# 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 it reduces allocative efficiency. The earnings gap between informed and uninformed traders does not widen with dark trading.

**JEL Classification Numbers**: C91, C92, G12, G14

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

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*We gratefully acknowledge the financial support from the National Research Foundation (NRF) CREATE -Future Resilient System II and the General Research Fund sponsored by the Hong Kong RGC (CityU 11500019).

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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 facilitating the transfer of assets from investors with lower valuations to the ones having greater gains from exchange.

There have been some attempts to theoretically study dark trading in financial markets. 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,

[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.

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 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 don't. This

[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.

is likely to result in stocks of some companies having information diffused quickly so that a larger fraction of investors are well informed of 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, and whether the effects are different in markets with varying degrees of access to fundamental information. Some stocks have information concentrated in the hands of a few investors, which could be due to investor networks with low density or less media coverage, etc. Yet other stocks may have densely connected investor networks leading to faster information diffusion. Does the effect of dark trading on the informational efficiency of prices and allocative efficiency depend on the underlying distribution of fundamental information among investors?

We design an experimental asset market with two parallel trading venues to address the above 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. Differences in dividends generate significant gains from exchange in both states. 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 a single lit exchange where all order submissions by a trader are observable to other traders, and another where two parallel trading venues exist. In the latter market institution, in addition to the lit exchange, investors can submit orders and transact in a dark 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.[4]

[4]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

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 under dark markets causes a significant decline in price efficiency when compared to a market institution with only a single lit exchange.

On the other hand, when the majority of investors have access to fundamental information, dark trading no longer harms price discovery. Instead, it now creates friction in the movement of the asset from the ones who desire it the least to the ones valuing it the most. That is, the channel through which dark markets reduce market efficiency is via the reduction in allocative efficiency. We are able to identify this effect as trading is not zero-sum in our design.

We further observe 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, the introduction of a dark venue for trading with hidden liquidity does not favor a specific group of investors. At the same time, we find that there is a higher demand for immediacy of execution among informed traders relative to uninformed ones. Moreover, 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.

Experimental research has been especially fruitful in assessing the performance of a trading institution in terms of informational efficiency of prices and allocation efficiency. 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 having the ability to control and change variables of interest to allow clean causal inferences.

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

efficiency measures is an important topic that we leave for future research.

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 the laboratory, 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.[5] Flood et al. (1999) construct a market in which there are seven competing dealers who 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.[6] Bloomfield and O'Hara (2000) report two experiments in which they consider whether transparent markets are competitive with nontransparent markets. The results show that low-transparency dealers outperform high-transparency types. 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.

Lamoureux and Schnitzlein (1997) implement markets with dealers but allow traders to bypass dealers and trade with each other through a bilateral search mechanism. They show that when traders cannot bypass dealers, dealer profits are high. These dealer 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

[5]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.

[6]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.

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.

Our study contributes to this small experimental literature on hidden liquidity and transparency in security markets. However, distinct from the studies mentioned above, we implement fragmented markets with separate lit and dark venues for trading. 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 so that we can 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. Section IV concludes.

# 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$23.26 in addition to a show-up fee of S$2.[7]

Upon arrival, subjects were seated at visually isolated computer workstations. Instructions were read aloud, and subjects also received a copy of the instructions.[8]

[7]Payoffs, inclusive of the show-up fee, ranged from S$x to S$x.

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

Participants were prohibited from talking during the experiment, and all communication took place via the experimental software. Each session consisted of three practice periods and 16 main periods.[9] 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 had the opportunity to exchange several units of a financial asset every period by participating in a virtual financial market. All accounting and trading were done in experimental currency units (ECU). The market was implemented using the z-Tree computer program (Fischbacher (2007)). 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 participants, where these types vary in terms of how much dividends they obtain per unit of the asset. Table I provides the dividend parameters used in the experiments. Agents in each session were partitioned into three types (designated as I, II, and III) according to dividend returns. 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. 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

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

**Table I**

## Experimental Design: Dividend Parameters

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

| | | Dividends | |
|---|---|---|---|
| Investor Type | Number of Investors | urn $A$ | urn $B$ |
| I | 4 | 40 | 10 |
| II | 4 | 30 | 15 |
| III | 4 | 12.5 | 17.5 |

units of the asset at any time, provided that they did not violate the short-selling (negative holdings) constraint. In addition, subjects were required to maintain a positive cash balance to make any purchases. If engaging in a trade would violate either the short-sale or cash-balance constraint, the computer program prohibited individuals from doing so. Throughout the trading stage, pertinent information such as 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.

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

**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, while in the *Dark* market, there is a parallel dark market in addition to the limit order market. Three (nine) out of the 12 investors are perfectly informed about the underlying urn in a period in sessions with a low (high) proportion of informed investors.

| Treatment | Trading Institution | Proportion of Informed Investors |
|---|---|---|
| *Lit Only-Low* | Single Limit Order Market | Low |
| *Dark-Low* | Parallel Markets | Low |
| *Lit Only-High* | Single Limit Order Market | High |
| *Dark-High* | Parallel Markets | High |

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.[10] 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.[11]

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.[12] Within each price level, orders submitted at an earlier time 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.[13] 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.[14]

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

[11]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.

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

[13]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*.

[14]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.

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.[15] 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 who are provided with information regarding the underlying state of nature.[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. 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.

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, double auction market 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 rational expectations equilibrium (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.

[15] 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).

[16] In all sessions, the first six periods constituted markets with no informed traders.

# II. Results

## *A. Market Efficiency: Prices*

One of the most widely accepted methods to measure market efficiency is to assess the ability of prices to reflect the information available to traders. 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. We define price efficiency measure as the absolute difference between the average transaction price in the lit exchange and the REE price divided by the REE price in a period, which is also referred to as the ratio of price deviation in the lit market. Using the mean transaction price in a period, the average value of this ratio goes up from 0.22 in the *Lit Only-Low* to 0.33 in the *Dark-Low* treatment, indicating a negative effect of dark trading when information is in the hands of a few investors. However, the ratio drops from 0.18 in the *Lit Only-High* to 0.13 in the *Dark-High* treatment, suggesting an improvement in price efficiency of introducing a dark venue for trading in markets with a higher proportion of informed investors.

To understand the effect of dark trading on the efficiency of asset prices, we perform a regression with the ratio of price deviation as the dependent variable. The regressors include the variable *Dark* (which takes a value of 1 if the treatment includes a dark market in addition to the lit exchange and 0 otherwise), *High* (which takes a value of 1 if the number of informed traders in the market is high and 0 otherwise), the interaction term *Dark* $\times$ *High*, *Urn* (which takes a value of 1 if the underlying state of nature is $A$ and 0 otherwise), and the period number. Specifications (1)-(4) use the mean transaction price in a period to calculate the ratio of price deviation, while specifications (5)-(8) use the median transaction price in a period. Certain specifications also include the average values of the demographic variables in the market.[17] The standard errors are clustered at the session level. Table III reports the results, and Table IV further summarizes the results from

## Table III

## OLS Regression of Ratio of Price Deviation in the Lit Market

This table presents the results of the OLS regression analysis of the ratio of price deviation, which is defined as the absolute difference between the mean/median transaction price 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 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). *Urn* takes a value of 1 if the underlying state of nature is $A$ and 0 if the state is $B$. Specifications (1)-(4) use the mean transaction price in a period to calculate the ratio of price deviation, while specifications (5)-(8) use the median transaction price in a period. Some 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.

| | Mean Price | | | | Median Price | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dark* | 0.11* | 0.11* | 0.06*** | 0.06*** | 0.12** | 0.12** | 0.06*** | 0.06*** |
| | (0.06) | (0.06) | (0.02) | (0.02) | (0.05) | (0.05) | (0.02) | (0.02) |
| *High* | -0.04 | -0.04 | -0.14*** | -0.14*** | -0.05 | -0.05 | -0.14*** | -0.14*** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) | (0.03) |
| *Dark* × *High* | -0.16** | -0.16** | -0.05 | -0.05 | -0.18** | -0.18** | -0.08** | -0.08** |
| | (0.07) | (0.07) | (0.04) | (0.04) | (0.06) | (0.06) | (0.03) | (0.03) |
| *Urn* | | 0.16** | | 0.16** | | 0.15** | | 0.15** |
| | | (0.06) | | (0.06) | | (0.06) | | (0.06) |
| *Period* | -0.01** | -0.01** | -0.01** | -0.01** | -0.01** | -0.01** | -0.01** | -0.01** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.01) |
| Constant | 0.34*** | 0.27*** | 0.42 | 0.35 | 0.37*** | 0.30*** | 0.42 | 0.35 |
| | (0.06) | (0.05) | (0.29) | (0.27) | (0.06) | (0.05) | (0.30) | (0.28) |
| No. of observations | 160 | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| No. of clusters | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 |
| $R^2$ | 0.19 | 0.38 | 0.27 | 0.46 | 0.23 | 0.39 | 0.30 | 0.46 |
| Control variables | No | No | Yes | Yes | No | No | Yes | Yes |

**Table IV**

**Linear Combination Test Results from OLS Regression of Ratio of Price Deviation in the Lit Market**

This table presents the results of the linear combination tests after the conduct of the OLS regression of the ratio of price deviation in the lit market. This table is to be viewed as a continuation of the results presented in Table III. *** indicates significance at the 1% level.

| | *Dark + Dark × High* | | *High + Dark × High* | |
|---|---|---|---|---|
| Specification | Coefficient | $p$-value | Coefficient | $p$-value |
| (1) | -0.05 | 0.12 | -0.20*** | 0.00 |
| (2) | -0.05 | 0.12 | -0.20*** | 0.00 |
| (3) | 0.00 | 0.91 | -0.19*** | 0.00 |
| (4) | 0.00 | 0.91 | -0.19*** | 0.00 |
| (5) | -0.06*** | 0.07 | -0.23*** | 0.00 |
| (6) | -0.06*** | 0.07 | -0.23*** | 0.00 |
| (7) | -0.01 | 0.70 | -0.22*** | 0.00 |
| (8) | -0.01 | 0.70 | -0.22*** | 0.00 |

relevant post-estimation linear combination tests.

Table III shows that adding an alternative venue for trading with unobservable liquidity negatively affects price efficiency when fundamental information is concentrated among a small group of investors. This negative effect, however, disappears when a larger fraction of investors has access to information, as indicated in Table IV. Therefore, whether and how dark markets affect price efficiency depends on how information is distributed among investors.

RESULT 1: *Dark trading causes a decline in price efficiency, but only when a few investors have access to information regarding fundamentals.*

[17]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).

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 mean transaction price in a period, the average ratio of price deviation drops by 18% 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 higher as the average ratio of price deviation drops by 61% with the increase in the number of informed traders. The regression results in Tables III and IV confirm this, with significant negative coefficients on *High* and *High* + *Dark* × *High*, and a larger effect for the latter. Therefore, our results demonstrate that there is more to gain by letting investors have wider access to fundamental information when dark trading is allowed.

RESULT 2: *The improvement in price efficiency owing to an increase in the proportion of informed investors is larger in the presence of dark trading.*

## B. Market Efficiency: Allocations

Our experimental design models trading as a non-zero-sum activity. This means, in 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 $A$ ($B$), and 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:

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

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

We perform a regression with the measure of allocation efficiency as the dependent variable. The regressors include the variable *Dark*, *High*, the interaction term *Dark* $\times$ *High*, *Urn*, and the period number. Table V reports the results, with specifications (1)-(4) using measure 1 and the remaining specifications using measure 2. Table VI summarizes the results from post-estimation linear combination tests. Using either measure, Table V 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. However, in general, a significant negative effect of dark markets on allocation efficiency is observed when a larger fraction of investors has access to information, as indicated in Table VI.

RESULT 3: *Dark trading causes a decline in allocative efficiency when the proportion of informed investors is high.*

Table V shows that an increase in the proportion of informed investors is accompanied by a significant improvement in allocative efficiency in the absence of dark trading. However, Table VI indicates that no such significant positive association is observed in markets with both lit and dark venues. This is true when using either measure of allocative efficiency. 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: *In the absence of dark trading, increasing the proportion of investors having access to fundamental information improves allocative efficiency.*

## *C. Trading Volume and Liquidity*

We now investigate the implications of dark trading on market trading activity and liquidity. Table VII reports the results of an OLS regression of total transaction volume in the market and the transaction volume in the lit exchange. The regressors

**Table V**

## 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 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). *Urn* takes a value of 1 if the underlying state of nature is $A$ and 0 if the state is $B$. Specifications (1)-(4) use measure 1 as the dependent variable, and specifications (5)-(8) use measure 2. Some 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.

| | Measure 1 | | | | Measure 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dark* | -0.02 | -0.02 | 0.04 | 0.04 | -0.05 | -0.05 | 0.05 | 0.05 |
| | (0.09) | (0.09) | (0.09) | (0.09) | (0.11) | (0.11) | (0.11) | (0.11) |
| *High* | 0.26*** | 0.26*** | 0.38*** | 0.38*** | 0.32*** | 0.32*** | 0.46*** | 0.46*** |
| | (0.05) | (0.05) | (0.10) | (0.10) | (0.07) | (0.07) | (0.14) | (0.14) |
| *Dark* × *High* | -0.09 | -0.09 | -0.26 | -0.26 | -0.13 | -0.13 | -0.30 | -0.30 |
| | (0.10) | (0.10) | (0.17) | (0.17) | (0.14) | (0.14) | (0.22) | (0.22) |
| *Urn* | | 0.25*** | | 0.25*** | | 0.44*** | | 0.44*** |
| | | (0.05) | | (0.05) | | (0.10) | | (0.10) |
| *Period* | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Constant | 0.28** | 0.16* | 1.05* | 0.93* | 0.11 | -0.08 | 0.56 | 0.37 |
| | (0.12) | (0.09) | (0.55) | (0.52) | (0.18) | (0.14) | (0.60) | (0.58) |
| No. of observations | 160 | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| No. of clusters | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 |
| $R^2$ | 0.23 | 0.48 | 0.27 | 0.52 | 0.15 | 0.46 | 0.19 | 0.51 |
| Control variables | No | No | Yes | Yes | No | No | Yes | Yes |

## Table VI

## Linear Combination Test Results from OLS Regression of Measures of Allocative Efficiency

This table presents the results of the linear combination tests after the conduct of the OLS regression of the measures of allocative efficiency. This table is to be viewed as a continuation of the results presented in Table V. * indicates significance at the 10% level, and ** indicates significance at the 5% level.

| | *Dark* + *Dark* × *High* | | *High* + *Dark* × *High* | |
|---|---|---|---|---|
| Specification | Coefficient | $p$-value | Coefficient | $p$-value |
| (1) | -0.11** | 0.02 | 0.17* | 0.07 |
| (2) | -0.11** | 0.02 | 0.17* | 0.07 |
| (3) | -0.22** | 0.04 | 0.13 | 0.17 |
| (4) | -0.22** | 0.04 | 0.13 | 0.17 |
| (5) | -0.19* | 0.06 | 0.19 | 0.16 |
| (6) | -0.19* | 0.07 | 0.19 | 0.16 |
| (7) | -0.25 | 0.11 | 0.17 | 0.12 |
| (8) | -0.25 | 0.11 | 0.17 | 0.12 |

are the same as the ones in Tables III and V. We find that dark trading does not affect the aggregate transaction volume in the market when the proportion of informed investors is low. Comparing *Lit Only-High* and *Dark-High* treatment, using a post-estimation linear combination test, the coefficient of *Dark* + *Dark* × *High* is 217.53 ($p$-value: 0.01) and 91.15 ($p$-value: 0.34) under specification (1) and (2), respectively. Therefore, market participation remains unaltered with dark trading.

The transaction volume at the lit exchange goes down significantly with the availability of the dark market as an additional venue for trading. Using specification (4) with the inclusion of demographic variables, the availability of a dark venue for trading lowers transactions at the lit exchange by 264.30 (significant at 5% level) in markets with low proportion of informed investors, and by 338.11 (significant at 5% level) in markets with high proportion of informed traders. As the aggregate trade volume remains the same with and without the additional dark market, we conclude that there is a substitution or crowding out of transactions from the lit exchange.

Table VII further presents OLS regression results using the following two liquid-

## Table VII

## 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 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). *Urn* takes a value of 1 if the underlying state of nature is $A$ and 0 if the state is $B$. ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

| | Total Transaction Volume | | Transaction Volume in Lit Exchange | | Effective Spread | | Depth | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dark* | 118.90 | 78.33 | -231.40 | -264.30** | -0.47 | -0.32** | -1007.00** | -1000.00 |
| | (170.70) | (110.40) | (145.30) | (111.80) | (0.27) | (0.13) | (466.30) | (591.40) |
| *High* | -17.37 | -72.04 | -17.38 | -15.94 | -0.12 | 0.42 | -379.50 | -1086.00 |
| | (96.43) | (107.60) | (96.43) | (117.40) | (0.38) | (0.34) | (485.60) | (639.00) |
| *Dark* × *High* | 98.65 | 12.82 | 115.00 | -73.78 | 0.82* | -0.09 | 874.60 | 1677.00 |
| | (188.00) | (147.50) | (173.50) | (169.80) | (0.46) | (0.46) | (818.60) | (1106.00) |
| *Urn* | 186.80*** | 186.80*** | 131.10*** | 131.10*** | 0.62** | 0.62** | -538.20** | -525.30** |
| | (48.47) | (49.11) | (32.81) | (33.25) | (0.23) | (0.23) | (241.50) | (241.10) |
| *Period* | 0.53 | 0.53 | 5.18 | 5.18 | -0.03 | -0.03 | 23.52 | 25.74 |
| | (8.08) | (8.19) | (6.09) | (6.17) | (0.03) | (0.03) | (36.06) | (35.69) |
| Constant | 576.20*** | 2986.00*** | 545.90*** | 2048.00** | 1342.00*** | -3997.00** | 1889.00** | 10850.00** |
| | (130.30) | (908.80) | (117.10) | (740.70) | (0.28) | (1.55) | (666.90) | (4581.00) |
| No. of observations | 160 | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| No. of clusters | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 |
| $R^2$ | 0.22 | 0.48 | 0.22 | 0.48 | 0.15 | 0.24 | 0.08 | 0.18 |
| Control variables | No | Yes | No | Yes | No | Yes | No | Yes |

ity 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. The results suggest that, after controlling for demographic variables, dark trading lowers the effective bid-ask 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. Taken together, we conclude that there is no consistent impact of dark trading on these liquidity measures.

RESULT 5: *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.*

## *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 $\Delta ECU_{it}$ 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 the difference between the value of a trader's portfolio at the end and at the start of a period. Table VIII 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), and *Dark* $\times$ *Informed* as regressors.

In markets with a low proportion of informed investors, the ones who are informed obtain significantly higher earnings than the uninformed traders. In markets with a single lit exchange, informed investors outperform uninformed ones by 1166 ECUs (significant at 1% 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 1088.60 ECUs higher in specification (2) (significant at 1%).

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

## Table VIII

## 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 which are 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 10% level, and *** indicates significance at the 1% level.

| | *Low* | | *High* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Dark* | -35.00 | -145.70 | -37.86 | -23.61 |
| | (76.76) | (89.04) | (135.70) | (131.30) |
| *Informed* | 1064.00*** | 1166.00*** | 473.80*** | 438.40*** |
| | (292.10) | (270.20) | (66.13) | (66.74) |
| *Dark* × *Informed* | -24.09 | -77.13 | -46.97 | -55.36 |
| | (500.00) | (402.70) | (145.40) | (172.30) |
| Constant | 114.90* | -885.10 | 178.80*** | 501.90 |
| | (58.96) | (828.70) | (43.01) | (685.90) |
| No. of observations | 960 | 960 | 960 | 960 |
| No. of clusters | 8 | 8 | 8 | 8 |
| $R^2$ | 0.09 | 0.14 | 0.05 | 0.05 |
| Control variables | No | Yes | No | Yes |

uninformed traders would get reduced due to competition among informed traders and signficant information leakage. Indeed, as shown in Table VIII, in *Lit Only-High* treatment, informed traders get 438.40 ECUs higher than the 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 383.05 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 IX reports the results of an OLS regression of the earnings gap in a period, which is defined as the difference between the average earnings among informed traders and uninformed traders in a period. The regressors are the same as the ones in Tables III, V, and VII. The coefficient of *Dark* (observed from Table IX) and *Dark* + *Dark* $\times$ *High* (obtained from post-estimation tests) are, in general, insignificant, indicating that the earnings gap remains unchanged with the introduction of a dark venue for trading.

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 (taking rate) is defined as the number of limit order (market order) submissions per unit of time 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* $\times$ *Informed*, *Period*, and demographic variables. Tables X and XI report the results for the *Low* and *High* treatments, respectively.

In markets with only a lit exchange, we find that informed investors submit a

## Table IX

# OLS Regression of Earnings Gap

This table presents the results of the OLS regression analysis of the earnings gap in a period, which is defined as the difference between the average earnings among informed and uninformed traders in a period. 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). *Urn* 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, and ** indicates significance at the 5% level.

| | All Types | | Type I | | Type II | | Type III | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dark* | -24.09 | -110.00 | 60.56 | 791.20 | -247.30 | -90.87 | 114.40 | 235.60** |
| | (488.50) | (499.00) | (1555.00) | (1175.00) | (466.00) | (371.10) | (88.63) | (108.10) |
| *High* | -590.00* | -469.60* | -1526.00 | -414.70 | -313.90* | -524.00** | 69.89 | 102.00 |
| | (292.60) | (264.60) | (927.80) | (1058.00) | (177.60) | (229.80) | (142.80) | (180.30) |
| *Dark* × *High* | -22.88 | -32.03 | 28.42 | -538.10 | 3.53 | -108.70 | -100.60 | -27.28 |
| | (508.70) | (435.60) | (1606.00) | (1645.00) | (488.8) | (398.40) | (235.30) | (241.50) |
| *Urn* | 735.30** | 735.30** | 2056.00** | 2056.00** | 226.90 | 226.90 | -76.98 | -76.98 |
| | (256.40) | (259.80) | (718.30) | (727.70) | (286.90) | (290.70) | (96.19) | (97.46) |
| Constant | 696.20** | -1180.00 | 1590.00* | 8552.00 | 467.20** | -3472.00 | 31.55 | 607.70 |
| | (250.50) | (3488.00) | (776.40) | (8813.00) | (192.60) | (2748.00) | (78.10) | (1202.00) |
| No. of observations | 160 | 160 | 160 | 160 | 160 | 160 | 160 | 160 |
| No. of clusters | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 |
| $R^2$ | | | | | | | | |
| Control variables | No | Yes | No | Yes | No | Yes | No | Yes |

## Table X

## 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 (taking rate) is defined as the number of limit order (market order) submissions per unit of time 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* | -303.70 | -20.10 | | -0.00 | 0.03 | |
| | (317.10) | (14.24) | | (0.04) | (0.06) | |
| *Informed* | -113.30 | 42.74** | 14.59 | -0.05 | 0.04 | 0.05 |
| | (363.80) | (20.19) | (22.03) | (0.06) | (0.08) | (0.06) |
| *Dark* × *Informed* | -20.21 | 0.08 | | 0.01 | -0.03 | |
| | (359.40) | (33.66) | | (0.09) | (0.13) | |
| *Period* | 15.89 | -0.79 | -0.17 | -0.00 | 0.01 | -0.01* |
| | (17.24) | (0.91) | (1.41) | (0.00) | (0.00) | (0.00) |
| Constant | 1410.00 | 80.98 | 226.30** | 0.73*** | 0.68** | 0.62** |
| | (1197.00) | (60.20) | (96.19) | (0.22) | (0.31) | (0.31) |
| No. of observations | 960 | 960 | 480 | 924 | 821 | 480 |
| No. of clusters | 96 | 96 | 48 | 96 | 96 | 48 |
| $R^2$ | 0.02 | 0.06 | 0.07 | 0.01 | 0.02 | 0.04 |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

**Table XI**

## 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 (taking rate) is defined as the number of limit order (market order) submissions per unit of time 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* | -102.40 | -15.01 | | 0.15** | -0.13 | |
| | (98.95) | (10.26) | | (0.07) | (0.08) | |
| *Informed* | 73.26 | 23.07** | 41.73** | 0.02 | 0.05 | 0.09 |
| | (89.35) | (10.71) | (17.06) | (0.07) | (0.08) | (0.05) |
| *Dark* × *Informed* | 25.35 | -0.23 | | -0.14* | 0.09 | |
| | (128.10) | (13.70) | | (0.08) | (0.10) | |
| *Period* | 1.30 | 1.73* | -0.36 | -0.00 | -0.00 | -0.01* |
| | (7.42) | (0.91) | (1.66) | (0.00) | (0.00) | (0.00) |
| Constant | 647.00* | 62.25 | 192.70 | 0.56** | 0.74** | 0.46 |
| | (342.90) | (41.71) | (124.60) | (0.23) | (0.32) | (0.30) |
| No. of observations | 960 | 960 | 480 | 941 | 868 | 477 |
| No. of clusters | 96 | 96 | 48 | 96 | 96 | 48 |
| $R^2$ | 0.04 | 0.06 | 0.04 | 0.03 | 0.03 | 0.08 |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |

larger number of market orders than uninformed ones. Post-estimation linear combination tests demonstrate that this observation remains true even in the presence of a dark venue for trading. The coefficient of *Informed* + *Dark* $\times$ *Informed* is 42.82 ($p$-value $< 0.1$) and 22.84 ($p$-value $< 0.05$) in *Dark-Low* and *Dark-High* treatments, respectively. In general, this observation points toward a higher demand for immediacy of execution among informed investors relative to uninformed ones.

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 additional observations regarding the immediacy demand. Using a linear combination test after the estimation of the OLS regression mentioned in Table XI, we observe that the coefficient of *Informed* + *Dark* $\times$ *Informed* is -0.13 ($p$-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.

There is some evidence to suggest that informed traders submit more dark orders, 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 attractive, even though dark submissions can be viewed as substitutes for limit order submissions for all traders.

RESULT 7: *Informed traders use more market orders and have more dark submissions than uninformed traders.*

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 a random effects GLS 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.[18,19] Table XII 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.[20] Overall, the group of investors that has a higher demand for immediacy is more responsive to the current rate of execution of their limit order submissions in the lit exchange and their dark order submissions.

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 et al. (2019)) and less than 50% of the private information is incorporated in prices (Page and Siemroth (2021)).

[18] $Spread_{t-1}$ 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.

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

[20] In the *Low* markets, as can be observed directly from Table XII, 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 XII

# GLS Regression of individual dark submission ratio

This table presents the results of the random effects GLS 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 the individual dark submission ratio of a trader 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 $Urn$ 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 |

In markets where a quarter of investors are perfectly informed, the mean ratio of price deviation equals 0.22 with a single lit exchange and 0.33 in the presence of dark trading. With three-fourths of the market being informed, this ratio drops to 0.18 and 0.13 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 poses a threat to 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. As a consequence, improving communication networks among investors or releasing more frequent information related to fundamentals about the company is likely to enhance price discovery by 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. Table XIII 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 even-

**Table XIII**

## 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.

| | 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% |

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

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 both informed and uninformed traders.[21] 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.[22] 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, the introduction of 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

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

[22]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.

alternative venue where others cannot publicly observe their offers. The prices at which these offers are executed are derived from the lit 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 when compared to a market institution with only a single lit exchange.

When the majority of investors have access to fundamental information, dark trading no longer harms price discovery. Instead, it now creates friction in the movement of the asset from the ones who desire it the least to the ones valuing it the most. In other words, in this case, the channel through which dark markets reduce market efficiency is via the reduction in allocative efficiency. We are able to identify this effect as trading is not zero-sum in our design.

The literature on experimental asset markets has provided several important insights with respect to double auction markets and call markets. 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.

## REFERENCES


[1] Albuquerque, R., S. Song, and C. Yao, 2020, The price effects of liquidity shocks: A study of SEC's tick-size experiment, *Journal of Financial Economics* 138, 700-724.

[2] Asparouhova, E., and P. Bossaerts, 2017, Experiments on percolation of information in dark markets, *The Economic Journal* 127, F518-F544.

[3] Bloomfield, R., and M. O'Hara, 2000, Can transparent markets survive?, *Journal of Financial Economics* 55, 425-459.

[4] Bloomfield, R., M. O'Hara, and G. Saar, 2015, Hidden liquidity: Some new light on dark trading, *Journal of Finance* 70, 2227-2274.

[5] Boulatov, A., and T. George, 2013, Hidden and displayed liquidity in securities markets with informed liquidity providers, *Review of Financial Studies* 26, 2095-2137.

[6] Buti, S., B. Rindi, and I. Werner, 2011, Diving into dark pools, Working Paper, Université Paris Dauphine.

[7] Comerton-Forde, C., and T. Putniņš, 2015, Dark pool trading and price discovery, *Journal of Financial Economics* 118, 70-92.

[8] Duffie, D., 2012, Dark Markets: Asset pricing and information transmission in over-the-counter markets, Princeton Lectures in Finance, Princeton University Press.

[9] Duffie, D., G. Giroux, and G. Manso, 2010, Information percolation, *American Economic Journal: Microeconomics* 2(1), 100-111.

[10] Duffie, D., S. Malamud, and G. Manso, 2009, Information percolation with equilibrium search dynamics, *Econometrica* 77, 1513-1574.

[11] Duffie, D., S. Malamud, and G. Manso, 2014, Information percolation in segmented markets, *Journal of Economic Theory* 153, 1-32.

[12] Duffie, D., and G. Manso, 2007, Information percolation in large markets, *American Economic Review* 97(2), 203-209.

[13] Fischbacher, U., 2007, z-Tree: Zurich toolbox for ready-made economic experiments, *Experimental Economics* 10, 171-178.

[14] Flood, M., Huisman, R., Koedijk, K., and R. Mahieu, 1999, Quote disclosure and price discovery in multiple-dealer financial markets, *Review of Financial Studies*

12(1), 37-52.
[15] Foley, S., and T. Putniņš, 2016, Should we be afraid of the dark? Dark pool trading and market quality, *Journal of Financial Economics* 122, 456-481.
[16] Glosten, R., and P. Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.
[17] Gozluklu, A. E., 2016, Pre-trade transparency and informed trading: Experimental evidence on undisclosed orders, *Journal of Financial Markets* 28, 91-115.
[18] Halim, E., Y. E. Riyanto, and N. Roy, 2019, Costly information acquisition, social networks, and asset prices: Experimental evidence, *Journal of Finance* 74, 1975-2010.
[19] Halim, E., Y. E. Riyanto, N. Roy, and Y. Wang, 2022, The bright side of dark markets: Experiments, *SSRN Working Paper* 4025127.
[20] Hatheway, F., A. Kwan, and H. Zhen, 2017, An empirical analysis of market segmentation on U.S. equities markets, *Journal of Financial and Quantitative Analysis* 52, 2399-2427.
[21] Hendershott, T., and C. M. Jones, 2005, Island goes dark: Transparency, fragmentation, and regulation, *Review of Financial Studies* 18, 743-793.
[22] Holt, C. A., and S. K. Laury, 2002, Risk aversion and incentive effects, *American Economic Review* 92, 1644-1655.
[23] Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.
[24] Lamoureux, C., and C. Schnitzlein, 1997, When it's not the only game in town: the effect of bilateral search on the quality of a dealer market, *Journal of Finance* 52(2), 683-712.
[25] Nimalendran, M., and S. Ray, 2014, Informational linkages between dark and lit trading venues, *Journal of Financial Markets* 17, 230-261.
[26] Noussair, C. N., and S. Tucker, 2013, Experimental research on asset pricing, *Journal of Economic Surveys* 27, 554-569.
[27] Page, L., and C. Siemroth, 2021, How much information is incorporated into financial asset prices? Experimental evidence, *Review of Financial Studies* 34, 4412-4449.

[28] Plott, C. R., and S. Sunder, 1982, Efficiency of experimental security markets with insider information: An application of rational-expectations models, *Journal of Political Economy* 90(4), 663-698.

[29] Reed, A. V., M. Samadi, and J. S. Sokobin, 2020, Shorting in broad daylight: Short sales and venue choice, *Journal of Financial and Quantitative Analysis* 55, 2246-2269.

[30] Ye, M., 2011, A glimpse into the dark: Price formation, transaction cost and market share of the crossing network, SSRN Working Paper 1521494.

[31] Ye, L., 2016, Understanding the impacts of dark pools on price discovery, Working Paper, SSRN Electronic Journal, 10.2139/ssrn.2874957.

[32] Zhu, H., 2014, Do dark pools harm price discovery? *Review of Financial Studies* 27, 747-789.