantially, but the dark pool volume \( V_d \) may only increase mildly or even decline. Thus, the dark pool market share can decrease in volatility \( \sigma \) for sufficiently large \( \sigma \), creating a hump-shaped relation between volatility and the dark pool market share. The model also generates a similar relation between the scaled spread \( S/\sigma \) and the dark pool market share \( V_d/V \), as shown on the right-hand plot of Figure 8. Although these hump-shaped patterns are not proved analytically here, they are consistent with the empirical findings of Ready (2010) and Ray (2010), and may help explain the mixed evidence regarding the relations between dark pool market shares and market characteristics such as volatility, volume, and spread. I further discuss these questions in Section 6.

### 3.3.4 Informed traders’ profits and liquidity traders’ costs

Finally, I calculate the expected net profits \( U_I \) of informed traders and the net expected costs \(-U_L\) of liquidity traders. These calculations help us understand whether adding a
Figure 8: Expected trading volume on the exchange and in the dark pool. The left-hand plot shows the volume in the two venues and the market share of the dark pool. The right-hand plot shows the dark pool market share as a function of the scaled spread $S/\sigma$. The vertical dotted line corresponds to the threshold volatility $\bar{\sigma}$. Parameters are those of Figure 4.

Figure 9 plots the comparative statics of $U_I/\sigma$ and $-U_L/\sigma$ with respect to the value $\sigma$ of information, with and without a dark pool. Naturally, a higher value of information

implies higher profits for informed traders. For $\sigma \leq \bar{\sigma}$, for example,

$$
\frac{d(U_I/\sigma)}{d\sigma} = \left[ \left(1 - \frac{S}{\sigma}\right) - \frac{1}{\sigma} F^{-1}\left(\frac{\mu_I}{\bar{\mu}}\right) - \mu_I \frac{\partial(1 - S/\sigma)}{\partial \mu_I} \right] \frac{d\mu_I}{d\sigma} + \frac{1}{\sigma^2} C_i
$$

$$
= -\mu_I \frac{\partial(1 - S/\sigma)}{\partial \mu_I} \frac{d\mu_I}{d\sigma} + \frac{1}{\sigma^2} C_i > 0.
$$

In the above calculation, the second equality follows from (21), and the inequality follows from the facts that $d\mu_I/d\sigma > 0$ and that $\partial(1 - S/\sigma)/\partial \mu_I < 0$. The calculation of $d(U_I/\sigma)/d\sigma$ for $\sigma > \bar{\sigma}$ is similar. In this example, adding a dark pool widens the exchange spread and reduces the profits of informed traders.

Figure 9 suggests that adding a dark pool has a mixed impact on the expected costs of liquidity traders. For a sufficiently large value $\sigma$ of information, adverse selection is so severe that the dark pool can reduce the expected transaction costs of liquidity traders by potentially saving them the exchange spread. However, for $\sigma \leq \bar{\sigma}$, Proposition 3 implies that $d\alpha_d/d\bar{r} > 0$ and that $d\mu_I/d\bar{r} < 0$. So,

$$
\frac{1}{\mu_z} \frac{d(-U_L/\sigma)}{d\bar{r}} = \left(G^{-1}(\alpha_d) - \frac{S}{\sigma}\right) \frac{d\alpha_d}{d\bar{r}} + (1 - \alpha_d) \frac{d(S/\sigma)}{d\bar{r}} > 0.
$$

That is, adding a dark pool, which is equivalent to an increase in $\bar{r}$, increases the total expected cost for liquidity traders. This seemingly counterintuitive result has a simple explanation. Although the dark pool reduces the trading costs for relatively patient liquidity traders, it raises the trading costs for relatively impatient ones. The net effect is that the latter dominates the former.

The impact of the dark pool on the trading costs for liquidity traders contrasts with the results of Foster, Gervais, and Ramaswamy (2007), who argue that adding a dark pool can provide a Pareto improvement over a market with only an exchange because the dark pool attracts latent liquidity traders. Their dark pool is “volume-conditional”—it executes orders only given a sufficiently large trading interest. Although the dark pool in both models attracts latent liquidity traders, the key difference is that liquidity traders (“hedgers”) in their model have binomially distributed delay costs—high or low. Under certain parameter conditions, adding a dark pool in their model has no impact on the exchange spread because hedgers with low delay costs never trade on the exchange even without a dark pool. In my model, by contrast, liquidity traders have a continuum of delay costs; migration of low-cost liquidity traders to the dark pool diverts additional liquidity traders with slightly higher delay costs, raising the exchange spread. The welfare implication of dark pools for liquidity traders,
Figure 9: The expected profit $U_I$ of informed traders (shown on the left) and the expected cost $-U_L$ of liquidity traders (shown on the right), both scaled by volatility $\sigma$. The vertical dotted line corresponds to the threshold volatility $\bar{\sigma}$. Parameters are those of Figure 4.

therefore, can be complicated and depend on the characteristics of traders.

4 Dark Pools as Nondisplayed Limit Order Books

So far we have studied a dark pool that crosses orders at the midpoint of the exchange bid and ask. In this section, I model a dark pool that operates as a nondisplayed limit order book, where traders can specify their own limit prices. As described in Section 2, this order-book mechanism is typically used in dark pools operated by major broker-dealers, and transaction prices in these dark pools are generally determined by the submitted limit orders. Aside from confirming the basic intuition of Section 3 in this alternative setting, this section offers additional insights regarding the impact of dark pool mechanisms on the participation incentives of informed traders.

Compared with midpoint-matching dark pools, dark pools operating as nondisplayed limit order books allow more discretion in execution prices. Such price discretion, however, is limited by “best-execution” regulations. In the United States, for example, the Order Protection Rule, also known as the “trade through” rule, stipulates that transaction prices in any market center—including dark pools, ECN, and broker-dealer internalization—cannot be strictly worse than the prevailing national best bid and offer (NBBO).\footnote{In Europe, MiFID uses a decentralized best-execution rule, by which investment firms decide whether an execution works for the best interest of investors.} For example, if the current NBBO is 10.00/10.50, then the transaction price in any market center must be in the interval $[10, 10.5]$. The trade-through
rule thus imposes a boundary on the execution prices in dark pools.

Going beyond the trade-through rule, regulators have also proposed a stricter “trade-at” rule. Under a trade-at rule, market centers not already quoting the best price cannot execute incoming orders at the best price. Instead, they must either provide incoming orders with sufficiently large price improvements, or route them to venues that quote the best price. For example, the Joint CFTC-SEC Advisory Committee (2011) recommends that the SEC consider “its rule proposal requiring that internalized or preferred orders only be executed at a price materially superior (e.g. 50 mils [0.5 cent] for most securities) to the quoted best bid or offer.” With a trade-at rule, displayed orders that establish the market-wide best price have strictly higher execution priority than nondisplayed orders at the same price. Execution prices in dark pools must then be sufficiently better than the best bid or offer on exchanges.

I now describe and solve a simple model of a dark pool that operates as a nondisplayed limit order book. The dark pool executes orders by price priority and is modeled as a double auction. I model the effect of a trade-at rule, by assuming that transaction prices in the dark pool must be within the interval \([-xS, xS]\), where \(S > 0\) is the exchange spread and \(x \in [0, 1]\) captures the strictness of the trade-at rule. The trade-through rule currently applied in the United States corresponds to \(x = 1\), indicating a mandatory price improvement of zero. A midpoint-matching mechanism corresponds to \(x = 0\), indicating a price improvement of the entire effective spread \(S\). With the exception of this trade-at rule, the model of this section is identical to that of Section 3. Because of intractability, I can only characterize equilibria in which all informed traders avoid the dark pool. Nonetheless, this equilibrium offers useful insight into how the trade-at rule affects the dark pool participation of informed traders.

I start by fixing candidate equilibrium participation rates (\(\beta = 0, \alpha_d, \alpha_e = 1 - \alpha_d\)). I then calculate the execution price and execution probabilities in the dark pool, as well as the optimal limit prices chosen by liquidity traders. Finally, I derive incentive-compatibility conditions under which informed traders choose not to participate in the dark pool.

I let \(y^+: [-xS, xS] \to [0, \infty)\) be the aggregate downward-sloping demand schedule of liquidity buyers in the dark pool, and let \(y^-: [-xS, xS] \to [0, \infty)\) be the aggregate upward-sloping supply schedule of liquidity sellers. For each \(p\), \(y^+(p)\) is the mass of liquidity buyers with a limit price of \(p\) or higher, and \(y^-(p)\) is the mass of liquidity sellers with a limit price of \(p\) or lower. Because the dark pool crosses orders by price

---

20. This model of nondisplayed limit order book differs from models of displayed limit order books. For models of the latter, see the survey of Parlour and Seppi (2008).
priority, its execution price $p^*$ is

$$p^* = \begin{cases} 
  xS, & \text{if } y^+(p) > y^-(p) \text{ for all } p \in [-xS, xS], \\
  -xS, & \text{if } y^+(p) < y^-(p) \text{ for all } p \in [-xS, xS], \\
  \{p : y^+(p) = y^-(p)\}, & \text{otherwise.} 
\end{cases} \quad (52)$$

I proceed under the conjecture that the set $\{p : y^+(p) = y^-(p)\}$ contains at most one element, in which case $p^*$ of (52) is uniquely well-defined. I later verify this conjecture. Once $p^*$ is determined, buy orders with limit prices above or equal to $p^*$ are matched, at the price of $p^*$, with sell orders whose prices are at most $p^*$. If there is a positive mass of buy or sell orders at the price $p^*$, then traders setting the limit price $p^*$ are rationed pro-rata, as before.

I now derive the optimal limit prices of liquidity traders in the dark pool, under the conjecture that the probability distribution of $p^*$ has no atom in $(-xS, xS)$. This no-atom conjecture, verified later, implies that a liquidity trader quoting a price of $p \in (-xS, xS)$ has her order filled with certainty (is not rationed) if $p^* = p$. Thus, a liquidity buyer who has a delay cost of $c \in [0, xS]$ and quotes a price of $p$ in the dark pool has the expected payoff (negative cost)

$$X_d(p; c) = -E \left[ I_{\{p \geq p^*\}} p^* + I_{\{p < p^*\}} c \right] = -c - \int_{-xS}^p (p^* - c) dH(p^*), \quad (53)$$

where $I(\cdot)$ is the indicator function and $H(p^*)$ is the cumulative distribution function of $p^*$. Because there is no adverse selection in the dark pool, the execution cost for this liquidity buyer is either the payment $p^*$ or the delay cost $c$. Conjecturing that $H(p^*)$ is differentiable with $H'(p^*) > 0$ for $p^* \in (-xS, xS)$, properties that are also verified later, we obtain

$$\frac{dX_d(p; c)}{dp} = -(p - c)H'(p). \quad (54)$$

Because (54) shows that the sensitivity of expected payoff to the limit price $p$ is positive for $p < c$ and negative for $p > c$, the optimal limit price for the liquidity buyer is her delay cost $c$. Symmetrically, the optimal limit price for a liquidity seller with a delay cost of $c \in [0, xS)$ is $-c$. This “truth-telling” strategy is also ex-post optimal, in that no one wishes to deviate even after observing the execution price.\(^{21}\)

\(^{21}\)This strategy is reminiscent of the truth-telling strategy of MacAfee (1992), who considers a double auction with finitely many buyers and sellers. The double auction here has the institutional restriction that transaction prices are bounded by the trade-at rule.
The first-order condition (54) also implies that \( xS \) is the highest limit price in the dark pool, and that \(-xS\) is the lowest limit price.\textsuperscript{22} A liquidity buyer with a delay cost of \( c > xS \) may wish to quote a limit price of \( c \), but the trade-at rule forces her to quote \( xS \). This “corner solution” suggests a strictly positive mass of liquidity buyers quoting the highest limit price \( xS \), and a strictly positive mass of liquidity sellers quoting the lowest limit price \(-xS\).

Let \( y(p) \) be the downward-sloping demand schedule in the dark pool if \( Z^+ = 1 \). Because a limit price \( p \in [0, xS) \) is submitted by the liquidity buyer with the delay cost \( p \),

\[
y(p) = \alpha_d - G\left(\frac{\max(0, p)}{\sigma}\right), \quad -xS < p < xS.
\]

(55)

By symmetry, the liquidity buyers’ demand schedule and the liquidity sellers’ supply schedule in the dark pool are, respectively,

\[
y^+(p) = Z^+ y(p),
\]

(56)

\[
y^-(p) = Z^- y(-p).
\]

(57)

Because the equation \( y^+(p) = y^-(p) \) has at most one root, we have verified our earlier conjecture that the dark pool execution price \( p^* \) is uniquely well-defined.

Given \( y(p) \), the execution price \( p^* \) in the dark pool is

\[
p^* = \begin{cases} 
+xS, & \text{if } [\alpha_d - G\left(\frac{xS}{\sigma}\right)] Z^+ \geq \alpha_d Z^-, \\
+\sigma G^{-1} \left[ \alpha_d \left( 1 - \frac{Z^+}{Z^-} \right) \right], & \text{if } [\alpha_d - G\left(\frac{xS}{\sigma}\right)] Z^+ < \alpha_d Z^- \leq \alpha_d Z^+, \\
-\sigma G^{-1} \left[ \alpha_d \left( 1 - \frac{Z^-}{Z^+} \right) \right], & \text{if } [\alpha_d - G\left(\frac{xS}{\sigma}\right)] Z^- < \alpha_d Z^+ \leq \alpha_d Z^-, \\
-xS, & \text{if } [\alpha_d - G\left(\frac{xS}{\sigma}\right)] Z^- \geq \alpha_d Z^+.
\end{cases}
\]

(58)

Because the mass \( Z^+ \) of liquidity buyers and the mass \( Z^- \) of liquidity sellers are identically distributed, the dark pool execution price \( p^* \) has a mean of zero. By the differentiability of \( G \) and of the distribution function of \( Z^-/Z^+ \), \( H(p^*) \) is continuous, differentiable, and strictly increasing on \((-xS, xS)\), as conjectured earlier.

What remains to be shown are the incentive-compatibility conditions of liquidity traders who set the limit price \( xS \) or \(-xS\) in the dark pool, as well as the incentive-compatibility condition of informed traders who avoid the dark pool. A liquidity buyer\textsuperscript{22}If the maximum limit price were smaller, say \( p_0 < xS \), then a liquidity buyer with a delay cost of \( p_0 + \epsilon \) for some small \( \epsilon > 0 \) would deviate to the dark pool and quote \( p_0 + \epsilon \). This deviating buyer has an execution probability of 1 and pays at most \( p_0 + \epsilon < xS \leq S \), which is better than execution on the exchange. The argument for the lowest limit price is symmetric.
quoting the limit price $xS$ in the dark pool has an execution probability of

$$\bar{r}_x = \mathbb{E} \left[ \min \left( 1, \frac{\alpha_d Z^-}{(\alpha_d - G(xS/\sigma))Z^+} \right) \right],$$

(59)

and an expected payoff, given the delay cost $c$, of

$$X_d(xS; c) = -(1 - \bar{r}_x)(c - xS).$$

(60)

This expected payoff calculation follows from the fact that $\mathbb{E}(p^*) = 0$ and the fact that failing to cross in the dark pool incurs a delay cost of $c$ but saves the payment $xS$.

Because informed traders avoid the dark pool with probability 1 in the conjectured equilibrium, an informed buyer who deviates to the dark pool also has the crossing probability $\bar{r}_x$. Moreover, in order to get the highest priority, this deviating informed trader sets the highest limit price $xS$. Her expected profit in the dark pool is thus

$$W_d = \sigma - (1 - \bar{r}_x)(\sigma - xS).$$

(61)

As before, for any delay cost $c \leq \sigma$,

$$W_d - X_d(xS; c) = \sigma \bar{r}_x + c(1 - \bar{r}_x) \leq \sigma = W_e - X_e.$$

(62)

That is, an informed buyer behaves in the same way as a liquidity buyer who has a delay cost of $\sigma$. For informed buyers to avoid the dark pool, the marginal liquidity buyer with a delay cost of $\sigma$ must also weakly prefer the exchange. The argument for sellers is symmetric. Because the marginal liquidity trader indifferent between the two venues has a delay cost of $G^{-1}(\alpha_d)\sigma$, we look for an equilibrium in which $\alpha_d \leq G(1)$. In that equilibrium, $\beta = 0$.

**Proposition 4.** In a market with an exchange and a dark pool that implements a double auction, there exists a unique threshold volatility $\bar{\sigma}(x) > 0$ with the property that, for any $\sigma \leq \bar{\sigma}(x)$, there exists an equilibrium $(\beta = 0, \alpha_d = \alpha_d^*, \alpha_e = 1 - \alpha_d^*)$, where $\alpha_d^* \in (0, G(1)]$ and $\mu_I^*$ solve

$$\left[ G^{-1}(\alpha_d) - \frac{xS}{\sigma} \right] (1 - \bar{r}_x) = \frac{\mu_I}{\mu_I + (1 - \alpha_d)\mu_z},$$

(63)

$$\mu_I = \bar{\mu} F \left( \frac{(1 - \alpha_d)\mu_z}{\mu_I + (1 - \alpha_d)\mu_z} \sigma \right).$$

(64)

In this equilibrium with a fixed $x$: 

35
1. The dark pool execution price is given by (58).

2. If \( c \in [0, xS) \), a liquidity buyer (resp. seller) with a delay cost of \( c \) quotes a limit price of \( c \) (resp. \( -c \)) in the dark pool. If \( c \in [xS, G^{-1}(\alpha_d^*)\sigma] \), then a liquidity buyer (resp. seller) with a delay cost of \( c \) quotes a limit price of \( xS \) (resp. \( -xS \)) in the dark pool. Liquidity traders with delay costs higher than \( G^{-1}(\alpha_d^*)\sigma \) trade on the exchange.

3. The dark pool participation rate \( \alpha_d \) of liquidity traders, the mass \( \mu_I \) of informed traders, and the scaled exchange spread \( S/\sigma \) are all strictly increasing in the value \( \sigma \) of information.

Moreover, for \( x \in (0,1) \), the volatility threshold \( \sigma(x) \) is strictly decreasing in \( x \).

Proof. See Appendix B.

The equilibrium of Proposition 4 with a double-auction dark pool is qualitatively similar to the equilibrium characterized in Case 1 of Proposition 1. It is determined by the marginal liquidity trader who is indifferent between the two venues, shown in (63), and the marginal for-profit trader who is indifferent about whether to acquire the information, shown in (64). If multiple equilibria exist, I select the equilibrium with the lowest \( \alpha_d^* \) among those with the property that, as \( \alpha_d \) varies in a neighborhood of \( \alpha_d^* \), the left-hand side of (63) crosses the right-hand side from below. The expression of \( \sigma(x) \) in equilibrium is provided in Appendix B.

The left-hand plot of Figure 10 shows the dark pool orders in the equilibrium of Proposition 4, for \( x = 0.8 \). That is, the dark pool must provide a price improvement equal to 20% of the exchange spread \( S \). In this example, about 85% of liquidity traders in the dark pool set the most aggressive limit price, \( \pm xS \). The dark pool transaction price in this case is about 0.03. The right-hand plot of Figure 10 shows that the volatility threshold \( \sigma(x) \) is strictly decreasing in \( x \). With midpoint crossing \( (x = 0) \), informed traders avoid the dark pool if the value \( \sigma \) of information is lower than about 0.6. Under the current trade-through rule \( (x = 1) \), this volatility threshold is reduced to about 0.3.

In addition to confirming the basic intuition of Proposition 1, Proposition 4 offers new insights on the effect of a trade-at rule for dark pool participation of informed traders. Because \( \sigma(x) \) is decreasing in \( x \), the stricter the trade-at rule, the less likely are informed traders to use the dark pool. The intuition is as follows. If an informed buyer deviates to the dark pool, she selects the most aggressive permissible limit price, \( xS \), in order to maximize her execution probability. Although she will be rationed at the price \( xS \), she competes only with those liquidity traders who have a delay cost of \( xS \).
Figure 10: A dark pool as a nondisplayed limit order book. The left-hand plot shows the limit orders in the dark pool, where \( y^+(p) \) and \( y^-(p) \) denotes the demand schedule and supply schedule, respectively. The right-hand plot shows the range of \( \sigma \) for which the equilibrium of Proposition 4 exists, that is, informed traders avoid the dark pool. Model parameters are those of Figure 4. The left-hand plot also uses \( x = 0.8, \sigma = \sigma(0.8) = 0.35 \), and realizations \( Z^+ = 2.2 \) and \( Z^- = 2 \).

or higher. The lower is \( x \), the less scope there is for the informed trader to “step ahead of the queue” and gain execution priority. In particular, a midpoint dark pool with \( x = 0 \) has the greatest effectiveness in discouraging informed traders to participate.

The effect of the trade-at rule on informed participation in dark pools complements prior fairness-motivated arguments, which suggest that displayed orders should have strictly higher priority than nondisplayed orders at the same price (Joint CFTC-SEC Advisory Committee, 2011). Proposition 4 predicts that implementing a trade-at rule is likely to reduce informed participation in dark pools. Proposition 4 also predicts that dark pools operating as limit order books are more likely to attract informed traders and impatient liquidity traders, compared to dark pools crossing at the midpoint. I further discuss these implications in Section 6.

5 Dynamic Trading

This short section generalizes the basic intuition of Section 3 to a dynamic market. Under natural conditions, all equilibria have the property that, after controlling for delay costs, an informed trader prefers the exchange to the dark pool, relative to a liquidity trader.

Time is discrete, \( t \in \{1, 2, 3, \ldots \} \). As before, an asset pays an uncertain dividend \( v \) that is \( +\sigma \) or \( -\sigma \) with equal probabilities. The dividend is announced at the beginning
of period $T \geq 2$, where $T$ is deterministic, and paid at the end of period $T$. The trading game ends immediately after the dividend payment.

In each period before the dividend payment, a new set of informed traders and liquidity traders arrive. To simplify the analysis, I drop endogenous information acquisition in this section. (Equivalently, it costs zero to acquire information.) The mass of informed traders arriving in period $t$, $\mu_I(t) > 0$, is deterministic. Informed traders observe the dividend $v$ and trade in the corresponding direction. The mass of liquidity buyers and the mass of liquidity sellers arriving in period $t$ are $Z^+(t) > 0$ and $Z^-(t) > 0$, respectively, with commonly known probability distributions. The public does not observe $v$ or the realizations of $Z^+(t)$ or $Z^-(t)$.

As before, a lit exchange and a dark pool operate in parallel. In contrast with the model of Section 3, both venues are open in all periods. At the beginning of period $t$, the exchange market maker posts a bid price $B_t$ and an ask price $A_t$. Any order sent to the exchange is immediately executed at the bid or the ask. After execution of exchange orders in each period, the market maker announces the exchange buy volume and the exchange sell volume. The public information $\mathcal{F}_t$ at the beginning of period $t$ consists of all exchange announcements prior to period $t$. Thus, the conditional distribution of asset value $v$ at the beginning of period $t$ is represented by the likelihood ratio

$$R_t = \frac{P_t(v = +\sigma)}{P_t(v = -\sigma)},$$

(65)

where $P_t$ denotes the conditional probability based on $\mathcal{F}_t$. By construction, $R_0 = 1$. The public’s conditional expectation of the asset value at the beginning of period $t$ is therefore

$$V(R_t) = \sigma(P_t(v = +\sigma) - P_t(v = -\sigma)) = \frac{R_t - 1}{R_t + 1} \sigma.$$  

(66)

The dark pool executes orders in each period, simultaneously with the execution of exchange orders. I assume that the dark pool implements a double auction with a trade-at rule, as in Section 4. Midpoint crossing, which offers a price improvement of the exchange spread, is a special case of this double auction. Liquidity traders are distinguished by their delay costs, as in Section 3. If a liquidity trader of cost type $\gamma$ does not trade in period $t$, then she incurs a delay cost of $c(\gamma; R_t)$, which is strictly increasing in $\gamma$. A trader only incurs delay costs after she arrives.

I make the additional assumption that informed traders also incur positive delay costs, before they execute their orders. A type-$\gamma$ informed trader incurs the delay cost $c(\gamma; R_t)$ in period $t$ if she fails to execute her order in that period. Thus, a type-$\gamma$ informed buyer (resp. seller) and a type-$\gamma$ liquidity buyer (resp. seller) differ only in
their information about \( v \).

I now fix a cost type \( \gamma \geq 0 \) and focus on the payoffs of buyers. For any \((R_t, t)\), I let

\[
W_e(R_t, t) = \sigma - A_t \tag{67}
\]

\[
X_e(R_t, t) = V(R_t) - A_t \tag{68}
\]

be the payoffs of a type-\( \gamma \) informed buyer and a type-\( \gamma \) liquidity buyer, respectively, for trading immediately on the exchange. These payoffs do not depend on the cost type \( \gamma \) because exchange execution involves no delays. I let \( W_d(R_t, t; \gamma) \) and \( X_d(R_t, t; \gamma) \) be the corresponding continuation values of entering an order in the dark pool. Finally, I let \( W(R_t, t; \gamma) \) and \( X(R_t, t; \gamma) \) be the continuation values of the informed buyer and liquidity buyer, respectively, at the beginning of period \( t \), before they make trading decisions. For \( t = T \), \( W(R_T, T; \gamma) = X(R_T, T; \gamma) = 0 \). For \( t < T \), the Bellman Principal implies that

\[
W(R_t, t; \gamma) = \max \left[ W_e(R_t, t), W_d(R_t, t), \mathbb{E}_t(W(R_{t+1}, t + 1; \gamma)) \right], \tag{69}
\]

\[
X(R_t, t; \gamma) = \max \left[ X_e(R_t, t), X_d(R_t, t), \mathbb{E}_t(X(R_{t+1}, t + 1; \gamma)) \right], \tag{70}
\]

where the three terms in the \( \max(\cdot) \) operator represents a trader’s three choices: sending her order to the exchange, sending her order to the dark pool, and delaying trade.

The following proposition shows equilibrium conditions under which, controlling for delay costs, the liquidity-versus-informed payoff difference \( X_d(R_t, t; \gamma) - W_d(R_t, t; \gamma) \) in the dark pool is at least as high as the corresponding payoff difference \( X_e(R_t, t) - W_e(R_t, t) \) on the exchange. It is in this “difference-in-difference” sense that the dark pool is more attractive to liquidity traders, and that the exchange is more attractive to informed traders.

**Proposition 5.** In any equilibrium, if \( W_d(R_t, t; \gamma) \geq \mathbb{E}_t[W(R_{t+1}, t + 1; \gamma)] \), then

\[
X_d(R_t, t; \gamma) - W_d(R_t, t; \gamma) \geq X_e(R_t, t) - W_e(R_t, t). \tag{71}
\]

*Proof.* See Appendix B.

Proposition 5 identifies a restriction (71) that must be satisfied by all equilibria, provided that an informed buyer does not strictly prefer delaying trade to using the dark pool. The intuition for this result is as follows. Because the exchange guarantees to execute all buy orders at the same price \( A_t \), the exchange payoff difference, \( X_e(R_t, t) - W_e(R_t, t) \), reflects only the value of private information. The dark pool payoff difference
\[ X_d(R_t, t; \gamma) - W_d(R_t, t; \gamma), \] by contrast, reflects both the value of information and the execution risk. Compared with a liquidity buyer, an informed buyer in the dark pool is less likely to fill her order and, conditional on a trade, more likely to pay a higher price. This execution risk is costly for the informed buyer in equilibrium as long as she prefers dark pool trading to waiting, as captured by \[ W_d(R_t, t; \gamma) \geq \mathbb{E}_t[W_d(R_{t+1}, t+1; \gamma)]. \] I isolate this dark pool execution risk from the value of information by taking the “difference-in-difference” of payoffs in (71).

Appendix A solves a dynamic equilibrium explicitly under a slightly different setting.

6 Implications

This section discusses some implications of these results, both in light of recent empirical evidence and in relation to the current policy debate on the impacts of dark pools on price discovery and liquidity.

The discussion follows two organizing questions. First, what are the relations between dark pool market share and observable market characteristics? Second, what are the impacts of dark pool trading on price discovery and liquidity? For each question, I first state some empirical implications of the results of this paper and then discuss these implications in the context of related evidence. Some recent related empirical papers are summarized in Table 2.

6.1 Determinants of dark pool market share

**Prediction 1.** All else equal, dark pool market share is lower if the execution probability of dark pool orders is lower.

**Prediction 2.** All else equal, if volatility (spread, total volume) is low, then dark pool market share is low, and increasing in volatility (spread, total volume).

**Prediction 3.** All else equal, informed participation in dark pools is higher for higher-volatility stocks and days, and for dark pools that allow more discretion in execution prices.

**Prediction 4.** All else equal, dark pool market share is lower for trading strategies relying on shorter-term information. The use of dark pools is also lower for trading strategies that trade multiple stocks simultaneously, compared with strategies that trade individual stocks one at a time.
Table 2: Some recent (academic) empirical studies on dark pools and market fragmentation. The first five papers focus on dark pools. The next three papers focus on market fragmentation (by dark and lit venues).

<table>
<thead>
<tr>
<th>Paper</th>
<th>Sample trading venues</th>
<th>Sample period</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buti, Rindi, and Werner (2010a)</td>
<td>11 anonymous dark pools</td>
<td>2009, daily</td>
<td>Voluntary SIFMA survey</td>
</tr>
<tr>
<td>Weaver (2011)</td>
<td>Trade reporting facilities</td>
<td>10/2010, intraday</td>
<td>TAQ</td>
</tr>
</tbody>
</table>
Prediction 1 follows from the results of Section 3 and Section 4. A lower execution probability, captured by a lower $\bar{r}$ or $\bar{r}_x$, discourages both types of traders from participating in the dark pool.\footnote{This relation can be analytically proved for $\sigma < \bar{\sigma}$ in Proposition 1 and for $\sigma < \bar{\sigma}(x)$ in Proposition 4.} Ye (2010b) constructs a proxy for execution probability in eight dark pools from their SEC Rule 605 reports.\footnote{Under Rule 605 of Reg NMS, market centers are required to make monthly electronic reports. These reports, according to FINRA, “include information about each market center’s quality of execution on a stock-by-stock basis, including how market orders of various sizes are executed relative to the public quotes. These reports must also disclose information about effective spreads (the spreads actually paid by investors whose orders are routed to a particular market center). In addition, market centers must disclose the extent to which they provide executions at prices better than the public quotes to investors using limit orders.” For more details, see http://www.finra.org/Industry/Regulation/Guidance/SECRule605/.} He focuses on the relationship between non-execution probabilities and market characteristics such as price impacts and effective spreads. He does not, however, study how non-execution probability is related to the market share of dark pools. Using daily data collected by SIFMA from eleven anonymous dark pools in 2009, Buti, Rindi, and Werner (2010a) find that order imbalance as a percentage of total volume is negatively related to dark pool market share. The absolute depth imbalance on lit venues, too, is negatively related to dark pool market share. Prediction 1 is consistent with their findings.

Prediction 2 suggests that dark pool market share is low if volatility, spread, or total volume is low, as discussed in Section 3.3. Existing empirical evidence in this respect is mixed. Using transaction data from 2005 to 2007 covering three block-crossing dark pools, Liquidnet, Posit, and Pipeline, Ready (2010) documents that dark pool usage is lower for stocks with the lowest spreads per share. Ready attributes this finding to soft-dollar arrangements: because institutions need to execute some orders through brokers (instead of dark pools), they send stocks with the lowest spreads to brokers and incur the lowest transaction costs. The model of this paper gives an alternative interpretation, namely that low-spread stocks are less costly to trade on exchanges than in dark pools, because dark pool execution is subject to delays.\footnote{Admittedly, small orders of this model are different from the large institutional orders in the data of Ready (2010), and I do not model brokers. However, to the extent that transaction costs on large orders and with brokers are proportional to the exchange spreads, the model of this paper can still be applicable.} In contrast to Ready (2010), both Buti, Rindi, and Werner (2010a) and Ye (2010b) find that the market share of dark pools is higher for lower-spread stocks and higher-volume stocks. In the time series, Buti, Rindi, and Werner (2010a) find that, fixing a stock, dark pool market share is higher on days with wider quoted spreads.

A relatively consistent result across these studies is that dark pool market share is lower when volatility is higher, but not all of these studies agree on this point. Using the SIFMA sample of eleven dark pools, Buti, Rindi, and Werner (2010a) document
a negative relationship between dark pool market share and volatility, as measured by the intraday range, the standard deviation of midpoint returns, and the average absolute returns. Similarly, Ye (2010b) finds that the market shares of his sample of eight dark pools are lower when the standard deviations of stock returns are higher. Using the absolute monthly returns as a proxy of volatility, Ray (2010) reaches the same conclusion. In contrast to these studies, Ready (2010) estimates a structural model and finds that stocks with higher return volatilities are more likely to be routed to his sample of the three block-crossing dark pools.

One potential explanation for these contrasting results is that dark pool market share may not be monotone in volatility, spread, or volume, as discussed in Section 3.3. Indeed, Ready (2010) finds that dark pool market share first increases in the total volume and then decreases. Using a sub-sample of Ready’s data, Ray (2010) finds a similar hump-shaped relation between dark pool market share and the relative bid-ask spread. Another potential explanation is sample selection. For example, the Ready (2010) sample uses early data (2005-2007), Nasdaq stocks, and three dark pools, whereas the Buti, Rindi, and Werner (2010a) sample and the Ye (2010b) sample cover more recent data (2009 and 2010, respectively), NYSE and Nasdaq stocks, and more dark pools (eleven and eight, respectively).

Prediction 3 suggests (at least in the model setting) that dark pools with discretionary execution prices are more attractive to informed traders and to impatient liquidity traders than dark pools crossing at the midpoint. To my knowledge, this prediction is not yet tested in the data, perhaps due to the lack of transaction data that can be assigned to individual dark pools. For a given dark pool, Prediction 3 also suggests that dark pool orders are more informative on average when information asymmetry is severe. Nimalendran and Ray (2011) provide some evidence for this, using data from an anonymous dark pool. They put each transaction in their data into one of three baskets, buy, sell, and unsigned, depending on whether the transaction price is above, below, or equal to the prevailing exchange midpoint. Then they construct a portfolio that buys the “buy basket” and sells the “sell basket.” In a two-hour horizon, this strategy makes a profit if implemented on the most illiquid securities (those with the widest relative spread), but results in a loss if implemented on the most liquid securities. Their finding is consistent with the prediction of the model proposed here: illiquid stocks are more likely suffer from information asymmetry and therefore are more likely to attract informed trading in dark pools. Because informed traders tend to post aggressive limit prices and execute their orders at prices relatively far away from the exchange midpoint, the signed dark pool transactions of illiquid stocks can
contain price-relevant information. By contrast, aggressive buying and selling of the most liquid securities are more likely to come from impatient liquidity traders, whose signed order flow is unlikely to predict future returns.

**Prediction 4** provides strategy-level implications on dark pool activity. Strategies relying on shorter-term information have higher execution risks in dark pools because relevant information can become stale faster. Related to this prediction, Ready (2010) finds that the usage of three block-crossing dark pools is lower for institutions with higher turnover, which is consistent with the notion that short-term strategies are best implemented in venues that guarantee execution. Because dark pools cannot guarantee the simultaneous execution of trades in multiple stocks, we also expect dark pools to be less attractive for strategies tracking stock indices or “arbitraging” perceived mispricing among similar securities. For these strategies, partial execution in dark pools can be particularly costly.

### 6.2 Effects of dark pools on price discovery and liquidity

**Prediction 5.** All else equal, a higher dark pool market share is associated with higher order informativeness on the exchange in the form of wider spreads and higher price impacts of trades.

**Prediction 6.** All else equal, a higher dark pool market share increases the correlation of volumes across different stocks in lit exchanges. This cross-stock volume correlation is lower in dark pools than in lit exchanges.

**Prediction 7.** All else equal, dark pool execution implies a positive adverse-selection cost, in that shares bought in dark pools tend to have low short-term returns and that shares sold in dark pools tend to have high short-term returns. This cost, however, is lower than the exchange spread at the time of execution.

**Prediction 5** holds under the conditions stated in Proposition 3. For example, adding a dark pool increases the informativeness of exchange orders when the value of information is relatively low, when the mass of informed traders is relatively insensitive to the value of information, or when the dark pool execution probability is relatively low. We observe that higher price discovery and higher liquidity need not imply each other, as they tend to have opposite effects for spreads and price impacts.

This price-discovery effect of dark pools is consistent with the findings of Degryse, de Jong, and van Kervel (2011), who examine the impact of dark trading on characteristics of lit venues in Dutch equity markets. In their paper, dark venues include
dark pools and over the counter markets, whereas lit venues include exchanges and “multilateral trading facilities.” Higher market share of dark trading, they conclude, is associated with higher price impacts, higher quoted spreads, higher realized spreads, and smaller depths on lit markets. Using transaction data from an anonymous dark pool, Nimalendran and Ray (2011) find that following dark pool transactions, bid-ask spreads tend to widen and price impacts tend to increase, especially if the relative bid-ask spreads are already high. By contrast, Buti, Rindi, and Werner (2010a) find in the SIFMA data that higher dark pool trading is associated with lower spreads, higher depths, and lower volatility. The conflict between these conclusions could be the result of different data or empirical methods. In early studies, for which dark pools had much lower market shares, Gresse (2006) and Fong, Madhavan, and Swan (2004) conclude that dark pool trading does not harm the market quality of the London Stock Exchange and the Australian Stock Exchange, respectively. Due to endogeneity—dark pool trading and market characteristics affect each other—we should interpret these results with caution.

For the case of dark pools in the form of nondisplayed limit order books, Hendershott and Jones (2005) find that price discovery for exchange-traded funds (ETFs) on Island ECN, a limit-order market, worsened after Island stopped displaying its limit orders. Because Island ECN was the dominant market for affected ETFs, it differed from today’s equity dark pools, which rely on exchanges prices as reference. Extending the Kyle (1985) framework, Boulatov and George (2010) model a nondisplayed market by allowing informed market makers to hide their liquidity-supply schedules from the public view. They find that this opacity enhances competition among market makers, leading to more informative quotes. Since the nondisplayed market of Boulatov and George (2010) has no competitors, their model is different from the two-venue model of this paper.

Because dark pools account for a substantial portion of total off-exchange trading, a related question is how off-exchange trading affects price discovery and liquidity. To answer this question, O’Hara and Ye (2011) use the market share of trade reporting facilities (TRFs) as a proxy of market fragmentation. Using a TRF sample of early 2008, they find that higher fragmentation is associated with faster execution, lower transaction costs, and more efficient prices (prices are closer to random walks). Using a more recent TRF sample of 2010, Weaver (2011) finds that stocks with higher levels of off-exchange trading tend to have wider spreads, higher price impacts, and higher

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26Multilateral trading facility (MTF) is a type of transparent venues in Europe. An MTF is similar to an exchange.
volatilities. Weaver (2011) attributes the difference between his results and those of O’Hara and Ye (2011) to the status changes of two lit venues, BATS and DirectEdge, which reported to TRF for the period covering the data used by O’Hara and Ye (2011), but later became registered exchanges. Transactions on BATS and DirectEdge were therefore not included in the Weaver (2011) sample. In their analysis of Dutch equity markets, Degryse, de Jong, and van Kervel (2011) find that the degree of fragmentation of trading among lit venues has a non-monotone relation with liquidity. Moderate lit fragmentation increases depths, lowers spreads, and lowers price impacts, but too much lit fragmentation has the opposite effects. Together, these findings suggest that dark and lit fragmentation could have opposite impacts on price discovery and liquidity.

Prediction 6 can be viewed as the mirror image of Prediction 4. Since dark pools are less attractive to strategies executing multiple stocks simultaneously, those strategies should be more concentrated on lit venues than in dark pools. The volume correlation across stocks, consequently, should be higher on lit venues than in dark pools.

Finally, Prediction 7 follows from the results of Section 3. If a liquidity trader is willing to participate in the dark pool despite the potential delay cost, the adverse-selection cost in the dark pool must be lower than the exchange spread. Using proprietary transaction data from institutional investors, Conrad, Johnson, and Wahal (2003) and Næs and Odegaard (2006) document lower trading costs in dark pools compared to traditional execution methods, such as brokers. Similar results have been documented more recently by Brandes and Domowitz (2010) in a selection of nondisplayed venues in Europe. Domowitz, Finkelshteyn, and Yegerman (2009) find that a scheduled dark pool has lower transaction costs than a peer group of continuous dark pools. Nonetheless, these studies do not measure the ex-post costs of adverse selection, that is, whether shares bought (sold) in dark pools have lower (higher) returns shortly after order execution. Næs and Odegaard (2006) provide anecdotal evidence that filled orders in a dark pool are subject to such adverse selection. A full test of Prediction 7 is likely to require detailed data on all orders submitted to a dark pool, not only executed orders.

Short-term adverse selection in dark pools can reduce the transaction quality of institutional investors, as discussed by Mittal (2008) and Saraiya and Mittal (2009). The Securities and Exchange Commission (2010), too, has noted that “[i]n theory, short-term price swings that hurt investors on one side of the market can benefit investors on the other side of the market. In practice, professional traders, who have the time and resources to monitor market dynamics closely, are far more likely than investors to be on the profitable side of short-term price swings.” The SEC has further added that “[w]here the interests of long-term investors and short-term professional traders
diverge, the Commission repeatedly has emphasized that its duty is to uphold the interests of long-term investors.”

7 Concluding Remarks

In recent years, dark pools have become an important part of equity market structure. Although it has often been suspected that dark pools harm price discovery, existing empirical studies have not found conclusive evidence supporting this suspicion. This paper provides a potential explanation of this puzzle: Liquidity traders prefer dark pools more than informed traders do. Under natural conditions, adding a dark pool reduces the noise in exchange order flow induced by liquidity traders, and thus improves price discovery.

Some relevant aspects of dark pools are not modeled in this paper. One of these is size discovery. Institutions trade large blocks of shares in dark pools without revealing their trading intentions to the broad markets. This size-discovery benefit of dark trading has been widely acknowledged by market participants and regulators. Today, only a handful of dark pools specialize in such block-crossing services (Securities and Exchange Commission, 2010). A model of size discovery in dark pools could also be a model of competing execution methods, such as algorithms that probe different dark pools, algorithms that split orders in the lit markets, and conventional OTC market makers. Ye (2010a) provides an analysis of how a large informed trader splits his orders between an exchange and a dark pool.

Second, this paper does not consider communications in dark pools. For example, a dark pool may send an “indication of interest” (IOI), which contains selected order information such as the ticker, to potential counterparties in order to facilitate a match. In this sense, these dark pools are not completely dark.28 The Securities and Exchange Commission (2009) proposed to treat actionable IOIs—IOIs containing the symbol, size, side, and price of an order—as quotes, which must be disseminated to the broad market immediately.

Third, this paper assumes that all investors have access to the dark pool. In practice, fair (non-discriminatory) access to dark pools is not warranted. For example, the U.S. regulation does not require dark pools to provide fair access unless the dark pool concerned reaches a 5% volume threshold. Whether investors suffer from the lack of

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27 Models of splitting orders include those of Seppi (1990), Bernhardt and Hughson (1997), Bertsimas and Lo (1998), and Back and Baruch (2007).

28 In Buti, Rindi, and Werner (2010b), for example, selected traders are informed of the state of the dark pool.
fair access can depend on perspective. On the one hand, it seems plausible that the lack of fair access can reduce trading opportunities and the welfare of excluded traders. On the other hand, “some dark pools attempt to protect institutional trading interest by raising access barrier to the sell-side or certain hedge funds,” observes SEC Deputy Director James Brigagliano. Credit Suisse, a broker-dealer, has also opened a “Light Pool” ECN that aims to exclude “opportunistic” traders, including, for example, some high-frequency trading firms.

Finally, this paper assumes that investors fully understand the operational mechanics of dark pools and their users. That is, although dark pool orders are invisible, the trading rules of the dark pool are transparent. Innocuous in most contexts, this assumption may be worth further investigation for dark pools. For example, a Greenwich Associates survey of 64 active institutional users of dark pools reveals that, on many occasions, dark pools do not disclose sufficient information regarding the types of orders that are accepted, how orders interact with each other, how customers’ orders are routed, what anti-gaming controls are in place, whether customer orders are exposed to proprietary trading flows, and at what price orders are matched (Bennett, Colon, Feng, and Litwin, 2010). The International Organization of Securities Commissions (2010) also observes that “[l]ack of information about the operations of dark pools and dark orders may result in market participants making uninformed decisions regarding whether or how to trade within a dark pool or using a dark order.” Opaque operating mechanics of dark pools can make it more difficult for investors and regulators to evaluate the impact of dark pools on price discovery and liquidity.

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Appendix

A Dynamic Trading with Stochastic Crossing

This appendix explicitly characterizes a family of equilibria in which informed traders do not participate in the dark pool. The setting of this section is different from Section 5 in that I assume continuous time and assume that event times follow Poisson processes. This Poisson assumption gives rise to tractable stationary equilibria.

Time is continuous, \( t \geq 0 \), and the market opens at time 0. As before, an asset pays an uncertain dividend \( v \) that is \( +\sigma \) or \( -\sigma \) with equal probabilities. The time of the dividend payment is exponentially distributed with mean \( 1/\lambda_F \), for \( \lambda_F > 0 \). Two types of risk-neutral traders—liquidity traders and informed traders—have independent Poisson arrivals with respective mean arrival rates of \( \lambda_L \) and \( \lambda_I \). (Traders are thus “discrete.”) Each trader can buy or sell one unit of the asset. As in Section 5, I do not consider endogenous information acquisition here. Upon arrival, an informed trader observes \( v \) perfectly. Liquidity traders, who are not informed regarding the dividend, arrive with an unwanted position in the asset whose size is either +1 or −1, equally likely and independent of all else.

As before, a lit exchange and a dark pool operate in parallel. A competitive and risk-neutral market maker on the exchange continually posts bid and ask prices for one unit of the asset, as in Glosten and Milgrom (1985). Any order sent to the exchange is immediately executed at the bid or the ask, and trade information is immediately disseminated to everyone. By competitive pricing, the bid price at any time \( t \) is the conditional expected asset value given the arrival of a new sell order at time \( t \) and given all public information up to, but before, time \( t \). The ask price is set likewise.

The market maker also maintains a public “mid-market” price that is the conditional expected asset value given all public information up to but before time \( t \). Once an exchange order is executed, the market maker immediately updates her bid, ask, and mid-market prices.

The dark pool accepts orders continually, and an order sent to the dark pool is observable only by the order submitter. The dark pool executes orders at the mid-market price and at the event times of a Poisson process with intensity \( \lambda_C \) that is independent of all else. Allocation in the dark pool is pro-rata on the heavier side, as in Section 3. For analytical tractability, I assume that unmatched orders in the dark pool are immediately sent to the exchange market maker, who then executes these orders at the conditional expected asset value given all past public information and
given the quantity and direction of unmatched orders from the dark pool.

As in Section 5, the conditional likelihood ratio of \( v \) at time \( t \) is

\[
R_t = \frac{\mathbb{P}_t(v = +\sigma)}{\mathbb{P}_t(v = -\sigma)},
\]

where \( \mathbb{P}_t \) denotes the market maker’s conditional probability. By construction, \( R_0 = 1 \).

The conditional expected asset value is, as in Section 5,

\[
V(R_t) = \sigma (\mathbb{P}_t(v = +\sigma) - \mathbb{P}(v = -\sigma)) = \frac{R_t - 1}{R_t + 1} \sigma.
\]

To calculate the bid and ask prices, I let \( \lambda_t \) be the time-\( t \) arrival intensity (conditional mean arrival rate) of traders of any type to the exchange, and let \( \mu_t \) be the time-\( t \) conditional probability that an arriving exchange trader is informed. Then,

\[
q_t = \mu_t + (1 - \mu_t)0.5 = 0.5 + 0.5\mu_t
\]

is the probability that an exchange trader arriving at \( t \) is “correct,” that is, buying if \( v = +\sigma \) and selling if \( v = -\sigma \). The likelihood ratio

\[
z_t = \frac{q_t}{1 - q_t}
\]

then represents the informativeness of a time-\( t \) exchange order.\(^{31}\) For example, if a buy order hits the market maker’s bid at time \( t \), then Bayes’ Rule implies that

\[
R_t = \frac{\mathbb{P}_t(v = +\sigma | Q = 1)}{\mathbb{P}_t(v = -\sigma | Q = 1)} = \frac{\mathbb{P}_t(Q = 1 | v = +\sigma)}{\mathbb{P}_t(Q = 1 | v = -\sigma)} \cdot \frac{\mathbb{P}_t(v = +\sigma)}{\mathbb{P}_t(v = -\sigma)} = R_{t-} z_t,
\]

where \( \mathbb{P}_t \) denotes the market maker’s probability conditional on all exchange transactions up to but before time \( t \), and where \( R_{t-} \equiv \lim_{s \uparrow t} R_s \). Similarly, if an exchange sell order arrives at time \( t \), then

\[
R_t = \frac{\mathbb{P}_t(v = +\sigma | Q = -1)}{\mathbb{P}_t(v = -\sigma | Q = -1)} = \frac{R_{t-}}{z_t}.
\]

To break even, the market maker quotes a time-\( t \) bid price of \( V(R_{t-} z_t^{-1}) \) and a time-\( t \) ask price of \( V(R_t z_t) \). Because \( V(\cdot) \) is nonlinear, \( V(R_t) \) is generally not identical to the bid-ask midpoint, \( (V(R_t z_t) + V(R_{t-} z_t^{-1}))/2 \). Nonetheless, for simplicity I refer to \( V(R_t) \)

\(^{31}\)In the equilibria characterized in this section, the information content of a buy order is equal to that of a sell order, so there is no need to specify them separately.
as the “mid-market” price.

Liquidity traders must hold collateral equal to the expected loss on their unwanted risky positions. With probability \( \kappa_j \) and independently of all else, an arriving liquidity trader incurs a cost of \( \gamma_j \) per unit of time for every unit of collateral support in her risky position, where \((\kappa_j)_{j=1}^J\) and \((\gamma_j)_{j=1}^J\) are commonly-known constants and satisfy

\[
0 \leq \gamma_1 < \gamma_2 < \cdots < \gamma_{J-1} < \gamma_J, \quad (78)
\]

\[
\sum_{j=1}^J \kappa_j = 1. \quad (79)
\]

Before executing her order, a liquidity buyer of type \( j \) incurs a flow cost of

\[
c^j_t = \gamma_j \mathbb{E}_t[\max(0, v - V(R_t))] = \gamma_j \frac{R_t}{R_t + 1} \cdot \left(1 - \frac{R_t - 1}{R_t + 1}\right) \sigma = \gamma_j \frac{2R_t}{(R_t + 1)^2} \sigma. \quad (80)
\]

A liquidity seller of type \( j \) has the same flow cost \( c^j_t \) because

\[
\gamma_j \mathbb{E}_t[\max(0, V(R_t) - v)] = \gamma_j \frac{1}{R_t + 1} \cdot \left(\frac{R_t - 1}{R_t + 1} - (-1)\right) \sigma = \gamma_j \frac{2R_t}{(R_t + 1)^2} \sigma. \quad (81)
\]

By independent splitting of Poisson processes, the arrival intensities of type-\( j \) liquidity buyers and type-\( j \) liquidity sellers are both \( 0.5\kappa_j \lambda_L \).

Without loss of generality, we focus on the strategies of informed buyers and liquidity buyers, whose payoffs are denoted \( W(R_t) \) and \( X(R_t) \), respectively. For simplicity, I use \( \mathbb{E}_t^i[\cdot] \) as a shorthand for \( \mathbb{E}_t[\cdot | v = \sigma] \), where the superscript “\( i \)” stands for “informed.” Because I look for stationary equilibria, the payoffs \( W(R_t) \) and \( X(R_t) \) depend on the public information \( R_t \) but not on time \( t \).

**Proposition 6.** For fixed integer \( M \in \{0, 1, \ldots, J\} \), define

\[
z_c = \frac{\lambda_I + 0.5 \sum_{i=M}^J \kappa_i \lambda_L}{0.5 \sum_{i=M}^J \kappa_i \lambda_L}. \quad (82)
\]
Under the conditions
\[ \lambda_C < \frac{\sum_{i=M}^{J} \kappa_i \lambda_L}{2 \lambda_I} \lambda_F, \]  
(83)

\[ \gamma_j < (\lambda_C + \lambda_F) \frac{z_e - 1}{z_e}, \quad 1 \leq j < M, \]  
(84)

\[ \gamma_j > (\lambda_C + \lambda_F) (z_e - 1) + \left( \lambda_I + \sum_{i=M}^{J} \kappa_i \lambda_L \right) \frac{(z_e - 1)^3}{z_e(\sqrt{z_e} + 1)^2}, \quad M \leq j \leq J, \]  
(85)

there exists an equilibrium in which:

1. Informed traders trade on the exchange immediately upon arrival.
2. Type-\(j\) liquidity traders, \(M \leq j \leq J\), trade immediately on the exchange upon arrival.
3. Type-\(j\) liquidity traders, \(1 \leq j < M\), enter orders in the dark pool. If the dark pool has not crossed by the time that the dividend is paid, they cancel their dark pool orders and trade immediately on the exchange.
4. At time \(t\), the market maker quotes a bid of \(V(R_t z_e^{-1})\) and an ask of \(V(R_t z_e)\). Moreover, immediately after a dark pool crossing, the market maker executes all outstanding orders at a price of \(V(R_t)\). Immediately after the dividend \(v\) is paid, the market maker executes all outstanding orders at the cum-dividend price of \(v\).

Proof. See Appendix B. \(\square\)

A key step in the equilibrium solution of Proposition 6 is that informed traders expect the exchange price to move against them over time, but liquidity traders expect the exchange spread to narrow over time. Thus, informed traders are relatively impatient, whereas liquidity traders are relatively patient. These different expectations of future prices, as formally stated in the following lemma, underlie the partial separation between informed traders and liquidity traders in the equilibria of Proposition 6.

**Lemma 1.** Let \(Q\) be the direction of the next exchange order that arrives before the dividend payment, that is, \(Q = 1\) denotes a buy order and \(Q = -1\) denotes a sell order. Under the strategies stated in Proposition 6:

- The asset value is a martingale for liquidity traders and the public, in that
  \[ V(R_t) = \mathbb{E}_t[V(R_t z_e^Q)]. \]  
(86)

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• The exchange ask price is a submartingale for informed buyers, in that

\[ V(R_tz_e) < \mathbb{E}_t[V(R_tz_e^Qz_e)]. \] (87)

• The exchange ask price is a supermartingale for liquidity buyers, in that

\[ \mathbb{E}_t[V(R_tz_e^Qz_e)] = V(R_tz_e) - \frac{2R_t^2(z_e - 1)^3}{(R_t + 1)^2(R_tz_e + 1)(R_tz_e^2 + 1)} \sigma. \] (88)

Proof. See Appendix B.

In Proposition 6, \( z_e \) reflects the degree of information asymmetry on the exchange because it is the ratio of the mean arrival rate of traders in the “correct” direction versus the mean arrival rate of traders in the “wrong” direction. Proposition 6 says that an informed trader trades immediately on the exchange if the crossing frequency \( \lambda_C \) of the dark pool is sufficiently low relative to the risk that her private information becomes stale. A liquidity trader sends her order to the dark pool if and only if her delay cost \( \gamma \) is sufficiently low compared to the potential price improvement obtained by trading at the market midpoint. Moreover, because the exchange order informativeness \( z_e \) is increasing in \( M \), the more liquidity traders trade in the dark pool, the more informative are exchange orders. This property is a dynamic analogue of the two-period equilibrium of Section 3.

We now briefly discuss the comparative statics of the equilibria, based on the tightness of the incentive constraints (83)-(85). First, a higher crossing frequency \( \lambda_C \) tightens (83), suggesting that informed traders are more likely to participate in the dark pool if the crossing frequency is higher. On the other hand, a higher \( \lambda_C \) relaxes (84) but tightens (85), making the dark pool more attractive to liquidity traders. As long as \( \lambda_C \) is sufficiently low, informed traders avoid in the dark pool. Second, a higher arrival rate \( \lambda_F \) of information relaxes (83), suggesting that informed traders are less likely to trade in the dark pool if they face a higher risk of losing their information advantage. By contrast, a higher \( \lambda_F \) makes the dark pool more attractive to liquidity traders by shortening their expected waiting time, as in (84)-(85). Third, a higher delay cost \( \gamma \) makes the dark pool less attractive to liquidity traders, without affecting the incentives of informed traders.
B Proofs

B.1 Proof of Proposition 1

It is clear that $\beta < 1$, as otherwise the exchange spread would be zero and informed traders would deviate to trade on the exchange. Thus, in equilibrium either $\beta = 0$ or $0 < \beta < 1$.

We first look for an equilibrium in which $\beta = 0$. By (17), $\alpha_0 = 0$ and $\alpha_e = 1 - \alpha_d$. The indifference condition of the marginal liquidity trader is given by (20). For notational simplicity, we write the left-hand side of (20) as $-\tilde{X}_d(\alpha_d)$ and the right-hand side as $-\tilde{X}_e(\alpha_d)$. For each $\alpha_d$, $\mu_I$ is uniquely determined by (21). We have

$$-\tilde{X}_d(0) = 0 < -\tilde{X}_e(0),$$

$$-\tilde{X}_d(G(1)) = 1 - \bar{r} \geq \frac{\hat{\mu}_I(\sigma)}{\hat{\mu}_I(\sigma) + (1 - G(1))\mu_z} = -\tilde{X}_e(G(1)),$$

where the second inequality follows from (19), (21), and (18). So there exists a solution $\alpha^*_d \in (0, G(1)]$ that satisfies (20).

Now we look for an equilibrium in which $\beta > 0$, that is, informed traders are indifferent between the exchange and the dark pool. What remains to be shown is that the incentive-compatibility conditions (23)-(25) have a solution. For simplicity, we write the left-hand side of (23) as $\tilde{W}_d(\beta)$ and the right-hand side of (23) as $\tilde{W}_e(\beta)$. For each $\beta \geq 0$, $\mu_I$ is unique determined by (25) and is increasing in $\beta$. Under condition (22) and for each $\alpha_d > 0$,

$$\tilde{W}_d(0) = \bar{r} > 1 - \frac{\hat{\mu}_I(\sigma)}{\hat{\mu}_I(\sigma) + (1 - G(1))\mu_z} = \tilde{W}_e(0),$$

$$\tilde{W}_d(1) = r^- < 1 = \tilde{W}_e(1),$$

where the first inequality follows from (19), (21), and (18). So there exists a solution $\beta^* \in (0, 1)$ to (23), as a function of $\alpha_d$. Because $\mu_I$ increases in $\beta$, we see that $\tilde{W}'_d(\beta) < 0$ and $\tilde{W}'_e(\beta) > 0$, holding $\alpha_d$ fixed. Thus, the solution $\beta^*$ to (23) is unique for each $\alpha_d$.

Moreover, (23) implies that in equilibrium $r^-$ is bounded away from 0. So there exists some $r_0 > 0$ such that $r^- > r_0$. So for sufficiently small $\alpha_d > 0$,

$$G(1) - G\left(\frac{r^-}{r^+ + r^-}\right) > G(1) - G\left(\frac{1 - r_0}{1 + r_0}\right) > \alpha_d.$$

So there exists a solution $\alpha^*_d \in (0, G(1)]$ to (24). The equilibria characterized by (23)-
(25) thus exist. To show that (22) is necessary for the existence of equilibria in which \( \beta > 0 \), suppose for contradiction that (22) does not hold. Then, for all \( \alpha_d \) and \( \beta > 0 \), \( \tilde{W}_e(\beta) > \tilde{W}_e(0) \geq \tilde{W}_d(0) > \tilde{W}_d(\beta) \), which implies that all informed traders wish to deviate to the exchange, contradicting \( \beta > 0 \).

B.2 Proof of Proposition 2

Because \( \beta, \alpha_d, \alpha_e, \mu, S, r^+ \) and \( r^- \) are implicitly defined by differentiable functions in each case of Proposition 1, they are continuous and differentiable in \( \sigma \) in each of the two intervals \([0, \bar{\sigma}]\) and \((\bar{\sigma}, \infty)\). At the volatility threshold \( \sigma = \bar{\sigma} \), differentiability refers to right-differentiability in Case 1 of Proposition 1, and left-differentiability in Case 2.

**Have a dark pool and \( \sigma \leq \bar{\sigma} \)**

For \( \sigma \leq \bar{\sigma} \), \( \beta = 0 \). Total differentiation of (20)-(21) with respect to \( \sigma \) yields

\[
\begin{align*}
\left[\frac{dG^{-1}(\alpha_d)}{d\alpha_d} (1 - \bar{r}) - \frac{\partial (S/\sigma)}{\partial \alpha_d}\right] \frac{d\alpha_d}{d\sigma} - \frac{\partial (S/\sigma)}{\partial \mu_I} \frac{d\mu_I}{d\sigma} &= 0, \\
\left[1 - \bar{\mu} F'(\sigma - S)\right] \frac{d\mu_I}{d\sigma} = \bar{\mu} F'(\sigma - S) \frac{\partial (\sigma - S)}{\partial \alpha_d} \frac{d\alpha_d}{d\sigma} + \bar{\mu} F'(\sigma - S) \left(1 - \frac{S}{\sigma}\right),
\end{align*}
\]

where the first term of (89) is positive because of equilibrium selection. If \( d\alpha_d/d\sigma \leq 0 \) at, say, some \( \sigma_0 \), then (90) implies that \( d\mu_I/d\sigma > 0 \) at \( \sigma_0 \). But then (89) cannot hold. Thus, \( d\alpha_d/d\sigma > 0, d\mu_I/d\sigma > 0 \), and \( d(S/\sigma)/d\sigma > 0 \), by (20).

**Have a dark pool and \( \sigma > \bar{\sigma} \)**

Now suppose that \( \sigma > \bar{\sigma} \). I denote by \( r^+ \) and \( r^- \) the derivatives of \( r^+ \) and \( r^- \) with respect to \( \beta \mu_I/\alpha_d \). We have \( r^+ > 0 \) and \( r^- < 0 \). Total differentiation of (23)-(25)
with respect to \( \sigma \) yields
\[
\left( r^-, \frac{1}{\alpha_d} - \frac{\partial(1 - S/\sigma)}{\partial(\beta \mu_I)} \right) \frac{d(\beta \mu_I)}{d\sigma} = \frac{\partial(1 - S/\sigma)}{\partial \mu_I} \frac{d\mu_I}{d\sigma} + r^- \beta \mu_I \frac{d\alpha_d}{d\sigma},
\]
(91)
\[
\left[ 1 - G' \left( \frac{r^+ - r^-}{r^+ + r^-} \right) \frac{2(r^+ r^- - r^{-'} r^+)}{(r^+ + r^-)^2} \beta \mu_I \right] \frac{d\alpha_d}{d\sigma} = -G' \left( \frac{r^+ - r^-}{r^+ + r^-} \right) \frac{2(r^+ r^- - r^{-'} r^+)}{(r^+ + r^-)^2} \frac{1}{\alpha_d} \frac{d(\beta \mu_I)}{d\sigma},
\]
(92)
\[
\left[ 1 - \bar{\mu} F' (\sigma - S) \frac{\partial(1 - S/\sigma)}{\partial \mu_I} \right] \frac{d\mu_I}{d\sigma} = \bar{\mu} F' (\sigma - S) \frac{\partial(1 - S/\sigma)}{\partial(\beta \mu_I)} \frac{d(\beta \mu_I)}{d\sigma} + \bar{\mu} F' (\sigma - S) \left( 1 - \frac{S}{\sigma} \right),
\]
(93)
where the first term of (92) is positive because of equilibrium selection.

We can show that \( d\alpha_d/d\sigma \) cannot switch signs in \([\bar{\sigma}, \infty)\). To see why, suppose otherwise, and \( d\alpha_d/d\sigma \) switches signs at some \( \sigma_0 \). By continuity, at \( \sigma_0, d\alpha_d/d\sigma = 0 \). But (92) and (91) imply that \( d(\beta \mu_I)/d\sigma = 0 = d\mu_I/d\sigma \) at \( \sigma_0 \) as well, which contradicts (93). Thus, \( d\alpha_d/d\sigma \) cannot switch signs in \([\bar{\sigma}, \infty)\); nor can it be zero.

At \( \sigma = \bar{\sigma}, \beta = 0 \) and \( d\beta/d\sigma \geq 0 \). Then, by (92),
\[
\left. \frac{d(\beta \mu_I)}{d\sigma} \right|_{\sigma = \bar{\sigma}} = \left. \mu_I \frac{d\beta}{d\sigma} \right|_{\sigma = \bar{\sigma}} \geq 0 \Rightarrow \frac{d\alpha_d}{d\sigma} \right|_{\sigma = \bar{\sigma}} \leq 0.
\]
Because \( d\alpha_d/d\sigma \) cannot be zero, it must be strictly negative for all \( \sigma \in [\bar{\sigma}, \infty) \). By (92)-(93), for all \( \sigma \in [\bar{\sigma}, \infty) \), \( \beta \mu_I \) and \( \mu_I \) are both strictly increasing in \( \sigma \). Then, (23) implies that
\[
\frac{d(S/\sigma)}{d\sigma} = -\frac{dr^-}{d\sigma} = -r^{-'} \frac{d}{d\sigma} \left( \frac{\beta \mu_I}{\alpha_d} \right) > 0.
\]
The spread itself, \( S = \sigma \cdot (S/\sigma) \), obviously increases in \( \sigma \) as well. Finally,
\[
\frac{dr^+}{d\sigma} = r^+ \frac{d}{d\sigma} \left( \frac{\beta \mu_I}{\alpha_d} \right) > 0, \quad \frac{dr^-}{d\sigma} = r^- \frac{d}{d\sigma} \left( \frac{\beta \mu_I}{\alpha_d} \right) < 0.
\]

No dark pool

The comparative statics for Corollary 1 are similar to that for the first case of Proposition 1 and are omitted.
B.3 Proof of Proposition 3

Have a dark pool and \( \sigma \leq \bar{\sigma} \)

For \( \sigma \leq \bar{\sigma} \), adding a dark pool is equivalent to increasing \( \bar{r} \). Total differentiation of (20)-(21) with respect to \( \bar{r} \) yields

\[
\left[ (1 - \bar{r}) \frac{\partial \alpha_d}{\partial \alpha_d} - \frac{\partial (S/\sigma)}{\partial \alpha_d} \right] \frac{d\alpha_d}{d\bar{r}} = G^{-1}(\alpha_d) + \frac{\partial (S/\sigma)}{\partial \mu_I} \frac{d\mu_I}{d\bar{r}},
\]

(94)

\[
\left[ 1 - \bar{F}'(\sigma - S) \frac{\partial}{\partial \alpha} (\sigma - S) \right] \frac{d\mu_I}{d\bar{r}} = \bar{F}'(\sigma - S) \frac{\partial (\sigma - S)}{\partial \alpha_d} \frac{d\alpha_d}{d\bar{r}},
\]

(95)

where the first term on the left-hand side of (94) is positive because of the equilibrium selection. If \( d\alpha_d/d\bar{r} \leq 0 \) at any \( \sigma_0 \), then (95) implies that \( d\mu_I/d\bar{r} \geq 0 \) at \( \sigma_0 \). But that contradicts (94). Thus, \( d\alpha_d/d\bar{r} > 0 \) and \( d\mu_I/d\bar{r} < 0 \). Adding a dark pool, which is equivalent to an increase in \( \bar{r} \), raises \( \alpha_d \) and reduces \( \alpha_e = 1 - \alpha_d \). The total participation rate of liquidity traders in either the dark pool or the exchange is \( \alpha_d + \alpha_e = 1 \), higher than a market without a dark pool. Moreover, by (21), a lower \( \mu_I \) implies a wider spread \( S \) on the exchange.

Have a dark pool and \( \sigma > \bar{\sigma} \)

Now suppose that \( \sigma > \bar{\sigma} \). In a market with a dark pool, \( \alpha_e = 1 - G(1) \), a constant. Substituting it into (26) and we have

\[
\frac{\mu_I}{\mu_I + (1 - G(1))\mu_z} < 1.
\]

So the equilibrium \( \alpha_e \) without a dark pool resides in the interval \((1 - G(1), 1)\). That is, adding a dark pool reduces \( \alpha_e \).

Moreover, adding a dark pool increases the exchange spread if and only if \( \alpha_e \) in the equilibrium of Corollary 1 is larger than \((1 - G(1))/(1 - \beta)\), where \( \beta > 0 \) is determined in Proposition 1. By the equilibrium selection rule and by (23),

\[
\alpha_e > \frac{1 - G(1)}{1 - \beta} \iff G^{-1} \left( 1 - \frac{1 - G(1)}{1 - \beta} \right) > \frac{\mu_I}{\mu_I + \mu_z(1 - G(1))/(1 - \beta)} = 1 - \bar{r}^-,
\]

(96)
where the $\mu_I$ is given by

$$\mu_I = \bar{\mu} F\left(\frac{(1 - G(1))\mu_z}{(1 - \beta)\mu_I + (1 - G(1))\mu_z}\right).$$

We rearrange (96) and obtain

$$\beta < \frac{G(1) - G(1-r)}{1 - G(1-r)}.$$ 

On the other hand, because the left-hand side of (23) is decreasing in $\beta$ and the right-hand side is increasing in $\beta$, the above condition is equivalent to (28).

As $F(c) \to 1$ for all $c > 0$, (25) implies that $\mu_I \to \bar{\mu}$, a constant. Holding $\mu_I = \bar{\mu}$ fixed, we now show that if $G''(1-r) \leq 0$, then (28) holds for all $r^{-} \in [0, \bar{r}]$. At $r^{-} = \bar{r}$, we have $\sigma = \bar{\sigma}$ and (28) holds by the definition of $\bar{\sigma}$. At $r^{-} = 0$, (28) also holds trivially. Take the first and second derivatives of the right-hand side of (28) with respect to $r^{-}$ and we obtain

$$\frac{d[rhs\,(28)]}{dr^{-}} = \frac{\bar{\mu}\mu_z G''(1-r^{-})}{[\bar{\mu} + (1 - G(1-r^{-}))\mu_z]^2} > 0,$$

$$\frac{d^2[rhs\,(28)]}{d(r^{-})^2} = \mu\mu_z \frac{G''(1-r^{-})[\bar{\mu} + (1 - G(1-r^{-}))\mu_z] - 2\mu_z[G'(1-r^{-})]^2}{[\bar{\mu} + (1 - G(1-r^{-}))\mu_z]^3} < 0.$$ 

Thus, the right-hand side of (28) is concave and (28) holds for all $r^{-} \in [0, \bar{r}]$.

If the condition (30) holds, we have

$$\begin{align*}
r^{-} \leq \bar{r} \leq 1 - \frac{\bar{\mu}}{\bar{\mu} + (1 - G(1))\mu_z} & \leq 1 - \frac{\mu_I}{\mu_I + (1 - G(1-r^{-}))\mu_z}. 
\end{align*}$$

### B.4 Proof of Proposition 4

If informed traders do not participate in the dark pool, an equilibrium is determined by a marginal liquidity trader who is indifferent between the dark pool and the exchange. Given $\alpha_d$, this liquidity trader has a delay cost of $G^{-1}(\alpha_d)\sigma$. So we must have $X_d(x; S; G^{-1}(\alpha_d)) = -S$, or (63). We want to find an equilibrium in which $\alpha^*_d \leq G(1)$.

We first calculate the comparative statics, assuming the existence of an equilibrium, and then show conditions under which the stated equilibrium exists. Total differentia-
tion of (63) and (64) with respect to \( \sigma \) yields

\[
\left( \frac{\partial[lhs(63)]}{\partial \alpha_d} - \frac{\partial[rhs(63)]}{\partial \alpha_d} \right) \frac{d\alpha_d}{d\sigma} + \left( \frac{\partial[lhs(63)]}{\partial \mu} - \frac{\partial[rhs(63)]}{\partial \mu} \right) \frac{d\mu_I}{d\sigma} = 0, \tag{97}
\]

\[
\left( 1 - \frac{\partial[rhs(64)]}{\partial \mu_I} \right) \frac{d\mu_I}{d\sigma} = \frac{\partial[rhs(64)]}{\partial \alpha_d} \frac{d\alpha_d}{d\sigma} + \bar{\mu} F'(\sigma - S) \left( 1 - \frac{S}{\sigma} \right). \tag{98}
\]

As before, if \( d\alpha_d/d\sigma \leq 0 \) at some \( \sigma_0 \), then (97) implies that \( d\mu_I/d\sigma \leq 0 \) at \( \sigma_0 \) as well. But this contradicts (98). Thus, the comparative statics with respect to \( \sigma \) follow. And given the equilibrium, the dark pool execution price \( p^* \) and the optimal limit prices follow from calculations done in the text.

Now I characterize the condition for the existence of an equilibrium and the threshold volatility \( \bar{\sigma}(x) \). For \( x \in [0, 1] \), I define \( \bar{K}(x) \) implicitly by

\[
(1 - x\bar{K}(x)) \left\{ 1 - \mathbb{E} \left[ \min \left( 1, \frac{G(1)Z}{[G(1) - G(x\bar{K}(x))]} \right) \right] \right\} = \bar{K}(x). \tag{99}
\]

This \( \bar{K}(x) \) is uniquely well-defined because the left-hand side of (99) is decreasing in \( \bar{K}(x) \) and the right-hand side is strictly increasing in \( \bar{K}(x) \). Moreover, total differentiation of (99) with respect to \( x \) yields

\[
\left( \frac{\partial[lhs(99)]}{\partial \bar{K}(x)} - 1 \right) \bar{K}'(x) + \frac{\partial[lhs(99)]}{\partial x} = 0.
\]

So we have \( \bar{K}'(x) < 0 \).

On the other hand, given \( \bar{K}(x) \), I define \( \mu_I^*(x) \) by

\[
\frac{\mu_I^*(x)}{\mu_I^*(x) + (1 - G(1))\mu_z} = \bar{K}(x),
\]

and define \( \bar{\sigma}(x) \) by

\[
\mu_I^*(x) = \bar{\mu} F \left( \frac{(1 - G(1))\mu_z}{\mu_I^*(x) + (1 - G(1))\mu_z} \bar{\sigma}(x) \right).
\]

Because \( \mu_I^*(x) \) is strictly increasing in \( \bar{K}(x) \) and because \( \bar{\sigma}(x) \) is strictly increasing in \( \mu_I^*(x) \), \( \bar{\sigma}(x) \) is strictly increasing in \( \bar{K}(x) \). Because \( \bar{K}'(x) < 0 \), \( \bar{\sigma}'(x) < 0 \).

What remains to be shown is that, for \( \sigma \leq \bar{\sigma}(x) \), an equilibrium characterized by
Proposition 4 exists. Clearly, once $\alpha_d$ is determined, $\mu_I$ is uniquely determined by (64). For sufficiently small $\alpha_d$, the left-hand side of (63) is negative, whereas the right-hand side is strictly positive. For $\alpha_d = G(1)$, (64) implies that

$$
\mu_I = \mu F \left( \frac{(1 - G(1)) \mu_z}{\mu_I + (1 - G(1)) \mu_z} \sigma \right),
$$

which is no larger than $\mu_I^*(x)$. Thus,

$$
K \equiv \frac{\mu_I}{\mu_I + (1 - G(1)) \mu_z} = \frac{S}{\sigma} \bigg|_{\alpha_d = G(1)} \leq \bar{K}(x),
$$

and, by the definition of $\bar{K}(x)$,

$$
(1 - xK) \left\{ 1 - \mathbb{E} \left[ \min \left( 1, \frac{G(1) Z^-}{(1 - G(xK)) Z^+} \right) \right] \right\} > K.
$$

That is, at $\alpha_d = G(1)$, the left-hand side of (63) is weakly higher than the right-hand side. Therefore, there exists a solution $\alpha^*_d \in (0, G(1))$ to (63) and an equilibrium exists.

**B.5 Proof of Proposition 5**

Suppose that $W_d(R_t, t; \gamma) \geq \mathbb{E}_t[W(R_{t+1}, t + 1; \gamma)]$ in an equilibrium. I denote by $\hat{X}(R_t, t; \gamma)$ the “auxiliary payoff” of a type-$\gamma$ liquidity buyer who “imitates” the strategy of a type-$\gamma$ informed buyer. That is, the imitating buyer behaves as if $v = +\sigma$. Clearly, such imitation is suboptimal for the liquidity buyer, so $X(R_t, t; \gamma) \geq \hat{X}(R_t, t; \gamma)$ for all $R_t$, $t$, and $\gamma$. For notional simplicity, in the calculations below I suppress the cost type $\gamma$ and likelihood ratio $R_t$ as function arguments.

Suppose that the informed buyer enters an order in the dark pool at time $t$. The imitating liquidity buyer does the same, by construction. Let $\hat{X}^+_d$ be the dark pool payoff of the imitating buyer conditional on $v = +\sigma$, and let $\hat{X}^-_d$ be the dark pool payoff of the imitating buyer conditional on $v = -\sigma$. I define $\hat{X}^+_e$ and $\hat{X}^-_e$ similarly. Then, we have

$$
\hat{X}_d(t) - W_d(t) = \frac{R_t}{R_t + 1} \hat{X}^+_d(t) + \frac{1}{R_t + 1} \hat{X}^-_d(t) - W_d(t)
$$

$$
= \frac{1}{R_t + 1} \left( \hat{X}^-_d(t) - \hat{X}^+_d(t) \right),
$$

where the last equality follows from the fact that, conditional on the true dividend, the expected payoff $W_d$ of the informed buyer is the same as the payoff $\hat{X}^+_d$ of the imitating
liquidity buyer. If we can show that $\hat{X}_d^+(t) - \hat{X}_d^-(t) \leq 2\sigma$, then

\[ X_d(t) - W_d(t) \geq \hat{X}_d(t) - W_d(t) \geq -\frac{2\sigma}{R_t + 1} = X_e(R_t, t) - W_e(R_t, t). \]

Now I prove that $\hat{X}_d^+(t) - \hat{X}_d^-(t) \leq 2\sigma$. I denote by $\mathcal{C}$ the event that the imitating buyer’s order is crossed in the dark pool, and let

\[ k_t^+ \equiv \mathbb{P}_t[\mathcal{C} | v = +\sigma], \]
\[ k_t^- \equiv \mathbb{P}_t[\mathcal{C} | v = -\sigma], \]

be the crossing probabilities of the imitating buyer in the dark pool in period $t$, conditional on $v = +\sigma$ and $v = -\sigma$, respectively. Then, we have

\[
\hat{X}_d^+(t) = k_t^+[+\sigma - \mathbb{E}_t(p^* | \mathcal{C}, v = +\sigma)] + (1 - k_t^+)\mathbb{E}_t(\hat{X}^+(t + 1)),
\]
\[
\hat{X}_d^-(t) = k_t^-[-\sigma - \mathbb{E}_t(p^* | \mathcal{C}, v = -\sigma)] + (1 - k_t^-)\mathbb{E}_t(\hat{X}^-(t + 1)),
\]

where $p^*$ is the execution price in the dark pool in period $t$, and $\hat{X}^+$ and $\hat{X}^-$ are the imitating buyer’s payoffs conditional on $v = +\sigma$ and $v = -\sigma$, respectively. Because informed buyers have either a zero or positive mass in the dark pool in period $t$, we have

\[ k_t^+ \leq k_t^-, \]
\[ \mathbb{E}_t(p^* | \mathcal{C}, v = +\sigma) \geq \mathbb{E}_t(p^* | \mathcal{C}, v = -\sigma). \]

Because $W_d(t) \geq \mathbb{E}_t[W(t + 1)]$, we have $\hat{X}_d^+(t) \geq \mathbb{E}_t(\hat{X}^+(t + 1))$. Thus,

\[
\hat{X}_d^+(t) - \mathbb{E}_t(\hat{X}^+(t + 1)) = k_t^+[-\sigma - \mathbb{E}_t(p^* | \mathcal{C}, v = +\sigma) - \mathbb{E}_t(\hat{X}^+(t + 1))] + (1 - k_t^-)\mathbb{E}_t(\hat{X}^-(t + 1)),
\]

which implies that

\[
\hat{X}_d^+(t) - \hat{X}_d^-(t) \leq 2\sigma k_t^- + (1 - k_t^-)\mathbb{E}_t[\hat{X}^+(t + 1) - \hat{X}^-(t + 1)]. \tag{100}
\]

I now prove that $\hat{X}_d^+(t) - \hat{X}_d^-(t) \leq 2\sigma$ and that $\hat{X}^+(t) - \hat{X}^-(t) \leq 2\sigma$, by backward induction. We use the fact that, for all $t < T$, $X^+_e(t) - X^-_e(t) = 2\sigma$. Because $v$ is revealed in period $T$, $\hat{X}^+(T) = \hat{X}^-(T) = 0$. By (100), $\hat{X}_d^+(T - 1) - \hat{X}_d^-(T - 1) \leq 2\sigma$. Because the venue choice of the imitating liquidity buyer does not depend on
realizations of \( v \),

\[
X^+(T - 1) - X^-(T - 1)
= \max \left[ X^+_e(T - 1) - X^-_e(T - 1), X^+_d(T - 1) - X^-_d(T - 1), \mathbb{E}_{T-1}(X^+(T) - X^-(T)) \right] \leq 2\sigma.
\]

For the induction step, suppose that \( \hat{X}^+(t + 1) - \hat{X}^-(t + 1) \leq 2\sigma \). Then, \( (100) \) implies that \( X^+(t) - X^-(t) \leq 2\sigma \). Thus,

\[
X^+(t) - X^-(t) = \max \left[ X^+_e(t) - X^-_e(t), X^+_d(t) - X^-_d(t), \mathbb{E}_{t}(X^+(t + 1) - X^-(t + 1)) \right] \leq 2\sigma,
\]

which completes the proof.

**B.6 Proof of Lemma 1**

Given the public information \( R_t \), the probability that \( v = +\sigma \) is \( R_t / (R_t + 1) \). Let \( q \) be implicitly defined by \( z_e = q / (1 - q) \). That is, \( q \) is the probability that an arriving exchange order is in the same direction as informed orders. Under a liquidity trader’s belief, the probability that the next exchange order is a buy order is

\[
\frac{R_t}{R_t + 1} \frac{q}{1} + \frac{1}{R_t + 1} (1 - q) = (1 - q) \frac{R_t z_e + 1}{R_t + 1}.
\]

Similarly, the probability that the next exchange order is a sell order is

\[
\frac{R_t}{R_t + 1} (1 - q) + \frac{1}{R_t + 1} q = q \frac{R_t z_e^{-1} + 1}{R_t + 1}.
\]

We can verify that identity

\[
(1 - q) \frac{R_t z_e + 1}{R_t + 1} V(R_t z_e) + q \frac{R_t z_e^{-1} + 1}{R_t + 1} V(R_t z_e^{-1})
= (1 - q) \frac{R_t z_e + 1}{R_t + 1} \left( 1 - \frac{2}{R_t z_e + 1} \right) \sigma + q \frac{R_t z_e^{-1} + 1}{R_t + 1} \left( 1 - \frac{2}{R_t z_e^{-1} + 1} \right) \sigma
= \left( 1 - \frac{2}{R_t + 1} \right) \sigma,
\]

which implies \( \mathbb{E}_t [V(R_t z_e^2)] = V(R_t) \), that is, the expected mid-market price is a martingale for liquidity traders.

Note that the identity \( (101) \) holds for all \( R_t \), including the informed trader’s likeli-
hood ratio \( \infty \). Using (101) again, we have that

\[
V(R_t z_e^e) = \left( 1 - \frac{2}{R_t z_e + 1} \right) \sigma
\]

\[
= (1 - q) R_t z_e + 1 \left( 1 - \frac{2}{R_t z_e + 1} \right) \sigma + q R_t z_e^{-1} + 1 \left( 1 - \frac{2}{R_t z_e^{-1} + 1} \right) \sigma
\]

\[
< (1 - q) z_e \left( 1 - \frac{2}{R_t z_e + 1} \right) \sigma + q z_e^{-1} \left( 1 - \frac{2}{R_t z_e^{-1} + 1} \right) \sigma
\]

\[
= \mathbb{E}_t[V(R_t z_e^Q z_e)].
\]

That is, the exchange ask price is a submartingale for informed buyers.

Finally, direct calculation gives

\[
\mathbb{E}_t[V(R_t z_e^Q z_e)] = V(R_t z_e) - \frac{2 R_t^2 (z_e - 1)^3}{(R_t + 1)^2 (R_t z_e + 1)(R_t z_e^2 + 1)} \sigma,
\]

\[
\mathbb{E}_t[V(R_t z_e^Q z_e^{-1})] = V(R_t z_e^{-1}) + \frac{2 R_t^2 (1 - z_e^{-1})^3}{(R_t + 1)^2 (R_t z_e^{-1} + 1)(R_t z_e^{-2} + 1)} \sigma.
\]

That is, for liquidity traders, the exchange ask price is a supermartingale and the exchange bid price is a submartingale.

**B.7 Proof of Proposition 6**

I prove Proposition 6 by direct verification. The quoting strategy of the market maker simply follows from risk neutrality and zero profit.

Under the proposed equilibrium strategy, the total arrival intensity of exchange orders is \( \lambda_t = \lambda_I + \sum_{i=M}^J \kappa_i \lambda_L \). The Hamilton-Jacobi-Bellman (HJB) equation of an informed buyer is

\[
W(R_t) = \max \left[ \sigma - V(R_t z_e), \frac{\lambda_t \mathbb{E}_t[W(R_t z_e^Q)] + \lambda_C (\sigma - V(R_t))}{\lambda_t + \lambda_C + \lambda_F} \right],
\]

where the profit of immediate trading on exchange is \( \sigma - V(R_t z_e) \) and the expected profit of trading in the dark pool is the weighted sum of:

- \( \mathbb{E}_t[W(R_t z_e^Q)] \), the expected profit if the next event is the arrival of an exchange order.
- \( \sigma - V(R_t) \), the profit if the next event is a dark pool cross.
- \( 0 \), the profit if the next event is the dividend payment.
To verify that $W(R_t) = \sigma - V(R_t z_e)$, it is sufficient to verify that, for all $t$ and all realizations of random variable $R_t$,

$$\sigma - V(R_t z_e) > \frac{\lambda_t \mathbb{E}_t[\sigma - V(R_t z_e^Q)] + \lambda_C(\sigma - V(R_t))}{\lambda_t + \lambda_C + \lambda_F}. \quad (102)$$

By Lemma 1, the expected profit for informed buyers to trade on the exchange is a supermartingale, that is, $\sigma - V(R_t z_e) > \mathbb{E}_t[\sigma - V(R_t z_e^Q)]$. Thus, a sufficient condition for (102) is

$$\lambda_C + \lambda_F > \sup_{R \in (0, \infty)} \left\{ \frac{\lambda_C \sigma - V(R)}{\sigma - V(R z_e)} = z_e \lambda_C, \right.$$  

which simplifies to (83).

Now we turn to a type-$j$ liquidity buyer, whose HJB equation is

$$X(R_t) = \max \left[ -(V(R_t z_e) - V(R_t)), \frac{\lambda_t \mathbb{E}_t[X(R_t z_e^Q)] - c^j_t}{\lambda_t + \lambda_C + \lambda_F} \right].$$

Her cost of liquidation $C(R_t)$ satisfies the HJB equation

$$C(R_t) = -X(R_t) = \min \left[ V(R_t z_e) - V(R_t), \frac{\lambda_t \mathbb{E}_t[C(R_t z_e^Q)] + c^j_t}{\lambda_t + \lambda_C + \lambda_F} \right].$$

There are two cases, depending on $j$.

If $1 \leq j < M$, to verify that $C(R_t) < V(R_t z_e) - V(R_t)$, it suffices to verify

$$V(R_t z_e) - V(R_t) > \frac{\lambda_t \mathbb{E}_t[V(R_t z_e^Q z_e) - V(R_t z_e^Q)] + c^j_t}{\lambda_t + \lambda_C + \lambda_F}, \quad (103)$$

where $C(R_t z_e^Q)$ is replaced by the higher cost of $V(R_t z_e^Q z_e) - V(R_t z_e^Q)$, as implied by the conjectured equilibrium. Because the ask spread is a supermartingale for liquidity buyers (Lemma 1), a sufficient condition for (103) is

$$\lambda_C + \lambda_F > \sup_{R \in (0, \infty)} \left\{ \frac{c^j_t}{V(R z_e) - V(R)} \right\} = \sup_{R \in (0, \infty)} \left\{ \frac{\gamma_j \cdot 2R/(R + 1)^2 \cdot \sigma}{V(R z_e) - V(R)} \right\} = \frac{\gamma_j}{z_e} \frac{z_e}{z_e - 1},$$

which simplifies to (84).

If $M \leq j \leq J$, to verify that $C(R_t) = V(R_t z_e) - V(R_t)$, it suffices to verify

$$V(R_t z_e) - V(R_t) < \frac{\lambda_t \mathbb{E}_t[V(R_t z_e^Q z_e) - V(R_t z_e^Q)] + c^j_t}{\lambda_t + \lambda_C + \lambda_F},$$

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that is, by Lemma 1,

$$(\lambda_C + \lambda_F)[V(R_tz_e) - V(R_t)] < -\lambda_t \frac{2R_t^2(z_e - 1)^3}{(R_t + 1)^2(R_t z_e + 1)(R_tz_e^2 + 1)} \sigma + \gamma_j \frac{2R_t}{(R_t + 1)^2} \sigma,$$

A sufficient condition for (104) is

$$\gamma_j > \sup_{R \in (0,\infty)} \left\{ (\lambda_C + \lambda_F) \frac{(R + 1)(z_e - 1)}{Rz_e + 1} \right\} + \sup_{R \in (0,\infty)} \left\{ \lambda_t \frac{R(z_e - 1)^3}{(Rz_e + 1)(Rz_e^2 + 1)} \right\}$$

$$= (\lambda_C + \lambda_F)(z_e - 1) + \lambda_t \frac{(z_e - 1)^3}{z_e(\sqrt{z_e} + 1)^2}.$$ 

The argument for sellers is symmetric and yields the same parameter conditions.
# C  List of Model Variables

This appendix summarizes key variables used in Section 3 and Section 4.

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