The Bright Side of Dark Markets: Experiments

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Abstract

We design an experiment to study the effects of dark trading on incentives to acquire costly information, price efficiency, market liquidity, and investors' earnings in a financial market. When the information precision is high, adding a dark pool alongside a lit exchange encourages information acquisition, crowds out liquidity from the lit market, and results in a non-linear relationship between price efficiency and dark pool participation. At modest levels, dark pools enhance information aggregation. Investors with stronger signals use the lit exchange relatively more, and uninformed traders are better off when they trade more in the dark pool.

JEL Classification Numbers: C91, C92, G12, G14

Keywords: Market institutions, dark pools, information aggregation, the efficiency of security markets, costly information acquisition, experiments

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In the last few decades, there has been a proliferation of equity trading systems, among which dark pools have rapidly grown in popularity.[1] In a dark pool, investors can buy and sell stocks without publicly displaying their orders. As opposed to traditional stock exchanges, these dark venues lack pre-trade transparency. Traders in dark pools submit buy and (or) sell orders, and trades are executed using prices derived from the exchanges. As markets are becoming fragmented and a significant part of liquidity is increasingly unobserved, it questions the long-held view that prices are a valuable source of information (Hayek (1945), Fama (1970)). Would prices at the exchanges continue to convey meaningful information? Indeed, dark pools have raised regulatory concerns in that they may harm price discovery in financial markets.[2]

While dark trading has existed in stock markets for quite some time now in the form of either over-the-counter (OTC) decentralized trading (Duffie, Gârleanu, and Pedersen (2005), Duffie, Malamud, and Manso (2009), Duffie (2012), Duffie, Malamud, and Manso (2014), Malamud and Rostek (2017), Rostek and Yoon (2020)) or special hidden order types on exchanges (Blume and Goldstein (1997), Madhavan, Porter, and Weaver (2005), Baruch (2005), Boulatov and George (2013), Buti and Rindi (2013)), the emergence of dark pools as alternative trading system operating fully outside transparency requirements has attracted enormous trade volumes. Several of these dark pools are broker-dealer owned and are typically run by investment banks (CrossFinder, Sigma X, Citi-Match, MS Pool). In contrast, others are operated by independent companies (Instinet, Liquidnet, ITG Posit).

[1]Dark pools accounted for 13.66% of US equity trading volume in Nov. 2021, as opposed to 7.51% in 2008 (Rosenblatt Securities: Let There Be Light - US Edition). In Nov. 2021, dark venues executed 18.84% of pan-European on-venue turnover, and dark MTFs hit a market share high (Rosenblatt Securities: Let There Be Light - European Edition).

[2]For example, in 2014, then-SEC-Chair Mary Jo White remarked that "we must continue to examine whether dark pool trading volume is approaching a level that risks seriously undermining the quality of price discovery provided by lit venues." Before the Securities Traders Association's 82^{nd} Annual Market Structure Conference in Sep. 2015, then-SEC-Commissioner Kara M. Stein mentioned that "as more and more trading is routed to dark venues that have restricted access and limited reporting, I am concerned that overall market price discovery may be distorted rather than enhanced." As recent as Aug. 2021, on CNBC's Squawk Box, the SEC-Chair Gary Gensler pointed out that dark pools have been increasingly common during the recent rise in retail investing and asserted that the agency is "looking very closely" at market structure and dark pools of trading hidden from the public until execution to promote transparency. He was responding to allegations from retail traders that hedge funds and other "big actors" may be manipulating markets.

Given the prominence of the issue, there has been significant interest within academic research in recent years to investigate the effect of dark trading on the informational efficiency of prices. Theoretical studies have yielded conflicting results, with Ye (2011) showing that the addition of a dark pool strictly harms price discovery, while Zhu (2014) proves that dark trading improves the informational efficiency of prices at the exchange.[3] Empirical papers also differ in their results on the impact of dark pools on price and market quality measures.[4,5]

While it is essential to study how dark trading influences the ability of asset prices to aggregate diverse information already available in the market, it is of utmost significance to analyze how the amount of new information produced by traders at the outset is affected by the presence of a dark pool. The literature has given significant attention to the former question. Still, the latter issue of the causal effect of dark pool trading on costly information acquisition remains largely unexplored.[6]

[3]Ye (2011) studies the venue choice of a large informed trader in the Kyle (1985) framework and shows that the addition of a dark pool harms price discovery on the exchange. In contrast, Zhu (2014) demonstrates that adding a dark pool alongside an exchange results in the self-selection of venues by informed and uninformed traders, concentrates price-relevant information into the exchange, and improves price discovery. Ye (2016) further finds that, in equilibrium, traders with strong signals trade in exchanges, traders with moderate signals trade in dark pools, and traders with weak signals do not trade. As a result, whether adding a dark pool enhances or impairs price discovery depends on the information precision of signals in the market. Theoretical models have also shown that traders in dark pools impose positive ("liquidity-begets-liquidity") and negative ("crowding out") externalities on each other (Hendershott and Mendelson (2000)).

[4]For example, while Buti, Rindi, and Werner (2011), Jiang, McInish, and Upson (2012), Fleming and Nguyen (2013) find that dark trading improves price discovery, several studies find that dark trading has a negative effect on price discovery (Hendershott and Jones (2005)) and harms overall market quality (Hatheway, Kwan, and Zhen (2017)). Albuquerque, Song, and Yao (2020) demonstrate that stocks subjected to the "trade at" provision experience larger price errors, suggesting that dark trading improves informational efficiency on an intraday basis. Comerton-Forde and Putniņš (2015) report that low levels of non-block dark trading are benign or even beneficial for informational efficiency, but high levels are harmful. Foley and Putniņš (2016) find that dark limit order markets benefit market quality and informational efficiency, but dark midpoint crossing systems do not significantly affect market quality.

[5]Relatedly, various papers find evidence that informed traders utilize dark pools (Boulatov and George (2013), Reed, Samadi, and Sokobin (2020), Ye and Zhu (2020), Hu, Jones, and Zhang (2021)), and this may have implications for price discovery at the exchanges.

[6]Utilizing weekly dark pool trading data from September 2014 to December 2017 provided by the Financial Industry Regulatory Authority (FINRA), and using Weller's (2018) jump ratio and the future earnings response coefficient (FERC) as two measures of information acquisition, a recent study by Brogaard and Pan (2021) find that a higher level of dark pool trading is associated with more information acquisition.

In this paper, we examine the effect of introducing a dark pool alongside a lit exchange on investors' decisions to invest in information production and the choice of venue by informed and uninformed traders. We also investigate how the presence of a dark venue for trading affects overall market performance as captured by various informational efficiency and liquidity measures. Specifically, we ask the following questions. Given that markets are now fragmented, and a substantial portion of the liquidity is anticipated to be hidden, does the incentive to acquire costly information about stock fundamentals increase compared to the benchmark of a centralized trading institution with full pre-trade transparency? How does the relative usage of the dark pool vis-à-vis the lit exchange depend on the relative strength of private information held by an investor? Are informational efficiency of prices and market quality necessarily degraded when dark trading occurs?

We design an experimental asset market with the endogenous acquisition of costly information to address the above questions. We assume two equally likely states of nature, A and B, and a single asset, namely, an Arrow-Debreu security that provides a payoff only in state A. Before trading, some individuals can acquire costly, imperfect signals about the state of nature. Signals are binary and are independent and identically distributed (i.i.d.), conditional on the state. In the experiments, we implement markets with either low or high precision of signals. We investigate two market structures, one with a single lit exchange where all order submissions by a trader are observable to other traders, and another where two parallel trading venues exist. In the latter institution, in addition to the lit exchange, traders can submit orders and transact in a dark pool where order submissions of other investors are unobservable. Transaction prices in the dark pool are derived from the existing buy and sell offer prices in the lit exchange.

Experiments provide a useful complement to theoretical and empirical studies on the consequences of dark pool trading. In the laboratory, one can employ a trading mechanism close to the one used in actual markets while still having the ability to control and change variables to allow clean causal inferences. The novelty of our analysis stems from the fact that we consider fragmented markets in the laboratory where traders can exchange an Arrow-Debreu security either in a lit market with a fully transparent limit order book or in a dark pool where order submissions are hidden.

We find that, while a significant portion of liquidity on the lit exchange is substituted away to the dark pool (the *crowding out effect*) irrespective of the information precision of signals, there are two positive effects of adding a dark pool, the extent of which depends on the informativeness of the signals acquired by investors. First, investors acquire a greater number of signals in the presence of a dark pool (*information acquisition effect*). Second, traders with stronger signals use the lit exchange relatively more than traders with moderate signals or uninformed ones (*sorting effect*). Both these positive effects are significant when information precision is high; however, with low precision of signals, the *information acquisition effect* is weak, and the *sorting effect* is non-existent.

We find little evidence that adding a dark pool alongside a lit exchange alters the informational efficiency of prices at the aggregate. However, price volatility at the exchange goes up when information precision in the market is high. While the addition of a dark pool does not affect the aggregate trading volume in the market, market depth at the exchange declines in markets with either a low or high level of precision. Additionally, quoted and effective bid-ask spreads increase with dark trading only when information precision is high. Therefore, the overall effect of dark trading on aggregate outcomes is significant when the signal informativeness is high and is somewhat muted for markets with low precision of signals.

A closer look at the data reveals that price efficiency greatly varies with the level of dark pool participation that arises endogenously when traders decide the fraction of orders to be submitted to the dark pool. With high precision of signals, at modest level of dark trading, the combination of *information acquisition effect* and *sorting effect* outweighs the *crowding out effect*. As the dark market participation goes up, the *crowding out effect* grows stronger and eventually exceeds the positive effects. Consequently, compared to the benchmark of trading in a single lit exchange, the ability of prices to aggregate existing information and forecast the underlying state of nature first improves and then deteriorates as the dark trading volume as a percentage of total volume increases. This non-linear association suggests that the price quality improves against the baseline of no dark trading at a modest level of dark trading. Therefore, our results strongly support the view that there is a concern with dark trading affecting price discovery only if it exceeds a certain threshold.

We also find that the addition of a dark pool in itself does not affect the earnings of either the uninformed or informed traders. In general, with a single lit exchange or with two parallel trading venues, those with strong signals are able to outperform those who are uninformed. Information rents are greater when information precision is low as prices at the lit exchange reveal less information regarding the underlying state of nature. Furthermore, in the presence of a dark pool, there is a positive relationship between the relative usage of the dark pool and earnings for uninformed traders. Still, no such association exists for informed traders. This points toward an adverse selection risk for the uninformed investors trading primarily at the lit exchange and indicates that adding a dark venue allows some uninformed traders to mitigate part of the risk.

In laboratory markets, hidden liquidity has been investigated in a single limit order book environment by providing traders with the ability to hide orders (Bloomfield, O'Hara, and Saar (2015), Gozluklu (2016)). Bloomfield, O'Hara, and Saar (2015) report that order strategies are greatly affected by allowing hidden liquidity, with traders substituting nondisplayed for displayed shares and changing the aggressiveness of their trading. Additionally, most aggregate market outcomes such as liquidity and informational efficiency are not affected. Using iceberg markets, Gozluklu (2016) finds that, without information friction, market opacity enhances liquidity. Under informed trading, adverse selection drives market outcomes mainly around news announcements.[7] In contrast to these studies, we implement fragmented markets with separate lit and dark venues and allow for endogenous information acquisition.

The literature on costly information acquisition in laboratory markets has shown that the market value of information approaches zero when traders submit sealed bids in an environment with perfect information (Copeland and Friedman (1992), Sunder (1992)). In contrast, in a setting where private information is imperfect, it is valued by the market participants (Ackert, Church, and Shehata (1997)). Huber, Angerer, and Kirchler (2011) demonstrate that it is possible for informed traders to

[7] Iceberg markets allow both displayed and partially displayed orders (i.e., a minimum size must be displayed, and the remainder can be nondisplayed).

obtain lower net profits on average compared to uninformed traders.

Page and Siemroth (2017) show that traders are more likely to acquire costly information if they have a larger endowment in terms of cash and assets, if their existing information is inconclusive, and if they are less risk-averse. Halim, Riyanto, and Roy (2019) demonstrate that social communication among investors results in lower information acquisition due to a trader's temptation to free ride on the signals purchased by her neighbors. A recent study by Asparouhova, Bossaerts, and Yang (2019) reports that participants with no initial information in decentralized markets remain willing to pay for information, in contrast to the centralized markets in Sunder (1992). To the best of our knowledge, ours is the first paper to study the question of how the presence of a dark pool affects price efficiency and market outcomes with costly and endogenous information acquisition in experimental asset markets.

The remainder of the paper is organized as follows. Section I describes our experimental markets, the treatments, and controls that constitute our experimental design. Section II presents our results on information acquisition, the informational efficiency of prices, trading volume and liquidity, dark pool usage by informed and uninformed traders, and trading profits. In Section III, we provide a discussion of our experimental findings. Section IV concludes.

I. Experimental Design

A. General Structure

The data for this study were gathered from 24 experimental sessions conducted at Nanyang Technological University (NTU), Singapore. We had 288 participants in total, with 12 participants in each session. Participants were recruited from the population of undergraduate and graduate students at NTU from various majors ranging from Social Sciences, Business and Economics, Humanities, Engineering, and Sciences. No subject participated in more than one session of this experiment. Sessions lasted approximately two hours, and participants earned on average S$19.02 in addition to a show-up fee of S$2.[8]

[8]Payoffs, inclusive of the show-up fee, ranged from S$9 to S$30.

Upon arrival, subjects were seated at visually isolated computer workstations. Instructions were read aloud, and subjects also received a copy of the instructions.[9] Participants were prohibited from talking during the experiment, and all communication took place via the experimental software. Each session consisted of three practice periods and 20 main periods.[10] Activity during the practice periods did not count toward final earnings.

We employed the ball-and-urn setup of the experiments conducted by Anderson and Holt (1997).[11] At the start of each period, a virtual urn (A or B) was randomly selected by the computer, with each urn having an equal chance of being chosen. Both types of urn contained ten balls in total, with each ball being of either black or white color. Urn A contained more black balls than urn B, while urn B contained more white balls than urn A. All of this information was common knowledge to the participants. The realization of the urn was fully revealed to the subjects only at the end of a period.

Traders had the opportunity to exchange several units of a financial asset every period by participating in a virtual financial market. All accounting and trading were done in experimental currency units (ECU). The market was implemented using the z-Tree computer program (Fischbacher (2007)). At the end of each period, one unit of the asset paid a dividend of either 10 ECU if the underlying urn was A or 0 ECU if the urn was B.

Each period, all participants started with the same initial endowment of 600 ECU and 40 assets. The endowment and earnings from one period could not be carried forward to the next period; that is, each period was independent of the other. Prior to trading, some participants could acquire private information at a cost. This information was provided in the form of balls drawn independently and with replacement from the underlying urn; that is, each signal was i.i.d., conditional on the underlying state of nature. Out of the twelve traders in a market, only eight

[9] A sample copy of the instructions is provided in the Appendix.

[10] At the end of the instructions phase and prior to the start of the experiment, all participants had to complete a quiz to ensure that they understood the concepts and instructions required for the experiment. We started the experiment only after everyone in the room answered all quiz questions correctly.

[11] We followed Page and Siemroth (2017) and Halim, Riyanto, and Roy (2019) in explaining the ball-and-urn setting to the participants.

were allowed to acquire costly information. These potentially informed traders were given 60 seconds during which they could acquire up to ten draws at the cost of 6 ECU each. The remaining four traders were uninformed, which implies that the only information they possess is the prior probability that each of the urns has an equal likelihood of being selected as the underlying urn.[12]

The ball draws revealed to participants provided them with information about the underlying state of nature and hence about the value of the asset. For instance, observing more black ball draws would indicate that urn A was more likely to be the underlying urn. Each informed trader has imperfect information about the asset's value, and thus, trading on private information is still risky for informed traders. We briefly explained the concept of posterior probability and the procedure for computing the posterior in the instructions. Participants were not required to calculate the posterior themselves. Instead, the computer program displayed the posterior for each subject according to their ball draws. For the uninformed traders, traders who could acquire information but decided not to, and traders who drew an even number of balls with the same number of balls of each color, the posterior remained at the prior level of 0.5.

After the information-acquisition stage was over, participants entered the trading stage. A trading phase lasted for two minutes, within which all subjects were free to purchase and sell units of the asset at any time provided that they did not violate the short-selling (negative holdings) constraint. In addition, subjects were required to maintain a positive cash balance to make any purchases. If engaging in a trade would violate either the short-sale or cash-balance constraint, the computer program prohibited individuals from doing so. Throughout the trading stage, pertinent information such as the profile of draws revealed to them, and the posterior probability of the underlying urn being A given their draw profiles (only for the informed traders), as well as their ECU and asset balance available for trading were displayed on a participant's trading window.[13] Once trading closed, the underlying

[12]Subjects knew their type: uninformed or (potentially) informed, as well as the fact that there were a total of four uninformed traders and eight potentially informed traders in a market. They also knew that everyone had the same initial endowment of cash and assets.

[13]For the uninformed traders, the computer screen mentioned that the likelihood of urn A is 50%, equaling the prior.

urn was revealed together with the subject's earnings and the average transaction price in the period.

Following completion of the last period, subjects were required to participate in a standard risk-elicitation task (Holt and Laury (2002)). Participants were also asked to answer a questionnaire aimed at collecting additional information such as gender, age, prior trading experience, study background, etc. At the end of the experiment, the program randomly selected three of the 20 periods for the purpose of payment. Subjects were paid the average of the payouts from these three periods.

B. Treatments

We implemented four treatments with a 2×2 between-subject design. We varied the trading institution by having only a lit market or adding a dark pool alongside a lit exchange and the information precision of the privately acquired signal. This choice of treatments allows us to study the implications of dark trading for information acquisition and market quality conditional on the precision of informative signals available in the market. The experimental design is summarized in Table I.

Under the *Lit Only* trading institution, the market was organized as a multiple-unit double auction (MUDA) market. It was set up like a typical electronic limit order book where traders can enter buy or sell limit orders. Limit orders to buy or sell a security had prices between 0 and 10 ECU.[14] All buy/sell offers were publicly displayed on the order book. Once a trader entered an order, the book of publicly displayed shares was updated on all traders' computer screens. During the trading period, traders could enter as many orders as they desire subject to the non-negative cash balance and short-selling constraints and cancel any of their unexecuted limit orders in the book at any time. All transactions were reported immediately to all traders, indicating the price and the transaction volume.[15]

Trades occurred whenever a trader entered a limit order that crossed with an existing limit order by stating a bid price greater than or equal to an existing ask

[14]Subjects could place limit orders with offer prices rounded up to one decimal place.

[15]Traders continuously observed on the screen their current position in terms of ECUs (cash) and shares of the asset, the number of shares they bought and sold, and the prices they paid for the shares they bought or sold. In addition, all past trading prices in the current period and the number of units transacted were continuously shown on subjects' screens.

Table I

Experimental Design: Summary of Treatments

This table presents our experimental design. Data are drawn from 24 sessions of twelve traders each. We implement a 2×2 between-subjects design by varying the trading institution and the information precision of a signal. In the *Lit Only* market, subjects could trade only in the lit exchange, while in the *Dark* market, a dark pool is added alongside a lit exchange. For the low information precision environment, urn A contained six black balls and four white balls, while urn B contained four black balls and six white balls. For the high information precision environment, urn A contained seven black balls and three white balls, while urn B contained three black balls and seven white balls.

Treatment	Trading Institution	Information Precision	No. of Sessions	Total Subjects
Lit Only-Low	Lit Only	Low	6	72
Dark-Low	Dark	Low	6	72
Lit Only-High	Lit Only	High	6	72
Dark-High	Dark	High	6	72

or entering an ask price less than or equal to an existing bid. Partial executions of submitted limit orders were possible, and orders were executed following strict price and time priority rules. A share at an attractive price had priority over a share at a worse price.[16] Within each price level, orders submitted at an earlier time were executed first.

Under the *Dark* trading institution, in addition to the MUDA market, which we refer to as the lit exchange, with the features discussed above, traders could submit their buy/sell offers to another market. In this second market, which we refer to as a dark pool, traders only submitted the shares of the asset that they wished to buy or sell.[17] The active offers and transactions of a trader in the dark pool were visible only to that trader and no one else. Thus, unlike the lit exchange, where the order book was publicly displayed, and information on transactions was immediately updated, others' order submissions and transactions in the dark pool and the market depth were not revealed to traders.[18]

Traders who submit their orders to a dark pool can conceal their information and their trading intention to others and avoid having their orders directly impact the price in the lit exchange. One can imagine that a dark pool may be appealing to an investor intending to trade a large order who wants to minimize the price impact of such block trades. On the other hand, the drawback of submitting orders to a dark pool is that traders are not sure if a counterparty can match their orders. Even when a match exists and a transaction occurs, orders may not be executed at the best price.

Traders couldn't specify any price for the orders sent to the dark pool. Transaction prices in the dark venue were derived from the existing buy and sell offer prices in the lit exchange. Specifically, offers in the dark pool were executed at the (latest) mid-point of the best buy and sell offer prices in the lit exchange.[19] This mid-point

[16]For example, a higher price for a buy order is more attractive. Similarly, a lower price for a sell order is more attractive.

[17]In the experiments, we used neutral terms for the markets. The MUDA market (or the lit exchange) was referred to as *Market X* and the dark pool was referred to as *Market Y*.

[18]Participants were told that their offers sent to the dark pool would be matched with another trader's offer confidentially and automatically by the computer whenever such a match exists. Partial matches and executions were possible.

[19]Dark pools generally use three primary pricing rules: (1) mid-point of the best bid and offer, (2) derived pricing, for example, the average price during the last five minutes of trading in the

price was continuously updated on traders' screens so that they were aware of the potential price improvement offered by the addition of the dark venue.

To manipulate the precision of informative signals, we changed the composition of black and white balls in the urns. Specifically, for the low information precision environment, urn A contained six black balls and four white balls, while urn B contained four black balls and six white balls. For the high information precision environment, urn A contained seven black balls and three white balls, while urn B contained three black balls and seven white balls. In both low- and high information precision environments, drawing a black ball implies that it is more likely that the chosen urn is A. However, this likelihood is greater in a high information precision environment.

II. Results

A. Information Acquisition

How does the addition of a dark pool affect the incentive to acquire costly information?

The period-average summary statistics for information acquisition in each treatment are reported in Table II. With a dark pool added, the number of signals acquired in the market goes up by around 10.9% in the low information precision environment and by 14.4% when the information precision is high. Out of the eight traders who can potentially acquire information, on average, more than six of them decide to acquire at least one signal. This number is also slightly higher in the presence of the dark venue, conditional on the information precision of the signals. In all treatments, close to half of the market has conclusive information; their posterior is different from their prior of 0.5.

Table III displays the results of regressing the number of signals acquired in the market ($S_{mkt.}$) on the variable *Dark* (which takes a value of 1 if the treatment in-

lit exchange before the execution of the dark trade, and (3) negotiated pricing similar to the OTC trading where a pair of buyer and seller trade directly (Ye (2016)). In their study, Nimalendran and Ray (2014) find that while not all trades are at the mid-point of National Best Bid and Offer (NBBO), about 57% of transactions are within .01% of the price around the mid-point.

Table II

Period-Average Information Acquisition Summary Statistics

This table presents the values of S_{mkt}, N_{mkt}, and θ_{mkt}, averaged across all periods of all sessions. Standard deviations are in parentheses. S_{mkt} denotes the number of signals acquired in the market in a period. N_{mkt} denotes the number of participants (out of the eight potentially informed traders) who acquired information in the market in a period. θ_{mkt} is the proportion of participants (out of the twelve traders) in a market having conclusive information, i.e., having an individual posterior different from the prior of 0.5.

	Lit Only-Low	*Dark-Low*	*Lit Only-High*	*Dark-High*
S_{mkt}	39.34	43.62	30.82	35.26
	(8.66)	(9.37)	(8.35)	(6.31)
N_{mkt}	6.51	7.01	6.19	6.75
	(1.22)	(1.00)	(1.57)	(1.04)
θ_{mkt}	46.67%	48.06%	46.81%	48.26%
	(11.09%)	(11.06%)	(13.54%)	(10.96%)
No. of observations	120	120	120	120

cludes a dark pool along with the lit exchange and 0 otherwise) and average values of the demographic variables in the market.[20] The standard errors are clustered at the session-level. Table III shows that the presence of a dark venue encourages information acquisition, with the results being significant when the information precision of signals in the market is high.

RESULT 1: *The addition of a dark pool alongside a lit exchange increases costly information acquisition.*

Table II also indicates that the incentive to acquire information is substantially diminished with a higher precision of signals. For example, in the markets with only a lit exchange available for trading, the number of signals acquired in the market declines by 21.7%. Similarly, when both lit exchange and dark venue are present,

[20]The demographic variables are *risk aversion* (a measure of how risk-averse a subject is; ranges from 1 to 11 corresponding to the respective subject's switching point in the Holt-Laury risk-elicitation procedure, with larger values indicating higher risk aversion),*age* (age of the participant in years), *male* (equals one if the participant is male and zero otherwise), and *Economics/Business major* (equals one if the subject is pursuing a business, or accountancy, or economics major).

Table III

OLS Regression of Number of Signals Acquired in a Market: Effect of Dark Pool

This table presents results of OLS regression analysis, with the dependent variable being the number of signals acquired in the market ($S_{mkt.}$). The baseline is the *Lit Only - Low* treatment in columns (1) and (2), and the *Lit Only - High* treatment in columns (3) and (4). Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. The demographic variables include *average risk aversion*, *average age*, the ratio of male traders, and the ratio of subjects with an Economics or Business major. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Dark	4.28	5.12	4.44*	6.37**
	(4.18)	(4.72)	(2.45)	(2.64)
Average risk aversion		-0.00		3.25*
		(1.36)		(1.55)
Average age		3.95		0.18
		(2.45)		(1.49)
Male ratio		19.72**		18.98*
		(8.66)		(10.13)
Economics/Business ratio		-2.91		-11.30
		(9.65)		(8.94)
Period	0.31*	0.31*	-0.38*	-0.38*
	(0.15)	(0.15)	(0.19)	(0.20)
Constant	36.08***	-59.96	34.84***	-1.29
	(3.28)	(47.40)	(2.26)	(29.32)
No. of observations	240	240	240	240
No. of clusters	12	12	12	12
R^2	0.09	0.33	0.17	0.32

moving from a market with low precision of signals to a high precision environment results in the drop of the total signals acquired in the market by 19.2%.

Table IV displays the results of regressing the number of signals acquired in the market ($S_{mkt.}$) on the variable *High* (which takes a value of 1 if the treatment includes high precision of signals and 0 otherwise) and average values of the demographic variables in the market. The standard errors are clustered at the session level. The table shows that a higher precision of signals discourages information acquisition irrespective of whether a dark pool is present or not.

RESULT 2: *Conditional on the market trading institution, higher precision of signals decreases costly information acquisition.*

Relative to the environment with only a lit exchange, investors would anticipate that a significant portion of the trading volume and liquidity is likely to be traded off-exchange in the presence of a dark pool. Traders would expect less information to be impounded into asset prices, conditional on the level of signals acquired in the market. This gives rise to a greater incentive to acquire private signals and provides the intuition behind result 1. Conditional on the market trading institution, the acquired signals are relatively more informative when the signal precision is high. Therefore, traders would need to acquire fewer signals now when compared to the low precision environment, and this aspect is reflected in result 2.

B. Prices: Information Aggregation, Forecasting, and Volatility

How does dark trading impact the ability of asset prices to reflect information available in the market and the propensity of prices to reveal the true state of nature?

To measure the fundamental value of the asset in our setting, for each market, we first calculate the Bayesian posterior probability of urn A given all draws in the market. This posterior multiplied by 10 provides the risk-neutral fundamental value of the asset. Note that this value differs across markets due to variation in the number of signals acquired and the difference in the information revealed by these signals. Taking the information-acquisition decisions as given, this Bayesian

Table IV

OLS Regression of Number of Signals Acquired in a Market: Effect of Information Precision

This table presents results of OLS regression analysis, with the dependent variable being the number of signals acquired in the market ($S_{mkt.}$). The baseline is the *Lit Only-Low* treatment in columns (1) and (2), and the *Dark-Low* treatment in columns (3) and (4). Standard errors (clustered at the level of independent session) are in parentheses. *High* takes a value of 1 if the treatment comprises of markets with a high precision of signals and 0 otherwise. The demographic variables include *average risk aversion*, *average age*, the ratio of male traders, and the ratio of subjects with an Economics or Business major. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Lit Only		Dark	
	(1)	(2)	(3)	(4)
High	-8.53**	-11.22***	-8.36**	-7.60***
	(3.40)	(1.09)	(3.45)	(1.53)
Average risk aversion		-2.57***		3.97***
		(0.42)		(0.52)
Average age		6.52***		-3.01***
		(1.04)		(0.88)
Male ratio		13.10*		15.42***
		(6.94)		(2.31)
Economics/Business ratio		-16.67***		10.00**
		(4.71)		(4.24)
Period	-0.27	-0.27	0.20	0.20
	(0.22)	(0.22)	(0.16)	(0.16)
Constant	42.16***	-84.72***	41.57***	73.05***
	(3.68)	(25.43)	(3.33)	(16.74)
No. of observations	240	240	240	240
No. of clusters	12	12	12	12
R^2	0.23	0.51	0.23	0.58

posterior times ten also gives the fully revealing rational expectations price. Figure 1 plots the expectation of the market price in the lit market conditional on the Bayesian posterior ($\mathbb{E}$(Price|Bayesian posterior)) in each of the four treatments (see the long-dashed curve plotted in Figure 1). The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin.

Visual inspection of Figure 1 suggests that adding a dark pool does not worsen the ability of prices to aggregate diverse information present in the market. Average prices vary between a narrow range near the prior of 5, with and without a dark pool, when information precision of signals is low. On the other hand, a significant amount of available information is impounded into the transaction prices in the lit market in both treatments under the high information precision environment. For example, when the Bayesian posterior in the market is close to zero (ten), the average price is close to 2 (8) in both *Lit Only-High* and *Dark-High* treatments.

With the data subdivided by the level of dark trading in a market, Figures 2 and 3 plot $\mathbb{E}$(Price|Bayesian posterior) in the lit market of *Dark-Low* and *Dark-High* treatments, respectively. The corresponding plot for the benchmark *Lit Only-Low* treatment in Figure 2 and *Lit Only-High* treatment in Figure 3 are shown as well for ease of comparison. Defining the dark transaction ratio as the ratio of transaction volume in the dark pool over the total transaction volume in a period, the level of dark trading is sub-divided into the following three categories:

- Modest Dark Trading- when dark transaction ratio is less than 0.2.
- High Dark Trading- when dark transaction ratio exceeds 0.2 but is less than 0.4.
- Very High Dark Trading- when dark transaction ratio exceeds 0.4.

When information precision is low, Figure 2 shows that average prices continue to vary within a narrow range near the prior of 5 for various levels of dark trading. Figure 3, on the other hand, indicates that, compared to the *Lit Only-High* benchmark, prices are far more revealing with the addition of a dark pool when there is modest dark trading but not when the dark trading level is either high or very high.

We define the linear absolute deviation (LAD) in a period as the absolute difference between the mean price in the lit market and the fully revealing price, that is,

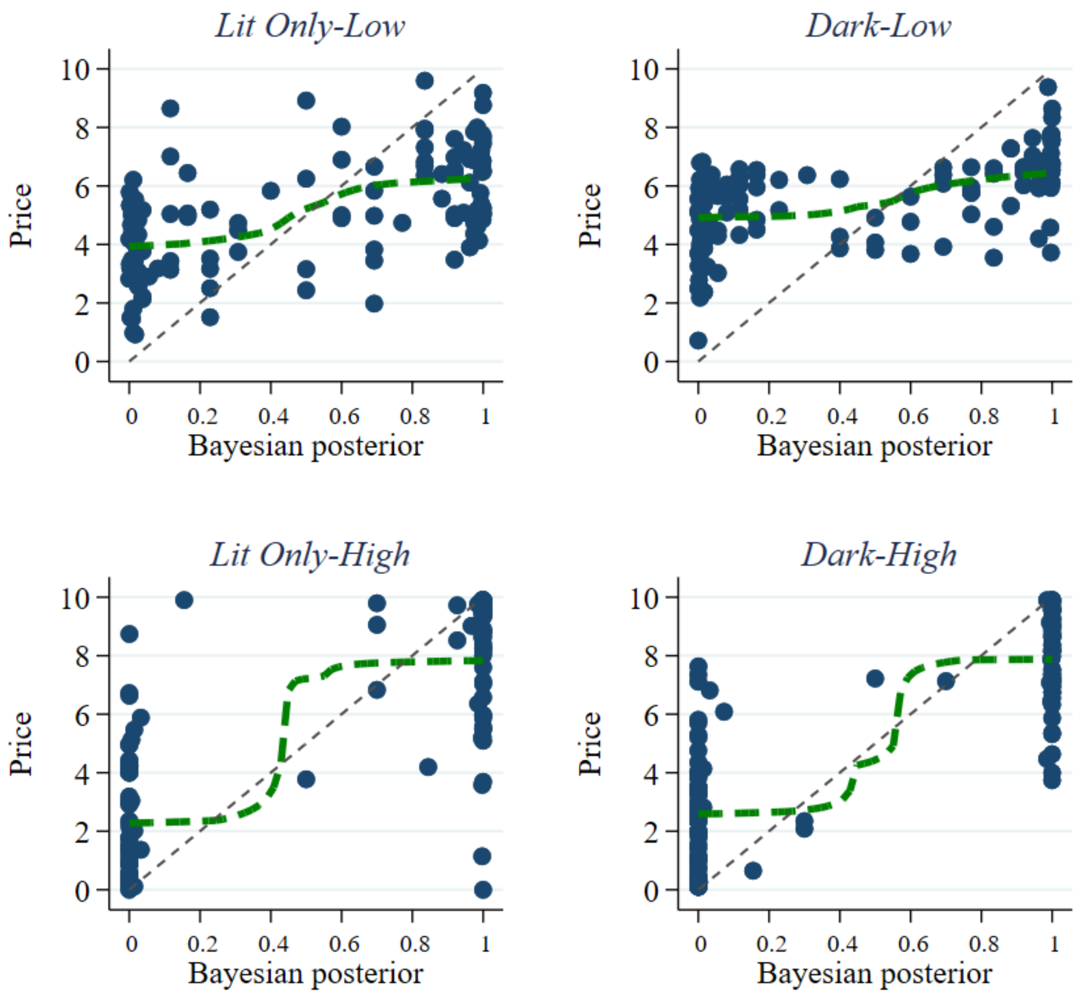

Figure 1. Precision of market prices in the lit market in each treatment. The long-dashed curve displays the average price in the lit market conditional on the Bayesian posterior in a market ($\mathbb{E}$(Price|Bayesian posterior)). The estimation is computed by local linear regression, using Epanechnikov kernel bandwidth of 0.2. The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin.

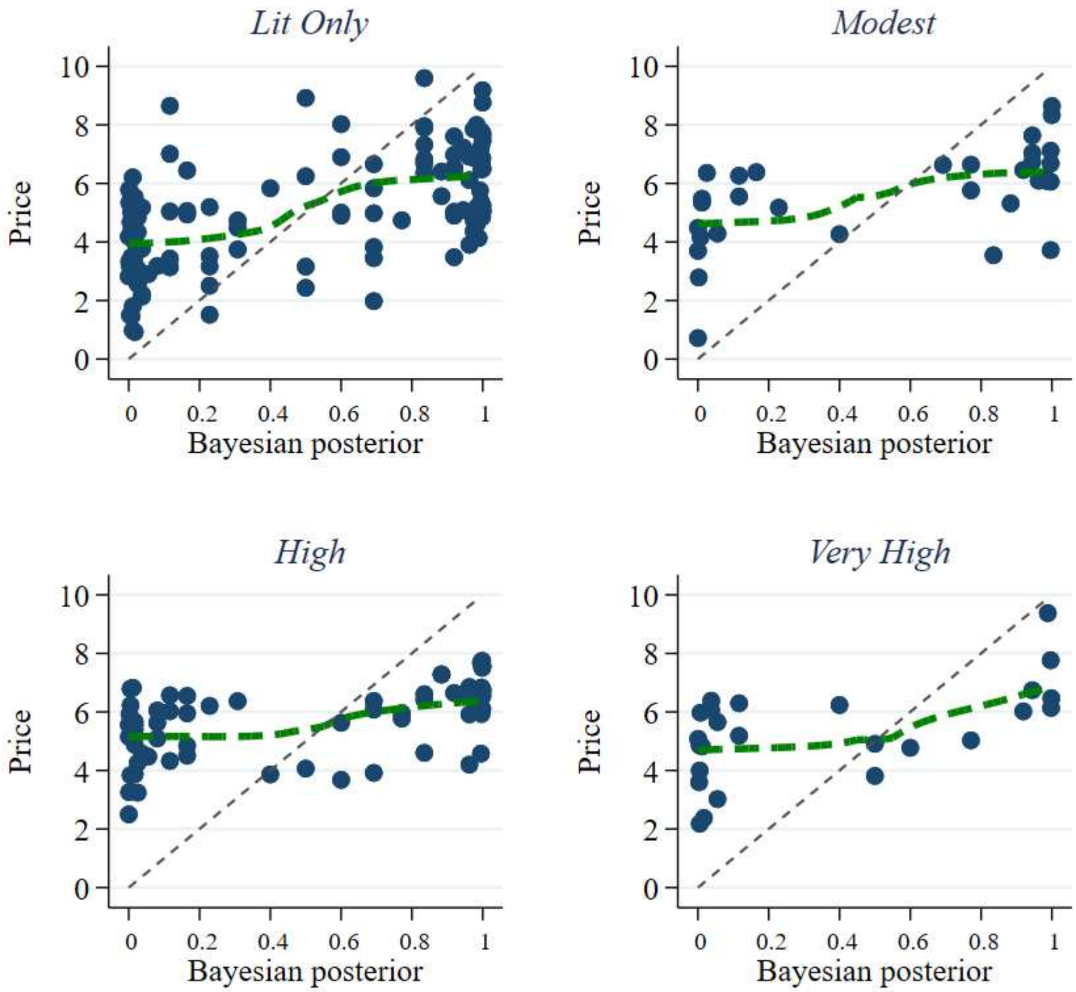

Figure 2. Precision of market prices in the lit market in *Lit Only-Low* and *Dark-Low* treatments. The data in the *Dark-Low* treatment is sub-divided by the level of dark trading: *modest*, *high*, and *very high*. The long-dashed curve displays the average price in the lit market conditional on the Bayesian posterior in a market ($\mathbb{E}$(Price|Bayesian posterior)). The estimation is computed by local linear regression, using Epanechnikov kernel bandwidth of 0.2. The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin.

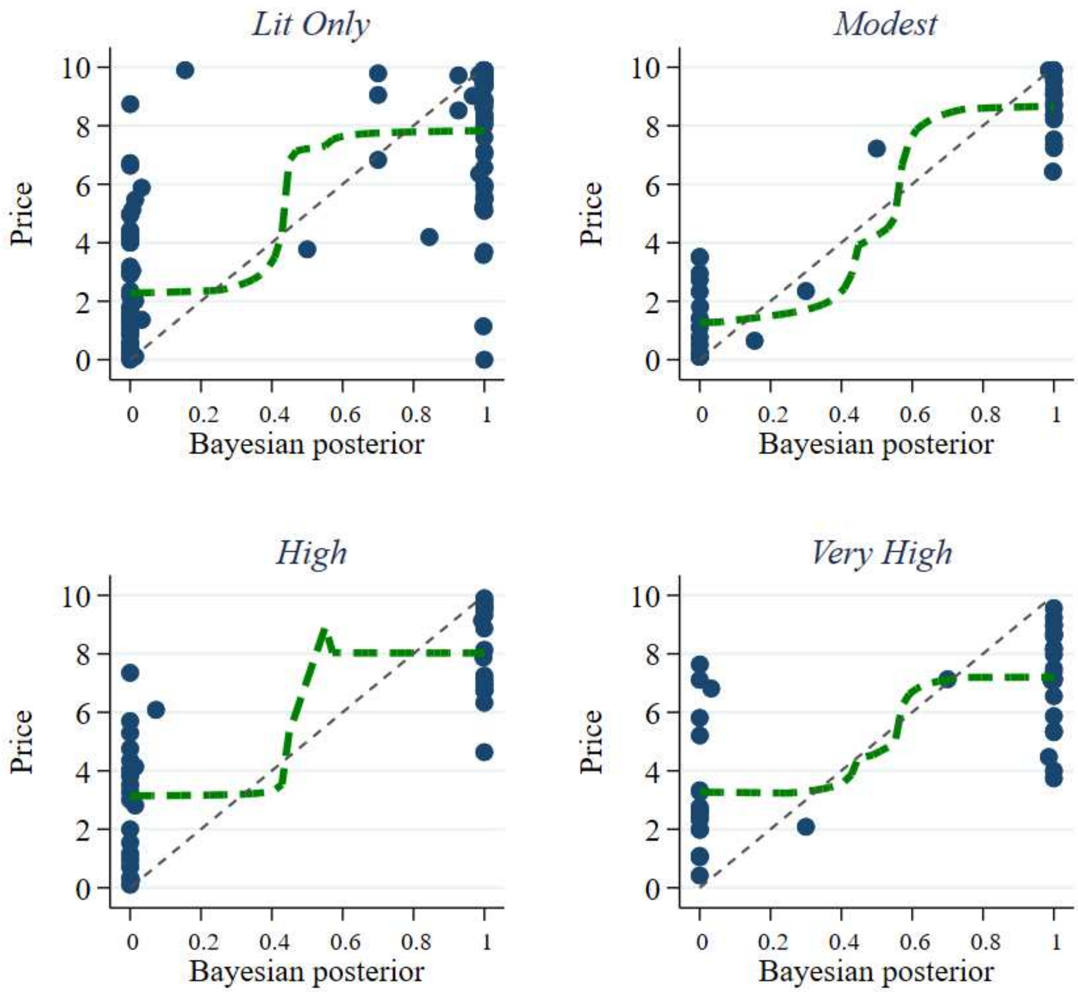

Figure 3. Precision of market prices in the lit market in *Lit Only-High* and *Dark-High* treatments. The data in the *Dark-High* treatment is sub-divided by the level of dark trading: *modest*, *high*, and *very high*. The long-dashed curve displays the average price in the lit market conditional on the Bayesian posterior in a market ($\mathbb{E}$(Price|Bayesian posterior)). The estimation is computed by local linear regression, using Epanechnikov kernel bandwidth of 0.2. The risk-neutral fundamental value of the asset is depicted by the straight short-dashed line starting from the origin.

LAD = |Mean price - 10(Bayesian posterior)|. To understand the effect of adding a dark pool alongside a lit exchange on the efficiency of asset prices, we perform a regression with LAD as the dependent variable. The regressors include the variable *Dark*, total transactions in the lit market, and the average values of the demographic variables in the market. Another specification includes the variables *Modest Dark Trading*, *High Dark Trading*, and *Very High Trading* instead of *Dark*.[21] Table V reports the results, separately for the treatments with low and high precision of signals. Overall, we find that the presence of a dark market does not affect the LAD. This is true irrespective of the precision of signals in the market.

At the same time, interestingly, when we break down the dark transaction ratio into modest, high, and very high categories, we obtain a more nuanced result. As shown in Table V, when information precision is high, compared to the *Lit Only-High* benchmark, LAD is significantly smaller with moderate dark trading, similar with high dark trading, and larger with very high dark trading. Therefore, we obtain a non-linear association between dark market participation and price efficiency. Such a relationship is absent in the low information precision environment.

RESULT 3: *When information precision of signals is high, compared to the lit only market, the addition of a dark pool improves (worsens) information aggregation in the lit market when dark pool participation is modest (very high). There is a non-linear relationship between dark market participation and the ability of prices at the lit market to aggregate available information.*

While the LAD measures price efficiency, that is, how close are transaction prices to the fully revealing values, another measure is used to gauge the quality of prices as forecasting tools. That is, how good are the prices in estimating the likelihood of the predicted event. We define the forecast error each period as the absolute difference between the mean transaction price and the true value of the asset. If the urn is A (B), the true value equals 10 (0). Similar to the OLS regression of LAD in

[21] *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise.

Table V

OLS Regression of Linear Absolute Deviation in the Lit Market

This table presents results of OLS regression analysis of linear absolute deviation (*LAD*), which is the absolute difference between the mean price and the fully revealing price in a period. The baseline is the *Lit Only* - *Low* treatment in columns (1) and (2), and the *Lit Only* - *High* treatment in columns (3) and (4). Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise. All regressions include the total transactions in the lit market and demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Dark	0.34		-0.23	
	(0.28)		(0.20)	
Modest Dark Trading		0.21		-0.66**
		(0.27)		(0.28)
High Dark Trading		0.41		0.09
		(0.32)		(0.21)
Very High Dark Trading		0.56*		0.59**
		(0.31)		(0.20)
Period	-0.02	-0.01	-0.11***	-0.09***
	(0.01)	(0.01)	(0.03)	(0.03)
Constant	-5.57	-4.81	-6.88**	-1.52
	(5.03)	(5.44)	(2.76)	(2.96)
No. of observations	240	240	238	238
No. of clusters	12	12	12	12
R^2	0.06	0.07	0.28	0.31

Table V, Table VI reports the results from an OLS regression with the forecast error as the dependent variable. The results are similar to those obtained with LAD, and we again identify a non-linear association between dark market participation and forecast error when the information precision is high.

RESULT 4: *When information precision of signals is high, compared to the lit only market, the addition of a dark pool enhances (deteriorates) the ability of prices in the lit market to reveal the underlying state of nature when dark pool participation is modest (very high).*

Another way to assess the quality of asset prices is to compare the volatility of prices. We define the price volatility measure ($VOLA$) in a period by the standard deviation of log returns (Stöckl, Huber, and Kirchler (2015)):

$$\sqrt{\frac{1}{T}\sum_{t=1}^{T}(RET_t - \overline{RET})^2},$$

where $RET_t = ln(P_t/P_{t-1})$, $\overline{RET}$ is the mean of log returns in a period, and T is the number of transactions in the lit exchange in a period. Similar to the regression analyses of LAD and forecast error, Table VII reports the results from an OLS regression with $VOLA$ as the dependent variable. In the high precision environment, we find that introducing a dark market increases price volatility. The effect is highly significant for a modest level of dark pool participation.

RESULT 5: *When information precision of signals is high, compared to the lit only market, the addition of a dark pool increases price volatility in the lit market when dark pool participation is modest.*

In summary, adding a dark pool does not lead to a deterioration of price efficiency at the aggregate level in either a low or high precision environment, when unconditioned on the dark transaction ratio. However, in markets with high precision of signals, price efficiency first improves and then worsens with higher dark

Table VI

OLS Regression of Forecast Error in the Lit Market

This table presents results of OLS regression analysis of forecast error which is defined as the absolute difference between the mean price and the true value of the asset in a period. The baseline is the *Lit Only - Low* treatment in columns (1) and (2), and the *Lit Only - High* treatment in columns (3) and (4). Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise. *Bayesian posterior accuracy* takes a value of 1 if the posterior in the market > (<) 0.5 and the underlying urn is A (B), and 0 otherwise. All regressions include the total transactions in the lit market and demographic variables as additional regressors. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Dark	0.21		-0.20	
	(0.23)		(0.19)	
Modest Dark Trading		0.14		-0.67**
		(0.21)		(0.29)
High Dark Trading		0.25		0.10
		(0.25)		(0.22)
Very High Dark Trading		0.27		0.72**
		(0.41)		(0.25)
Bayesian posterior accuracy	-1.98***	-1.98***	-3.11***	-3.14***
	(0.40)	(0.40)	(0.98)	(0.87)
Period	-0.02	-0.02	-0.11***	-0.09**
	(0.02)	(0.02)	(0.03)	(0.03)
Constant	-1.09	-0.74	-2.85	3.10
	(5.33)	(5.42)	(2.21)	(2.96)
No. of observations	240	240	238	238
No. of clusters	12	12	12	12
R^2	0.18	0.18	0.32	0.35

Table VII

OLS Regression of Price Volatility in the Lit Market

This table presents results of OLS regression analysis of the measure of price volatility ($VOLA$), which is defined as the standard deviation of log returns in a period. The baseline is the *Lit Only - Low* treatment in columns (1) and (2), and the *Lit Only - High* treatment in columns (3) and (4). Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise. All regressions include the total transactions in the lit market and demographic variables as additional regressors. * indicates significance at the 10% level, and *** indicates significance at the 1% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Dark	-0.04		0.10*	
	(0.06)		(0.05)	
Modest Dark Trading		-0.03		0.10***
		(0.07)		(0.03)
High Dark Trading		-0.04		0.10
		(0.05)		(0.08)
Very High Dark Trading		-0.05		0.12
		(0.07)		(0.11)
Period	0.00	0.00	0.01*	0.01*
	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.22	0.17	1.51***	1.60*
	(0.86)	(0.85)	(0.46)	(0.88)
No. of observations	240	240	235	235
No. of clusters	12	12	12	12
R^2	0.09	0.09	0.07	0.07

market participation. This non-linear relationship obtains from the effect of the presence of the dark pool on information acquisition, liquidity at the lit exchange, and the relative usage of the dark pool by informed and uninformed traders. While the first effect is already presented in the previous subsection, the findings related to the other two effects are mentioned in the following two subsections, and a comprehensive discussion regarding the relevant mechanisms at play is provided in section III.

C. Trading Volume and Liquidity

Is market trading volume and liquidity affected by addition of a dark pool?

Having investigated the effect of dark trading on the informational efficiency of prices, we now analyze the implications for market trading activity and liquidity. Tables VIII and IX report the results of an OLS regression of total transaction volume, the transaction volume in the lit exchange, and other liquidity measures for markets with low and high precision, respectively. The regressors include the variable *Dark*, period, the sum of acquired signals, and the average values of the demographic variables in the market. Another specification uses the dummies for various levels of dark transaction ratios.

We find that the addition of a dark pool does not affect the aggregate transaction volume in the market under either a low or high precision environment. This can be taken as a positive effect because this implies no alteration in market participation by investors with dark trading. However, the overall transaction volume in the lit exchange declines significantly in the presence of a dark pool. This is expected because, with market fragmentation, traders now use both lit and dark venues for their transactions. Given that the aggregate trade volume is similar with and without a dark pool, the dark pool now steals or substitutes transactions from the lit exchange. This effect is observed in low and high precision markets, and higher dark market participation is associated with a stronger crowding out effect.

RESULT 6: *When a dark pool is added alongside a lit exchange, compared to the lit-only market, the total transaction volume remains unchanged while there is a decline*

Table VIII

OLS Regression of Total Transaction Volume and Liquidity Measures in the Lit Exchange in Low Precision Markets

This table presents results of OLS regression analysis of the total transaction volume in the market, transaction volume in the lit exchange, depth, quoted, and effective spread in a period in markets with low precision of signals. Depth is defined as the sum of all orders up to two points from the closing best bid, and best ask prices in a period. Quoted and effective spreads are defined as the (volume-weighted) average best bid-ask spread evaluated at each submission and transaction in a period, respectively. The baseline is the *Lit Only - Low* treatment. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise. All regressions include the sum of acquired signals in the market and demographic variables as additional regressors. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Total Transaction Volume		Transaction Volume in Lit Exchange		Depth		Quoted Spread		Effective Spread	
Dark	-8.44		-61.64***		-63.65**		0.36		0.27	
	(20.92)		(13.16)		(24.33)		(0.39)		(0.34)	
Modest Dark Trading		-25.62		-41.53**		-77.15**		0.21		0.15
		(20.23)		(14.05)		(30.38)		(0.39)		(0.36)
High Dark Trading		7.07		-52.63***		-82.78***		0.53		0.42
		(21.16)		(14.51)		(23.99)		(0.39)		(0.34)
Very High Dark Trading		-15.88		-120.50***		8.44		0.25		0.15
		(22.59)		(13.63)		(22.75)		(0.34)		(0.28)
Period	-0.58	-0.38	0.02	-0.18	-0.25	-0.14	0.01	0.01	-0.00	-0.00
	(0.52)	(0.46)	(0.79)	(0.55)	(1.26)	(1.05)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-102.70	-33.78	117.50	50.58	-329.0	-290.7	0.40	1.05	0.28	0.79
	(318.60)	(298.90)	(201.70)	(197.50)	(659.6)	(622.1)	(7.11)	(6.74)	(5.99)	(5.67)
No. of observations	240	240	240	240	240	240	239	239	238	238
No. of clusters	12	12	12	12	12	12	12	12	12	12
R^2	0.33	0.36	0.38	0.48	0.06	0.10	0.13	0.16	0.10	0.13

Table IX

OLS Regression of Total Transaction Volume and Liquidity Measures in the Lit Exchange in High Precision Markets

This table presents results of OLS regression analysis of the total transaction volume in the market, transaction volume in the lit exchange, depth, quoted, and effective spread in a period in markets with high precision of signals. Depth is defined as the sum of all orders up to two points from the closing best bid, and best ask prices in a period. Quoted and effective spreads are defined as the (volume-weighted) average best bid-ask spread evaluated at each submission and transaction in a period, respectively. The baseline is the *Lit Only - High* treatment. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. *Modest Dark Trading* takes a value of 1 if the dark transaction ratio in the market is less than 0.2 and 0 otherwise, *High Dark Trading* takes a value of 1 if the dark transaction ratio in the market is between 0.2 and 0.4 and 0 otherwise, and *Very High Dark Trading* takes a value of 1 if the dark transaction ratio in the market exceeds 0.4 and 0 otherwise. All regressions include the sum of acquired signals in the market and demographic variables as additional regressors. * indicates significance at the 1% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Total Transaction Volume		Transaction Volume in Lit Exchange		Depth		Quoted Spread		Effective Spread	
Dark	-11.98		-64.05**		-69.67*		0.68**		0.47*	
	(27.77)		(27.00)		(33.08)		(0.25)		(0.22)	
Modest Dark Trading		-17.66		-32.76		-98.34***		0.70**		0.42*
		(26.49)		(25.84)		(25.74)		(0.30)		(0.21)
High Dark Trading		1.17		-60.38**		-40.31		0.55**		0.46*
		(28.45)		(26.32)		(42.08)		(0.25)		(0.25)
Very High Dark Trading		-18.74		-131.1***		-53.12*		0.85**		0.57
		(42.61)		(35.68)		(27.62)		(0.38)		(0.35)
Period	-0.63	-0.55	0.26	-0.70	1.09	1.74	0.01	0.01	-0.00	0.00
	(0.95)	(1.05)	(1.05)	(1.02)	(2.49)	(2.71)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	-671.5	-669.40	-286.80	-633.40	-756.00	-582.60	12.19*	12.81*	13.03**	13.55**
	(420.7)	(468.2)	(439.1)	(434.0)	(421.4)	(392.1)	(5.99)	(6.47)	(4.90)	(5.60)
No. of observations	240	240	240	240	239	239	218	218	218	218
No. of clusters	12	12	12	12	12	12	12	12	12	12
R^2	0.11	0.11	0.20	0.29	0.10	0.11	0.17	0.18	0.15	0.16

in the volume of transactions at the lit exchange. This observation holds irrespective of the information precision of signals.

Tables VIII-IX also present OLS regression results using various liquidity measures. The following three measures of market liquidity are used: per-period depth, defined as the sum of all orders up to two points from the closing best bid and best ask prices in a period, quoted spread each period, defined as the (volume-weighted) average best bid-ask spread evaluated at each submission in a period, and effective spread each period, defined as the (volume-weighted) average best bid-ask spread evaluated at each transaction in a period.

The results show that, under a low precision environment, while there is an overall negative impact of dark trading on the depth at the exchange, both quoted and effective spreads remain largely unaffected. On the other hand, when the information precision in the market is high, the depth at the exchange goes down, and the spread widens, implying a significant adverse effect on overall liquidity at the exchange.

RESULT 7: *There is a negative impact of dark trading on liquidity at the lit exchange. The effects are more pronounced when the information precision of signals is high.*

D. Order Informativeness and Dark Pool Usage

How does the relative usage of the dark pool vis-à-vis the lit exchange depend on the relative strength of private information held by an investor?

We define an uninformed trader as the one whose individual Bayesian posterior belief of state A equals 0.5. This includes the traders who cannot acquire or choose not to acquire information and, thus, by design, have an individual posterior equal to the prior and those traders who acquire information, but their information is not conclusive. Traders having an individual posterior different from 0.5 are referred to as informed traders. When there is only a lit market available for trading, the period-average informed-to-uninformed submission ratio equals 1.06 under low precision of signals and 1.24 under high precision environment. With the introduction of an additional dark venue for trading, this ratio equals 1.07 in the lit exchange and 1.43 in the dark pool when information precision is low. With high precision of signals, the informed-to-uninformed ratio becomes 1.30 in the lit exchange and 1.03 in the dark pool. This suggests that the order informativeness at the lit exchange remains unchanged with the addition of a dark pool alongside a lit market.[22]

We classify the informed traders further into ones having either moderate signal (if the individual posterior lies in $[0.25, 0.50)$ or $(0.50, 0.75]$) or strong signal (if the individual posterior lies in $[0, 0.25)$ or $(0.75, 1]$). Table X provides the composition of order submission volume in a market. Given that there are more traders with strong signals and fewer traders with moderate signals in a market with high information precision than the one with low precision of signals, the table shows that the corresponding entries for the moderately informed traders are smaller and for the strongly informed traders are greater under high precision.

More importantly, in markets with low precision, the composition of order submissions at the lit exchange remains almost the same with only the lit market being present or when both venues for trading exist. On the other hand, when the precision of information is high, while the percentage of submitted orders at the lit exchange attributable to uninformed traders remains the same before and after the addition of a dark pool, the percentage of orders at the lit exchange that can be attributed to strongly (moderately) informed traders goes up (down) substantially. Therefore, although the informed-to-uninformed ratio does not vary at the lit exchange with or without a dark pool, a larger proportion of the informed orders are now coming from the investors with strong signals.

To better understand whether the strength of the individual posterior held by a trader influences her decision to use the dark pool relatively more, we conduct an OLS regression of two individual-level variables in the treatments with both trading venues: individual net dark submission volume defined as the submission volume in the dark pool minus the submission volume at the lit exchange of a subject in

[22] Order informativeness captures the relative informative content of submitted orders, and we use the informed-to-uninformed submission ratio at a trading venue as the measure of order informativeness. An alternative measure would be the fraction of total orders that are submitted by informed traders.

Table X

Composition of Order Submissions

This table presents the percentage of submission volume in a market submitted by each type of trader- uninformed, moderately informed, or strongly informed. An uninformed trader has an individual Bayesian posterior belief of state A equal to the prior of 0.5. A moderately informed trader has an individual posterior that lies in $[0.25, 0.50)$ or $(0.50, 0.75]$, and a strongly informed trader has an individual posterior that lies in $[0, 0.25)$ or $(0.75, 1]$. The sum of the values in each column adds up to 100.

		Dark-Low			*Dark-High*	
	Lit Only -Low	Lit Exchange	Dark Pool	*Lit Only - High*	Lit Exchange	Dark Pool
Uninformed	48.3	48.2	43.2	44.1	44.0	46.8
Moderately Informed	27.9	26.5	30.8	18.4	12.6	14.4
Strongly Informed	23.8	25.3	26.1	37.5	43.4	38.8

a period, and individual dark pool usage defined as the ratio of dark submission volume over total submission volume for a subject in a period. The regressors include *Individual posterior strength* which is defined as the absolute deviation of an individual trader's posterior from 0.5, and the trading period. We also include several demographic variables as additional regressors.[23] The standard errors are clustered at the level of an individual subject. Table XI reports the results of the regression analysis.

In the low precision environment, we observe no relationship between the strength of the individual posterior held by a trader and her relative dark pool usage. In contrast, when information precision of signals is high, as the individual posterior deviates farther away from 0.5, compared to the benchmark of uninformed traders, an individual is more likely to use the lit exchange for order submissions. With high precision, many traders with strong signals are likely to cluster on the same side of the market, which raises the execution risk in the dark pool. Therefore, traders

[23] As defined earlier, these variables are *risk aversion*, *age*, *male*, and *Economics/Business major*.

Table XI

OLS Regression of Individual Net Dark Submission Volume and Individual Dark Pool Usage: *Dark-Low* and *Dark-High* Markets

This table presents results of OLS regression analysis of the individual net dark submission volume in columns (1) and (3) and individual dark pool usage in columns (2) and (4). Individual net dark submission volume is defined as the submission volume in the dark pool minus the submission volume at the lit exchange of a subject in a period. Individual dark pool usage is defined as the ratio of dark submission volume over total submission volume for a subject in a period. Standard errors (clustered at an individual subject level) are in parentheses. *Individual posterior strength* is defined as the absolute deviation of an individual trader's posterior from 0.5. All regressions include the demographic variables as additional regressors. * indicates significance at the 10% level, and ** indicates significance at the 5% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Individual posterior strength	-42.34	-0.00	-47.33**	-0.17**
	(27.14)	(0.10)	(21.96)	(0.08)
Period	-0.87**	-0.00	-1.08**	-0.00
	(0.43)	(0.00)	(0.43)	(0.00)
Constant	-20.34	0.33*	-38.77	0.24
	(40.95)	(0.18)	(87.90)	(0.26)
No. of observations	1440	1387	1440	1402
No. of clusters	72	72	72	72
R^2	0.07	0.07	0.02	0.02

having higher posterior strength are more likely to utilize the lit exchange for faster execution. As a consequence, the adverse selection risk for the uninformed traders becomes more elevated at the lit exchange than in the dark pool.[24]

RESULT 8: *Traders with stronger signals have a relatively lower dark pool usage when the information precision is high.*

E. Trader's Earnings

Are informed traders better off with the introduction of a dark pool? Are earnings higher with a relatively higher dark pool usage?

We calculate the (gross) profits of trader i in period t as $\Delta ECU_{it}+10\Delta Assets_{it}$ if the urn was A and ΔECU_{it} if the urn was B, where ΔECU_{it} measures the difference between cash endowment at the end (post-trade) and the start (pre-trade) of a period before subtracting the information-acquisition costs, and $\Delta Assets_{it}$ denotes the stock balance at the end of a period minus the initial stock endowment. Thus, gross profit is the difference between the value of a trader's portfolio at the end and at the start of a period (without subtracting the cost of information acquisition).

With gross profits as the dependent variable, we perform OLS regression analysis to understand whether informed traders outperform uninformed ones, strongly informed traders earn more and if the addition of a dark pool increases the overall earnings of any type of trader. Various specifications are considered, and the results are reported in Table XII. Columns (1) and (3) show that informed traders are able to outperform the uninformed ones in markets with low precision as well as high precision. In general, the extent of outperformance is greater when information precision is low than when it is high.[25] Columns (2) and (4) further indicate

[24]Given that informed traders utilize both lit exchange and dark pool, the risk of trading with someone with superior information is present in both venues. However, the exchange's adverse selection risk is greater with the relatively higher usage of lit exchange by the traders with stronger signals.

[25]As the table shows when there is only a lit market, informed traders' gross profits are higher by 47.79 points in *Lit Only-Low* and by 28.68 points in *Lit Only-High* treatment. Further calculations show that the gross profits of the informed traders exceed by 54.34 (41.75) points in *Dark-Low* (*Dark-High*) treatment, both values being significant at the 1% level.

that traders with strong signals can reap substantial benefits when compared to the uninformed ones. However, the moderately informed traders get similar profits as the uninformed traders.[26]

Table XII effectively provides evidence for two critical observations. First, the availability of an additional dark venue for trading in itself does not affect the earnings of each type of trader, and those with stronger signals are able to comfortably outperform uninformed ones irrespective of the trading institution. Second, there is a significant adverse selection risk for uninformed traders while trading with investors with strong signals. This is present in all markets, with and without the addition of a dark pool, irrespective of low or high precision of signals.[27]

To understand how the relative transactions of an individual trader in the dark market affect her gross earnings, we conduct an OLS regression of gross profits for each type of trader- uninformed, moderately informed, and strongly informed, using data from the *Dark-Low* and *Dark-High* treatments. Table XII reports the results. We observe that, while informed traders' earnings are not affected significantly by their relative use of the dark pool vis-à-vis the lit exchange, uninformed traders who have a higher net dark transaction volume obtain higher profits. This indicates that uninformed traders face a higher adverse selection risk at the lit exchange than at the dark pool. The addition of a dark pool allows them to use the additional trading venue to mitigate part of the adverse selection risk.

RESULT 9: *Uninformed traders who trade relatively more in the dark pool have higher earnings.*

III. Discussion

The previous section shows that the impact of trading in dark pools on information acquisition, informational efficiency of prices, and market outcomes depends

[26]The earnings of the moderately informed traders exceed the uninformed ones by 18.62 (significant at only 10% level) under *Dark-Low* and fall short by 1.28 (but insignificant) under *Dark-High* treatment.

[27]We note that although the difference in the profits of the strongly informed and uninformed is more elevated in markets with low precision, there are fewer such traders with strong signals when compared to markets with high precision. There is greater competition among traders with strong signals in the latter markets.

Table XII

OLS Regression of Individual Gross Profits

This table presents results of OLS regression analysis of the individual gross profits, defined as the difference between the values of trader portfolios at the end and the beginning of each period, excluding the cost of information acquisition. Standard errors (clustered at an individual subject level) are in parentheses. The baseline is the individual gross profits obtained by uninformed traders in *Lit Only-Low* treatment in columns (1) and (2), and in *Lit Only-High* treatment in columns (3) and (4). *Informed* takes a value of one if the trader is informed, i.e., has an individual Bayesian posterior different from 0.5. *Moderately Informed* takes a value of one if the trader is moderately informed, i.e, the individual posterior of the trader lies in $[0.25, 0.50)$ or $(0.50, 0.75]$. *Strongly Informed* takes a value of one if the trader is strongly informed, i.e, the individual posterior of the trader lies in $[0, 0.25)$ or $(0.75, 1]$. *Dark* takes a value of 1 if the treatment includes a dark pool along with the lit exchange and 0 otherwise. All regressions include the demographic variables as additional regressors. *** indicates significance at the 1% level.

	Low Precision		High Precision	
	(1)	(2)	(3)	(4)
Informed	47.79***		28.68***	
	(12.92)		(7.66)	
Moderately Informed		11.15		4.72
		(12.45)		(11.67)
Strongly Informed		100.10***		41.28***
		(19.35)		(8.43)
Dark	-3.55	-3.44	-5.13	-5.19
	(9.37)	(9.39)	(5.81)	(5.80)
Informed × *Dark*	6.56		13.07	
	(16.35)		(11.15)	
Moderately Informed × *Dark*		7.47		-6.00
		(16.63)		(16.52)
Strongly Informed × *Dark*		-0.02		15.00
		(23.44)		(12.68)
Constant	-15.45	-10.74	31.46	31.07
	(41.60)	(39.81)	(32.42)	(30.90)
No. of observations	2880	2880	2880	2880
No. of clusters	144	144	144	144
R^2	0.02	0.05	0.02	0.03

Table XIII

OLS Regression of Individual Gross Profits: ***Dark-Low*** and ***Dark-High*** Markets

This table presents results of OLS regression analysis of the individual gross profits in a period. Standard errors (clustered at an individual subject level) are in parentheses. *Individual net dark transaction volume* is defined as the transaction volume in the dark pool minus the transaction volume at the lit exchange of a subject in a period. All regressions include the demographic variables as additional regressors. * indicates significance at the 10% level, and ** indicates significance at the 5% level.

	Low Precision			High Precision		
	Uninformed	Moderately Informed	Strongly Informed	Uninformed	Moderately Informed	Strongly Informed
Individual net dark	0.71**	0.03	0.42	0.46**	0.45	-1.02
transaction volume	(0.35)	(0.46)	(0.36)	(0.22)	(0.49)	(1.30)
Constant	-44.50	-176.70**	223.90*	65.24	-135.4	123.4
	(79.69)	(80.44)	(124.20)	(52.68)	(136.60)	(116.10)
No. of observations	639	369	289	630	158	450
No. of clusters	66	47	44	66	31	45
R^2	0.02	0.01	0.02	0.03	0.02	0.06

crucially on the informativeness of the signals acquired by investors. As listed in results 6-7, there is a strong negative *crowding out effect* on liquidity at the lit exchange irrespective of the information precision of signals. There are two positive effects of the addition of a dark pool: *information acquisition effect* whereby investors acquire a greater number of signals, and a *sorting effect* wherein traders with stronger signals use the lit exchange relatively more than either traders with moderate signals or uninformed ones. These positive effects are significant when information precision is high (results 1 and 8). On the other hand, with low precision of signals, the *information acquisition effect* is insignificant, and the *sorting effect* is absent too.

With high precision of signals, at modest level of dark trading, the combination of *information acquisition effect* and *sorting effect* outweighs the *crowding out effect*. As the dark market participation goes up, the *crowding out effect* grows stronger and eventually exceeds the positive effects.[28] This results in a non-linear relationship between the informational efficiency of prices and the level of dark trading in the market.[29] In contrast, when information precision is low, none of the positive effects are observed, and only the negative effect is seen. Even then, price efficiency does not decline significantly with dark trading and only starts to deteriorate when dark market participation is very high.

Our results can be related to the existing theoretical models that study traders' venue choice and price discovery when a dark pool is added alongside a lit exchange.

[28]While the extent of *sorting effect* is likely to be endogenously associated with the level of dark trading, the *information acquisition effect* is entirely a causal effect as the information acquisition stage precedes the trading stage, and the level of dark market participation is not an exogenous control in our experiments.

[29]Overall, the addition of a dark pool does not cause the price efficiency to deteriorate, as can be seen from Table V.

The closest theoretical papers are by Zhu (2014) and Ye (2016).[30,31] Using a model of strategic venue selection by informed and liquidity traders, Zhu (2014) shows that relatively more informed traders are pushed into the lit exchange while relatively more uninformed traders go to the dark pool. As a result of this self-selection, there is a reduction in the noisiness of demand and supply on the exchange, which improves price discovery.

The self-selection result in Zhu (2014) occurs because of the difference in execution risk of informed orders and liquidity orders in the dark pool. Given that informed orders are positively correlated with the asset's value 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. On the other hand, liquidity orders are less correlated, are less likely to cluster on the heavy side of the market, and have higher execution probabilities in the dark pool.

While Zhu (2014) considers perfectly informed traders, Ye (2016) assumes that informed traders receive noisy and heterogeneous signals about the asset's fundamental value and characterizes an equilibrium where traders with strong signals trade in exchanges, traders with moderate signals trade in dark pools, and traders with weak signals do not trade. As a result, when information precision is high, most informed traders trade in the exchange and adding a dark pool enhances price discovery. On the other hand, when information precision is low, the majority of the informed traders trade in the dark pool, and adding a dark pool impairs price discovery.

The *sorting effect* that we observe under high information precision environ-

[30]We emphasize that while there are several similarities in the basic framework between our laboratory market and the theoretical formulation considered in Zhu (2014) and Ye (2016), like the existence of parallel lit and dark venues for trading, and both informed and uninformed traders being present in the market, there are other features of the models that are absent in our experimental markets. For example, the theory assumes immediate execution in the lit exchange guaranteed by a market maker, explicit delay costs for liquidity traders, differences in costs of information acquisition among informed traders, for-profit traders not acquiring information not trading, etc. Therefore, our research should not be viewed as a direct test of these models. Instead, we identify the fundamental mechanisms that start operating when an additional dark pool is added to an existing lit exchange.

[31]Another related paper is by Ye (2011), which studies the venue choice of a large informed trader in the Kyle (1985) framework. Ye (2011) assumes that only the informed trader can freely select trading venues and finds that the addition of a dark pool harms price discovery on the exchange. In contrast, we allow both informed and uninformed traders to select venues in our experiments.

ment is consistent with the predictions of both Zhu (2014) and Ye (2016). Although informed traders in our experiment do not have perfect information, when the information precision of signals is high, the strongly informed traders have close to perfect information. They will cluster on the heavy side of the market and suffer lower execution probabilities in the dark pool. As a result, they are more likely to migrate to the lit exchange for faster execution. With low precision of signals, the proportion of traders with strong signals in the market is much lower, and information risk is substantial, and hence the *sorting effect* disappears.

The relationship between the self-selection of venues by traders and price discovery is not as apparent as suggested by theory. As shown in Table V, on average, adding a dark pool neither promotes nor impairs price discovery on the exchange.[32] Though there is no overall effect of the addition of a dark pool on price discovery, traders with stronger signals find it extremely difficult to execute their orders in the dark pool and populate the lit exchange relatively more when the dark market participation is modest in the market with high information precision, thereby impounding information into asset prices. Additionally, in our experiments, traders acquire information, and as reported earlier, information acquisition goes up when a dark pool is added when information precision is high. This *information acquisition effect* is not present in the theoretical models.

The self-selection result of the theoretical models implies that adding a dark pool would discourage information acquisition when the information precision of signals is sufficiently high. However, as reported earlier, we find that dark trading encourages costly information acquisition among investors, significantly so in the high information precision environment. We believe there are two reasons for this observation. First, investors would anticipate that a sizeable number of orders will now be traded off-exchange given that markets are fragmented, resulting in less information being impounded into prices of transactions at the exchange. This would incentivize traders to acquire a larger number of signals.[33] Second, it seems

[32]This observation is similar to the finding in Bloomfield, O'Hara, and Saar (2015), who report that in a single limit order book environment, the ability to hide orders affects traders' strategies but does not affect informational efficiency.

[33]This is because, as shown in Table XII, information is precious irrespective of whether precision is low or high. Informed traders outperform the uninformed ones. Given that prices are not fully revealing in markets with low precision. Even when they fully reveal the available information in

likely that some traders would acquire more information in the hope that they will trade in the dark pool and be able to prevent the information leakage that would have resulted from placing orders in the lit exchange.[34]

We note that our information acquisition results are not influenced by changes in the informational efficiency of prices in the lit exchange when both trading venues are open. This is because, in our design, the information acquisition stage precedes the trading stage. Even if traders are aware of the non-linear relationship between dark market participation and price efficiency being borne out in the data, they can't predict the eventual dark market participation that will materialize when they decide how many signals to acquire.

Finally, in the context of laboratory markets, most studies use the centralized double auction trading institution with an open order book (Sunder (1995), Deck and Porter (2013), Noussair and Tucker (2013), Palan (2013)). Does an increase in opacity necessarily lead to the deterioration of prices as information aggregation tools? Recent experimental studies suggest that the absence of pre-trade transparency may not be detrimental for information aggregation in markets with hidden liquidity (Bloomfield, O'Hara, and Saar (2015), Gozluklu (2016)) as well as in decentralized markets (Asparouhova and Bossaerts (2017), Asparouhova, Bossaerts, and Yang (2019)). Our research demonstrates that the introduction of dark pools opens up additional channels (the *information acquisition effect* and *sorting effect*) that positively affect the informational efficiency of prices, although liquidity at the exchange is impacted negatively. Furthermore, these effects are stronger when the information precision of acquired signals is sufficiently high.

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several of the markets with high information precision, it takes time to do so, informed traders are able to outperform uninformed ones, and incentive to acquire information is present in all our markets (Grossman (1976), Grossman and Stiglitz (1980), Verrecchia (1982)).

[34]Whether or not these traders are able to use the dark pool for performing their transactions though depend on several endogenous factors, like the execution risk and wait time in the dark pool. It is likely that if orders have to wait much longer for execution in the dark pool, then the ongoing mid-point price may change adversely by the time the order is finally matched to a counterparty offer if at all it is executed.

IV. Conclusion

In modern financial markets, investors can trade not only in traditional lit exchanges but also in alternative trading venues such as dark pools. We investigate the effects of adding a dark pool alongside a lit exchange on the incentives to acquire costly information, price efficiency, and market liquidity. We report data from a series of laboratory markets for an asset whose terminal payoff is contingent on an unknown state of the world. Prior to trading, investors can purchase noisy signals at a cost. In addition to a lit exchange organized as a multiple-unit double auction market, traders can send their orders to a dark pool where others do not publicly observe their offers. These offers are executed at prices derived from the lit exchange.

The effect of dark trading on the efficiency of asset prices and market quality depends on the information precision of the acquired signals. When informative signals have high precision, the presence of a dark venue promotes information acquisition. This, in turn, positively influences the price discovery process in a financial market for a modest level of dark market participation and harms price efficiency only for a very high level of dark trading. While evaluating the pros and cons of dark trading, our study strongly indicates that regulatory authorities must consider the effect of dark pools on information acquisition. This bright side of dark markets should not be overlooked.

Given our research questions, and as a starting point for studying the impact of introducing a dark pool running parallel to a limit order market in experimental asset markets, we assume that all investors are identical in their initial endowments of cash and shares of assets. It would be worthwhile to explore the implications of allowing heterogeneous endowments to capture the notion of institutional investors who can potentially transact using the dark venue without impacting the lit market with their large orders. Relatedly, other variations of our design include changing the price of the matched orders in the dark pool, varying the tick size, and implementing different execution priority rules for orders sent to dark pool.[35]

[35]Instead of the orders in the dark pool being matched at the mid-point of the best buy and best sell offer prices in the lit exchange, dark orders can be designated as passive or aggressive. A passive buy (sell) order can be matched at the best buy (sell) offer price, while an aggressive buy (sell) order can be matched at the best sell (buy) offer price.

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Appendix: Instructions for the experiment (Treatment *Dark-High*)

GENERAL INFORMATION

Dear participant, welcome to our experiment. **Please pay attention to the information provided here and make your decisions carefully. If you have questions at any time, please raise your hand, and we will attend to you in private.**

Please note that unauthorized communication is prohibited. Failure to adhere to this rule would force us to stop the experiment, and you may be held liable for the cost incurred in this experiment. You have the right to withdraw from the study at any point in time, and if you decide to do so, your payments earned will be forfeited. By participating in this study, you will be able to earn a considerable amount of money. The amount depends on the decisions you make.

At the end of this session, this money will be paid to you privately and in cash. It would be contained in an envelope (indicated with your unique user ID). Your **unique user ID will be clearly stated on your computer screen**. At the end of the study, you will be asked to fill in your user ID and other information about your earnings from this study in the payment receipt. **Please fill in the correct user ID to ensure that you will get the correct amount of payment**.

Your **anonymity will be preserved** for the study. Your user ID will only identify you in our data collection. All information collected will **strictly be kept confidential** for the sole purpose of this study.

PAYMENT

There are two sections in this experiment, and your total payoff from the experiment will be as follows:

1. The earnings made from decisions in **Section 1** will be in terms of Experimental Currency Units (ECU), and these earnings in ECU will then be converted to Singapore dollars (SGD) for your payment with the following exchange rate: **50 ECU = 1.00 SGD.**

2. The earnings made from decisions in Section 2 will be in terms of SGD.

3. There will also be a separate show-up fee of SGD 2, on top of the payment from your experiment.

In summary, your payment will be as follows:

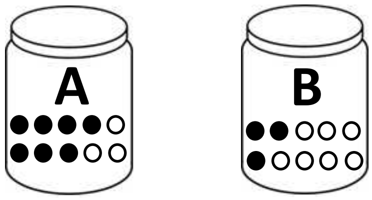
Category		**Payment**
Experiment	Section 1	Final ECU obtained from experiment converted with an exchange rate of **50 ECU = 1.00 SGD**
	Section 2	In SGD, the amount of reward depending on decisions made in this section
Show-up fee		SGD 2

SECTION 1A - EXPLANATION OF "BALL & URN" SETUP

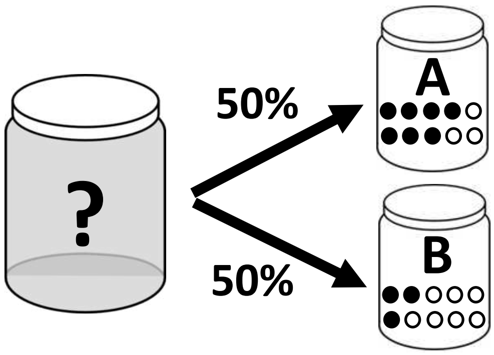
You will take part in a virtual financial environment, where you can buy and (or) sell dividend-bearing assets. The currency used in this experiment is called ECU. There will be several periods in this section, and your final payoff for this section will be given by the **averag**e of the payoffs from **3** randomly chosen periods.

Asset dividends depend on events that are still unknown to traders. In this experiment, we represent the uncertain market conditions (dividends) through the random selection of urns with different compositions of colored balls.

There are 2 types of urns (A & B).



Urn A contains **7 black balls and 3 white balls**, while urn B contains **3 black balls and 7 white balls**. In every period, **each urn has an equal likelihood of being chosen as the underlying urn**. You will not be informed of the chosen urn.

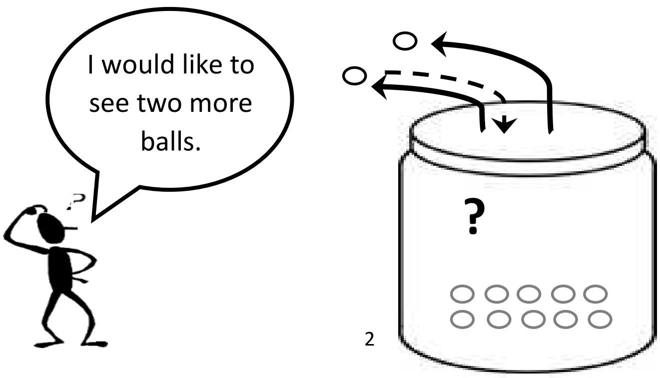


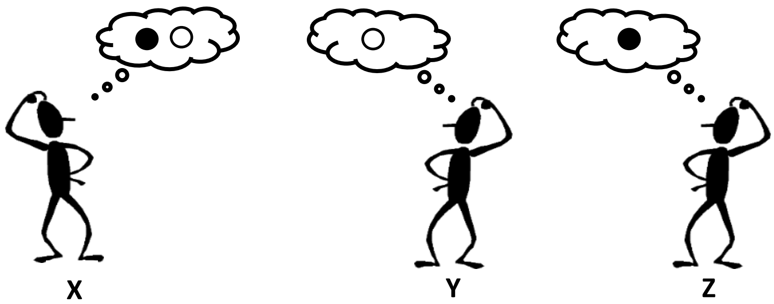
You will have the opportunity to buy and (or) sell assets that will be worth:

- **10 ECU** if the underlying urn is **urn A**
- **0 ECU** if the underlying urn is **urn B**

Some of you will be able to **acquire information** that would allow you to infer the likelihood that the underlying urn chosen was either urn A or urn B by drawing balls from the underlying urn a **cost**. **This information will only be revealed to you**. Note that each drawn ball is placed back into urn before the next ball is drawn.

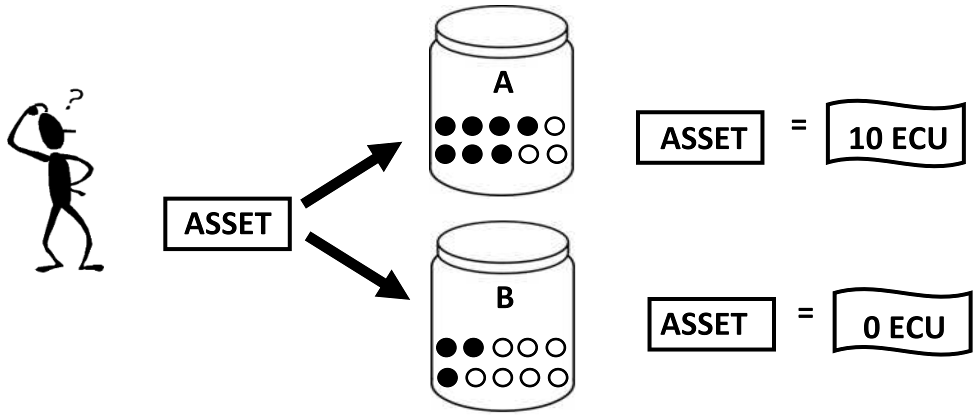
The same goes for the other traders. **They may also acquire several balls from the underlying urn at a cost, which will be known only to them.**





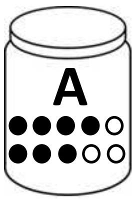
Individuals' information is private

Next, you will enter a **Trading Stage,** where you will be able to **BUY** and/or **SELL** the assets. At the end of the trading stage, the chosen underlying urn will be revealed, and the value of your assets for that period will be determined. For example, if the urn is A, each asset you own will be worth 10 ECU. If the urn is B, each asset you own will be worth 0 ECU.



How can you interpret the drawn balls?

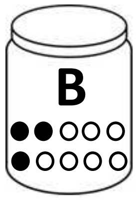
The balls drawn gives you some clues about the likelihood that urn A or urn B is the underlying urn. For example, with two balls, the likelihood that the underlying urn is A is calculated as follows:



Likelihood of getting:

● = 70%
○ = 30%

● ● = 70%× 70% = **49%**
● ○ = (70% × 30%) + (30% × 70%) = **42%**
○ ○ = 30% × 30% = **9%**



Likelihood of getting:

● = 30%
○ = 70%

● ● = 30% × 30% = **9%**
● ○ = (30% × 70%) + (70% × 30%) = **42%**
○ ○ = 70% × 70% = **49%**

Likelihood of urn A being the underlying urn given the following drawn balls:

$$\bullet\bullet \quad = \frac{49\%}{49\%+9\%} = \mathbf{84\%}$$

$$\bullet\circ \quad = \frac{42\%}{42\%+42\%} = \mathbf{50\%}$$

$$\circ\circ \quad = \frac{9\%}{9\%+49\%} = \mathbf{16\%}$$

Hence, if two black balls have been drawn, there is a 84% likelihood of urn A being the underlying urn. If one black ball and one white ball have been drawn, there is a 50% likelihood of urn A as the underlying urn. If two white balls have been drawn, there is a 16% likelihood of urn A as the underlying urn.

Note that the system will compute and display the likelihood mentioned above. You <u>do not</u> need to compute this likelihood yourself.

In summary, having more black balls tend to indicate urn A as the underlying urn.

You should use this computed likelihood to assess the asset's expected value. If a computed **likelihood** of urn A being the underlying urn is 84%, the expected value of each asset should be given by:

$$(84\% \times 10\,ECU) + (16\% \times 0\,ECU) = 8.4\,ECU$$

This expected value can then be used as a guide for the price you want to buy and/or sell this asset during the trading period.

SECTION 1B - THE EXPERIMENT

We will now explain the rules of the experiment in detail. In the experiment, during each session, there will be 12 subjects. Among the 12 subjects, there are **2 types of traders, Type I and Type II** and you will be randomly assigned to one type. Specifically, there will be **4 Type I and 8 Type II Traders.**

Type I Traders would not be able to acquire balls to infer the urn state. All they know about the urn state is that the likelihood that the chosen underlying urn is Urn A is 50%.

In contrast, **Type II** Traders would be able to acquire balls at cost to have a better understanding about the urn state. Note the balls acquired by each Type II Trader may differ.

In each session, you will participate **in two parallel asset markets** (Market **X** and Market **Y**) in which you will trade dividend-bearing assets in each period. You can either buy and (or) sell in both two markets.

Each period of the experiment consists of a **two-stage decision-making process**. In the first stage, you would be allowed to acquire information on the asset at a cost. In the second stage, you will trade assets in a market setting. The chosen urn in each period **may not be the same**. For instance, the urn may be A in the 1st period with each asset worth 10 ECU, but the urn may be B in the 2nd period with each asset worth 0 ECU.

SECTION 1C - ACQUIRING INFORMATION

The Information Acquisition Stage allows **Type II** Traders to obtain ball draws from the urn at a cost. The **cost of acquiring a ball is 6 ECU**. The more balls you decide to acquire, the more information you will have about the underlying urn. You will be given 1 minute to decide how many balls you would like to draw (maximum of 10 balls).

All traders have the same initial endowment of **600 ECU** and **40 assets**. Note that at the start of each period, the initial endowment will be reset, and earnings from each period cannot be used in the next period. (i.e., **each period is a fresh start**).

SECTION 1D - TRADING STAGE

During the trading stage, you can trade with other subjects in both Market X and Market Y. The dividend will be paid at the end of each trading period. In each period, you will have **2 minutes of trading**. The remaining time (in seconds) will be displayed at the **screen's top right-hand corner**.

In Market X

To buy assets:

You can **submit a buy offer**, which specifies the **volume (number of assets)** (> 0) and the **price** (0.1-9.9) you wish other traders to **sell** to you. Note that you will successfully buy assets only if a seller's ask price matches (is lower than or equal to) your bid price.

For example (see the table below), if you submit a buy offer of 8 units of the asset for 6 ECU per unit, and in the order book, there are already corresponding sell offers of 5 units at 5 ECU per unit and another 5 units at 6 ECU per unit. Your buy order will be matched with the seller who submitted a sell offer of 5 units of the asset at 5 ECU per unit and the seller who submitted a sell offer of 5 units of the asset at 6 ECU per unit. You will thus buy 5 units of the asset at 5 ECU per unit and another 3 units of the asset at 6 ECU per unit.

Refer to the displayed Sell Offers List below:

Sell Offers (best sell offer on the top)

Price	Volume
5.0	5
6.0	5
7.0	10

0.1-4.9

If your buy price is in this interval, transaction **will NOT occur.**

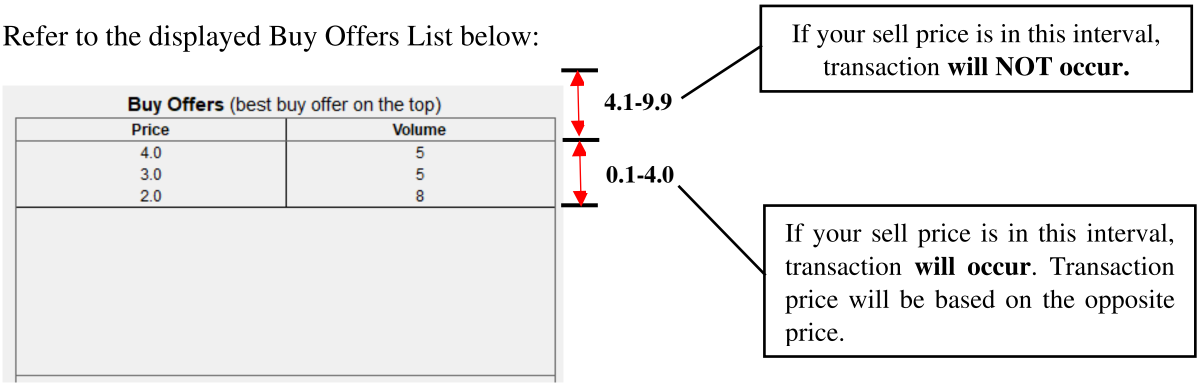
5.0-9.9

If your buy price is in this interval, transaction **will occur**.Transaction price will be based on the opposite price.

To <u>sell assets</u>:

Selling assets is similar to buying:

> You can **submit a sell offer**, which specifies the **volume (number of assets)** (> 0) and the **price** (0.1-9.9) you wish other traders to **buy** from you. Note that you will successfully sell assets only if a buyer's bid price matches (is higher than or equal to) your ask price.
>
> For example (see the table below), if you submit a sell offer of 8 units of the asset for 3 ECU per unit, and in the order book, there are already corresponding buy offers of 5 units at 4 ECU per unit and another 5 units at 3 ECU per unit. Your sell offer will be matched with the buyer who submitted a buy offer of 5 units of the asset at 4 ECU per unit and the buyer who submitted a buy offer of 5 units of the asset at 3 ECU per unit. You will thus sell 5 units of the asset at 4 ECU per unit and another 3 units of the asset at 3 ECU per unit.
>
> Refer to the displayed Buy Offers List below:



To summarize, a transaction occurs when a new submitted **buy offer's price is higher than or equal to the lowest sell** price on the **Sell Offers List**; or a new submitted **sell offer's price is lower than or equal to the highest buy price on the Buy Offers List**.

When there is more than 1 matching offer, the offer with the more attractive price and an earlier submission time will be executed first.

At all times during trading in Market X, you will be able to see all active offers and their respective trading prices and volumes. To create an offer, you enter buy (sell) price and volume and click either the "**Submit Buy Offer**" or "**Submit Sell Offer**" button to create a buy or sell offer, respectively.

Here are some important trading rules:

1. **Note that you should NEVER submit a buy (sell) price higher (lower) than your own sell (buy) price, as you are not allowed to transact with yourself.**

2. **Note that your buy (sell) offers can be partially matched and executed. For example, if your buy (sell) offer's volume is 15 units and the corresponding matched sell (buy) offer volume is 10 units, then 10 out of 15 units of your buy (sell) offer would be executed.**

3. **Do also note that your offers must be rounded up to 1 decimal place. For instance, you may key in a price of 4.5 or 5 but NOT a price of 4.55.**

4. **If you want immediate transactions, you may submit offers at better prices (lower sell prices or higher buy prices) than the offers on the Buy/Sell Offers List.**

In Market Y

Your active offers and transactions in Market Y are only visible to yourself. **Unlike in Market X, other traders in Market Y would not be able to see your submissions of offers.** Your offers will be matched with another trader's offer **confidentially** and **automatically** by the computer whenever a match exists. **The trading prices are based on the midpoint of the best bid (highest buy) and ask (lowest sell) offer prices in Market X.**

To <u>buy assets</u>:

You can create a buy offer by specifying the **volume (number of assets)** (> 0) you would like to buy in Market Y. You do not need to specify the price because the trading price is based on the midpoint of the best bid (highest buy) and best ask (lowest sell) offer prices in Market X, and then click "Submit Buy Offer." Please note that you will successfully buy assets only if your buy offer can be matched with an outstanding sell offer by the computer and that you have sufficient cash to execute the transaction.

To <u>sell assets</u>:

You can create a sell offer by specifying the **volume (number of assets)** (> 0) (you do not need to specify the price because the trading price is based on the midpoint of the best bid (highest buy) and best ask (lowest sell) offer prices in Market X) and then click "Submit Sell Offer." Please note that you will successfully sell assets only if your sell offer can be matched with an outstanding buy offer by the computer and that you have sufficient assets to execute the transaction.

Note that if there is no ask (sell) or bid (buy) offer in Market X, then the best bid price (highest buy) will be 0.1 ECU, and the best ask price (lowest sell) will be 9.9 ECU.

NOTE:

Here in Market Y, because the trading prices are based on the midpoint of the two best reference prices in Market X, and you do not need to specify the offer prices, there is **a trade-off between information protection and immediate execution**. On the one hand, because of the fixed pricing rule in Market Y, your price signals (balls given to you ahead of the trading stage) will not be revealed, and you will **keep your information advantages private**. On the other hand, because you cannot view other offers in Market Y, your **immediate execution may not be guaranteed** (only when there are corresponding offers on the opposite side can your offers be matched and executed).

Note that your buy (sell) offers can be partially matched and executed. For example, if your buy (sell) offer's volume is 15 units and the corresponding matched sell (buy) offer volume is 10 units, then 10 out of 15 units of your buy (sell) offer would be executed.

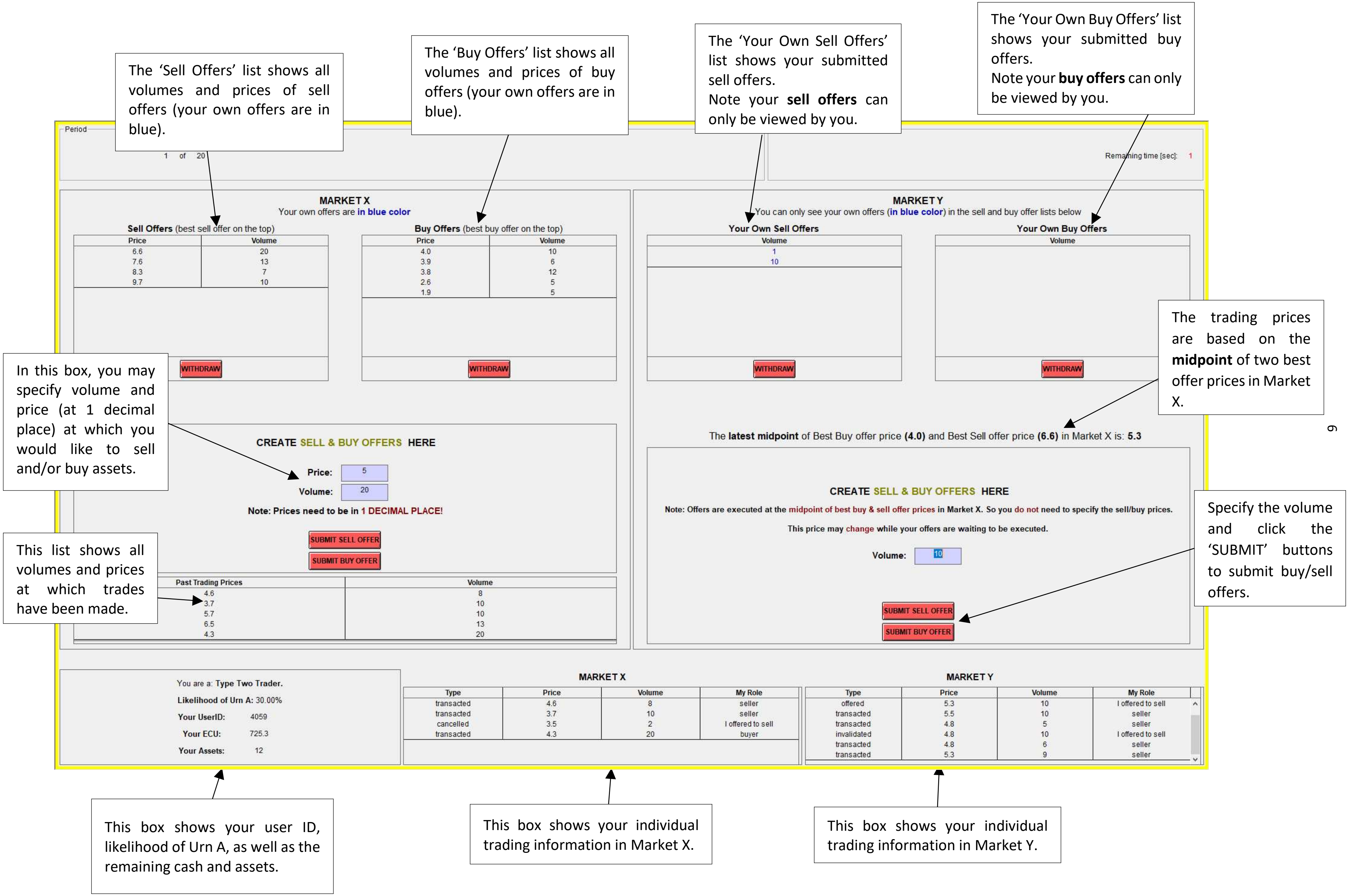
Also, note that **your <u>own</u> buy/sell offers** are also displayed in the list of offers in blue instead of black. You cannot accept your own offers, but you can select them and click "WITHDRAW" if you decide to withdraw your own offers.

Offers are removed from the offer lists when they are executed or withdrawn. Note also that if there are any buy/sell offer that you are no longer able to fulfill (either because you **do not have enough assets left for your sell offer** or **do not have enough ECU for your buy offer**), it will also be automatically removed.

After you have successfully made a trade, your ECU and asset balances will be updated accordingly.

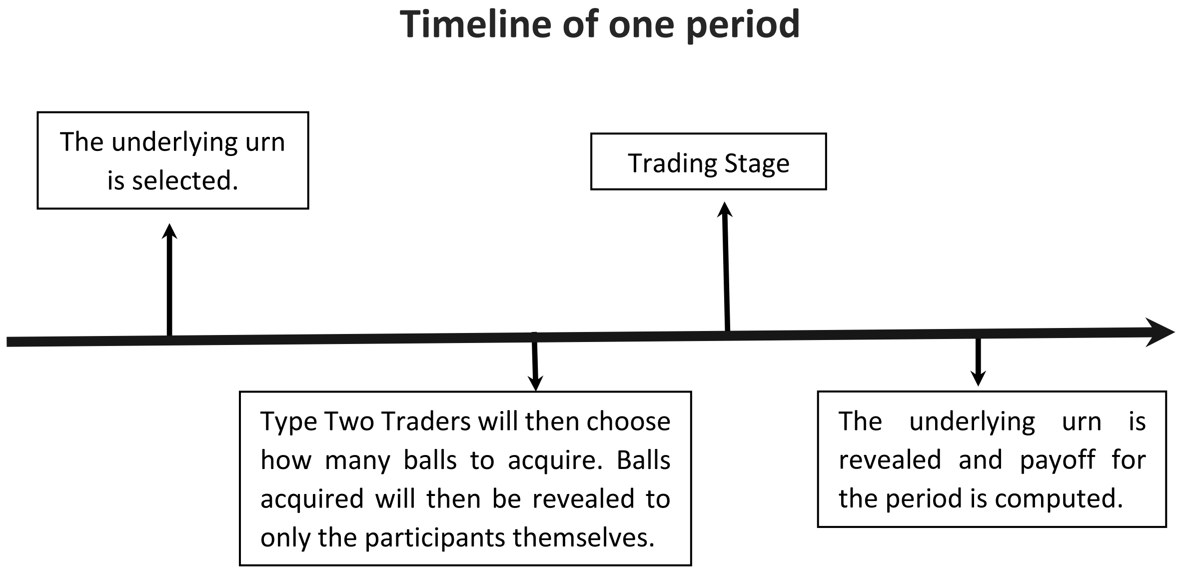
The last screen concludes the period. It will reveal the value of the assets in this period: either 0 or 10 ECU. Your payoff for each period is the **sum of ECU you have at the end of the period and the total dividends from the assets**. A new period begins once every trader clicks "OK" on this screen.

The following figure on next page shows the trading window:



The 'Sell Offers' list shows all volumes and prices of sell offers (your own offers are in blue).
The 'Buy Offers' list shows all volumes and prices of buy offers (your own offers are in blue).
The 'Your Own Sell Offers' list shows your submitted sell offers. Note your **sell offers** can only be viewed by you.
The 'Your Own Buy Offers' list shows your submitted buy offers. Note your **buy offers** can only be viewed by you.
Period
1 of 20
Remaining time [sec]: 1
MARKET X
Your own offers are in blue color
Sell Offers (best sell offer on the top)
Price Volume
6.6 20
7.6 13
8.3 7
9.7 10
WITHDRAW
Buy Offers (best buy offer on the top)
Price Volume
4.0 10
3.9 6
3.8 12
2.6 5
1.9 5
WITHDRAW
MARKET Y
You can only see your own offers (in blue color) in the sell and buy offer lists below
Your Own Sell Offers
Volume
1
10
WITHDRAW
Your Own Buy Offers
Volume
WITHDRAW
The trading prices are based on the **midpoint** of two best offer prices in Market X.
In this box, you may specify volume and price (at 1 decimal place) at which you would like to sell and/or buy assets.
CREATE SELL & BUY OFFERS HERE
Price: 5
Volume: 20
Note: Prices need to be in 1 DECIMAL PLACE!
SUBMIT SELL OFFER
SUBMIT BUY OFFER
The latest midpoint of Best Buy offer price (4.0) and Best Sell offer price (6.6) in Market X is: 5.3
CREATE SELL & BUY OFFERS HERE
Note: Offers are executed at the midpoint of best buy & sell offer prices in Market X. So you do not need to specify the sell/buy prices.
This price may change while your offers are waiting to be executed.
Volume: 10
SUBMIT SELL OFFER
SUBMIT BUY OFFER
Specify the volume and click the 'SUBMIT' buttons to submit buy/sell offers.
This list shows all volumes and prices at which trades have been made.
Past Trading Prices Volume
4.6 8
3.7 10
5.7 10
6.5 13
4.3 20
You are a: Type Two Trader.
Likelihood of Urn A: 30.00%
Your UserID: 4059
Your ECU: 725.3
Your Assets: 12
MARKET X
Type Price Volume My Role
transacted 4.6 8 seller
transacted 3.7 10 seller
cancelled 3.5 2 I offered to sell
transacted 4.3 20 buyer
MARKET Y
Type Price Volume My Role
offered 5.3 10 I offered to sell
transacted 5.5 10 seller
transacted 4.8 5 seller
invalidated 4.8 10 I offered to sell
transacted 4.8 6 seller
transacted 5.3 9 seller
This box shows your user ID, likelihood of Urn A, as well as the remaining cash and assets.
This box shows your individual trading information in Market X.
This box shows your individual trading information in Market Y.

The timeline summarizing the flow of events in each period is shown below:



There will be **3 practice rounds** for you to get used to the experiment before the actual periods of the experiment begin. Note that the **practice rounds will not be selected as payment rounds**.

The first practice period for you to familiarize yourself with Market X;
The second practice period for Market Y;
In the third practice period, you will trade in both Market X and Y.

If you have any questions that have not been fully answered by the instructions, please raise your hand and ask for assistance before proceeding. Please beware that you might suffer losses if you enter the experiment without fully understand the instruction!

SECTION 2 - DECISION PROBLEM STAGE

In this part of the experiment, you will be asked to make a series of choices. How much you receive will depend partly on chance and partly on the choices you make. The decision problems are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose.

For each line in the table in this stage, there are two options:

1) Option A: 1 SGD
2) Option B: 0 SGD or 3 SGD with varying chances stated for each line

Please select the option which you prefer for each line. Notice that there are a total of 10 lines in the table but **just one line will be randomly selected for payment**. You do not know which line will be paid when you make your choices. Hence, you should pay attention to the choice you make in every line.

After you have completed all your choices, the computer will randomly determine which line is going to be paid. Your earnings for the selected line depend on which option you chose. If you chose option A in that line, you will receive **1 SGD with certainty**. If you chose option B in that line, the computer will randomly determine if your payoff is **3 SGD or 0 SGD** based on the chances stated in option B of the selected line.

QUESTIONNAIRE

In this final part of the experiment, you will be required to answer a questionnaire. When you are done, we will prepare your earnings and ask you to sign a receipt, and the experiment will be over. Thank you again for your participation!