How Dark Trading Harms Financial Markets? *

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Abstract

We design an experiment to analyze the consequences of dark trading in a financial market. The channel through which dark trading affects market efficiency depends critically on how information regarding fundamentals is distributed among investors. When information is concentrated in the hands of a few investors, possibly due to sparse investor connectedness or low media coverage, dark trading primarily impacts market efficiency by deteriorating the quality of asset prices. When information is diffused, dark trading no longer harms price discovery, but the unobserved liquidity entails welfare loss. Dark trading does not widen the earnings gap between informed and uninformed traders.

JEL Classification Numbers: C91, C92, G12, G14

Keywords: Market microstructure, dark markets, asymmetric information, the efficiency of security markets, experiments

*We gratefully acknowledge the financial support from the General Research Fund sponsored by the Hong Kong RGC (CityU 11500019) and the National Research Foundation (NRF) CREATE -Future Resilient System II. The paper benefited from discussions during presentations at the 2023 Asia-Pacific ESA Meeting in Seoul, the IAREP-SABE 47th International Conference in Nice, the 2023 ESA World Meeting in Lyon, the 2023 SAET annual conference in Paris, and the 2023 Asian Meeting of the Econometric Society in Singapore. We especially thank Elena Asparouhova, Lawrence Choo, Cary Deck, John Duffy, Nobuyuki Hanaki, Todd Kaplan, Charles Noussair, and Jason Shachat for their helpful comments.

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The last decade has seen equity trading markets becoming increasingly fragmented, with dark pools rising in popularity as alternative trading systems. In January 2023, dark venues accounted for 13.75% of US equity trading volume (Rosenblatt Securities: Let There Be Light - US Edition).[1] This proliferation of off-exchange trading has brought back some long-standing questions on the relationship between market transparency and efficiency of equity markets.

The lack of pre-trade transparency in dark markets has been repeatedly raised as a concern by the relevant authorities.[2] How does dark trading affect the functioning of financial markets? Our objective is to evaluate the dark market as a trading institution against the benchmark of a limit order market with a fully transparent order book. In doing so, we design an experiment to investigate the effect of dark trading on price discovery at the lit exchange and on traders' welfare.

There have been some attempts to study dark trading in financial markets theoretically. Much of the theoretical literature models dark markets as over-the-counter (OTC) decentralized markets where negotiation is private between two parties, similar to the bilateral search framework (Duffie (2012)). These models are based on the idea of 'percolation' in stochastic process theory and show that when the market participants have observable roles of natural buyers and natural sellers and the information is dispersed among them, decentralized markets can eventually achieve the informational efficiency of competitive equilibrium (Duffie and Manso (2007), Duffie, Malamud, and Manso (2009), Duffie, Giroux, and Manso (2010), Duffie, Malamud, and Manso (2014)).

In Ye (2011), Zhu (2014), and Ye (2016), the theoretical framework considers dark trading as having multiple parallel venues for market participants to trade, with a dark pool added alongside an exchange. Ye (2011) studies the venue choice of a large informed trader in the Kyle (1985) framework and shows that dark trading harms price discovery on the exchange. On the other hand, Zhu (2014) finds that dark trading improves price discovery as it results

[1] These dark pools could be operated by independent companies like Instinet, Liquidnet, ITG Posit, etc., or broker-dealer owned and run by investment banks like CrossFinder, Sigma X, Citi-Match, MS Pool, etc.

[2] On June 8, 2022, during the remarks before the Piper Sandler Global Exchange Conference, SEC Chair Gary Gensler notes that while technology continues to transform our equity markets and has led to some good things like retail investors having greater access to markets than any time in the past, it has also led to challenges, including market segmentation, concentration, and potential inefficiencies. The markets have become increasingly hidden from view. He observes that during the meme stock events, the off-exchange trading accounted for around 47% of U.S. equity volume. Furthermore, 90-plus percent of retail marketable orders are routed to a small, concentrated group of wholesalers that pay for this retail market order flow. Finally, the SEC Chair notes that, with such market segmentation and concentration and with an uneven playing field, it's not clear whether the current national market system is as fair and competitive as possible for investors.

in the self-selection of venues by informed and uninformed traders, thereby concentrating price-relevant information on the exchange. 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, the impact of dark trading on price discovery depends on the information precision of signals in the market.

Substantial empirical research yields conflicting results on the impact of dark pools on price and market quality measures. Hendershott and Jones (2005) find that dark trading has a negative effect on price discovery, and Hatheway, Kwan, and Zhen (2017) report that dark trading harms overall market quality. In contrast, Buti, Rindi, and Werner (2011) find that dark trading improves price discovery. 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.[3]

While the existing literature has significantly advanced our understanding of the effects of dark trading on the informational efficiency of prices, the question of how the impact of dark trading depends on the distribution of fundamental information among market participants has received less to no attention. Some companies have more frequent press releases than others, have more widespread media coverage, and may have a very strongly connected investor base, while others do not. This will likely result in some companies' stocks having information diffused quickly so that a larger fraction of investors are well-informed about the fundamentals. Yet, other companies may have relevant information being held by a small group of investors. Therefore, the way the addition of a dark pool will impact the informational efficiency of prices is arguably a function of the existing distribution of relevant information among traders. Furthermore, the effect of dark trading on allocative efficiency, i.e., the ability of markets to allocate the asset to the agents with higher valuation, remains unexplored.

In this paper, we are interested in understanding the primary channel through which dark trading affects financial markets. Does the effect of dark trading on the informational efficiency of prices and allocative efficiency depend on the underlying distribution of fun-

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

damental information among investors? We design an experimental asset market with two parallel trading venues to address this question. We assume two equally likely states of nature, A and B, and a single asset that pays a dividend to its holder, which differs across individuals and depends on the randomly drawn state of nature.[4] Before trading, some individuals are endowed with perfect information about the state of nature. In the experiments, we vary the proportion of informed investors in a market.

We implement two market structures, one with only a single lit exchange where all order submissions by a trader are observable to other traders and another where two parallel trading venues exist, consisting of a lit exchange and a dark pool. In the latter market institution, in addition to the lit exchange, investors can submit orders and transact in another venue where order submissions of other traders are unobservable. Transaction prices in the dark market are derived from the existing buy and sell offer prices in the lit exchange.[5]

We find that how dark trading affects market efficiency depends critically on how information regarding fundamentals is distributed among investors. When information is concentrated in the hands of a few investors, dark trading primarily impacts market efficiency by deteriorating the quality of asset prices. In this case, learning from publicly observable order submissions is crucial to price discovery, and the crowding out of liquidity from the lit exchange under dark markets causes a significant decline in price efficiency compared to a market institution with only a single lit exchange.

On the other hand, when most investors have access to fundamental information, the crowding-out effect has less impact on price discovery as a substantial fraction of information is nevertheless impounded into the price. Therefore, in this case, dark trading no longer harms the informational efficiency of asset prices. However, the role of observable liquidity is not limited to enhancing asset price quality alone. Order flow transparency continues to be an important element that facilitates the movement of the asset from the ones who desire it the least to the ones valuing it the most. Thus, dark trading may result in welfare losses even though prices are equally informationally efficient with or without dark pools. We are able to identify this effect on welfare as trading is not zero-sum in our design.

[4]Following Plott and Sunder (1982, 1988), the difference in dividends across investors has been a standard way of inducing significant gains from exchange in both states and the "no trade" theorem does not apply even when everyone has the same information. The difference could be due to different tax brackets or risk preferences. Moreover, instead of being viewed as a security, the traded object could also be viewed as a resource being traded among the owners of alternative production technologies.

[5]In the experiments, all investors have the same initial endowments. Although our study abstracts from heterogeneous endowments, we stress that the study of large order flows of certain investors (e.g., institutional investors) in the presence of a dark venue and its impact on market efficiency measures is an important topic that we leave for future research.

We further observe that while information has a first-order effect on earnings, the market institution itself does not significantly alter the edge of informed investors over the uninformed. Therefore, introducing a dark venue for trading with hidden liquidity does not favor a specific group of investors. At the same time, we observe that informed traders find dark pools relatively more appealing than uninformed investors. Additionally, informed traders are more responsive to the execution rate of their limit order submissions in the lit exchange and their dark order submissions than uninformed traders, thereby revealing a higher demand for immediacy of execution.

Experimental research has been especially fruitful in assessing the performance of a trading institution in terms of informational efficiency of prices and allocation efficiency (Plott (2001)). We believe our laboratory investigation provides a useful complement to the theoretical and empirical studies on the consequences of the dark trading institution. In the laboratory, one can employ a trading mechanism close to the one used in actual markets while still being able to control and change variables of interest to allow clean causal inferences. Furthermore, controlled experiments permit us to vary the trading environment by switching on and off the dark trading venue, ceteris paribus.

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) find that while most aggregate market outcomes, such as informational efficiency and liquidity, largely remain unaffected, order strategies are affected by allowing for hidden orders. Traders substitute nondisplayed for displayed shares and change the aggressiveness of their trading. Gozluklu (2016) implements iceberg markets in a single limit order book in the laboratory as well, allowing for both displayed and partially displayed orders, and finds that, without information friction, market opacity enhances liquidity. Under informed trading, adverse selection drives market outcomes mainly around news announcements.

Few studies have examined market transparency and disclosure requirements in a market with dealers.[6] Flood et al. (1999) construct a market in which seven competing dealers trade a single security with informed and liquidity traders. They find that markets with no disclosure are more efficient than those with public disclosure, though transparent markets are more liquid and have higher volume than opaque ones.[7] Bloomfield and O'Hara (2000)

[6]These studies are motivated by the theoretical literature with early seminal contributions by Kyle (1985) and Glosten and Milgrom (1985) and consider the interaction between the market makers, informed and uninformed traders. Noussair and Tucker (2013) provide an excellent survey on related asset market experiments, including a discussion on market microstructure experiments on transparent and opaque markets.

[7]In their transparent market setting, all bids and asks are presented on the trading screens of every market maker, and in the opaque treatment, they are not.

investigate whether transparent markets can survive when faced with direct competition from less transparent markets. The results show that low-transparency dealers outperform high-transparency types as the low-transparency dealers can set prices to make it more likely that they have the inside spread, while high-transparency dealers are constrained by their informational disadvantage.[8] Using a second experiment with endogenous transparency, they show that most dealers choose to be of lower transparency.

Lamoureux and Schnitzlein (1997) implement markets with dealers but allow traders to bypass them and trade with each other through a bilateral search mechanism. The authors find that when traders cannot bypass dealers, dealer profits are high. However, these profits decrease to very low levels when traders can trade with each other directly. Liquidity traders lose money on average, and insiders make high profits because their information is very valuable. However, market efficiency is similar whether or not there are private two-party trades that take place in the search market. Motivated by the theory of information percolation, Asparouhova and Bossaerts (2017) experimentally study decentralized markets where negotiation is private between two parties. They report that decentralized markets do not fare that badly, with participants trading more than 75% of the time at prices within narrow bands of the fully revealing price. Asparouhova, Bossaerts, and Yang (2019) further show that participants with no initial information in decentralized markets remain willing to pay for information, unlike centralized markets.

Our study contributes to this small experimental literature on hidden liquidity and transparency in security markets. However, distinct from the above-mentioned studies, we implement fragmented markets with separate lit and dark venues for trading.[9] Finally, a recent paper by Halim et al. (2022) report that adding a dark pool alongside a lit exchange can positively affect markets by encouraging information acquisition, provided the informativeness of signals is high enough. Similar to that study, we have parallel venues for trading. However, the focus of our study is not on information acquisition, and we consider markets with explicit gains from exchange to study the effect of dark trading on allocative efficiency, which was not possible using the design of Halim et al. (2022).

The remainder of the paper is organized as follows. Section I describes the design and procedures of the experiment, and in section II, we present the data. We provide a discussion of our experimental findings in section III. The final section concludes.

[8]Market transparency is manipulated by altering the information received by investors about actual trades of the dealers. The trades of the 'high-transparency' dealers are revealed to all participants, while the trades of the 'low-transparency' dealers are not revealed to the market.

[9]In the context of laboratory markets, most studies use a single double auction trading institution with an open order book (Sunder (1995), Deck and Porter (2013), Noussair and Tucker (2013), Palan (2013)).

I. Experimental Design

A. General Structure

The data for this study were gathered from 16 experimental sessions conducted at Nanyang Technological University (NTU), Singapore. We had 192 participants in total, with 12 participants in each session. Subjects 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$21.26 and a show-up fee of S$2.[10]

Upon arrival, subjects were seated at visually isolated computer workstations. Instructions were read aloud, and subjects also received a copy of the instructions.[11] Participants were prohibited from talking during the experiment, and all communication occurred via the experimental software. Each session consisted of three practice periods and 16 main periods.[12] Activity during the practice periods did not count toward final earnings.

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. 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. Subjects could 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)). Each unit of the asset paid a single dividend to its holder at the end of the period, which differed across individuals and depended upon the randomly drawn state of nature.

Differences in dividends resulted in trading being non-zero-sum and led to the existence of gains from exchange and market activity. This feature is chosen deliberately as we are interested in studying the effect of dark trading on allocative efficiency and not just on price efficiency in markets. Following Plott and Sunder (1982), we assign different types to the

[10]Payoffs, inclusive of the show-up fee, ranged from S$9 to S$50.

[11]A sample copy of the instructions is provided in the appendix.

[12]At the end of the instructions phase and before 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.

Table I

Experimental Design: Dividend Parameters and Initial Endowments

This table presents the dividend values of different types of investors per unit of the asset and the initial endowments. The dividends are paid at the end of a period and differ depending on the selected urn.

		Dividends		Initial Endowments	
Investor Type	Number of Investors	urn A	urn B	Cash (ECUs)	Assets
I	4	40	10	50,000	100
II	4	30	15	50,000	100
III	4	12.5	17.5	50,000	100

participants, where these types vary in terms of how much dividends they obtain per unit of the asset in each state.[13] Table I provides the dividend parameters and initial endowments used in the experiments. Agents in each session were partitioned into three types (designated as I, II, and III) according to dividend returns.[14] There were four investors of each type.

In each period, each investor had an initial endowment of 100 assets. In addition, each agent was given 50,000 ECU in working capital which was returned to the experimenter at the end of the period.[15] 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. In each period, investors could participate in the trading phase, which lasted for three minutes. During this stage, 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. Subjects were also 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 ECU and asset balance available for trading were displayed on a participant's trading window. Once trading closed, the underlying urn was revealed together with the subject's earnings and the average transaction price in the period.

[13]Alternatively, one could generate explicit gains from exchange by inducing consumption smoothing incentive, as in Asparouhova et al. (2016), Crockett, Duffy, and Izhakian (2019), and Halim, Riyanto, and Roy (2022).

[14]The dividend parameters were chosen to ensure enough dispersion of valuations in one of the states but not in the other. This allows us to compare the allocative efficiency in markets conditional on the distribution of valuations.

[15]It was possible for a subject to incur losses in a period in case she failed to return the initial working capital.

Table II

Experimental Design: Summary of Treatments

This table presents the treatments. Data are drawn from 16 sessions of twelve traders each. We implement a 2×2 between-subjects design by varying the trading institution and the proportion of informed investors in a market. In the *Lit Only* market, subjects could trade only in the single limit order market with a publicly observable order book. In contrast, in the *Dark* market, there is a parallel dark market in addition to the limit order market. In periods 1-6, the rational expectations equilibrium (REE) price equals the prior expected value of the asset, i.e., 25 ECUs and type-I traders are predicted to hold the assets. In periods 7-16, in state A (B), REE price equals 40 (17.5) with type-I (type-III) investors holding the assets.

Treatment	Trading Institution	Number of Informed Investors (out of 12)	
		Periods 1-6	Periods 7-16
Lit Only-Low	Single Limit Order Market	0	3
Dark-Low	Parallel Markets	0	3
Lit Only-High	Single Limit Order Market	0	9
Dark-High	Parallel Markets	0	9

Following the 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 five of the 16 periods for the purpose of payment. Subjects were paid the average of the payouts from these five 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 having an observable order book or adding a dark market alongside a lit exchange and the proportion of informed investors in a market. The summary of the treatments is provided in Table II.

Under the *Lit Only* trading institution, the market was organized as 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 50 ECU.[16] 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.[17]

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 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.[18] Within each price level, orders submitted earlier were executed first.

Under the *Dark* trading institution, in addition to the limit order market with the publicly observable order book, which we refer to as the lit exchange, traders could submit their buy/sell offers to another market. In this second market, which we refer to as a dark market, traders only submitted the shares of the asset that they wished to buy or sell.[19] The active offers and transactions of a trader in the dark market 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 market and the market depth were not revealed to traders.[20] Figure 1 provides a screenshot of the trading platform in markets with both trading venues.

Traders couldn't specify any price for the orders sent to the dark market. 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. The mid-point pricing rule is very

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

[17]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 the subjects' screens.

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

[19]In the experiments, we used neutral terms for the markets. The lit exchange was referred to as *Market X*, and the dark market was referred to as *Market Y*.

[20]Participants were told that their offers sent to the dark market 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.

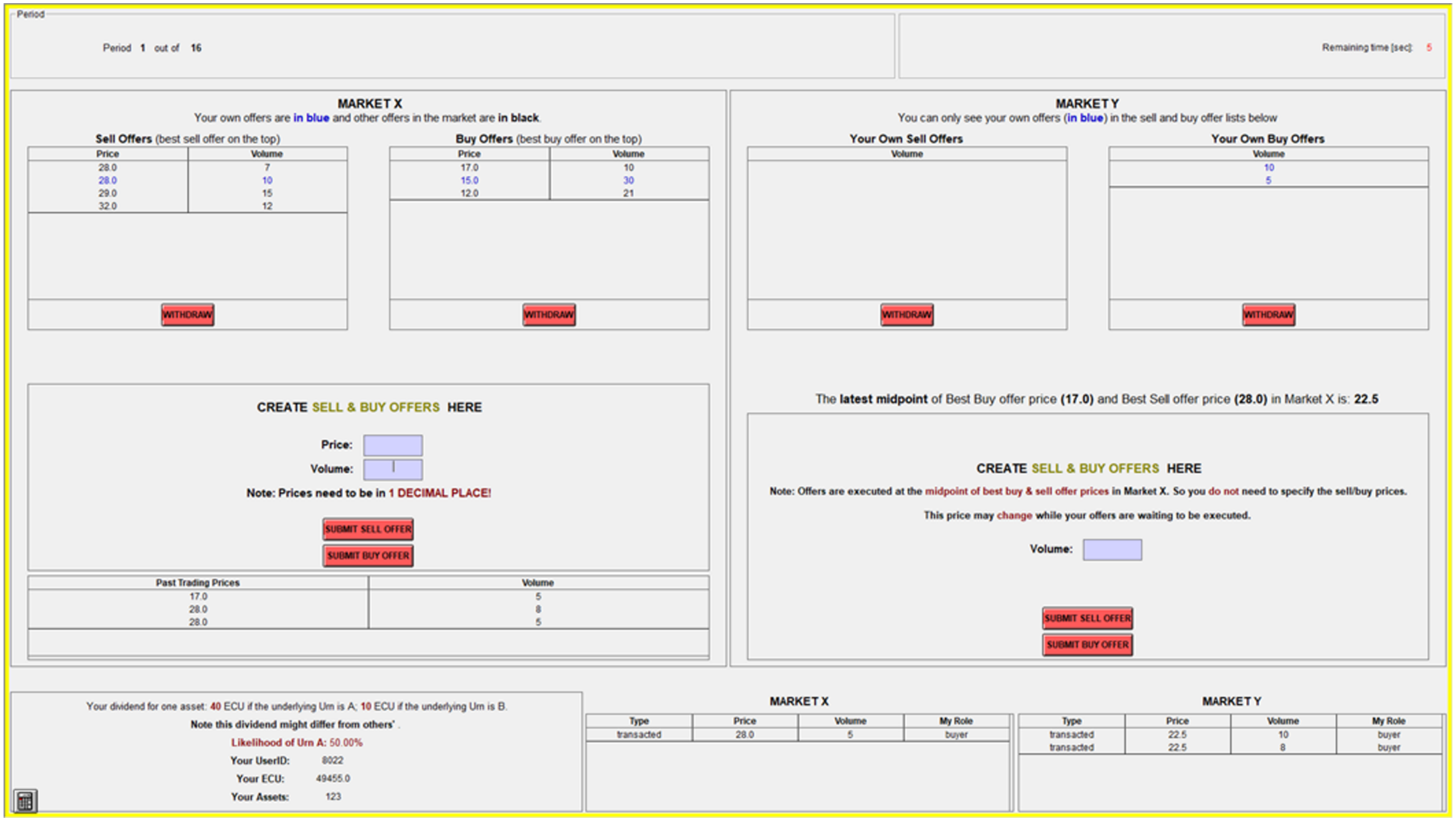


Figure 1. Trading Interface in markets under *Dark* trading institution.

common. For example, Nimalendran and Ray (2014) find that about 57% of transactions are within .01% of the price around the mid-point of National Best Bid and Offer (NBBO).[21] This mid-point 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.

In the other dimension, we vary the number of subjects provided with information regarding the underlying state of nature. In all sessions, however, the first six periods constituted markets with no informed traders. In this environment, the rational expectations equilibrium (REE) price equals the prior expected value of the asset, i.e., 25 ECUs and type-I traders are predicted to hold the assets. With no private information to be reflected in asset prices, markets with no information provide the simplest of settings to analyze the effects of adding a dark pool.

In periods 7-16, three out of the 12 traders in a market, one from each type, received perfect information about the selected urn in the *Low* sessions. In the *High* sessions, nine traders, with three out of four from each type, were perfectly informed in these last ten periods. Markets with a high proportion of informed traders could be interpreted as stocks with investors having wider access to information, possibly due to better media coverage, densely connected investor networks, etc., leading to faster information diffusion. In contrast, in the *Low* markets, information is concentrated in the hands of a few investors. This allows us to study whether the effects of dark trading are different in markets with varying degrees of access to fundamental information.[22]

We provided informed traders with perfect information for two reasons. First, we wanted to keep the information environment as simple as possible for the subjects as the trading environment is arguably more complex with the introduction of an additional dark market relative to a single lit exchange usually employed in experimental asset markets. Imperfect signals would have resulted in heterogeneous belief updating for informed traders and introduced more noise into the system. Future studies could implement markets with imperfect signals within the dark market setup. Second, the REE prediction remains the same across all treatments: in state A (B), price equals 40 (17.5) with type-I (type-III) investors holding the assets. This allows for easier comparison across treatments with respect to price and allocative efficiency.

[21] However, we note that there are alternative pricing rules. For example, 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.

[22] A subject knew whether or not she was informed about the selected urn in a period and that other subjects could be either informed or uninformed. However, participants did not know the exact composition of informed and uninformed traders in a period.

II. Results

A. Crowding-Out of Liquidity

We start by analyzing the implications of adding a dark pool on trading activity and liquidity in our experimental markets. Table III reports the results of an OLS regression of total transaction volume in the market and the transaction volume in the lit exchange. The regressors include the variable *Dark* (which takes a value of 1 if the market includes a dark pool in addition to the lit exchange and 0 otherwise), *State* (which takes a value of 1 if the underlying state of nature is A and 0 otherwise), and the period number. For periods 7-16, the regressions further consist of the variable *High* (which takes a value of 1 if the number of informed traders in the market is high and 0 otherwise) and the interaction term *Dark* $\times$ *High* indicating *Lit Only-Low* as the baseline treatment. The standard errors are clustered at the session level.[23]

The regression results show that dark trading does not affect the aggregate transaction volume in the market in periods 1-6 when there are no informed traders in the market and also in periods 7-16 when the proportion of informed investors is low. Using a post-estimation linear combination test, the coefficient of *Dark* + *Dark* $\times$ *High*, which captures the impact of adding a dark pool on total volume when there is a high fraction of informed investors, is 91.15 (p-value: 0.34). Therefore, market participation remains unaltered with dark trading.

We also observe that the transaction volume at the lit exchange goes down significantly with the availability of the dark market as an additional venue for trading: by 340.80 (significant at 1% level) in markets with no informed traders, 264.30 (significant at 5% level) in markets with a low proportion of informed investors and by 338.11 (significant at 5% level) in markets with a high proportion of informed traders. As the aggregate trade volume remains the same while the trade volume in the lit exchange goes down with the introduction of the additional dark venue for trading, we conclude that substitution or crowding out of transactions from the lit exchange is an immediate consequence of dark trading.

[23] The regressions also control for the average values of the demographic variables in the market. 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 Transaction Volume and Liquidity Measures

This table presents the results of OLS regression analysis of the total transaction volume in the market, transaction volume in the lit exchange, effective spread, and depth in a period. Effective spread is defined as the volume-weighted average of the best bid-ask spread evaluated at each transaction in a period, and depth is defined as the sum of all orders up to 10 points from the closing best bid and best ask prices in a period. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the market includes a dark pool in addition to the lit exchange and 0 otherwise. *High* takes a value of 1 (0) if the number of informed traders in the market is high (low). *State* takes a value of 1 if the underlying state of nature is A and 0 if the state is B. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Periods 1-6				Periods 7-16			
	Total Volume	Volume in Lit Exchange	Effective Spread	Depth	Total Volume	Volume in Lit Exchange	Effective Spread	Depth
Dark	3.61	-340.80***	0.32	-48.12	78.33	-264.30**	-0.32**	-1000.00
	(90.82)	(86.93)	(0.20)	(165.70)	(110.40)	(111.80)	(0.13)	(591.40)
High					-72.04	-15.94	0.42	-1086.00
					(107.60)	(117.40)	(0.34)	(639.00)
Dark × *High*					12.82	-73.78	-0.09	1677.00
					(147.50)	(169.80)	(0.46)	(1106.00)
State	38.06	20.03	0.07	-59.58	186.80***	131.10***	0.62**	-525.30**
	(28.34)	(26.54)	(0.11)	(80.40)	(49.11)	(33.25)	(0.23)	(241.10)
Period	28.47*	20.80	-0.15***	18.73	0.53	5.18	-0.03	25.74
	(14.80)	(14.96)	(0.05)	(22.16)	(8.19)	(6.17)	(0.03)	(35.69)
Constant	2333.00**	1083.00	3.72	4375.00**	2986.00***	2048.00**	-3997.00**	10850.00**
	(961.30)	(760.30)	(2.77)	(1941.00)	(908.80)	(740.70)	(1.55)	(4581.00)
No. of obs.	96	96	96	96	160	160	160	160
No. of clusters	16	16	16	16	16	16	16	16
R^2	0.22	0.42	0.34	0.22	0.48	0.48	0.24	0.18

Table III further presents OLS regression results using the following two liquidity measures: effective spread, defined as the volume-weighted average of the best bid-ask spread evaluated at each transaction in a period, and depth, defined as the sum of all orders up to 10 points from the closing best bid and best ask prices in each period.[24] The results suggest dark trading does not affect either the effective bid-ask spread or depth in periods 1-6, although it lowers spread while the depth remains unaffected in markets with a low proportion of informed traders. Post-estimation linear combination tests further show no significant effect of dark trading on liquidity measures when the proportion of informed investors is high.[25] Taken together, we conclude that dark trading has no consistent impact on these liquidity measures.

RESULT 1: *Dark trading does not affect the total transaction volume and liquidity measures, although there is a decline in the volume of transactions at the lit exchange owing to the crowding out effect brought about by dark trading.*

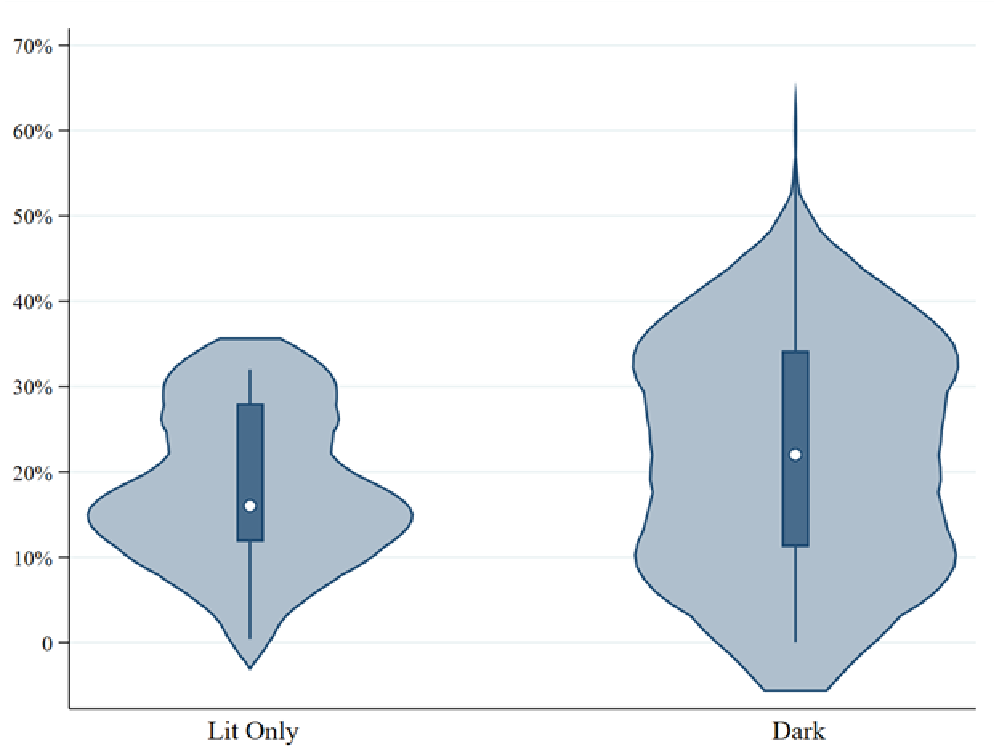
B. Informational Efficiency of Prices

We now explore the effect of adding a dark pool alongside a lit exchange on the ability of prices to reflect the information available to traders. We define the price efficiency measure as the absolute difference between the average (median) transaction price in the lit exchange and the REE price divided by the REE price in a period. In periods 1-6, prices closer to the prior expected value of the asset are more efficient. In contrast, in periods 7-16, given that there are investors with perfect information in all markets, the closer the prices are to the fully revealing REE price, the more efficient they are. Lower values of the price efficiency measure imply more efficient markets. Figure 2 graphs the violin plots of the price efficiency measure for the different types of markets in our experiment. Table IV further shows the results of an OLS regression of the price efficiency measure with the same set of regressors as in Table III.

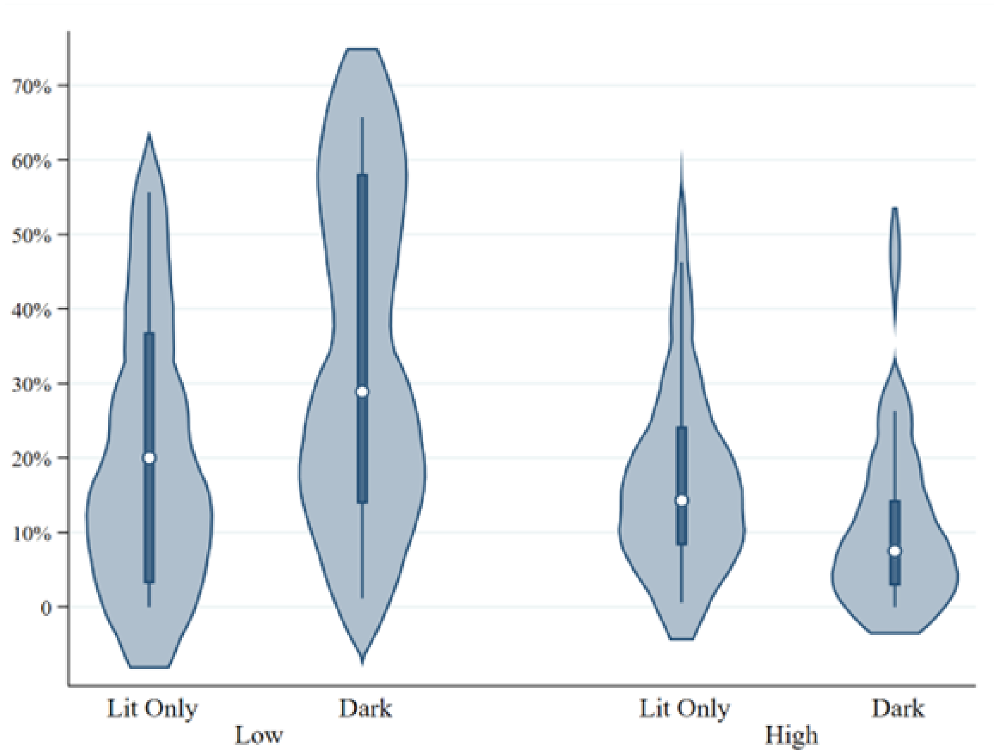
Figure 2 suggests that prices are less efficient with dark trading in periods 1-6. Table IV, however, shows that this decline in efficiency is not significant. Concurrently, it can be observed from the violin plot that while most of the observations are concentrated close to the median in markets with a single lit exchange, there is no distinct peak for the distribution of the price efficiency measure when dark pools are introduced. Therefore, although dark

[24] The definition of depth follows Bloomfield, O'Hara, and Saar (2015).

[25] The coefficient of $Dark + Dark \times High$ equals -0.41 (p-value: 0.39) for spread and 676.88 (p-value: 0.41) for depth.



(a) Periods 1-6



(b) Periods 7-16

Figure 2. Violin Plot of Price Efficiency Measure.

Table IV

OLS Regression of Price Efficiency Measure

This table presents the results of the OLS regression analysis of the price efficiency measure, defined as the absolute difference between the median transaction price in the lit market and the rational expectations equilibrium (REE) price divided by the REE price in a period. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the market includes a dark pool in addition to the lit exchange and 0 otherwise. *High* takes a value of 1 (0) if the number of informed traders in the market is high (low). *State* takes a value of 1 if the underlying state of nature is A and 0 if the state is B. Some specifications use demographic variables as additional regressors. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Periods 1-6				Periods 7-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dark	0.04	0.04	0.07	0.07	0.12**	0.12**	0.06***	0.06***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)
High					-0.05	-0.05	-0.14***	-0.14***
					(0.03)	(0.03)	(0.02)	(0.03)
Dark × *High*					-0.18**	-0.18**	-0.08**	-0.08**
					(0.06)	(0.06)	(0.03)	(0.03)
State		0.00		0.00		0.15**		0.15**
		(0.01)		(0.01)		(0.06)		(0.06)
Period	0.00	0.00	0.00	0.00	-0.01**	-0.01**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Constant	0.17***	0.17***	-0.76	-0.77	0.37***	0.30***	0.42	0.35
	(0.04)	(0.04)	(0.61)	(0.61)	(0.06)	(0.05)	(0.30)	(0.28)
No. of obs.	96	96	96	96	160	160	160	160
No. of clusters	16	16	16	16	16	16	16	16
R^2	0.04	0.04	0.16	0.16	0.23	0.39	0.30	0.46
Control variables	No	No	Yes	Yes	No	No	Yes	Yes

trading does not significantly affect the efficiency measure's average value, the spread is uniform over a larger range of the data set.

In periods 7-16, with the availability of a dark venue for trading, the violin plots suggest worsening price efficiency in *Low* markets. This is confirmed by the positive and significant coefficient of *Dark* in Table IV. From a casual inspection, Figure 2 suggests that in *High* markets, adding a dark venue for trading improves price efficiency, although a post-estimation linear combination test shows no significant effect of dark trading on price efficiency.[26] Therefore, whether dark markets affect price efficiency depends on how information is distributed among investors.

RESULT 2: *Dark trading causes a decline in price efficiency, but only when a few investors have access to information regarding fundamentals.*

Conditional on the market institution, one would expect that a larger fraction of the information would be impounded into asset prices in markets with more investors having access to fundamental information. Using the median transaction price in a period, the price efficiency improves by around 20% in markets with a single lit exchange when the proportion of informed investors goes up. The improvement in price efficiency in markets with both lit and dark venues is even greater as the average measure is lower by almost 67% with the increase in the number of informed traders. This is confirmed by the significant negative coefficients on *High* (as shown in Table IV) and $High + Dark \times High$ (obtained from post-estimation linear combination test), with a larger effect for the latter.[27] Therefore, our results demonstrate that there is more to gain by allowing investors wider access to fundamental information when dark trading is allowed.

RESULT 3: *The improvement in price efficiency owing to an increase in the proportion of informed investors is larger in the presence of dark trading.*

C. Allocations and Welfare

Our experimental design models trading as a non-zero-sum activity. This means, in

[26]The coefficient of $Dark + Dark \times High$, capturing the effect of dark pool on price efficiency in *High* markets, equals -0.06 (p-value: 0.07) for specifications (5) and (6), and -0.01 (p-value: 0.70) for specifications (7) and (8).

[27]The coefficient of $High + Dark \times High$, capturing the impact of a larger fraction of informed investors on price efficiency in markets with parallel trading venues, equals -0.23 (p-value < 0.01) for specifications (5) and (6), and -0.22 (p-value < 0.01) for specifications (7) and (8).

addition to prices, we can compare the performance of the two trading institutions with respect to allocations relative to the predictions of the REE. We consider the following two measures of allocative efficiency.

- Measure 1- Ratio of the sum of assets held by type-I (type-III) traders in state A (B) and equilibrium allocation predicted by the REE in a period. The equilibrium predicts that type-I (type-III) traders hold all the assets in state A (B), so the denominator is always 1200 in this ratio.

- Measure 2- Ratio of total dividends of all traders in a market in a period net of total dividends under autarky (no trade) and total dividends under the REE net of total dividends under autarky[28]:

$$\frac{\sum_{n=1}^{12} D_n - \sum_{n=1}^{12} D_n^{Autarky}}{\sum_{n=1}^{12} D_n^{REE} - \sum_{n=1}^{12} D_n^{Autarky}}$$

  This measure is zero if no trading takes place and defines the efficiency of the REE allocation to be 100 percent.

Using data from periods 7-16, Table V presents the values of the two measures of allocative efficiency as well as the percentage of assets held by each investor type in all four treatments, subdivided by the dividend state. A closer look at this data shows that the allocations in state A are similar in markets with a single lit exchange and the ones with both lit and dark venues. Therefore, when there is enough variation in the heterogeneous valuations among investor types, dark trading is not causing any significant change in the eventual allocations. Importantly, the decline in price efficiency with the introduction of dark pool in *Low* markets is not associated with a corresponding fall in allocative efficiency when valuations are fairly dispersed.

Table V further shows that in the *Low* markets, both *Lit Only* and *Dark* trading institutions result in very low efficiency, with about one-fourth of the assets held by type-III investors who value the asset most in state B. However, the allocations among investor types are markedly different with and without dark trading in state B and when the proportion of informed investors is high. Thus, when there is less variation in heterogeneous valuations, markets with hidden liquidity continue to negatively impact welfare by creating friction in

[28]This measure follows that of Plott and Sunder (1982) and Camerer and Weigelt (1991).

Table V

Allocative Efficiency and Allocations

This table presents the values of the two measures of allocative efficiency and the percentage of assets held by each investor type in every treatment, subdivided by the dividend state. Data from periods 7-16 are used.

	State A					State B			
	Lit Only -Low	*Dark -Low*	*Lit Only -High*	*Dark -High*		*Lit Only -Low*	*Dark -Low*	*Lit Only -High*	*Dark -High*
					Allocative Efficiency				
Measure 1	59.71%	58.06%	73.28%	71.67%		26.70%	23.97%	65.75%	44.95%
Measure 2	60.15%	55.17%	70.42%	68.07%		2.96%	-2.99%	56.42%	21.37%
					Allocation				
Type-I	60%	58%	73%	72%		28%	31%	12%	25%
Type-II	35%	34%	21%	22%		45%	45%	22%	30%
Type-III	5%	8%	6%	7%		27%	24%	66%	45%

the movement of the asset to the group having the highest gains from exchange even though the informational efficiency of prices is not reduced.

Next, we perform a regression with the measure of allocation efficiency as the dependent variable and the same set of regressors as in Table III. Table VI reports the results, with specifications (1)-(4) using data from periods 1-6 and the remaining specifications using data from periods 7-16. Dark trading does not cause any decline in allocative efficiency in markets with all uninformed traders. Furthermore, Table VI reveals that adding a dark venue for trading alongside a lit exchange does not affect allocative efficiency when the number of informed investors is low, regardless of the measure used. Post-estimation linear combination tests, however, indicate a significant negative effect of dark markets on allocative efficiency when a larger fraction of investors has access to information.[29] Finally, in markets with informed investors, allocative efficiency is significantly higher when the dividend state is A.

RESULT 3: *Dark trading causes a decline in allocative efficiency when the proportion of*

[29]The coefficient of $Dark + Dark \times High$, capturing the effect of dark pool on allocative efficiency in *High* markets, equals -0.22 (p-value: 0.04) for specifications (5) and (6), and -0.25 (p-value: 0.11) for specifications (7) and (8).

Table VI

OLS Regression of Measures of Allocative Efficiency

This table presents the results of the OLS regression analysis of the measures of allocative efficiency. Two measures are used, with measure 1 being defined as the ratio of the sum of assets held by type-I (type-III) traders in state A (B) and equilibrium allocation predicted by the REE in a period. Measure 2 is defined as the ratio of total dividends in data net of total dividends under autarky and total dividends under REE net of total dividends under autarky in a period. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the market includes a dark pool in addition to the lit exchange and 0 otherwise. *High* takes a value of 1 (0) if the number of informed traders in the market is high (low). *State* takes a value of 1 if the underlying state of nature is A and 0 if the state is B. All specifications use demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Periods 1-6				Periods 7-16			
	Measure 1		Measure 2		Measure 1		Measure 2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dark	-0.08	-0.08	0.22	0.22	0.04	0.04	0.05	0.05
	(0.05)	(0.05)	(0.20)	(0.20)	(0.09)	(0.09)	(0.11)	(0.11)
High					0.38***	0.38***	0.46***	0.46***
					(0.10)	(0.10)	(0.14)	(0.14)
Dark × *High*					-0.26	-0.26	-0.30	-0.30
					(0.17)	(0.17)	(0.22)	(0.22)
State		0.00		-1.14***		0.25***		0.44***
		(0.02)		(0.18)		(0.05)		(0.10)
Period	0.01	0.01	-0.07	-0.07	0.01	0.01	0.02	0.01
	(0.01)	(0.01)	(0.07)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	1.51**	1.51**	-4.56**	-3.97*	1.05*	0.93*	0.56	0.37
	(0.62)	(0.63)	(2.09)	(2.11)	(0.55)	(0.52)	(0.60)	(0.58)
No. of observations	96	96	96	96	160	160	160	160
No. of clusters	16	16	16	16	16	16	16	16
R^2	0.30	0.30	0.06	0.46	0.27	0.52	0.19	0.51

informed investors is high and there is less variation in heterogeneous valuations.

Conditional on the market institution, how does increasing the proportion of informed investors affect allocative efficiency? Table VI shows that in the presence of a single lit exchange, giving more investors access to fundamental information significantly improves allocative efficiency. Such a positive association, however, is not observed in markets with both lit and dark venues.[30] The presence of dark trading is preventing the improvement in allocative efficiency when moving from a market environment with only a few informed investors to one where information is more dispersed.

RESULT 4: *Increasing the proportion of investors having access to fundamental information improves allocative efficiency, but only in the absence of dark trading.*

D. Trader's Earnings: Informed vs. Uninformed Traders

We calculate the earnings of trader i in period t as $\Delta ECU_{it} + d_{it}\Delta Assets_{it}$, where ΔECU_{it} measures the difference between cash endowment at the end (post-trade) and the start (pre-trade) of a period, d_{it} is the dividend per asset, and $\Delta Assets_{it}$ denotes the stock balance at the end of a period minus the initial stock endowment. Thus, earnings are defined as the difference between the value of a trader's portfolio at the end and at the start of a period. Table VII presents the results of an OLS regression of trader's earnings with *Dark*, *Informed* (which takes a value of 1 if the subject is an informed trader and 0 otherwise), *Dark* × *Informed*, and the period number as regressors.

In markets with a low proportion of informed investors, traders who are informed obtain significantly higher earnings than uninformed traders. In markets with a single lit exchange, informed investors outperform uninformed ones by 993.90 ECUs (significant at 5% level) after controlling for demographic variables. With a dark venue added, informed traders get 1039.76 ECUs more than uninformed traders in specification (1) (significant at 5%) and 932.14 ECUs higher in specification (2) (significant at 5%).

When the markets have a higher proportion of informed investors, one would expect that the amount by which informed traders' earnings exceed that of the uninformed traders would get reduced due to competition among informed traders and significant information leakage. Indeed, as shown in Table VII, in *Lit Only-High* treatment, informed traders get

[30]The coefficient of *High* + *Dark* × *High*, capturing the impact of a larger fraction of informed investors on allocative efficiency in markets with parallel trading venues, equals 0.13 (p-value: 0.17) for specifications (5) and (6), and 0.17 (p-value: 0.12) for specifications (7) and (8).

Table VII

OLS Regression of Individual Trader's Earnings

This table presents the results of the OLS regression analysis of the individual trader's earnings in a period, defined as the difference between the value of a trader's portfolio at the end and at the start of a period. Standard errors (clustered at the level of independent session) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark market in addition to the lit exchange and 0 otherwise. *Informed* takes a value of 1 if the subject is an informed trader and 0 otherwise. Specifications (1)-(2) use data from *Lit Only-Low* and *Dark-Low* treatments only, while specifications (3)-(4) use data from *Lit Only-High* and *Dark-High* treatments only. Specifications (2) and (4) use demographic variables as additional regressors. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Low		*High*	
	(1)	(2)	(3)	(4)
Dark	-35.00	-21.62	-37.86	-81.20
	(76.80)	(99.78)	(135.70)	(189.10)
Informed	1064.00***	993.90**	473.80***	453.90***
	(292.20)	(299.80)	(66.17)	(68.89)
Dark × *Informed*	-24.09	-61.72	-46.97	-0.71
	(500.20)	(422.50)	(145.50)	(211.80)
Period	-15.69	-15.69	51.38***	51.38***
	(17.54)	(17.58)	(13.11)	(13.14)
Constant	311.00	55.36	-463.40**	192.50
	(217.60)	(768.40)	(169.20)	(651.00)
No. of observations	960	960	960	960
No. of clusters	8	8	8	8
R^2	0.09	0.12	0.07	0.08
Control variables	No	Yes	No	Yes

453.90 ECUs more than uninformed investors after controlling for the demographic variables, which is much smaller when compared to the difference in *Lit Only-Low* treatment. With a dark venue added, informed traders get 426.84 ECUs more than uninformed traders in specification (3) (significant at 5%) and 453.14 ECUs higher in specification (4) (significant at 5%).

Having established that, on average, informed traders outperform uninformed traders, next, we investigate whether the earnings gap increases with dark trading. Table VIII reports the results of an OLS regression of the earnings gap in a period, defined as the difference between the average earnings among informed and uninformed traders in a period. The regressors are the same as the ones in Table III. The coefficients of *Dark* (observed from Table VIII) and *Dark* + *Dark* × *High* (obtained from post-estimation tests) are insignificant, indicating that the earnings gap remains unchanged with the introduction of a dark venue for trading.[31]

RESULT 6: *The earnings gap between informed and uninformed traders does not widen with dark trading.*

E. Order Submissions: Informed vs. Uninformed Traders

We conduct OLS regressions with different types of individual order submissions as the dependent variable. The limit order, market order, and dark order denote the number of limit order submissions in the lit exchange, the number of market orders, and the number of orders submitted in the dark market by a subject in a period, respectively. The submission rate is defined as the number of shares in limit orders divided by the total number of shares submitted in both limit and marketable orders by a subject in a period (Bloomfield, O'Hara, and Saar (2015)). The taking rate is defined as the number of shares a trader executes using marketable orders divided by the total number of shares traded by a subject in a period. The dark submission ratio is defined as the dark submission volume over the total submission volume of one subject in a period. The regressors include the variable *Dark*, *Informed*, *Dark* × *Informed*, *Period*, and demographic variables. Tables IX and X report the results for the *Low* and *High* treatments, respectively.[32]

In markets with only a lit exchange, informed traders submit a larger number of limit and

[31]The coefficient of *Dark* + *Dark* × *High* equals -46.97 (p-value: 0.75), -348.02 (p-value: 0.49), 88.98 (p-value: 0.83), -718.18 (p-value: 0.46), -243.72 (p-value: 0.12), -184.80 (p-value: 0.54), 13.84 (p-value: 0.95), 150.59 (p-value: 0.60) for specifications (1)-(8), respectively.

[32]The regression analysis is performed after removing the data points identified as outliers.

Table VIII

OLS Regression of Earnings Gap

This table presents the results of the OLS regression analysis of the earnings gap in a period, defined as the difference between the average earnings among informed and uninformed traders. Standard errors (clustered at the level of independent session) are in parentheses. Specifications (1) and (2) use data from all types of traders, while specifications (3)-(4), (5)-(6), and (7)-(8) use data from traders of type I, II, and III, respectively. *Dark* takes a value of 1 if the treatment includes a dark market in addition to the lit exchange and 0 otherwise. *High* takes a value of 1 (0) if the number of informed traders in the market is high (low). *State* takes a value of 1 if the underlying state of nature is A and 0 if the state is B. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	All Types		Type I		Type II		Type III	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dark	-24.09	-126.20	60.56	1176.00	-247.30	-39.34	114.40	146.60
	(490.00)	(497.30)	(1560.00)	(1465.00)	(467.50)	(451.90)	(88.92)	(122.20)
High	-590.00*	-715.90	-1526.00	-852.90	-313.90*	-469.50	69.89	7.91
	(293.50)	(547.50)	(930.80)	(1161.00)	(178.20)	(318.90)	(143.20)	(179.70)
Dark × *High*	-22.88	-221.90	28.42	-1894.00	3.53	-145.50	-100.60	3.95
	(510.40)	(869.20)	(1611.00)	(2049.00)	(490.40)	(512.70)	(236.10)	(300.80)
State	744.40***	744.40***	2079.00***	2079.00**	230.90	230.90	-77.31	-77.31
	(248.40)	(251.70)	(699.00)	(708.30)	(286.10)	(289.90)	(95.71)	(96.98)
Period	-72.86***	-72.86***	-189.50***	-189.50**	-31.79	-31.79	2.68	2.68
	(20.32)	(20.59)	(64.02)	(64.87)	(26.44)	(26.79)	(9.89)	(10.02)
Constant	1602.00***	820.30	3946.00***	12160.00	862.60**	-2732.00	-1.80	1058.00
	(423.10)	(3708.00)	(1314.00)	(10636.00)	(369.50)	(2136.00)	(179.60)	(1443.00)
No. of observations	160	160	160	160	160	160	160	160
No. of clusters	16	16	16	16	16	16	16	16
R^2	0.28	0.33	0.25	0.31	0.07	0.15	0.02	0.06
Control variables	No	Yes	No	Yes	No	Yes	No	Yes

Table IX

OLS Regression of Individual Order Submissions: ***Low***

This table presents the results of the OLS regression analysis of individual order submissions in the *Lit Only-Low* and *Dark-Low* treatments. The limit order, market order, and dark order denote the number of limit order submissions in the lit exchange, the number of market orders, and the number of dark order submissions by a subject in a period, respectively. The submission rate is defined as the number of shares in limit orders divided by the total number of shares submitted in both limit and marketable orders by a subject in a period. The taking rate is defined as the number of shares a trader executes using marketable orders divided by the total number of shares traded by a subject in a period. The dark submission ratio is defined as the dark submission volume over the total submission volume of one subject in a period. Standard errors (clustered at the level of an individual subject) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark market in addition to the lit exchange and 0 otherwise. *Informed* takes a value of 1 if the subject is an informed trader and 0 otherwise. All specifications use demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Limit Order	Market Order	Dark Order	Submission Rate	Taking Rate	Dark Submission Ratio
Dark	-14.62	-20.10		0.04	0.03	
	(39.81)	(14.24)		(0.04)	(0.06)	
Informed	209.90**	42.74**	14.59	-0.06	0.04	0.05
	(87.02)	(20.19)	(22.03)	(0.06)	(0.08)	(0.07)
Dark × *Informed*	-213.40**	0.08		0.01	-0.03	
	(94.71)	(33.66)		(0.08)	(0.13)	
Period	3.97	-0.79	-0.17	0.00	0.01	-0.01
	(3.38)	(0.91)	(1.41)	(0.00)	(0.00)	(0.00)
Constant	465.60**	80.98	226.30**	0.74***	0.68**	0.61*
	(185.00)	(60.20)	(96.19)	(0.20)	(0.31)	(0.33)
No. of observations	894	960	480	894	821	479
No. of clusters	96	96	48	96	96	48
R^2	0.08	0.06	0.07	0.02	0.02	0.03
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table X

OLS Regression of Individual Order Submissions: ***High***

This table presents the results of the OLS regression analysis of individual order submissions in the *Lit Only-High* and *Dark-High* treatments. The limit order, market order, and dark order denote the number of limit order submissions in the lit exchange, the number of market orders, and the number of dark order submissions by a subject in a period, respectively. The submission rate is defined as the number of shares in limit orders divided by the total number of shares submitted in both limit and marketable orders by a subject in a period. The taking rate is defined as the number of shares a trader executes using marketable orders divided by the total number of shares traded by a subject in a period. The dark submission ratio is defined as the dark submission volume over the total submission volume of one subject in a period. Standard errors (clustered at the level of an individual subject) are in parentheses. *Dark* takes a value of 1 if the treatment includes a dark market in addition to the lit exchange and 0 otherwise. *Informed* takes a value of 1 if the subject is an informed trader and 0 otherwise. All specifications use demographic variables as additional regressors. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Limit Order	Market Order	Dark Order	Submission Rate	Taking Rate	Dark Submission Ratio
Dark	-2.47	-15.01		0.11*	-0.13	
	(45.12)	(10.26)		(0.06)	(0.08)	
Informed	123.70***	23.07**	41.73**	0.01	0.05	0.10*
	(45.47)	(10.71)	(17.06)	(0.06)	(0.08)	(0.06)
Dark × *Informed*	-104.60	-0.23		-0.11	0.09	
	(70.02)	(13.70)		(0.07)	(0.10)	
Period	8.63	1.73*	-0.36	-0.00	-0.00	-0.01**
	(6.40)	(0.91)	(1.66)	(0.00)	(0.00)	(0.00)
Constant	225.60	62.25	192.70	0.61***	0.74**	0.47
	(211.40)	(41.71)	(124.60)	(0.21)	(0.32)	(0.30)
No. of observations	910	960	480	910	868	471
No. of clusters	96	96	48	96	96	48
R^2	0.04	0.06	0.04	0.04	0.03	0.09
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

market orders than uninformed ones. Post-estimation linear combination tests demonstrate that, with the addition of a dark venue, informed investors continue to submit more market orders than uninformed traders, with the coefficient of *Informed* + *Dark* $\times$ *Informed* being 42.82 (p-value < 0.1) and 22.84 (p-value < 0.05) in *Dark-Low* and *Dark-High* treatments, respectively. At the same time, there is no difference in the limit order submissions of informed and uninformed traders in the presence of a dark market, as the coefficient of *Informed* + *Dark* $\times$ *Informed* is -3.50 (p-value$= 0.94$) and 19.14 (p-value$= 0.73$) in *Dark-Low* and *Dark-High* treatments, respectively.

Tables IX and X further show that informed traders submit more dark orders than the uninformed, especially in the *Dark-High* treatment. Submissions in the dark venue do not contribute to price discovery and do not result in any information leakage to uninformed traders. Therefore, for informed investors, a dark venue is arguably more appealing. The limit order submissions of uninformed traders remain the same across both market institutions. However, the coefficient of *Dark* + *Dark* $\times$ *Informed* is -228.03 (p-value < 0.05) and -107.03 (p-value < 0.05) in *Low* and *High* markets, respectively. This implies that limit order submissions go down for informed investors when a dark pool is added. Therefore, viewing dark submissions as substitutes for limit order submissions, informed traders are relatively more attracted to the dark pool when compared to uninformed traders.

Additionally, when there is competition among informed traders, as in the treatments with a higher proportion of informed investors, the OLS regressions of limit order submission rate and taking rate provide observations regarding the immediacy demand of executions. Using a linear combination test after the estimation of the OLS regression mentioned in Table X, we observe that the coefficient of *Informed* + *Dark* $\times$ *Informed* is -0.10 (p-value < 0.01) for limit order submission rate and 0.15 (p-value < 0.01) for taking rate. Therefore, in the presence of a dark market and competition among informed traders, the ones who are informed have a lower rate of limit order submissions and a higher taking rate when compared to uninformed traders.

RESULT 7: *Informed traders are relatively more attracted to the dark market than uninformed.*

Next, we analyze the determinants of dark order submissions by an investor within a trading period and compare them across informed and uninformed traders. We first divide the 180 seconds in a period into six intervals of 30 seconds each and perform an OLS regression of the individual dark submission ratio in an interval t ($DSR_{i,t}$), which is defined as the dark submission volume over the total submission volume of a subject in one interval during a period. The regressors include *High*, $DSR_{i,t-1}$, $Spread_{t-1}$, $FR^{Lit}_{i,t-1}$, $FR^{Dark}_{i,t-1}$, and the interaction terms. $Spread_{t-1}$ is the volume-weighted average of the effective best bid-ask spread during the previous interval. $FR^{Lit}_{i,t-1}$ ($FR^{Dark}_{i,t-1}$) denotes the individual filling rate in the lit exchange (dark market), which is defined as the number of executed limit orders over the number of submitted limit orders for a trader in the lit exchange (dark market) during the previous interval.[33] Table XI reports the results separately for the informed and uninformed traders.

We find that, within a period, for both uninformed and informed investors, the individual dark submission ratio in an interval is decreasing in the previous interval's filling rate in the lit exchange and increasing in the previous interval's filling rate in the dark market.[34] Informed traders are more responsive to the current rate of execution of their limit order submissions in the lit exchange and their dark order submissions. In general, this suggests that informed investors have lower patience and demand higher immediacy of execution of their orders when compared to uninformed traders.

RESULT 8: *Informed traders are more responsive to the execution rate of their order submissions than uninformed traders.*

III. Discussion

We start this section by commenting on the informational efficiency of asset prices in our experimental markets. Early studies reported that prices adjust immediately to near rational-expectations prices, and the profits of informed traders are virtually indistinguishable from uninformed traders (Plott and Sunder (1982)). However, recent research finds that in markets with private information held by investors, prices are not strong-form informationally efficient (Halim, Riyanto, and Roy (2019)) and less than 50% of the private information is incorporated in prices (Page and Siemroth (2021)). Corgnet et al. (2022)

[33] We also control for the interval number, period, and demographic variables. The regression for the informed traders further includes *State* as an additional regressor.

[34] In the *Low* markets, as can be observed directly from Table XI, the effects of individual filling rates in the lit exchange and the dark market on individual DSR are highly significant. Post-estimation tests show that, for *High* markets, the effect of $FR^{Lit}_{i,t-1}$ is -0.10 (significant only at 10% level) for the uninformed and -0.03 (p-value > 0.1) for the informed traders. In the *High* markets, the effect of $FR^{Dark}_{i,t-1}$ is 0.07 (p-value > 0.1) for the uninformed and 0.14 (significant at 1%) for the informed investors. Thus, while the signs are consistent, the values are less significant in the *High* markets.

Table XI

OLS Regression of Individual Dark Submission Ratio

This table presents the results of the OLS regression of the individual dark submission ratio of an informed and uninformed trader in an interval t ($DSR_{i,t}$) where the 180 seconds in a period are divided into six intervals of 30 seconds each. Standard errors (clustered at the individual trader level) are in parentheses. $DSR_{i,t-1}$ is a trader's individual dark submission ratio in the previous interval. $Spread_{t-1}$ is the volume-weighted average of the effective best bid-ask spread during the previous interval. $FR^{Lit}_{i,t-1}$ ($FR^{Dark}_{i,t-1}$) denotes the individual filling rate in the lit exchange (dark market), which is defined as the number of executed limit orders over the number of submitted limit orders for a trader in the lit exchange (dark market) during the previous interval. The regressions control for the interval number, period, and demographic variables. Furthermore, for the informed traders, *State* is also included as an additional regressor. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Informed Trader	Uninformed Trader
High	-0.04	-0.15
	(0.09)	(0.19)
$DSR_{i,t-1}$	-0.09	-0.02
	(0.16)	(0.24)
$Spread_{t-1}$	0.01	-0.05*
	(0.03)	(0.03)
$FR^{Lit}_{i,t-1}$	-0.16***	-0.13**
	(0.05)	(0.06)
$FR^{Dark}_{i,t-1}$	0.30***	0.19***
	(0.03)	(0.04)
$High \times DSR_{i,t-1}$	0.27	0.08
	(0.20)	(0.36)
$High \times Spread_{t-1}$	-0.01	0.06**
	(0.03)	(0.03)
$High \times FR^{Lit}_{i,t-1}$	0.13*	0.03
	(0.07)	(0.07)
$High \times FR^{Dark}_{i,t-1}$	-0.16***	-0.12
	(0.05)	(0.12)
Constant	0.59*	-0.24
	(0.31)	(0.30)
No. of observations	510	296
No. of clusters	41	37
R^2	0.11	0.13

further report that information aggregation in asset markets is fragile and should only be expected in limited circumstances.

In markets where a quarter of investors are perfectly informed, the average ratio of price deviation equals 0.22 with a single lit exchange and 0.34 in the presence of dark trading.[35] With three-fourths of the market being informed, this ratio drops to 0.18 and 0.11 without and with the addition of a dark venue for trading, respectively. Additionally, informed traders are able to outperform uninformed ones, even when an overwhelming majority of investors are endowed with perfect information. Thus, consistent with recent studies, we observe that not all private information is incorporated in prices, and hence, markets are informationally inefficient.

The fundamental concern about dark trading is that it results in crowding out of liquidity away from the lit exchange, and this unobservable liquidity can potentially be detrimental to the functioning of financial markets. While the existing theoretical and empirical studies are concerned primarily with whether dark markets harm price discovery at the exchange, given our experimental design, we are able to comment beyond the effect on prices. We also explore the consequences of adding a dark venue for trading alongside a lit exchange on the allocation of assets across investors having heterogeneous valuations.

Our primary result on the effect of dark trading on asset prices is fairly intuitive. Dark trading threatens informational efficiency only when fundamental information is not widely disseminated to market participants. Off-exchange trading results in a significant movement of liquidity away from public observation that impairs price discovery at the exchange. Consequently, improving communication networks among investors or releasing more frequent information related to fundamentals about the company is likely to enhance price discovery to a greater extent in the presence of dark pools when compared to a market environment with a single lit exchange.

The impact on allocative efficiency is, however, less straightforward. Dark trading does not cause any significant change in the eventual allocations when the heterogeneous valuations among investor types are fairly dispersed. However, when a majority of investors have access to information and there is less variation in the valuations, the hidden liquidity continues to harm welfare by creating friction in the movement of the asset to the group having the highest gains from exchange even though the informational efficiency of prices is not reduced.

Taken together, our study finds a negative effect of dark trading on financial markets.

[35]The ratio of price deviation is defined as the absolute difference between the median transaction price in the lit exchange and the REE price divided by the REE price in a period.

Unless there exist additional channels through which dark pools operate, they are detrimental to the functioning of markets. Brogaard and Pan (2022) and Halim et al. (2022) identify information acquisition as a mechanism through which dark pools positively affect markets. Adding a dark trading venue encourages costly information acquisition, which may be beneficial for price efficiency compared to the benchmark of a single lit exchange.

Although our experimental design shares similarities with the theoretical framework of Zhu (2014) and Ye (2016) with respect to the modeling of dark trading, the implications of these models cannot be tested in our experiments. This is because, unlike the theoretical models, the experimental design involves different gains from exchange for informed and uninformed traders.[36] In theory, the basic mechanism that causes dark trading to either improve or deteriorate the informativeness of asset prices at the exchange relies on the choice of venue by informed and uninformed traders.[37] Halim et al. (2022) provide a discussion based on this mechanism using their experimental data.

Finally, our study shows that while information has a first-order effect on earnings, the market institution itself does not significantly alter the edge that the informed investors have over the uninformed. Therefore, introducing a dark venue for trading with hidden liquidity does not favor a specific group of investors. Having advantageous asymmetric access to information regarding fundamentals is critical, not whether one can "trade in the dark".

IV. Conclusion

Trading in dark markets with hidden liquidity is becoming increasingly popular in several countries with lower regulations on such practices. We systematically investigate the effects of allowing dark trading on market efficiency. We report data from a series of laboratory markets for an asset whose terminal payoff is contingent upon an unknown state of the world, with this payoff varying among investors to give rise to strong gains from exchange. In addition to a lit exchange organized as a multiple-unit double auction market, investors can send their orders to an alternative venue where others cannot publicly observe their offers. The prices at which these offers are executed are derived from the lit exchange.

[36]As mentioned earlier, having different gains from exchange is essential to analyze allocative efficiency in our setting.

[37]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. In our experiments, informed orders may not necessarily cluster on the heavy side of the market as different informed traders have varying degrees of gains from exchange.

Our results demonstrate that how dark trading affects market efficiency depends critically on how information regarding fundamentals is distributed among investors. When information is concentrated in the hands of a few investors, possibly due to sparse investor connectedness or low media coverage, dark trading primarily impacts market efficiency by deteriorating the quality of asset prices. In this case, learning from publicly observable order submissions is crucial to price discovery, and the crowding out of liquidity under dark markets causes a significant decline in price efficiency compared to a market institution with only a single lit exchange.[38]

When most investors can access fundamental information, dark trading no longer harms price discovery. However, we find that order flow transparency continues to be an important element that facilitates the movement of the asset from the ones who desire it the least to the ones valuing it the most. Therefore, dark trading may still result in welfare losses even though prices are equally informationally efficient with or without dark pools.

The literature on experimental asset markets has provided several important insights with respect to market institutions, for example, the double auction, the posted price, and call markets, among others. The emergence of dark markets provides an enormous opportunity to undertake laboratory studies that can complement theoretical and empirical research on this relatively new trading institution. For example, our understanding of the effect of changing the price of matched orders in the dark trading venue is still limited. Furthermore, questions related to dark market regulations, like implementing exogenous caps on dark trading, could be investigated.

[38]As dark trading becomes more prevalent, our results suggest promoting the diffusion of fundamental information among investors to mitigate the negative impact of unobserved liquidity on market efficiency. One way to do so is by encouraging the proliferation of social trading platforms allowing information exchange among market participants. Recent research has shown that social networks enhance the ability of asset prices to reflect investors' private information (Halim, Riyanto, and Roy (2019)) and facilitate the incorporation of public information into prices (Hirshleifer, Peng, and Wang (2023)). As investor connectedness increases, leading to faster diffusion of relevant information, the negative impact of dark trading on price efficiency is expected to be limited. However, concerns regarding the adverse effect on allocative efficiency still remain.

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INTERNET APPENDIX

Instructions for the experiment- Lit and Dark Market

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. The exchange rate is: **125 ECU = 1 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 2 SGD, 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 **125 ECU = 1.00 SGD**
	Section 2	In SGD, the amount of reward depending on decisions made in this section
Show-up fee		2 SGD

SECTION 1A - THE EXPERIMENT

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 16 periods in this section, and your final payoff for this section will be given by the **average** of the payoffs from **5** randomly chosen periods.

Asset dividends in the real world depend on events that are unknown to traders. In this experiment, we **represent these uncertain market conditions (dividends) through randomly selected urns**. Every period, an urn is randomly selected as the underlying urn to represent the market conditions.

There are 2 types of urns, Urn A and Urn B. In every period, **each urn has an equal likelihood (50%) of being chosen as the underlying urn**. You will **not be informed of the chosen urn until the end of each period**. The dividend of the asset depends on the underlying urn. **Also note dividend might differ from person to person.**

You will enter a **<u>Trading Stage</u>,** where you will be able to **BUY** and/or **SELL** the assets by trading with other participants. At the end of the trading stage, the underlying urn will be revealed, and the value (dividends) of your assets for that period will be determined. The underlying urn in each period may not be the same.

We will now explain the rules of the experiment in detail. In the experiment, during each session, there will be 12 subjects.

In every period:

- **All traders** start with an initial endowment of **50000 ECUs** and **100 assets**, and **50000 ECU would be returned at the end of each period**. Thus you payoff for one period would be:
  Final cash + Final assest * Asset dividend – Initial cash (50000).
- You will participate **in a virtual financial environment** in which you can buy and/or sell dividend-bearing assets.

SECTION 1B - TRADING STAGE

During the trading stage, you can trade with other participants in both Market X and Market Y. In each period, you will have **3 minutes of trading**. The remaining time (in seconds) will be displayed at the **screen's top right-hand corner**. The dividend will be paid at the end of each trading period. Hence, it will not be carried forward to the next period.

In Market X

To <u>buy assets</u>:

> You can **submit a buy offer**, which specifies the **volume of assets** (> 0) and the **price** you wish other traders to **sell** to you. Note your submitted buy price must be lower than or equal to the current best (lowest) sell price on the sell offer list. You will successfully buy assets only if a seller's sell price matches (equal to) your buy price.
>
> For example (see the table below), in the order book (list of sell offers) there are outstanding sell offers of 15 units at 20 ECU per unit, 15 units at 24 ECU per unit and another 25 units at 28 ECU per unit. If you submit a buy offer of 30 units at 20 ECU per unit, your buy order will be matched with the seller who submitted a sell offer of 15 units at 20 ECU per unit. You will thus buy 15 units of the asset at 20 ECU per unit, the remaining 15 units will rest on the buy offer list.

Refer to the displayed Sell Offers List below:

Sell Offers (best sell offer on the top)

Price	Volume
20.0	15
24.0	15
28.0	25

0.1-19.9

If your buy price is in this interval, transaction **will NOT occur and your submitted buy offer will rest on the list.**

20.0

If your buy price is 20 ECU, transaction **will occur** at the price of 20 ECU. You can not submit a buy price higher than 20 ECU as price crossing is not allowed.

To <u>sell assets</u>:

Selling assets is similar to buying:

You can **submit a sell offer**, which specifies the **volume of assets** (> 0) and the **price** you wish other traders to **buy from you**. Note your submitted sell price must be higher than or equal to the current best (highest) buy price on the buy offer list. You will successfully sell assets only if a buyer's buy price matches (equal to) your sell price.

For example (see the table below), in the order book (lists of buy offers) there are outstanding buy offers of 15 units at 27 ECU per unit, 15 units at 25 ECU per unit and another 10 units at 22 ECU per unit. If you submit a sell offer of 30 units at 27 ECU per unit, your sell offer will be matched with the buyer who submitted a buy offer of 15 units at 27 ECU per unit. You will thus sell 15 units at 27 ECU per unit, the remaining 15 units will rest on the sell offer list.

Refer to the displayed Buy Offers List below:

Buy Offers (best buy offer on the top)

Price	Volume
27.0	15
25.0	15
22.0	10

27.1-50

If your sell price is in this interval, transaction **will NOT occur and your submitted buy offer will rest on the list.**

27.0

If your sell price is 27 ECU, transaction **will occur** at the price of 27 ECU. You can not submit a sell price lower than 27 ECU as price crossing is not allowed.

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

When there is more than one matching sell offer, the sell offer with an earlier submission time will be executed first. Likewise, when there is more than one matching buy offer, the buy offer with 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 on the offer lists. To create a buy or sell offer, you enter buy or sell price and volume and click either the "**Submit Buy Offer**" or "**Submit Sell Offer**" button, respectively.

Here are some important trading rules:

1. **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. **Your buy (sell) offers can be partially matched and executed. For example, if your buy (sell) offer's volume is 40 units and the corresponding matched sell (buy) offer's volume is 20 units, then 20 out of 40 units of your buy (sell) offer would be executed.**

3. **Your offer price must be rounded up to 1 decimal place. For instance, you may key in a price of 25.1 or 25.2 but NOT a price of 25.15.**

4. **If you want immediate transactions, you may submit offers at best prices (lowest sell price or highest buy price) to match the existing offers on the lists.**

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 best ask (lowest sell) prices in Market X.**

To buy assets:

You can create a buy offer by specifying the **volume 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) 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 sell assets:

You can create a sell offer by specifying the **volume of assets** (> 0) you would like to sell 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) 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:

Here in Market Y, because the trading prices are based on the midpoint of the best (lowest) sell and best (highest) buy prices in Market X, and you do not need to specify the offer prices, there are advantages and disadvantages in Market Y. As for the advantages, the first advantage is the potential price improvement due to the mid-point pricing rule; the second advantage is the information protection. Because of the fixed pricing rule in Market Y, your price signals will not be revealed to others. As for the disadvantages, the first disadvantage is that an immediate execution is not guaranteed. Because you cannot view other offers in Market Y, your immediate execution may not be guaranteed. The second disadvantage is that you may face risk that the mid-point prices derived from Market X might change adversely while your offers in Market Y are waiting for their counterparties.

Note that your buy (sell) offers can be partially matched and executed. For example, if your buy (sell) offer's volume is 40 units and the corresponding matched sell (buy) offer's volume is 20 units, then 20 out of 40 units of your buy (sell) offer would be executed.

Additionally, **orders placed earlier will be matched first**.

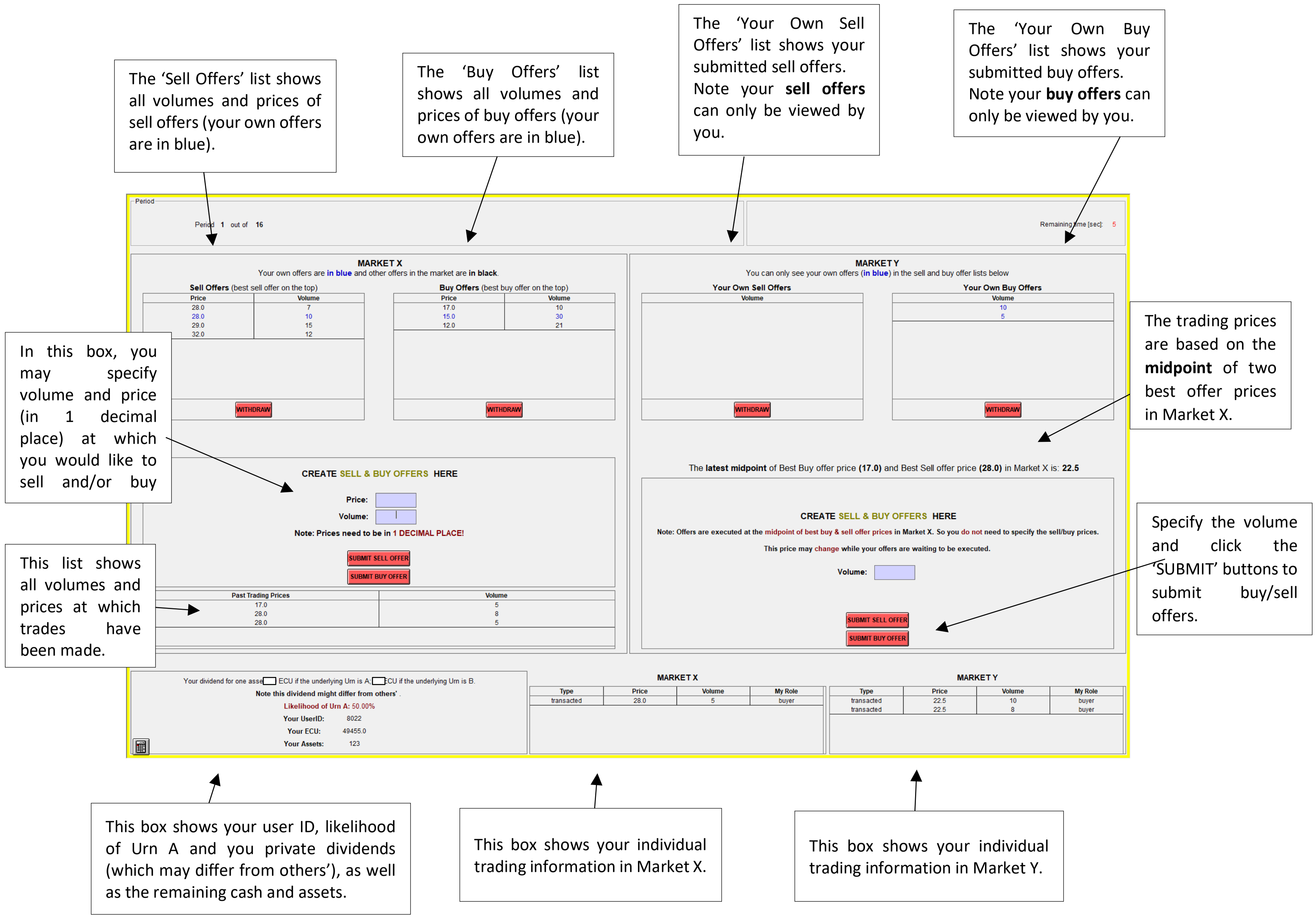
Also, note that **your <u>own</u> buy/sell offers** are displayed on the lists of offers in blue instead of black. You cannot accept your own offers, but you can select them and click "WITHDRAW" if you decide to withdraw your own offers.

Offers are removed from the offer lists when they are executed or withdrawn. Also note that if there is 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.

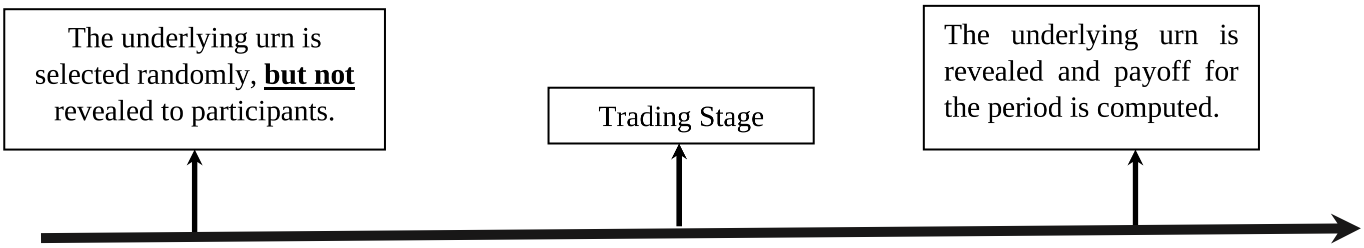
After you have successfully made a trade, your ECU and asset balances will be updated accordingly.

The last screen concludes the period. It will reveal your dividend (which might differ from others') of the assets in this period. Your payoff for each period is the **sum of ECU adding the total dividends from the assets you have at the end of the period SUBTRACTING 50000 ECU (initial cash endowment)**. 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.
In this box, you may specify volume and price (in 1 decimal place) at which you would like to sell and/or buy
This list shows all volumes and prices at which trades have been made.
The trading prices are based on the **midpoint** of two best offer prices in Market X.
Specify the volume and click the 'SUBMIT' buttons to submit buy/sell offers.
This box shows your user ID, likelihood of Urn A and you private dividends (which may differ from others'), 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.
Period
Period 1 out of 16
Remaining time [sec]: 5
MARKET X
Your own offers are in blue and other offers in the market are in black.
Sell Offers (best sell offer on the top)
Buy Offers (best buy offer on the top)
WITHDRAW
CREATE SELL & BUY OFFERS HERE
Price:
Volume:
Note: Prices need to be in 1 DECIMAL PLACE!
SUBMIT SELL OFFER
SUBMIT BUY OFFER
Past Trading Prices
MARKET Y
You can only see your own offers (in blue) in the sell and buy offer lists below
Your Own Sell Offers
Your Own Buy Offers
The latest midpoint of Best Buy offer price (17.0) and Best Sell offer price (28.0) in Market X is: 22.5
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.
Note this dividend might differ from others'.
Likelihood of Urn A: 50.00%
Your UserID: 8022
Your ECU: 49455.0
Your Assets: 123

Timeline of one period



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 understanding the instruction!

SECTION 1C - INFORMATION STAGE

During the remaining periods, some of you might know the urn state at the beginning of each period. To be specific, you will be in the **Information Stage** where only some of you might be perfectly informed about the realized urn state. **This information will only be revealed to you**.

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!