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Motive and Opportunity: Order Choice in a Limit Order Book With Dispersed Information

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ABSTRACT

We test predictions of market microstructure theory relating to the determinants of order choice in a limit order book where information is dispersed among traders. Using an experimental limit order book, with a large state space, we find that informed traders exhibit patience, compatible with the 'waiting game' behaviour described in Foster and Viswanathan. In responding to expected profits, informed traders prefer limit orders that disguise their information as predicted by Roşu and Riccó et al.

1 | Introduction

The limit order book market has become the predominant mechanism for trading equities around the world, and it can operate electronically without the direct participation of exchange officials in the trading process. In this paper, we use a laboratory-based limit order book to test two important theoretical predictions relating to order choice where information is dispersed among investors. First, informed traders in such a setting will trade slowly, and second, they will disguise their information signal as they do this by trading on the opposite side of the market to their signal. We find that informed trades do exhibit these characteristics and our empirical analysis uncovers how the expected profits of the informed traders provide their *motivation* to trade in this manner and how the trading behaviour of uninformed traders gives them the *opportunity* to do this.

We consider a situation where information is dispersed among traders, no single trader or group of traders holds perfect information, and where each information component is independent and combines additively to determine the intrinsic value of an asset. In a dispersed information setting, theory indicates that there are gains to patient trading. Foster and Viswanathan (1996) use a Kyle (1985) framework to study price convergence over the trading interval with different correlation structures for the information signals. For almost perfectly correlated signals, they predict a rapid incorporation of information into price, consistent with Holden and Subrahmanyam (1992), which they label a 'rat race'. Support for such behaviour in an experimental setting comes from Bloomfield et al. (2005) who find that when endowing their two informed traders with perfect signals they observe them using market orders aggressively from the outset of trading and switching to limit orders only when the information is fully reflected in price.

By contrast, when the correlation between information signals is low, Foster and Viswanathan (1996) show that informed traders have an incentive to trade slowly, specifically by placing smaller market orders, which they call the 'waiting game'. As the trading period progresses, the market learns more accurately about the average signal than any individual signal, and so the remaining private information becomes more disparate over time (becoming negatively correlated with the prevailing market view). Traders perceive a lack of resilience in the market and sense that without their information there may be nothing to move price back in the right direction. Information is released more slowly in this case, and profits are higher at the start of trading for the low correlation case than for the high correlation case, providing the incentive for informed traders to play the 'waiting game'.[1] As the signal independence in our information framework is like the zero-correlation scenario in Foster and Viswanathan, in which their 'waiting game' is predicted, we will use our experimental framework to investigate whether trading where information is dispersed is characterised by more patience than was observed in the perfect information setting used by Bloomfield et al. (2005).[2]

The prediction that informed traders may seek to disguise their information is found in the model of Kumar and Seppi (1994). They combine informed 'value traders' who submit limit orders to exploit profitable opportunities in the limit order book but who have no need to trade, with liquidity traders who have to trade in response to inventory shocks. As both kinds of trader can submit market orders and limit orders, informed traders must do so to avoid detection. The reason that they would wish to do so is provided by Chakraborty and Yilmaz (2004) and Kyle (1985) who show that monopolistic information holders should release information slowly into the market to maximise their profits. The liquidity traders in our experimental setting have trading targets that provide them with a necessity to trade and, as we will show, the informed traders with an opportunity to disguise their information.

Order choice depends on the trade-off between immediacy (from a market order) and price improvement (from a limit order), and this trade-off is informed by the relative expected profits from the two alternatives.[3] Both types of order can present putative profits conditional on the trader's signal, or putative losses. Roşu (2020) explains why an informed trader would prefer a limit order and how this leads to information being disguised. Although they could cancel their limit orders (on the opposite side of the market) and use a market order, they do not do so. For example, suppose an informed trader has private information that an asset's expected value is \$105, and the bid and ask prices are \$102 and \$104, respectively. A market buy order, at \$104, sends a strong message into the market that this trade is from an informed trader with an information signal above the ask. By contrast, submitting a limit buy order, is putatively more profitable than the market order, and would be on the opposite side of the market to the signal. Roşu (2020, theorem 1, corollary 4) observes that by placing a limit order, instead of a market order, the activity of the informed trader is indistinguishable from that of an uninformed trader, who is seeking to improve their terms of trade (by placing a limit buy order [a bid price], compared to placing a market buy order [at the ask price]). Thus, the profit motive to place an opposite side limit order disguises information. Our experimental framework will be used to investigate whether there is a tendency for informed investors to use opposite side limit orders in preference to other kinds of order.

Riccó et al. (2021) expand the choice of limit orders featured in the model of Roşu (2020) to distinguish between competitive limit orders (those that improve on the best bid or ask) and uncompetitive limit orders, and we make this distinction in our analysis. They show that the probability of informed traders placing limit orders on the opposite side of the market to their signal depends on the proportion of informed traders in the market. The smaller the advantage held by informed traders, the more likely they are to disguise their information. While we do not vary the number of informed traders, the private signals received by the informed traders do vary in their distance from the public signal about the value of the asset being traded, and more extreme signals represent a greater advantage for informed traders.[4]

The extent to which information is being disguised by the order choices of informed traders will also be reflected in the convergence of prices in the order book towards intrinsic value. Using the same dispersed information setting as this paper, Schnitzlein et al. (2024), show that, on average, less than 12% of private information is incorporated into price by the end of the trading period. Moreover, where signals are more extreme, convergence is also significantly worse. In that study, the authors show how the observed use of unprofitable (conditional on the trader's signal) market orders assists information aggregation as the traders are inferring revisions to the asset value (away from their signal) from the trading activity. In this paper, we show how specific limit order choices are contributing to the disguising of private information.

Our experimental design shares many features with other papers in the growing experimental finance literature that study how the market design or information structure affects market efficiency. A very incomplete but representative list of issues that have been studied includes Schnitzlein (1996) who studies call versus continuous markets, Flood et al. (1999) who study transparency, Theissen (2000) who studies auction and dealer markets, and Bloomfield et al. (2009) who study the market impact of noise traders. Bossaerts et al. (2010) study the implications of the assumed information structure (ambiguity vs. risk), Carlin et al. (2013) assess the effect of asset complexity on asset trading, and Bourke et al. (2019) study maker-taker fees in a static setting.

Our paper complements empirical studies on how order choice varies between informed and uninformed traders. Using TORQ data, considering institutional traders as informed and others as uninformed, Anand et al. (2005) confirm Bloomfield et al.'s (2005) conclusion that the informed shift from market orders to limit orders over the course of the trading day, while the uninformed make the reverse shift. Menkhoff et al. (2010), using trader identified data from the Ruble inter-dealer market, examine how order choice responds to changes in spreads, volatility, depth, momentum, trading volume, trade duration and time of day. Their results indicate that informed traders are more sensitive to changing market conditions and that they use competitive (inside the spread) limit orders as substitutes for market orders. By contrast, competitive limit orders are seen as substitutes for uncompetitive limit orders by uninformed traders.

Our paper also complements studies of the relationship between measures of illiquidity and insider trading. Collin-Dufresne and Fos (2015) find that activist investors make extensive use of limit orders before they reach the 5% ownership level that requires Schedule 13D filings. Kacperczyk and Pagnotta (2019) screen the SEC investigations in their study 'for the use of limit orders and find that, of the 85 cases with well-identified order types, 73% involve limit orders'. Ahern (2020) show that insider traders, identified by SEC filings, use limit orders to try to hide information when noise trading is high. Akey et al. (2022) find evidence consistent with informed traders trading more aggressively when their information is more precise, while Goyal et al. (2025) find that informed short sellers capitalise on longer term price decreases by supplying liquidity rather than taking it out of the market, consistent with patient trading.

Our key findings are as follows. The use of limit orders declines as the trading interval progresses, while the use of market orders is broadly stable, with a gradual rise, throughout the trading period. The patterns that we observe in order submission strongly support the theoretical prediction of patient trading by partially informed traders, and are robust to whether traders have no experience of the experimental market or have participated previously, and whether traders have a moderate or more extreme information signal. The variation in use of order type through the trading interval generates depth that is concave across the interval. Specifically, the number of outstanding limit orders at the time of a market order is significantly higher during the middle of the trading interval than during either the early or later regions of the trading interval. As the bid-ask spread responds to the competition for execution, the depth concavity is accompanied by a convex spread pattern across the trading interval, whereby the bid-ask spread is significantly lower during the middle of the trading interval than at the opening or closing of the trading interval. These two findings are predicted in the theoretical work of Parlour (1998) and Foucault et al. (2005), and are also consistent with patient trading, as traders first wait for more competitive quotes but then can be exploited as the trading interval nears an end.

By carefully examining the expected and actual profits of particular order choices alongside the foregone profits of the next best market order, we identify the varied routes through which profit seeking will influence the choice between putatively profitable or unprofitable market orders and limit orders. As predicted by the theoretical models of Roşu (2020) and Riccó et al. (2021), we find significant evidence of informed traders placing relatively more limit orders on the opposite side of the market to their signal, which generates significantly greater expected and actual profits but also acts to disguise their information. While our analysis of expected profits establishes *motive* for a particular order type, we also show that the trading behaviour of uninformed traders provides informed traders with the *opportunity* to disguise their information. We also find that traders with more extreme signals can disguise their trading among those with less extreme signals. These findings show the importance of including strategic liquidity traders in models of order choice.

We combine measures of profit and patience, together with the spread as a representation of the order book, into a Multinomial Logit model. This shows that limit orders are preferred to market orders when the opportunity cost (foregone profit from a market order) is low, the spread is greater and there is more time remaining in the trading interval. The role of the spread is foreshadowed in Foucault (1999), while Zhu and Yamamoto (2022) provide empirical evidence of informed traders leaning towards limit orders when the spread is wider. The role of time and profit is at the heart of the immediacy and price improvement tradeoff first explored by Demsetz (1968) and Cohen et al. (1981). As our analysis considers the six different order types in Riccó et al. (2021), we are able to identify this trade-off in a more general setting and show that the role of time is more complex. We find that competitive limit orders are increasing in time. This is consistent with traders placing more aggressive limit orders as the trading period progresses to increase the likelihood of execution. By subdividing our samples by experience and signal strength, we find that the dependence of (putatively profitable) competitive opposite side orders on time is mostly not driven by experienced traders. This suggests that traders who have participated in at least one previous experimental session are learning to distinguish between order types and implies that they are getting better at playing a 'waiting game'.

The rest of the paper proceeds as follows. In Section 2, we describe the details and operation of our experimental limit order book. In Section 3, we present the results from our analysis of our experimental markets. First, we examine the evolution of liquidity supply and demand as evidence regarding waiting game behaviour. Second, we explore the frequency of limit orders of different types to find evidence as to whether informed traders are seeking to trade on the opposite side of the market to their signal. This comprises an examination of the profit potential and realisations and execution probabilities of the different limit order types to understand the relative attractiveness of different limit order types. While this establishes *motive*, we conclude this section with an analysis of *opportunity* by examining whether the uninformed traders are placing orders in a manner that can enable the informed traders to disguise their information, and whether informed traders with extreme signals can disguise their trades among the trades of informed traders with more moderate signals. Third, we use a Multinomial Logit analysis to identify the relative contribution of profit and patience on order choice. Section 4 summarises key results and offers our conclusions.

2 | Experimental Design

Our experiment uses a transparent electronic limit order book conducted on a series of networked personal computers with custom software. Each trader's screen provides continuously updated market information, comprising current bids and asks, transaction price history, whether transactions are at the bid or the ask, the net order imbalance (buyer-initiated trades less seller-initiated trades) and the time remaining in the trading period. In addition, for an individual trader, the screen identifies their inventory position and cash balance and either an information signal or a required end-of-period net position in the asset.

We conducted 19 sessions, with sessions taking place at two different universities and with subjects drawn from students that had studied trading or microstructure courses or had previously participated in financial market experiments. We conducted 10 sessions with fresh subjects, seven sessions from participants drawn from those attending the first 10 sessions and a further two sessions from participants from the second round of seven sessions.[5] Further details on the recruitment of each cohort of subjects are provided in Table A1. Each session lasted around 2 h including instruction and debrief time. Each session comprised 12 trading periods and we excluded the first two (compensated) periods from the analysis.[6] This generated a total of 190 trading periods for analysis, 100 with first-time participants and 90 with experienced participants.

The asset value each trading period is determined by the sum of three independent draws from a discrete integer uniform distribution on the interval [−6, +6] added to L$100. This generates a discrete bell-shaped profile for the asset value with an unconditional expected value of L$100, a range of L$37 (from L$82 to L$118) and a standard deviation of L$6.48 ($=\sqrt{42}$),[7] see Figure A1a. The ex-ante correlation between each signal and the intrinsic value is 0.57 ($=14/\sqrt{(14*42)}$), confirming the partial information characteristic of the signals. We employ nine sets of random draws across the 19 sessions, but never repeat a set of draws with subjects that participate more than once. We used three sets of draws with both inexperienced and experienced subjects to ensure differences by level of experience are not driven by differences in the draws.

Although the bell-shaped profile for the intrinsic value and it being the sum of additive signals are also consistent with Foster and Viswanathan (1996), and our signal independence corresponds to their zero-correlation scenario,[8] our information structure is also motivated by the complex structure of modern corporations. Information events affecting corporations may relate to factors such as labour relations, legal and liability developments, merger and acquisition activity, key personnel issues, developments pertaining to key competitors, technological innovation, patents and changes in government regulation. Since each piece of information is more likely to be known by a limited set of analysts with a specific focus or set of relationships with market participants it is plausible that there are multiple sources of informational advantage at any point in time, each pertaining to a different contributor to fundamental value and held by different groups of traders. In this setting, since new pieces of information are generated independently, new information combines additively to determine value.

In each of the sessions, there are 8 subjects, of which 6 are randomly selected to be informed traders. These roles are maintained throughout the 12 trading periods comprising the session. Each trading period uses an independent set of draws. Each informed trader learns (privately) one of the three independent draws (their signal) and the signals are allocated in pairs, to induce competition, such that subjects 1 and 4 learn signal (draw) 1, subjects 2 and 5 learn signal 2 and subjects 3 and 6 learn signal 3. The signal is displayed on the trader's screen. A sheet of figures displaying the distribution of the asset value conditional on each signal is given to each trader. Knowing a signal revises knowledge of the asset value as follows. The profile is now symmetric discrete triangular with mean shifted to the signal, a range reduced to 25 (12 integers either side of the mean), and standard deviation reduced to L$5.29 ($=\sqrt{28}$).[9] An example conditional distribution is in Figure A1b, for a signal of +4.

The other two traders are designated as liquidity traders. These traders are required to finish the trading period with a specified net position.[10] This net position is private to the trader and is determined independently for each trader by a draw from a discrete integer uniform distribution ranging from one to five units. For one liquidity trader, their drawn positions are always signed positive, and so they have to be a net buyer in all periods, while the other liquidity trader's positions are all signed negative, making them a net seller in all periods. The required position each period is displayed on the trading screen of the assigned liquidity traders. If a liquidity trader does not meet their required position by the end of the trading period, a penalty is imposed equal to 36 times the absolute value of the deviation between the required position and the actual position at the end of the period. This means that it is always worse to not meet the required position than to do so at the most unfavourable prices possible in the market.

At the beginning of each session, the subjects read the experimental instructions. The experimenter then reviewed the trading rules and protocols, the information structure and determination of the asset value, the unconditional and conditional asset value distributions, and the liquidity trader requirements. Before trading commenced, the subjects took a written quiz that tested their understanding of the relationship between the information signals and the asset value. Subjects had no difficulty with the quiz, but the correct answers were always discussed. Subjects receive a monetary endowment at the beginning of the first period. Informed and liquidity traders have starting cash balances of L$200 and L$300 respectively in the first nine sessions at University A. In the six sessions at University B and the last four sessions at University A, starting cash balances are L$280 and L$340.[11] Differences in starting cash balances are intended to minimise differences in profits by trader type. Subjects are not endowed with shares of the risky asset but are allowed to buy or sell-short an unlimited number of shares over the course of a trading period. If a trader goes bankrupt (such that the end-of-period cash balance drops below zero), the trader is not permitted further trading during the session; however, this is not disclosed to the other subjects.[12]

During each trading period, each trader is free to submit both limit and market orders and there is costless and unconstrained quote revision. Price and then time priority are enforced. The minimum tick size is $L0.01, and submitted price quotes are not restricted to be within the range of the asset value.[13] The only limit orders available for execution are those at the best bid and best ask, and new limit orders that equal but do not better the current bid or ask are available for execution in the order that they were submitted. There are no short sale constraints, or other limits to trading activity and there are no designated dealers. The only restriction is that each trade must be for one unit of the single asset, but traders may trade as frequently as they wish within the trading period. Each trading period is limited to 180 s of economic time, but as market activity can be fast the clock is paused following each trade until all participants acknowledge it, meaning that each period usually lasted between 6 and 12 min.[14] When a trade occurs, all traders learn the transaction price and whether it was at the bid or ask, but do not learn the identity of the traders. During the trading sessions the participants were not permitted to communicate with each other.

At the end of a trading period, each subject is informed of the intrinsic value of the asset and any penalties incurred (in case of the liquidity traders). Trading profits are calculated by closing out all remaining long or short positions at the intrinsic value. Each subject is informed of their end-of-period cash balance after liquidation of positions at the intrinsic asset value, and these are carried forward to the start of the next trading period.[15] After the completion of the final trading period, subjects were given a brief questionnaire that assessed their understanding of the experiment; ending cash balances are multiplied by the pre-announced exchange rate of 0.10 to convert L$ to the local currency, and each subject is paid their earnings in private.[16]

3 | Analysis

The 190 trading periods from our experimental markets generate a database of 3474 transactions (market orders) and 9859 limit order submissions. So, on average in a trading period, there were 18.3 trades (=3474/190). The first limit order is always placed within the first 6 s and mostly within the first second of the trading interval, as shown in Figure A2. Of the unexecuted limit orders, 5180 were subsequently cancelled within their trading period, and 1205 were outstanding in the order book at the end of their trading period. There was at least one limit order outstanding on both sides of the market in the book at the end of 97.3% (185) of the trading periods. The relative proportion of market and limit orders observed in our experimental markets are within the bounds of the empirical results for the limit order book on the Swedish stock exchange found by Hollifield et al. (2004) indicating that our markets are representative of field markets.

3.1 | A Waiting Game

To examine the degree of patience displayed by the partially informed traders we look at their time series of liquidity supply and liquidity demand. The informed traders submitted 7672 limit orders and 2571 market orders. We compute average limit order submission rates and average market order submission rates on a per trader basis. The limit order submission rate (or 'make rate') for a trader is the number of limit orders submitted during a period divided by the number of both limit orders submitted and market orders submitted by that trader in that period. The market order submission rate (or 'take rate') for a trader is the number of market orders submitted during a period divided by the number of both market orders and executed limit orders for that trader in that period.

We have six informed traders in each of 19 sessions featuring 10 trading periods, so an average is taken over a maximum of 1140 observations (trader-periods). As the theoretical models have suggested that the submission rates of orders may change across the trading interval, as there are benefits to patient trading, we break down the 3-min trading period into six 30 s sub-intervals and look at the average order submission rates in each sub-interval separately. We further divide the data to isolate the sessions with experienced traders and those that received a more extreme information signal. The submission rates for limit orders and market orders of the informed traders are shown in Figure 1a,b.

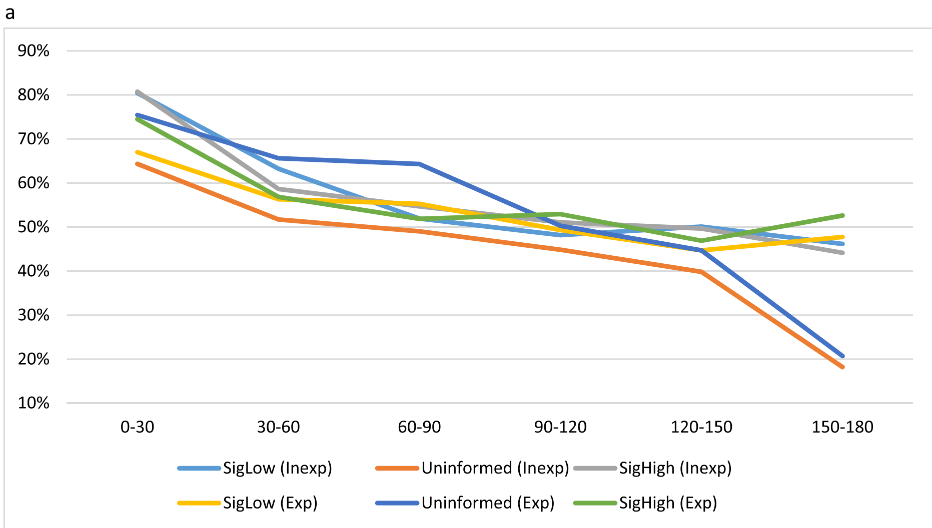
The key visual feature of Figure 1a,b is that for our (partially) informed traders the limit order submission rates are decreasing through the trading period while market order submission rates are increasing through the trading period. These results are entirely consistent with a 'waiting game', as these patterns in order submission rates indicate patience. However, they are in complete contrast to the findings in Bloomfield et al. (2005), who found a high initial demand for liquidity, from their perfectly informed traders, that subsequently declined and that the peak in supply of liquidity from these traders was reached further into the trading period.

We analyse these limit and market order submission rate data using a within-subjects design repeated-measures ANOVA, which is a conservative but robust procedure for analysing experimental data. In our analysis for each dependent variable, the Main Effects that we examine are the Extremeness of the Signal (2 categories: extreme [absolute value of the signal is greater than 3] and moderate), the experience level of the session participants (2 categories: inexperienced and experienced) and the market sub-interval (6 categories: Each consecutive 30 s sub-interval of the 3-min trading period). Interaction Effects between the independent variables allow us to observe whether the effects of experience and signal extremeness are dissimilar in different sub-intervals. Tests of pairwise differences between the categories of a given Main Effect while holding the category of the other Main Effects constant are adjusted for multiple comparisons using the Bonferroni method.

The submission rate of limit orders (liquidity 'making' rate) starts the trading period at around 80% and declines during the trading period, but can still be above 50% by the end of the trading period. However, the decline in the submission rate by the fourth sub-interval is statistically significant ($p < 0.001$), while for inexperienced traders, the decline is significant from the second sub-interval ($p < 0.001$). It also appears that experienced traders tend to increase their limit order submission rates at the end of the trading interval. This suggests that they are exercising market power to extract profits from liquidity traders as the trading interval nears its end. This finding is consistent with a prediction from the model of Foucault et al. (2005) where traders who still need to place market orders can be exploited by increases in the spread and limit order submissions by informed traders. Although this finding is not statistically significant, the overall stability in the submission rate of limit orders, following the more intense limit order submission activity immediately after the market opening, is certainly consistent with a 'waiting game'.

The market order submission rates (liquidity 'taking' rates) are also remarkably stable across the trading interval for all trader types, being mostly between 15% and 25%. Only in the case of experienced informed traders having a moderate signal can we conclude that the market order submission rate is higher in the final sub-interval of the trading period than it is in the first three sub-intervals, where it is as low as 8% ($p < 0.004$). Again, the stability is highly consistent with a 'waiting game', and in manifest contrast to the aggressive use of market orders predicted by Holden and Subrahmanyam (1992) and found in Bloomfield et al. (2005) for perfectly informed traders.

Since Bloomfield et al. (2005) include a pre-trade period during which limit orders can be entered but not transacted, it is possible that the flurry of market orders (and relatively lower limit order submission rates) at the opening of the trading period seen in their paper is the response to the availability of limit orders rather than being driven by their informed traders being perfectly informed. While it is likely that the high submission rate of limit orders at the opening of the trading period that we



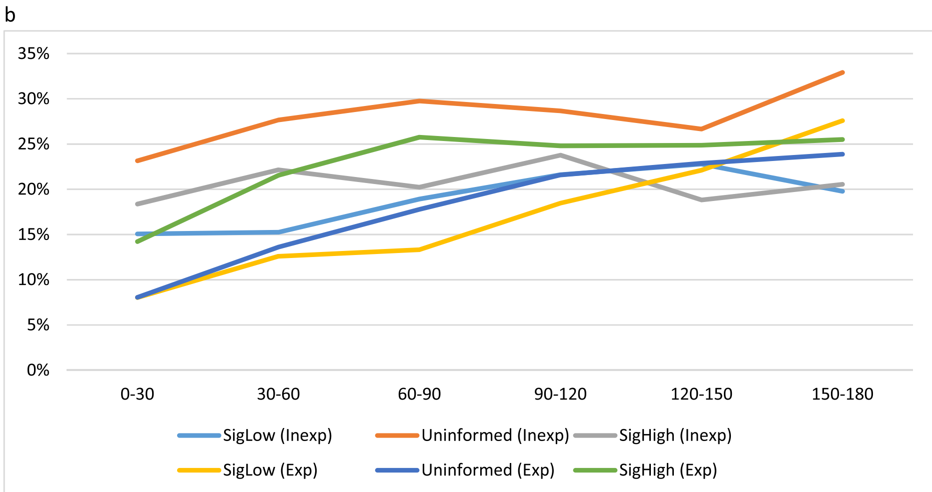


FIGURE 1 | (a) Limit order submission rates. The per trader average limit order submission rate within each 30 s sub-interval of the trading period. Informed traders have either an extreme signal (SigHigh) or a moderate signal (SigLow). Sessions either feature first-time (Inexp) or experienced (Exp) participants. There are 19 sessions (10 with first-time participants, 9 with experienced participants), each of 10 periods, each with 6 informed traders and 2 liquidity traders. (b) Market order submission rates. The per trader average market order submission rate within each 30 s sub-interval of the trading period. Informed traders have either an extreme signal (SigHigh) or a moderate signal (SigLow). Sessions either feature first-time (Inexp) or experienced (Exp) participants. There are 19 sessions (10 with first-time participants, 9 with experienced participants), each of 10 periods, each with 6 informed traders and 2 liquidity traders. [Colour figure can be viewed at wileyonlinelibrary.com]

observe reflects the fact that the book opens empty, it is in the behaviour of market orders that the key differences to the results of Bloomfield et al. (2005) arise.[17] If market order activity is responsive to limit order supply, then it would be expected that the market order submission rates of partially informed traders would closely follow the limit order submission rates of the partially informed traders. However, we do not see this. As reported above, limit order submission rates are in the order of 80%–50%, while market order submission rates never exceed 30% and are highly stable. This form of 'waiting game' behaviour reflects the partial information rather than perfect information endowment.

We also analysed the evolution of market depth and the bid-ask spread through the trading periods. We find that these are consistent with the submission rate and taking rate behaviour, providing further evidence of patient trading. We report this analysis in Figures A3a,b and A4 and accompanying text.

3.2 | Disguising Information in the Choice of Limit Order Type

In this section, we will examine whether, as predicted by Roşu (2020), informed traders will try to disguise their information by trading on the opposite side of the market to their signal. We first examine the frequencies of different order types and analyse the role of the profit potential of the different order types in influencing these frequencies. This enables us to establish whether there is evidence of trading on the opposite side of the market and whether a motive to do so arises from the profit potentials of the different order types. Having established motive, we must also establish opportunity. So, we follow this analysis by examining the behaviour of the uninformed investors. For informed investors to be able to hide their orders, the uninformed investors must be behaving in a similar manner to the informed investors, and so we will be looking for matching order flow patterns in the behaviour of the uninformed investors.

3.2.1 | The Order Choice of Informed Investor: *Motive*

Table 1 shows the frequencies of the different types of limit orders, classified by the experience level and signal extremeness of a trader. Limit orders are distinguished by whether they are inside the existing spread (I_) or outside it (O_), and by whether they are on the same (_S) or opposite (_O) side of the midpoint of the bid-ask spread as the signal. Orders inside [outside] the spread are classified as competitive [uncompetitive]. Using the example from the Introduction, of a signal of L$105, and an inside bid and ask of L$102 and L$104 respectively: Inside/opposite is a bid at L$102.1, outside/opposite is a bid at L$101.9, outside/same is an ask at L$104.1, while inside/same is an ask at L$103.9. In this example, the two opposite side orders are putatively profitable, while the two same side orders are putatively unprofitable conditional upon the signal. Outside/opposite orders (OO) will always be putatively profitable, and inside/opposite orders (IO) will also be putatively profitable except in the very rare circumstance that the order narrows the spread sufficiently to move the signal outside the spread, a possibility that is ruled out by the fixed spread in the theoretical model of Riccó et al. (2021), and occurs in less than 1% of cases in our data set. By contrast, inside orders (IS or OS) will be putatively profitable (unprofitable) when the trader's signal is nearer (farther) to the midpoint of the spread than the proposed limit order.

The volumes of opposite side orders are on average between 2.09 (moderate signal) and 2.86 (extreme signal) orders per trader per period for competitive orders (IO) and between 1.48 (moderate signal) and 1.96 (extreme signal) for uncompetitive orders (OO). These are greater than the volumes of same side orders that are between 0.73 (extreme signal) and 1.12 (moderate signal) for competitive orders (IS) and between 0.87 (extreme signal) and 1.35 (moderate signal) for uncompetitive orders (OS). The per trader per period order volume for competitive opposite side orders (IO) is significantly greater than any same side limit order type for each combination of experience level and signal extremeness ($p < 0.001$).[18]

As a robustness check of the constancy of these results across alternative subject characteristics, we repeat this analysis separately for each of the two universities from which the subjects were drawn. As these two countries differ in their levels of participation in and awareness of financial market trading among the general public, the comparison tests can act as an indicator of the wider applicability of our results. We find no significant differences between the frequencies of different trade types across the two jurisdictions for all combinations of experience and signal extremeness ($p > 0.226$), indicating some robustness to changes in subject characteristics.

The high proportion of opposite side limit orders that we find in our experimental markets is consistent with the prediction of Roşu (2020) that informed traders will try to disguise their information by trading on the opposite side of the market to their signal. Continuing with the example above, where a trader has a signal above the standing ask price, there is a putatively profitable order either by buying at the ask price or by submitting a limit buy order. As the limit order would be on the opposite side of the market to their signal, it would be much less likely to reveal information, because it is consistent with an uninformed trader improving his terms of trade. Moreover, the expected profits would be greater from the executed limit order than from the market order. We now examine the expected and actual profits from different order types and the execution frequency of limit orders to determine whether expected profits are motivating particular order choices and whether these are the order choices that are disguising information.

As well as computing the expected profits (profits conditional on the trader's signal) and actual profits obtained from a given order choice, we also introduce a measure of the opportunity cost of an order choice. This variable we call EPMO (Expected Profit from a Market Order) and it is the absolute value of the difference between the informed trader's signal and the inside bid (if the signal is below the inside bid) or the inside ask (if the signal is above the inside ask). This measures the opportunity cost (foregone profit) of placing an order other than a market order that is profitable conditional upon the trader's signal. This enables us to directly reveal the relative benefits of choosing the profitable trade that disguises information.

On average, informed traders expect to make significantly positive profits (conditional on their private signal) when placing opposite side limit orders, on average of between L$3.15 (with a moderate signal) and L$5.14 (with an extreme signal) for competitive orders (IO) and between L$3.76 (moderate signal) and L$5.80 (extreme signal) for uncompetitive orders (OO) ($p < 0.001$). There are no significant differences arising from experience or signal extremeness ($p > 0.392$),[19] except for inexperienced traders where a more extreme signal generates greater expected profits ($p < 0.001$). For same side orders, they expect to make losses, on average of between −L$0.26 (moderate signal) and −L$2.42 (extreme signal) for competitive orders (IS), although these are not significantly different from zero for experienced traders with a moderate signal ($p = 0.156$). For uncompetitive same side orders (OS), they expect to make profits of between L$1.07 (moderate signal) and L$0.02 (extreme signal), but these are not significantly different from zero for traders with an extreme signal ($p > 0.800$). There are no significant differences arising from experience or signal extremeness for same side orders, except for inexperienced traders placing a competitive order (IS) where a more extreme signal generates greater expected losses ($p = 0.011$). Expected profits for competitive opposite side orders (IO) are significantly greater than the expected losses for competitive same side orders (IS) ($p < 0.001$), and for uncompetitive orders, expected profits for opposite side orders (OO) are significantly greater than the expected profits for same side orders (OS) ($p < 0.001$). These results hold for each of the four combinations of experience level and signal strength.

Actual profits per trade from the executed limit orders of informed traders fall short of profits expected, and these differences are significant for opposite side orders placed by traders who have a moderate signal ($p < 0.001$), where it can be seen that the actual profits can be negative (on average). However, these losses and profits, on average of between –L$0.41 for competitive orders and L$0.49 for uncompetitive orders, are not

TABLE 1 | Limit orders choices: Expected profits, actual profits and volume.

	Opposite side limit orders								Same side limit orders							
	Competitive ('inside')				Uncompetitive ('outside')				Competitive ('inside')				Uncompetitive ('outside')			
	EPMO	Ex Prof	Act Prof	Vol	EPMO	Ex Prof	Act Prof	Vol	EPMO	Ex Prof	Act Prof	Vol	EPMO	Ex Prof	Act Prof	Vol
Informed traders (moderate signal)																
Inexperienced (sessions 1–10)																
Mean	1.00	3.15	0.36	2.09	1.08	3.76	0.49	1.74	0.81	−0.73	−1.78	1.12	0.98	1.07	−1.32	1.35
N [Obs]	224 [663]	139 [290] {40}		316	222 [552]		81 [159] {23}	316	123 [355]	73 [170] {42}		316	198 [426]	63 [109] {19}		316
Experienced (sessions 11–19)																
Mean	1.31	3.35	−0.41	2.38	1.47	4.40	−0.29	1.48	0.63	−0.26	0.76	1.05	1.13	0.83	−0.33	0.88
N [Obs]	200 [664]	126 [281] {39}		278	166 [414]		65 [152] {25}	278	110 [294]	53 [100] {29}		278	140 [247]	30 [47] {15}		278
Informed traders (extreme signal)																
Inexperienced (sessions 1–10)																
Mean	2.75	5.14	4.70	2.53	2.70	5.80	4.84	1.96	2.02	−2.42	−5.31	1.00	2.63	0.02	−4.55	0.87
N [Obs]	208 [721]	143 [324] {42}		284	210 [556]		72 [154] {20}	284	105 [285]	63 [142] {45}		284	139 [249]	34 [46] {17}		284
Experienced (sessions 11–19)																
Mean	2.29	4.38	3.23	2.86	2.39	5.03	2.40	1.76	1.51	−1.43	−2.10	0.73	2.05	0.07	−1.33	0.97
N [Obs]	198 [749]	133 [296] {36}		262	187 [462]	65 [137] {20}		262	88 [191]	54 [88] {42}		262	132 [255]	39 [66] {19}		262
Uninformed traders																
Inexperienced (sessions 1–10)																
Mean		−2.56		1.58		−3.38		0.64		2.63		1.77		0.43		1.04
N [Obs]	110 [315]	78 [148] {46}		200	75 [128]	27 [37] {28}		200	113 [354]	85 [162] {49}		200	101 [208]	38 [53] {24}		200
Experienced (sessions 11–19)																
Mean		−2.56		1.86		−2.13		0.71		2.38		2.38		1.85		0.92
N [Obs]	107 [334]	74 [131] {42}		180	70 [128]	29 [44] {30}		180	114 [428]	83 [155] {39}		180	81 [166]	30 [36] {21}		180

Note: This table contains the average value per trader per trading period of the volume of orders (Vol)and three measures of profit (average per trade). EPMO is the greater of zero or the profit expected from the most profitable market order conditional on the trader's signal. Expected profit is the profit expected from that order conditional on the trader's signal. Actual profit is the profit earned relative to the intrinsic value of the asset and is the one profit measure reported for uninformed traders. Opposite (same) side orders are on the opposite (same) same side of the midpoint of the spread as the trader's signal. Competitive (uncompetitive) orders (do not) improve the best bid or ask. There are 19 sessions each of 10 periods containing 6 informed traders, giving a total number of trader-periods of 1140 for each of the four order types. *N* in the volume column indicates how these 1140 trader-period divide up between traders with differing signal strength and level of experience. The left side *N* in the profit columns indicates in how many of these trader-periods there was an order of this type. The right-side *N* in the profit columns indicates in how many of these periods there were executed limit orders (generating Actual profits). Average per trader per trading period calculations use the corresponding *N* value as denominator. The number of observations is in brackets: limit orders placed [left side column]; limit orders executed [right-side column]. In parentheses {right hand side column}, are the percentage of orders executed (average per period).

significantly different from zero ($p > 0.273$). The profits from opposite side orders made by traders with an extreme signal, on average of between L$3.23 (experience) and L$4.70 (no experience) for competitive orders (IO) and of between L$2.40 (experience) and L$4.84 (no experience) for uncompetitive orders (OO), are significantly greater than zero ($p < 0.001$). For both competitive and uncompetitive same side limit orders, there are no significant differences between expected losses and actual losses for informed traders ($p > 0.999$), except for inexperienced traders either placing an uncompetitive order (OS) or, and only if holding an extreme signal, placing a competitive order (IS) ($p < 0.001$). Actual profits (losses if negative) for same side orders are on average of between L$0.76 (moderate signal) and −L$5.31 (extreme signal) for competitive orders (IS) and of between −L$0.33 (moderate signal) and −L$4.55 (extreme signal) (OS) for uncompetitive orders, but these are only significantly lower than zero in the case of periods with inexperienced traders ($p < 0.051$) and for experienced traders with an extreme signal placing inside orders (IS) ($p = 0.012$).

Signal extremeness influences the differences in actual profits between opposite side and same side limit orders. If traders have an extreme signal, then actual profits for competitive opposite side orders (IO) are significantly greater than the actual losses for competitive same side orders (IS) ($p < 0.001$), and similarly for uncompetitive orders, actual profits for opposite side orders (OO) are significantly greater than the actual losses for same side orders (OS) ($p < 0.001$). If traders have a moderate signal, then only in the case of competitive orders placed by inexperienced traders are the actual profits from opposite side orders (IO) significantly greater than the actual losses for same side orders (IS) ($p < 0.001$). Through a trading period, these actual profit differences between opposite and same side limit orders would gradually add to the evidence from expected profits that the former offer significantly greater profit opportunities. Although the expected profits from opposite limit orders were not significantly different between informed traders with moderate or extreme signals, as informed traders observe that their opposite side limit orders are being rewarded more when they have extreme signals than when they have moderate signals, this may further motivate them to choose opposite side limit orders when they have an extreme signal.

While we have seen that losses are expected from placing competitive same side orders (IS), that these can be significantly less than zero, and are not significantly different from the losses realised, informed traders nonetheless place these orders. So, while there is a strong profit motive to place opposite side orders, there must be a different motivation for placing competitive same side orders. We conjecture that the informed players could be deliberately trying to mislead the uninformed players, as doing so potentially increases the chance of an opposite side limit order, which is profitable, being executed. It is also possible that competitive inside orders are simply mistakes. If they are mistakes, we might expect their frequency to decline throughout a trading period, as the traders realise the losses from these orders. However, considering the six 30-s sub-intervals of the trading period and calculating the order frequency in each sub-interval, we find no evidence that these frequencies decline through the whole trading period ($p > 0.999$), with this result holding for each of the four combinations of experience level and signal strength. The stability of the frequency of these loss-making limit orders further adds to the ability of limit orders as a whole to disguise information, as this order type appears to be being used to deliberately conceal information.

We now turn to the choice between a limit order and a market order. For the informed traders, the average expected profit for opposite side limit orders is greater than EPMO (the profit from foregoing the best available market order at the time of placing the limit order). The differences are on average between L$2.04 (with a moderate signal) and L$2.39 (with an extreme signal) for competitive orders (IO) and between L$2.68 (moderate signal) and L$3.10 (extreme signal) for uncompetitive orders (OO). These differences are all significant ($p < 0.001$), indicating that there is a strong profit-based incentive in our experimental markets to choose a limit order in place of a market order and so disguise information.

Not only is this key result statistically significant, but we have reason to expect that it has economic significance also. Given the unconditional mean of the asset value is $L100, the profits and their differences are approximately the average basis points earned from that order choice, this L$2.68 represents a 268 basis approvement by choosing a limit order compared to a market order. Given the small profit margins that motivate automated trading algorithms in field markets, the magnitudes observed here are of economic importance. Moreover, the average expected and actual profit levels observed for some trades are in the region of 500 basis points, which would be acceptable compensation for even more passive trading. Furthermore, every informed trader in our markets knows that there is another informed trader that shares their signal. So, while the pursuit of profit would motivate them to trade patiently, they would also be aware that by trading sooner than the informed trader that shares their signal, they could potentially earn greater profits before the other trader's actions move price. This countervailing force makes it likely that our results understate what would be seen in field markets.

A further factor is choosing between market orders and limit orders is the execution rate of each type of limit order. Table 1 also shows these rates, separated by signal extremeness and experience level. For competitive limit orders from informed traders, the execution rates are on average between 36% and 42% for opposite side orders (IO) and between 29% and 45% for same side orders (IS), and for uncompetitive orders are between 20% and 25% for opposite side orders (OO) and between 15% and 19% for same side orders (OS). The differences between execution rates for corresponding competitive and uncompetitive orders are all significant ($p < 0.003$), except for same side orders for experienced traders with a moderate signal ($p = 0.171$). However, there are no significant differences between the execution rates for opposite side orders relative to same side orders, for any given level of experience or signal extremeness, for either competitive or uncompetitive orders ($p > 0.999$). We also see that execution rates are below 50%, on average. All but one of the average execution rates are significantly less than 50% ($p < 0.050$), the exception being for competitive same side orders from inexperienced informed traders with an extreme signal, which is significantly less than 53%

($p < 0.05$). So, overall, the chance of a limit order executing in our markets is rarely better than even, and differs little between order type indicating that relative execution rates are unlikely to be influencing the decision to place limit orders in preference to market orders. In empirical data for the Swedish stock exchange limit order book, Hollifield et al. (2004) also find execution rates below 50%, suggesting our experimental markets are representing this feature of field markets.

3.2.2 | The Order Choice of Uninformed Investors: *Opportunity*

For informed traders to disguise their orders, which they have a significant profit seeking motive to do, there must also be the opportunity to do so. This is provided by plentiful limit orders of similar type being placed by the uninformed investors. In this section, we examine whether the trading behaviour of the uninformed investors provides the opportunity for informed investors to disguise their orders.

The uninformed traders submitted 2187 limit orders and 903 market orders. In Figure 1a, we see that the limit order submission rates of the uninformed traders are strikingly similar to those of the informed traders, before a dramatic drop at the end of the period, to a level significantly less than that obtained in each of the earlier five sub-intervals ($p < 0.001$). This reduced level of limit order submission is also significantly different from that of informed traders at the end of the trading period ($p < 0.001$). This reduction in limit orders, which do not guarantee execution, is being driven by the need of the uninformed traders to meet their required position to avoid a penalty and so they switch to market orders to ensure execution, which can be seen in Figure 1b. By contrast, for all earlier sub-intervals of the trading interval and for a given experience level, there are no significant differences between the limit order submission rates for informed and uninformed traders ($p > 0.999$), except for inexperienced traders at the beginning of the session, where uninformed traders submit significantly fewer limit orders ($p < 0.025$). Thus, limit order submissions are plentiful and closely mirror those of the informed traders.

However, to be able to disguise their limit orders, informed traders also need the proportions of the type of limit orders used by the uninformed traders to match their intended proportions so as not to be conspicuous by the type of limit order being placed. For uninformed traders, the volumes of limit orders shown in Table 2 display a strong preference for competitive orders. The average number of competitive orders (per trader per period) on a given side of the market, of between 1.58 (no experience) and 1.86 (experience) for opposite side orders (IO) and of between 1.77 (no experience) and 2.38 (experience) for same side orders (IS), is greater than the number of uncompetitive orders, respectively of between 0.64 (no experience) and 0.71 (experience) for opposite side orders (OO) and of between 1.04 (no experience) and 0.92 (experience) for same side orders (OS).[20] These differences are all significant ($p < 0.002$), whether the traders are experienced or not. This preference for competitive orders reflects their greater chance of being executed. However, with the exception of uncompetitive same side orders (OS), these frequencies of order types are significantly different to those for informed traders, being lower for opposite side orders (IO, OO), and higher for same side orders (IS), than the corresponding order frequency for informed traders.[21] Table 2 also shows execution rates for limit orders from uninformed traders that range from 42% to 46% for IO, 39% to 49% for IS, 28% to 30% for OO and 21% to 24% for OS. None of these is significantly different to the corresponding execution rate for limit orders placed by informed traders ($p > 0.999$), further indicating the potential for limit orders from informed traders being undetectable.

So, while the submission rates of limit orders by uninformed traders and their execution rates are similar to that of the informed traders, there is some variability in the pattern across orders that means that informed traders cannot always be assured of being inconspicuous. However, it may also be the case that informed traders with a more extreme signal can hide their orders among those with a moderate signal, and so we also compare the submission rate, order type frequencies and limit order execution rates within informed traders but across signal extremeness. Figure 1a shows that the submission rates of informed traders with extreme signals are similar to those with a moderate signal, and for all sub-intervals differences between the submission rates are not significant ($p > 0.999$). Table 1 shows the frequency of order types separated by experience and signal extremeness and, for each level of experience, there is no significant difference between the frequency of a given order type in response to a change in signal extremeness ($p > 0.579$). This table also shows the corresponding execution rates for these limit orders and again there is no significant difference relating to signal extremeness ($p > 0.999$). Thus, informed traders with a more extreme signal may be able to disguise their orders among informed traders with a more moderate signal.

3.3 | Patience or Profit? A Multivariate Analysis of Strategic Order Choice

The results in Table 1 demonstrate that both the expected and actual profits of different limit order types appear to influence their relative frequencies, creating an incentive for informed traders to trade on the opposite of the midpoint of the spread to their signal. This incentive is greater for traders with a more extreme signal, as profits are found to be greater in this case. We also observed that expected profits from limit orders are greater than the expected profits from the best available market order, creating an incentive to prefer a limit order over a market order. Taken together, these incentivise disguising information, consistent with predictions in Roşu (2020).

Although there is a strong profit motive driving the choice of limit versus market order, we have also found that the execution of a limit order is far from assured. This suggests that order choice must have other determinants. In Section 3.1, we found clear evidence of patient trading, suggesting that the passage of time in a trading interval also influences order choice. In this section, we combine the two determinants in a multivariate Logit regression to attempt to apportion the relative influence of the two factors of patience and profit that, as originally identified by Demsetz (1968) and Cohen et al. (1981), are central to

TABLE 2 | Order choice: Limit order versus market order.

	EPMO	SPREAD	TIME	Pseudo R^2	N
All signal types All sessions (1–19)	−0.112*** (−2.65)	0.478*** (9.47)	0.0018 (0.12)	0.110	9624
Moderate signal Inexperienced sessions (1–10)	−0.123 (−1.24)	0.428*** (4.42)	0.0014 (0.83)	0.152	2644
Moderate signal Experienced sessions (11–19)	−0.210*** (−3.60)	0.628*** (7.56)	0.0011 (0.71)	0.186	2140
Extreme signal Inexperienced sessions (1–10)	−0.205*** (−3.77)	0.447*** (6.27)	0.0024 (1.26)	0.193	2434
Extreme signal Experienced sessions (11–19)	−0.126** (−2.56)	0.470*** (4.12)	0.0004 (1.64)	0.153	2406

Note: We report the results of logit regressions analysing the order choice of informed traders, for all sessions, separately for sub-sample combinations of sessions with inexperienced and experienced traders and traders with either a moderate signal or extreme signal. We analyse the choice between a limit order and a market order when there is a standing bid and ask at the time of order submission. The first explanatory variable is the difference between the inside bid and the informed trader's signal if the signal is below the midpoint of the bid-ask spread, or the difference between the signal and the inside ask if the signal is above the midpoint of the spread. This measures the difference between the informed trader's signal and the information in the market quotes and is the expected profit from a market order conditional on the trader's signal (EPMO). The second variable is the size of the inside spread at the time of the order submission (SPREAD). This captures the difference in expected profit (conditional on the signal) between submitting a limit order that is just exposed to the market and a market order. The third variable (TIME) is the number of seconds that have elapsed in the trading period. We additionally include fixed effects to control for dependencies across sessions and across the periods within sessions. We also include a variable that is the signed net required position of the liquidity traders, positive if they are net buying [selling] and the asset value is above [below] the conditional mean, and negative otherwise. We account for the possible autocorrelation in the residuals due to each trader making multiple decisions by estimating robust Z-statistics, clustering on each trader. Significance for a two-tailed test relative to zero at the 10%, 5% and 1% level are indicated with *, ** and *** respectively with t-statistics in parentheses. N is the number of observations.

the trade-off between immediacy and price improvement that is at the heart of order choice.

Our multivariate analysis of order choice is divided into two components. The first half considers the binary choice of market order versus limit order, while the second half considers a multinomial choice among the six different order categories. This features market orders that are either putatively profitable (MOP) or unprofitable (MOU) and the four types of limit order from Table 1 that are distinguished by whether they are inside the standing spread (competitive) or at or outside the spread (uncompetitive), and whether they are on the same side of the book as the trader's signal or on the opposite side of the book. Conditional on there being a standing bid and ask prior to the order being placed, so that all 6 order choices can be distinguished, there are 7083 limit orders and 2541 market orders placed by informed traders.

In Table 2, we show the results from formally modelling the determinants of the choice between market and limit orders using a logit regression for informed traders. Our first explanatory variable is EPMO, the expected profit from a market order that could have been obtained at the time the order was placed. Specifically, this is the difference between the inside bid and the informed trader's signal if the signal is below the midpoint of the bid-ask spread, or the difference between the signal and the inside ask if the signal is above the midpoint of the spread. This measures the difference between the informed trader's signal and the information in the market quotes. For a conditionally profitable market order, EPMO is equal to the expected profit on that order, while for limit orders and conditionally unprofitable market orders it captures the opportunity cost. The second variable is the size of the inside spread at the time of the order submission (SPREAD). This variable captures the difference in expected profit (conditional on the signal) between submitting a limit order that is just exposed to the market, and a market order. The inclusion of this variable is motivated by the theoretical prediction of the models of Foucault (1999) that the frequency of limit orders is increasing in the bid-ask spread. In this model, higher volatility of the asset price increases the likelihood of a limit order being picked off, leading liquidity suppliers to widen the spread. The increase in spread makes market orders less attractive than limit orders. The third variable (TIME) is the number of seconds that have elapsed in the trading period, and is motivated both by the experimental finding of Bloomfield et al. (2005) that order choice changes through the trading period and by the theoretical predictions of, for example, Parlour (1998) and Foucault et al. (2005), that trader impatience influences order choice, and of Foster and Viswanathan (1996) that in a dispersed information setting traders should play a waiting game. We further include fixed effects to control for dependencies across sessions and across the periods within sessions. We also take account of ongoing liquidity trading by including a variable that is the signed net required position of the two liquidity traders, signed positive if they are net buying (selling) and the asset value is above (below) the conditional mean, as the net liquidity position is reinforcing the direction of travel for price away from the unconditional mean. We sign it negative if the net liquidity requirement is in opposition to the location of the asset value around the unconditional mean.

We also included indicators for experience and for the extremeness of the trader's signal but these were never significant and so are omitted from the specifications whose results are displayed.[22] However, as these variables generated some differences among the profits to different order types, shown in Table 1, we also subdivided the sample by these categorizations to permit any weak effects to be revealed. We also note that comparison by signal extremeness permits us to examine the role of information precision as a more extreme signal implies a bigger revision of price from intrinsic value and is therefore more valuable. Since each trader makes multiple decisions, we account for the autocorrelation in residuals by estimating robust Z-statistics, clustering on each trader.[23]

In Table 2, we see that (relative to market orders) limit order submissions by informed investors are decreasing in Expected Profit Market Order ($p<0.01$) and increasing in the magnitude of the Inside Spread ($p<0.01$). This latter result is consistent with the predictions of Foucault (1999). The coefficient on Time is insignificant, indicating that the informed traders' choice between limit and market orders is relatively constant over the trading interval, when examined at this high level of granularity. This result is consistent with our earlier finding of a stability in submission rates of both limit and market orders for most of the trading period that supports the idea that our partially informed traders are trading cautiously. We also find that the coefficient on our control variable for liquidity trading is negative ($p<0.009$), which indicates that informed traders prefer limit orders when liquidity traders are trading against the direction of price. This is consistent with empirical results in Ahern (2020) that show that informed traders try to hide information when noise trading is high.

When we subdivide the sample of orders into whether they were placed by experienced traders or whether they were placed by traders with more extreme signals, we find that the significance of EPMO is driven by the trading behaviour of experienced traders, the presence of an extreme signal, or both ($p<0.01$). The influence of signal extremeness on the choice between limit and market orders is consistent with the predictions of Roşu (2020) that the more extreme the signal the more likely that traders are to use market orders. This is because a more extreme positive (say) signal implies greater chance of the order book drifting upwards in the future, pushing the future bid above the current ask. This makes a market buy now more attractive, as it will likely be below the future ask price and a current limit buy order will unlikely execute as it will quickly become stale.[24]

The choice between limit orders and market orders has further decision layers, since there are four types of limit order that present different putative profit potential and different relative competitiveness, as seen in Table 1. In Table 3, both types of market order and the four types of limit order are analysed together using a multinomial Logit regression. Again, we consider the full sample as well as partitions by experience and signal extremeness. In this analysis, we use a putatively profitable market order as the base case for the multinomial Logit estimation. We make this base case choice as it presents a clear alternative to the putatively unprofitable market order and the four kinds of limit order, and reflects also our use of EPMO as a measure of the opportunity cost of an order choice. This choice therefore provides the direct contrast between choosing to place a (putatively profitable) market order that would reveal information and a (putatively more profitable) opposite side limit order that would disguise information.

Considering first the full sample of all sessions, we see that all kinds of limit order are decreasing in EPMO ($p<0.01$) and increasing in the inside spread ($p<0.01$), which mirrors the results in Table 2. What the analysis in Table 3 adds, however, is showing that the dependence of order choice on Time is more nuanced than can be identified from a binary comparison of market versus limit order. Specifically, the two competitive limit orders, Inside Same (IS) and Inside Opposite (IO), are both increasing in Time. This is consistent with traders placing more aggressive limit orders as the trading period progresses to increase the likelihood of execution. We also see that putatively unprofitable market orders are also increasing in Time, also suggesting that traders are placing orders to ensure execution before the trading interval ends. From the samples subdivided by experience and signal strength, we can see that the dependence of competitive opposite orders (IO) on Time is mostly not driven by experienced traders. Since this order choice is both putatively profitable and also likely to be executed, it suggests that experienced traders are learning to distinguish between order types, are trading in a more sophisticated manner, or both. It would seem that they are getting better at playing a 'waiting game'.

4 | Discussion and Conclusions

Our paper uses a laboratory-based limit order book market to undertake a test of two predictions of the financial market microstructure theory relating to the determinants of order choice by traders in a limit order market, in a setting where those traders are partially informed. These are that the traders will trade slowly and, through strong profit incentives, choose order types that disguise their private information. Although the early contributions to theory placed considerable restriction on trader behaviour and market structure in order to generate testable predictions and explain some results being found in empirical data, more recent contributions have relaxed many of these restrictions and a rich array of predictions is now available for testing. Although some of the predictions have been explored and validated in empirical data, the evidence has sometimes been indirect and forced to proxy certain unobservable characteristics of the traders. Our laboratory setting provides the freedom to expand the state space beyond the limits of the current theoretical models and to observe otherwise unobservable characteristics of traders, such as whether they are informed and if so how strong their signal might be. We also include strategic liquidity traders enabling us to test some recent new theoretical insights.

By studying the submission rates of both market orders and limit orders during the trading period, we find significant evidence that our partially informed traders are playing a 'waiting game' consistent with predictions in Foster and Viswanathan (1996). Limit orders gradually decline through the trading period, while market orders gradually increase, but neither shows particularly dramatic changes over the trading interval. Order flow is remarkably stable. This is also consistent with empirical evidence in Ellul et al. (2007) that informed traders can be patient. Our results, taken in combination with the 'rat race' behaviour observed in Bloomfield et al. (2005) where market orders behave in the opposite manner to that seen here, confirm, in an experimental setting, the contrast between the behaviour of fully informed (high correlation signals) and partially informed (low correlation signals) traders that is predicted by Foster and Viswanathan (1996). Our results also mirror findings in recent

TABLE 3 | Multinomial analysis of order choice of informed traders.

	EPMO	SPREAD	TIME	Pseudo R^2	N	EPMO	SPREAD	TIME	Pseudo R^2	N	EPMO	SPREAD	TIME	Pseudo R^2	N
	All signal Types and all sessions					**Moderate signal and inexperienced sessions**					**Moderate signal and experienced sessions**				
MOU	−0.396***	0.116	0.0062***	0.077	9624	−0.598***	0.168	0.0052*	0.079	2644	−0.655***	−0.312*	−0.0015	0.089	2140
	(−5.62)	(1.37)	(3.87)			(−4.94)	(1.31)	(1.95)			(−4.57)	(−1.94)	(−0.49)		
IO	−0.123***	0.532***	0.0037**			−0.250***	0.513***	0.0048**			−0.075	0.503***	−0.0015		
	(−2.93)	(9.55)	(3.04)			(−2.47)	(5.26)	(2.28)			(−0.88)	(5.40)	(−0.71)		
OO	−0.174***	0.247***	−0.0002			−0.285***	0.182*	−0.0001			−0.071	0.282***	−0.0034		
	(−4.21)	(4.31)	(−0.18)			(−3.73)	(1.74)	(−0.05)			(−0.84)	(3.32)	(−1.44)		
OS	−0.283***	0.364***	0.0004			−0.375***	0.289***	−0.0008			−0.342***	0.278***	−0.0053*		
	(−6.09)	(6.24)	(0.25)			(−4.12)	(2.67)	(−0.34)			(−3.70)	(2.99)	(−1.93)		
IS	−0.330***	0.554***	0.0072***			−0.397***	0.490***	0.0054**			−0.383**	0.492***	0.0019		
	(−5.58)	(9.79)	(4.23)			(−3.07)	(5.03)	(2.28)			(−2.04)	(5.04)	(0.63)		

	EPMO	SPREAD	TIME	Pseudo R^2	N	EPMO	SPREAD	TIME	Pseudo R^2	N
	Extreme signal and inexperienced sessions					**Extreme signal and experienced sessions**				
MOU	−0.230***	0.265***	0.0048*	0.095	2434	−0.282**	0.051	0.0165***	0.077	2406
	(−2.76)	(2.81)	(1.78)			(−2.03)	(0.31)	(5.05)		
IO	−0.149***	0.539***	0.0055***			−0.088	0.590***	0.0047**		
	(−3.42)	(5.86)	(2.79)			(−1.51)	(4.93)	(1.99)		
OO	−0.252***	0.197**	−0.0003			−0.130**	0.341***	0.0029		
	(−5.37)	(2.09)	(−0.12)			(−2.20)	(3.75)	(1.03)		
OS	−0.218***	0.423***	−0.0003			−0.211***	0.495***	0.0066		
	(−3.24)	(4.84)	(−0.10)			(−2.52)	(3.31)	(1.98)		
IS	−0.381***	0.554***	0.0079**			−0.271***	0.673***	0.0125***		
	(−4.35)	(5.59)	(2.41)			(−2.66)	(5.22)	(3.45)		

Note: We report the results of multinomial logit regressions analysing order choice by informed traders, for all sessions, for sub-sample combinations of sessions with inexperienced and experienced traders and for traders with either a moderate signal or an extreme signal. We analyse the choice between the six types of order categorised in Table 1, when there is a standing bid and ask at the time of order submission. The determinants of each choice are estimated relative to a market order which is profitable conditional on the trader's signal, MOP. The other order types are: MOU: A putatively unprofitable market order; IO: A Limit Order *inside* the standing bid-ask spread on the *opposite* side of the book to the trader's signal; OO: A Limit Order at or *outside* the existing bid-ask spread on the *opposite* side of the book to the trader's signal; OS: A Limit Order at or *outside* the existing bid-ask spread on the *same* side of the book as the trader's signal; IS: A limit order *inside* the standing bid-ask spread on the *same* side of the book as the trader's signal. The first explanatory variable is the difference between the inside bid and the informed trader's signal if the signal is below the midpoint of the bid-ask spread, or the difference between the signal and the inside ask if the signal is above the midpoint of the spread. This measures the expected profit from a market order conditional on the trader's signal (EPMO). The second variable is the size of the inside spread at the time of the order submission (SPREAD). The third variable (TIME) is the number of seconds that have elapsed in the trading period. We additionally include fixed effects to control for dependencies across sessions. We also include a variable that is the signed net required position of the liquidity traders, positive if they are net buying [selling] and the asset value is above [below] the conditional mean, and negative otherwise. We account for the possible autocorrelation in the residuals due to each trader making multiple decisions by estimating robust Z-statistics, clustering on each trader. Significance for a two-tailed test relative to zero at the 10%, 5% and 1% level are indicated with *, ** and *** respectively with t-statistics in parentheses. N is the number of observations.

empirical studies of insider trading in limit order books, Collin-Dufresne and Fos (2015), Kacperczyk and Pagnotta (2019) and Ahern (2020) who show that insiders use limit orders to hide their information advantage. Goyal et al. (2025) find that informed short sellers seek to benefit from gradual price decreases by supplying liquidity rather than taking it out of the market, which is consistent with patience.

Since different types of limit order offer different profit opportunities, with those that offer greater profits also being those that enable informed traders a greater chance to disguise their information, we find clear evidence of a strategic behaviour in our data. Informed traders tend to choose those orders that maximise their profits, which are also those that are less likely to reveal their signals to other traders. This means that there are more orders placed on the opposite side of the market to the trader's signal, as these are the most profitable. While this establishes 'motive', we also observe that uninformed traders place orders in a similar pattern that then provides the 'opportunity' for the informed traders to hide their orders. This behaviour of informed traders is predicted in the models of Roşu (2020) and Riccó et al. (2021) and so our findings provide support for their theoretical predictions and point to the importance of modelling strategic liquidity traders.

When we combine measures of profit, impatience and the state of the order book in a multivariate model of order choice, we find clear evidence that the choice between limit orders and market orders is driven by the putative profits from the order (relative to the best profitable alternative order) and the size of the spread. The time remaining in the trading interval, which fuels trader impatience, becomes increasingly more important as it reduces. However, we go beyond the simple trade-off between immediacy and price improvement. Consistent with the theoretical model of Riccó et al. (2021), we split the limit orders between competitive and uncompetitive orders and between each side of the market, and we distinguish between market orders on each side of the market. By doing this we find that the relationship with time is more nuanced. We find that as the time remaining in the trading interval reduces, still controlling for expected profits and the inside spread, informed traders are seen to use putatively unprofitable market orders and competitive limit orders to ensure execution. Since competitive orders on the same side of the market as the trader's signal are putatively unprofitable also, our results suggest that trader impatience plays a greater role than profits at the end of the trading period. It could also suggest that informed traders are learning more about the average signal and are willing to trade beyond the information in their signal, but related evidence in Schnitzlein et al. (2024) suggests the informed traders in a dispersed information setting struggle to learn from market prices.

Overall, our study provides a wide-ranging examination of the order choice in limit order book markets of partially informed traders that supports two key theoretical predictions. These are that the pursuit of profit encourages informed traders to hide their information and to trade slowly, results that contrast with those of Bloomfield et al. (2005) that use a different information precision (incorporating fully informed traders). We examine a limit order book because it is the most widely used market structure and because it has demonstrated it can work well without specialists and dealers and can provide liquidity that is not constrained by periodic auctions. We have used an experimental setting with a large state space, combined traders with dispersed information reflecting plausible real-world information with strategic uninformed traders with private values, and a realistic market mechanism without short sale constraints or borrowing restrictions. Our experimental observations for the relative proportions of market and limit orders and execution rates are in line with the empirical results displayed in Hollifield et al. (2004), pointing to the wider relevance of our findings. Our results provide a complement to a prior experimental study of perfectly informed traders and to a growing body of empirical work.

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Ethics Statement

Aston Business School and the University of Central Florida provided ethical approval for this research.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] Back et al. (2000) develop a continuous time version of the Foster and Viswanathan (1996) model, which makes similar predictions though with slight differences regarding convergence and liquidity as the end of the trading period approaches. Roşu (2019) modifies the model by including a stochastic fundamental asset value and information that arrives with differing latency. He notes that this also prevents the 'rat race' observed by Holden and Subrahmanyam (1992) and provides an alternative characterisation of a dispersed information setting.

[2] Empirical evidence in Ellul et al. (2007) finds that informed traders on the NYSE can be patient in placing orders, not always using the automated execution system.

[3] Patient trading is at the heart of the trade-off between the immediacy of a market order and the price improvement from a limit order that combine to generate the bid-ask spread, as demonstrated in Cohen et al. (1981) and Demsetz (1968). Pioneering models of the strategic interaction between order choice and the state of the limit order book, Parlour (1998) and Foucault et al. (2005) introduce patience formally into their models. Early studies of limit order markets made the simplifying assumption that liquidity suppliers

were uninformed and liquidity demanders were informed, but more recent studies have allowed informed traders to also supply liquidity, including Chakravarty and Holden (1995), Kaniel and Liu (2006), Goettler et al. (2009), Brolley and Malinova (2021) and Roşu (2020). In the context of high frequency trading, examples include Hoffman (2014) and Bernales (2019). Surveys of the literature relating to limit order books are provided by Parlour and Seppi (2008) and Roşu (2012).

[4] While the models of Roşu (2020) and Riccó et al. (2021) provides useful insight for our experimental setting, we recognise that they are different to it in important ways. Specifically, our setting allows for the placement of multiple limit orders by a single trader, and a dynamic bid-ask spread, while their setting also considers non-informational motivations for trade for all trader types. This adds complexity and may influence order choice in ways not captured by the models.

[5] Our motivation for studying the effects of experience, and our use of subjects familiar with financial market operations, is to allay concerns that experimental subjects may not employ sophisticated strategies found in field markets. We find no differences between the order choices of twice experienced and once experienced traders and so report our results for all experienced traders collectively.

[6] We do this to reduce initial learning effects from influencing our results.

[7] Given the symmetry of each signal's distribution about its mean of zero, the variance of the sum of the three signals' distributions can be calculated as $3\times\left\{2\times\sum_{i=1}^{i=n} S_i^2\right\}/(2n+1)=3\times\left\{2\times\left[n(n+1)(2n+1)/6\right]\right\}/(2n+1)=n(n+1)$, where S_i is the signal of integer i and the element in square brackets is the formula for the series sum of squared integers. Thus, for $n = |\pm 6|$, we obtain a variance of 42.

[8] Formally, their model has the sum of normally distributed signals being a sufficient statistic for the intrinsic value.

[9] The distribution is symmetric triangular as the sum of two uniform distributions is symmetric triangular. This follows from the central limit theorem.

[10] The use of liquidity traders with trading targets is standard in experimental asset market research. A few examples include Lamoureux and Schnitzlein (1997), Cason (2000) and Bloomfield et al. (2005). This is also a feature of the Foster and Viswanathan model, where liquidity traders drive volume, that has (on average) offsetting trading positions.

[11] We adjusted the difference between informed and liquidity trader starting balances due to smaller informed trader profits than we expected in the initial nine sessions at University A. Adjusting these sorts of 'nuisance variables' has been shown to have little effect in asset market experiments (see e.g., Copeland and Friedman 1987).

[12] Across the 19 sessions, only one trader (a liquidity trader) in one session with first-time participants was removed from trading due to a negative cash balance.

[13] However, a price outside the range of the asset value, L\$82 to L\$118, was submitted only once in 9859 limit order submissions. It was not responsible for the one bankruptcy.

[14] Since we were interested in studying order choice and markets can move very fast for novice traders, our design allowed traders to consider the informational content of order choices before taking actions. Thus, the 'economic' time, during which decisions can be considered and strategies planned is longer than the trading period, is more representative of field markets. In addition, allocating the signals in pairs induces more competition than might be expected in small markets, especially given the fact that the signals had low correlation with the asset intrinsic value.

[15] Since traders' ability to buy shares is not constrained by their cash balance and since their ability to sell shares is not constrained by their share balance, this has no effect on buying or selling power. It does make final payments depend on performance in every period and not a randomly selected period (which is the case in some experimental designs). It does have the possible disadvantage of introducing wealth effects and so we repeated our logit and mlogit analyses of order choice reported in Tables 2 and 3 in Section 3.3 with the inclusion of a variable that measured the 'house money' at the start of each trading period. This variable was the difference between the start of session cash balance and the start of the current trading period cash balance. Among the 30 re-estimated order choice regressions, the house money variable was significant ($p<0.05$) on only 3 occasions, and in each case was causing an increase in the relatively less risky order choice. Therefore, we see no evidence that our cash balance protocol could increase risk taking through wealth effects.

[16] We believe in the importance of using economic incentives, by paying our subjects real money to reward their decision making (as is standard in the experimental literature). Obviously, the amounts are less than in field markets, but this is a limitation of all experimental studies.

[17] An empty order book is consistent with the models of Parlour (1998), Goettler et al. (2005) and Riccó et al. (2021). We note again that our framework places no restrictions on short sales or the type of order that can be placed, which further motivates the order book opening empty.

[18] Statistical analysis in this section is also undertaken with repeated-measures ANOVA, with main effects the signal extremeness, the experience level and the type of order. Pairwise mean comparisons are adjusted for multiple comparisons using the Bonferroni method. A companion analysis of the frequency of orders and the expected and actual profits for market orders can be found in Tables A2 and A3 and accompanying text.

[19] For reference and completeness, summary tables of the p-values (Bonferroni adjusted) of all the pairwise comparisons of the average profit measures across order type, experience and signal extremeness for informed traders can be found in Table A4.

[20] As uninformed traders do not receive a signal, we define, in a consistent manner, the same [opposite] side orders as those where the order is on the same side of the spread midpoint as the unconditional mean of the asset value distribution.

[21] More direct evidence is found from the corresponding ANOVA where a variable that interacts information level with type of limit order is found to be strongly significant ($p<0.001$), indicating that the different frequencies across order type are themselves different across information level. Discussion of the profits of the uninformed traders, which are also shown in Table 1, is in Appendix A, together with a logit regression of order choice on the inside spread and time (Table A3), which corroborates the findings depicted by Figure 1a,b.

[22] A recent survey of evidence on the stability of risk preferences, Shildberg-Hörisch (2018), points to the difficulties in obtaining a valid measure of risk aversion and so we do not include such in our regression analysis of order choice. We also included fixed effects for the nine signal sets, but these did not add to the significance of the regressions.

[23] To validate the inferences when using clustered standard errors in the presence of a large number of control variables, we repeat our estimation using bootstrap standard errors. The bootstrap p-values are less conservative than those using clustered standard errors, so we continue to report p-values from clustered standard errors. We further compare the results to the same specifications but excluding the session-period fixed effects to ensure that our use of a large number of fixed effects is not compromising the validity of the clustered standard errors. We find no substantial qualitative differences when we make this change to the specification. We provide the results in Table A5.

[24] To provide evidence of the stability of our results and, therefore, the wider applicability of them for other trader backgrounds, we compare

the results of University A subjects with those from University B, since these are in two different countries with quite different stock market participation rates and awareness among the general population. We repeat our mlogit analysis (Table 2) and observe the same pattern of significance for each country, see Table A6.

[25] This occurred after 13 s into period 7 of session 11, when both the standing bid and ask were successively cancelled prior to further limit orders being placed.

[26] Although depth and limit order submission rates are related, as without limit orders there can be no depth, the cancellation of limit orders during the period, to avoid quotes becoming stale or picked off, means that their behaviours can be quite different as we see in the comparison of Figures 1a and A3a,b. Philip (2020) estimates the option value of limit order cancellation to be 15% of its expected value.

[27] For limit orders, the median quote change is small (L$0.80), with the most frequent quote revision equal to (L$1.00).

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Appendix A

TABLE A1 | Cohorts, subjects and experience levels.

Session	Experience level	Subject background
University A: Cohort 1 (subjects 1–16)		
1	First session	MSc finance students recruited from a trading class
2	First session	MSc finance students recruited from a trading class
11	Second session	Four subjects from each of sessions 1 and 2
University A: Cohort 2 (subjects 17–40)		
3	First session	MSc finance students recruited from a trading class
4	First session	MSc finance students recruited from a trading class
5	First session	MSc finance students recruited from a trading class
12	Second session	The subjects from session 3
13	Second session	The subjects from session 4
14	Second session	The subjects from session 5
University A: Cohort 3 (subjects 41–56)		
6	First session	MSc finance students recruited from a trading class
7	First session	MSc finance students recruited from a trading class
15	Second session	Eight subjects from best performers in sessions 6 and 7
16	Third session	The subjects from session 15
University B: Cohort 4 (subjects 57–64)		
8	First session	Undergraduate students and MBA students recruited from an advanced elective in trading and market microstructure
17	Second session	The subjects from session 8
University B: Cohort 5 (subjects 65–80)		
9	First session	Undergraduate finance majors and graduate students in economics and business. All had previously participated in multi-unit auction experiments. Worst performing 25% excluded from the recruiting for this experiment
10	First session	
18	Second session	Eight subjects from best performers in sessions 9 and 10
19	Third session	The subjects from session 18

Note: Each session features 8 subjects and comprises 12 trading periods. Subjects maintain their role (six informed traders and two liquidity traders) over all 12 trading periods within a session but are randomly reassigned roles when returning for a second or third session.

Market Depth and the Bid-Ask Spread

Figure A3a,b shows the evolution of the depth (quantity available) at the inside bid and ask and the number of bid and ask quotes at the time of market orders (transactions) across the same trading period sub-intervals as for the submission and taking rates. The average quantity at the best bid (ask) for inexperienced [experienced] sessions is 1.10 (1.15) [1.07, (1.09)]. While these are all significantly greater than 1.0 ($p < 0.007$), there is much instability within a narrow range of values across the sub-intervals. To formally test the concavity in depth predicted by Parlour (1998) and Foucault et al. (2005), we group adjacent sub-intervals into three 1-min sub-intervals and compute the second difference of the average spreads across the three intervals. Using session averages as independent observations, we compute a one-tailed *t*-test of the null hypothesis that the second difference is zero. We are unable to reject the null hypothesis that there is no concavity at the inside bid and ask for sessions with either inexperienced or experienced participants ($p > 0.15$).

The average number of quotes at the bid (ask) for inexperienced [experienced] sessions is 3.77 (3.93) [3.23, (3.48)]. We find that searching across all of the 190 trading periods the order book is only once empty after the first limit order has been placed and then for just 1.25 s.[25] Furthermore, the median and modal elapsed time that the order book experiences being empty on one side of the market is less than one millisecond. So, although there are just two traders with trading targets (the uninformed traders) in each period, compared to six informed traders, there does not appear to be a lack of liquidity supply. We find evidence of a concavity in the number of quotes across the trading period ($p < 0.009$), at each of the bid and ask and for sessions with either inexperienced or experienced participants, which is consistent with the models of patient trading.[26]

In Figure A4, we show the evolution of the Inside Spread at the time of market orders (transactions) across the same trading period sub-intervals as for depth, volume and the submission and taking rates. The average spread is L\$1.53, which is 24% of the average level of the absolute difference between the asset value and the unconditional mean of the distribution of possible asset values.[27] We see that the spread appears convex in both cases of sessions with inexperienced participants and of those with experienced participants, as predicted with patient traders in the model of Foucault et al. (2005). We find that the average spreads with inexperienced participants are 20% greater than

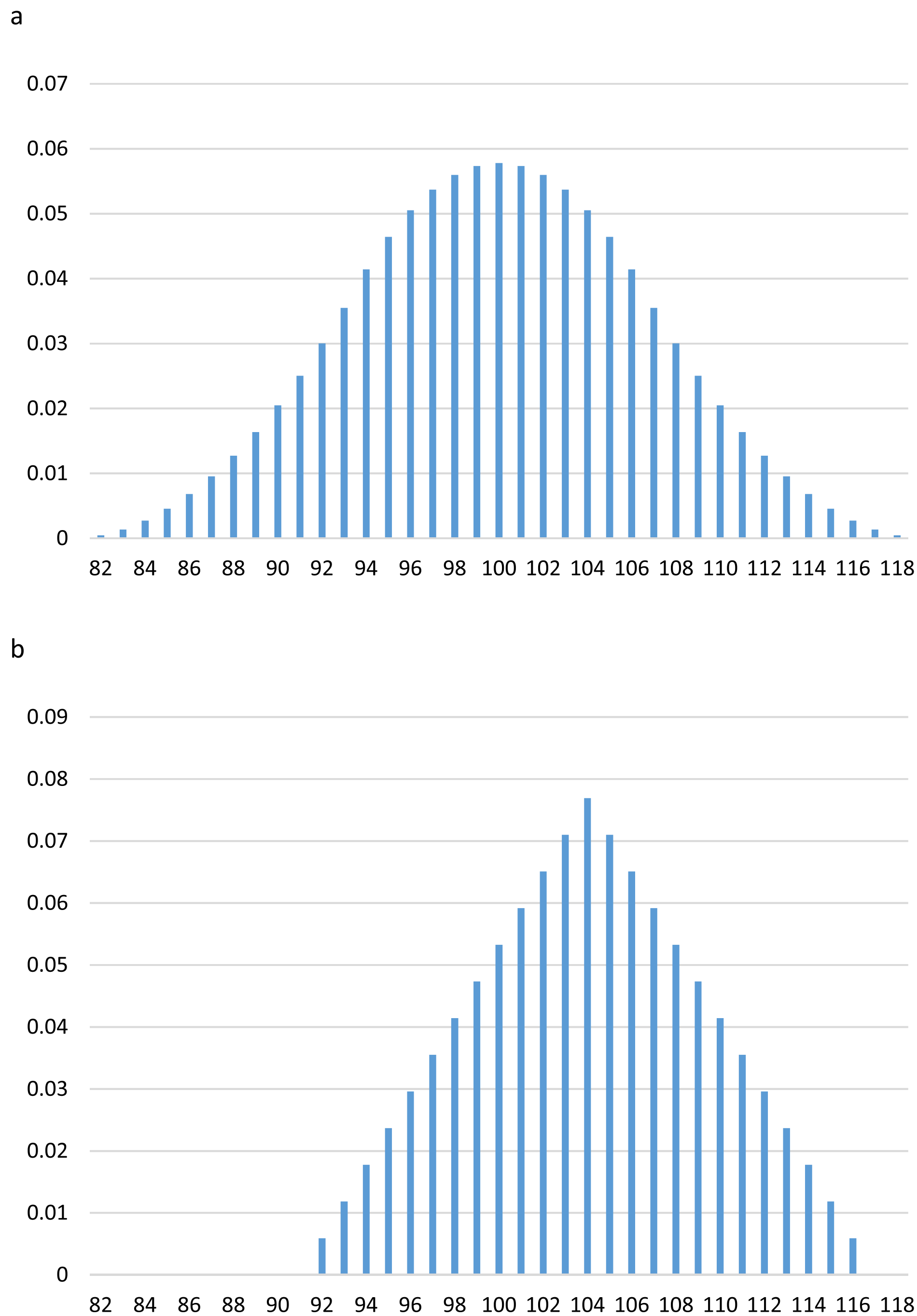


FIGURE A1 | (a) Asset value distribution (public information set). (b) Asset value distribution (conditional on a private signal of +4). [Colour figure can be viewed at wileyonlinelibrary.com]

those with experienced participants ($p<0.01$), although for a given sub-interval the differences are not significant ($p>0.999$). The initial competition to supply liquidity is reflected in the spread that is significantly higher in the first sub-interval than in any subsequent interval, except the second sub-interval, and higher in the second interval compared to the sub-intervals beyond the midpoint of the trading period, for both experienced and inexperienced traders ($p<0.022$). To formally test convexity, we again group adjacent sub-intervals into three 1-min sub-intervals and compute the second difference of the average spreads across the three intervals. The second differences are on average (across the sessions) 0.89 ($p=0.004$) and 1.02 ($p=0.002$), respectively for inexperienced and experienced sessions, and so we reject the null hypothesis that there is no convexity in the spread, which provides further evidence of patient trading behaviour being a feature of our markets.

Market Orders of Informed Traders

In Table A2, Panel A, we display the profits per trade of informed traders to placing market orders, also split by whether they are putatively profitable conditional upon the trader's signal (MOP) or putatively unprofitable (MOU). In the former case, expected profits equal EPMO by construction and are significantly positive ($p<0.001$) for each combination of trader type, signal extremeness and trader experience level. Informed traders can expect to earn an average profit per trade of between L\$1.84 (with a moderate signal) and L\$4.02 (with an extreme signal). Expected profits are greater if the trader has a more extreme signal, but only significantly so for inexperienced traders. For informed traders making putatively unprofitable market orders, expected profits are significantly negative ($p<0.001$) for each combination of signal extremeness and trader experience level. On average, expected losses from

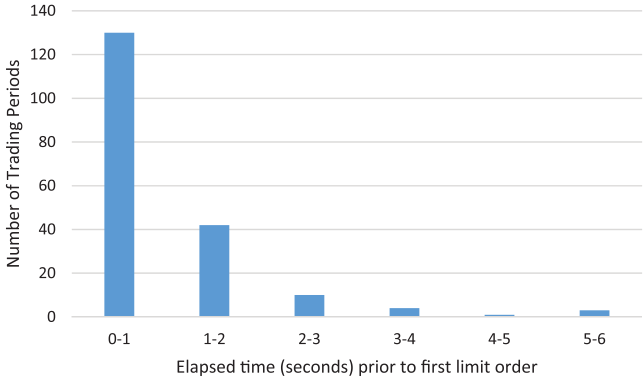


FIGURE A2 | Elapsed time before first limit order. [Colour figure can be viewed at wileyonlinelibrary.com]

putatively unprofitable market orders are between −L\$1.89 (with no experience) and −L\$4.39 (with experience) and are significantly lower than the expected profits for putatively profitable orders, for all signal extremeness and experience levels ($p<0.001$). While expected losses are worse in the case of orders from traders with more extreme signals, the difference compared with moderate signals is only significant for inexperienced traders ($p<0.001$).

In terms of the actual profits per trade earned by informed traders, we can see that the putatively unprofitable market orders do go on to generate losses, on average between −L\$0.87 and −L\$6.02, which while worse than expected (except for experienced traders with a moderate signal) are not significantly different ($p>0.999$) for all signal and experience levels. For putatively profitable market orders, actual profits are positive for traders with an extreme signal, on average between L\$2.72 (with experience) and L\$4.10 (with no experience) and are not significantly different to the expected profits from the same orders ($p>0.999$).

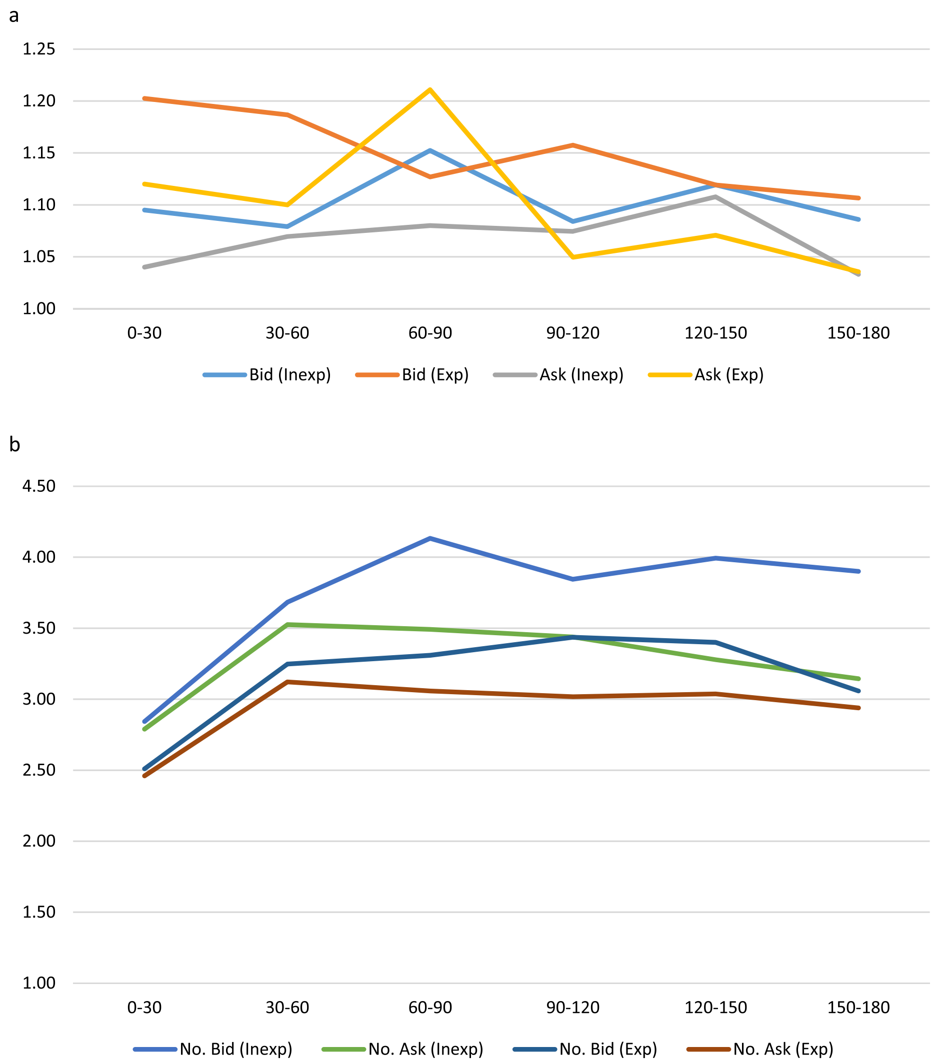


FIGURE A3 | (a) Evolution of the depth at the inside bid and ask. (b) Evolution of the order book. The number of outstanding limit orders at the best bid or ask at the time of a market order, averaged across trading periods, within each 30 s sub-interval of the trading period. Sessions either feature first-time (inexperienced) or experienced participants. There are 19 sessions (10 with first-time participants, 9 with experienced participants), each of 10 periods. The number of outstanding limit orders at the time of a market order, averaged across trading periods, within each 30 s sub-interval of the trading period. Sessions either feature first-time (inexperienced) or experienced participants. There are 19 sessions (10 with first-time participants, 9 with experienced participants), each of 10 periods. [Colour figure can be viewed at wileyonlinelibrary.com]

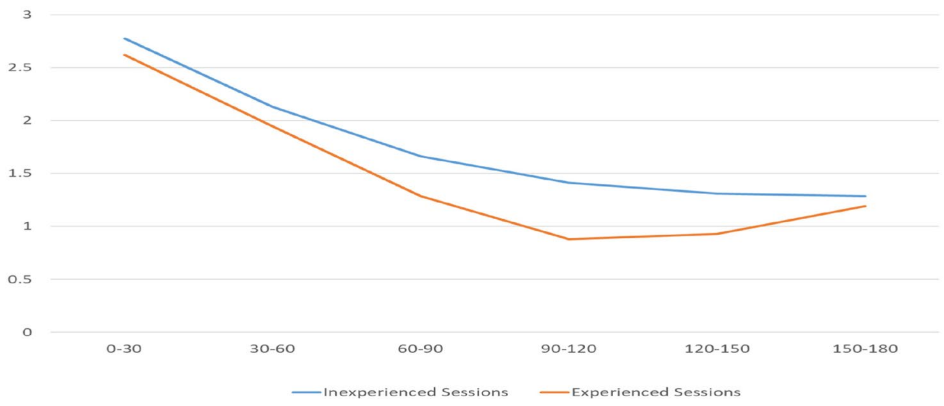


FIGURE A4 | Evolution of the inside spread. The inside spread in L$ at the time of a market order averaged across trading periods within each 30 s sub-interval of the trading period. Sessions either feature first-time (Inexperienced) or Experienced participants. There are 19 sessions (10 with first-time participants, 9 with experienced participants), each of 10 periods. There are 3424 market orders with a standing bid and ask. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A2 | Market orders: Expected profit, actual profit and volume.

	Panel A: Informed traders							
	Putatively profitable				Putatively unprofitable			
	EPMO	Ex. Prof.	Act. Prof.	Vol.	EPMO	Ex. Prof.	Act. Prof.	Vol.
Moderate signal								
Inexperienced (sessions 1 to 10)								
Mean	1.84	1.84	−0.56	1.18	0.71	−1.93	−2.61	0.87
N [Obs] {%}		129 [374] {75}		316		95 [274] {71}		316
Experienced (sessions 11 to 19)								
Mean	2.24	2.24	−1.83	1.27	1.07	−1.89	−0.87	0.60
N [Obs] {%}		125 [354] {67}		278		70 [167] {75}		278
Extreme signal								
Inexperienced (sessions 1 to 10)								
Mean	4.02	4.02	4.10	1.69	2.54	−4.39	−6.02	0.50
N [Obs] {%}		149 [480] {73}		284		61 [143] {78}		284
Experienced (sessions 11 to 19)								
Mean	3.46	3.46	2.72	2.35	1.91	−2.79	−3.22	0.51
N [Obs] {%}		150 [615] {65}		262		60 [134] {79}		262

	Panel B: Uninformed traders	
	Actual profit	Volume
Inexperienced (sessions 1 to 10)		
Mean	−0.51	1.44
N [Obs] {%}	186 [576] {82}	400
Experienced (sessions 11 to 19)		
Mean	−0.49	0.85
N [Obs] {%}	138 [307] {80}	360

Note: This table contains the average value per trader per trading period of the volume (Vol.) of market orders and three measures of profit (average per trade). EPMO is the greater of zero or the profit expected from the most profitable market order conditional on the trader's signal. Expected profit (Ex. Prof.) is the profit expected from that order conditional on the trader's signal. Actual profit (Act. Prof.) is the profit earned relative to the intrinsic value of the asset, and the only measure for uninformed traders. There are 19 sessions each of 10 periods containing 6 informed traders, giving a total number of trader-periods of 1140 for each of the two order types. *N* in the volume column indicates how these 1140 trader-period divide up between traders with differing signal strength and level of experience. *N* in the profit columns indicates in how many of these trader-periods there was an order of this type. Average per trader per trading period calculations use the corresponding *N* value as denominator. The number of observations of an order type is given in the square brackets. In parentheses is the % of trades with informed liquidity suppliers.

TABLE A3 | Order choice of uninformed traders: Limit order versus market order.

	SPREAD	TIME	Pseudo R^2	N
All sessions (1–19)	0.436*** (6.18)	−0.0067*** (−2.93)	0.259	2944
Inexperienced sessions (1–10)	0.424*** (5.64)	−0.0037 (−1.53)	0.268	1581
Experienced sessions (11–19)	0.453*** (2.63)	−0.0117*** (−3.00)	0.220	1363

Note: We report the results of logit regressions analysing the order choice of uninformed traders, for all sessions, and separately for sessions with inexperienced and experienced traders. We analyse the choice between a limit order and a market order when there is a standing bid and ask at the time of order submission. The first variable is the size of the inside spread at the time of the order submission (SPREAD). This captures the difference in expected profit between submitting a limit order that is just exposed to the market, and a market order. The second variable (TIME) is the number of seconds that have elapsed in the trading period. We additionally include fixed effects to control for dependencies across sessions and across the periods within sessions. We account for the possible autocorrelation in the residuals due to each trader making multiple decisions by estimating robust Z-statistics, clustering on each trader. Significance for a two-tailed test relative to zero at the 10%, 5% and 1% level are indicated with *, ** and *** respectively with t-statistics in parentheses.

Moreover, these profits are significantly greater than their losses for putatively unprofitable market orders ($p<0.001$). By contrast, traders with a moderate signal make losses with putatively profitable market orders, on average between −L$0.56 (with no experience) and −L$1.83 (with experience), which are significantly less than expected profits in both cases ($p<0.001$). However, for experienced traders, these losses are no different to those they obtained for putatively unprofitable orders ($p>0.999$). The differences between the profits (given an extreme signal) and losses (given a moderate signal) from putatively profitable market orders are significant ($p<0.001$).

Table A2, Panel A, also shows the frequency of different types of market orders, classified by the experience and signal extremeness of the traders. The average trading volume per trader per period seems to be reflecting the relative profits of putatively profitable and unprofitable orders, with an average of between 1.18 trades per trader per period (with no experience) and 2.35 trades (with experience) per trader per period for putatively profitable market orders and an average of between 0.87 trades (with no experience) and 0.50 trades (with experience) per trader per period for putatively unprofitable orders, in the case of the informed traders. These differences are significant for traders with an extreme signal, experience, or both ($p<0.018$).

The frequency of trading (ex-post) with an informed liquidity supplier ranges from 65% to 79% for informed traders placing market orders and from 80% to 82% for uninformed traders placing market orders. As these frequencies are on average not significantly different from 0.75 (i.e., the three to one ratio of informed to uninformed traders) ($p>0.710$), it is not surprising that there are no significant differences among them, due to signal extremeness, experience or order putative profitability, for either informed traders or uninformed traders ($p>0.999$), and no significant differences between informed and uninformed traders, for each combination of putative profitability type, signal extremeness or experience level ($p>0.999$).

Market Orders of Uninformed Traders

In Table A2, Panel B, we see that uninformed traders place an average of 1.44 (with no experience) and 0.85 (with experience) market orders, per trader per period. The difference in these volumes is significant ($p<0.001$). Uninformed traders make losses from market orders, on average of −L$0.51 (with no experience) and −L$0.49 (with experience). However, neither of these is significantly different from zero ($p>0.189$) nor from each other ($p>0.978$).

Limit Order Profits of Uninformed Traders

In Table 1, Panel B, (in the main body of the text) we see that for uninformed traders, placing opposite side limit orders, losses are on average −L$2.56 for competitive orders (IO) and of between −L$3.38 (no experience) and −L$2.13 (experience) for uncompetitive orders (OO) ($p<0.031$), with no significant difference related to experience level ($p>0.999$). When placing same side limit orders, they make profits on average of between L$2.63 (no experience) and L$2.38 (experience) with competitive orders (IS) and of between L$0.43 (no experience) and L$1.85 (experience) with uncompetitive orders (OS), although these are only significantly greater than zero for competitive orders (IS), if traders are experienced, or both ($p<0.011$). Losses from competitive opposite side orders (IO) are significantly lower than the profits from competitive same side orders (IS) ($p<0.001$).

Order Choice of Uninformed Traders

Given a standing bid and ask, there were 2061 limit orders and 883 market orders placed by liquidity traders. In Table A3, we see that both inside spread ($p<0.01$) and Time ($p<0.01$) are significant determinants of order choice. As the spread widens, so limit orders become more attractive, since there is a greater chance that they will encompass the asset value, making both orders placed at the Ask and at the Bid putatively profitable. As Time increases, so the liquidity traders reduce their limit order submissions and switch to market orders to ensure that their position requirements are met. The impact of time is stronger in the sessions with experienced participants.

TABLE A4 | Summary of pairwise means test p-values.

Differences across order type (given profit type, experience level and signal strength)												
	EPMO			Exp. profit			Actual profit			Volume		
	IO	OO	IS	IO	OO	IS	IO	OO	IS	IO	OO	IS
Inexperienced sessions, moderate signal (Inex/Mod)												
OO	> 0.999			> 0.999			> 0.999			> 0.999		
IS	> 0.999	> 0.999		< 0.001	< 0.001		< 0.001	0.001		< 0.001	0.015	
OS	> 0.999	> 0.999	> 0.999	< 0.001	< 0.001	< 0.001	0.157	0.226	> 0.999	< 0.001	> 0.999	> 0.999
Experienced sessions, moderate signal (Exp/Mod)												
OO	> 0.999			0.588			> 0.999			< 0.001		
IS	> 0.999	> 0.999		< 0.001	< 0.001		> 0.999	> 0.999		< 0.001	> 0.999	
OS	> 0.999	> 0.999	> 0.999	< 0.001	< 0.001	> 0.999	> 0.999	> 0.999	> 0.999	< 0.001	0.064	> 0.999
Inexperienced sessions, extreme signal (Inex/Ext)												
OO	> 0.999			> 0.999			> 0.999			0.086		
IS	> 0.999	> 0.999		< 0.001	< 0.001		< 0.001	< 0.001		< 0.001	< 0.001	
OS	> 0.999	> 0.999	> 0.999	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	> 0.999	< 0.001	< 0.001	> 0.999
Experienced sessions, extreme signal (Exp/Ext)												
OO	> 0.999			> 0.999			> 0.999			< 0.001		
IS	> 0.999	> 0.999		< 0.001	< 0.001		< 0.001	< 0.001		< 0.001	< 0.001	
OS	> 0.999	> 0.999	> 0.999	< 0.001	< 0.001	0.180	< 0.001	< 0.001	> 0.999	< 0.001	0.001	> 0.999

Differences across experience level or signal strength (given profit type and order type)								
	EPMO		Exp. profit		Actual profit	Volume		
	Inex/Mod	Exp/Ext	Inex/Mod	Exp/Ext	Inex/Mod	Exp/Ext	Inex/Mod	Exp/Ext
Inside opposite (IO)								
Exp/Mod	> 0.999	0.735	> 0.999	0.392	> 0.999	< 0.001	> 0.999	0.908
Inex/Ext	< 0.001	> 0.999	< 0.001	> 0.999	< 0.001	0.026	> 0.999	> 0.999
Outside opposite (OO)								
Exp/Mod	> 0.999	> 0.999	> 0.999	> 0.999	> 0.999	< 0.001	> 0.999	> 0.999
Inex/Ext	< 0.001	> 0.999	< 0.001	> 0.999	< 0.001	0.001	> 0.999	> 0.999
Inside same (IS)								
Exp/Mod	> 0.999	> 0.999	0.011	> 0.999	0.001	< 0.001	> 0.999	> 0.999
Inex/Ext	> 0.999	> 0.999	0.387	> 0.999	< 0.001	< 0.001	> 0.999	> 0.999
Outside same (OS)								
Exp/Mod	> 0.999	> 0.999	> 0.999	> 0.999	> 0.999	> 0.999	0.753	> 0.999
Inex/Ext	< 0.001	> 0.999	> 0.999	> 0.999	< 0.001	0.002	0.579	> 0.999

Differences across profit type (given order type, experience level and signal strength)								
	IO		OO		IS		OS	
	EPMO	Exp. profit	EPMO	Exp. profit	EPMO	Exp. profit	EPMO	Exp. profit
Inexperienced sessions, moderate signal								
Expected profit	< 0.001		< 0.001		0.035		> 0.999	
Actual profit	> 0.999	< 0.001	> 0.999	< 0.001	< 0.001	> 0.999	< 0.001	< 0.001

(Continues)

TABLE A4 | (Continued)

	Differences across profit type (given order type, experience level and signal strength)							
	IO		OO		IS		OS	
	EPMO	Exp. profit	EPMO	Exp. profit	EPMO	Exp. profit	EPMO	Exp. profit
Experienced Sessions, moderate signal								
Expected profit	< 0.001		< 0.001		> 0.999		> 0.999	
Actual profit	< 0.001	< 0.001	0.037	< 0.001	> 0.999	> 0.999	> 0.999	> 0.999
Inexperienced sessions, extreme signal								
Expected profit	< 0.001		< 0.001		< 0.001		< 0.001	
Actual profit	< 0.001	< 0.001	< 0.001	> 0.999	< 0.001	< 0.001	< 0.001	< 0.001
Experienced sessions, extreme signal								
Expected profit	< 0.001		< 0.001		< 0.001		< 0.001	
Actual profit	> 0.999	0.388	> 0.999	< 0.001	< 0.001	> 0.999	< 0.001	> 0.999

Note: This table contains the *p*-values (Bonferroni adjusted) from pairwise tests of the row-wise and column-wise differences in the average value per trader per trading period of the volume of orders (Volume) and three measures of profit (average per trade) given in Table 1, for the Informed Traders. EPMO is the greater of zero or the profit expected from the most profitable market order conditional on the trader's signal. Expected profit is the profit expected from that order conditional on the trader's signal. Actual profit is the profit earned relative to the intrinsic value of the asset. Opposite '.O' (same '.S') side orders are on the opposite (same) same side of the midpoint of the spread as the trader's signal. Inside 'I.' (Outside 'O.') orders (do not) improve the best bid or ask.

TABLE A5 | Order choice: Limit order versus market order (excluding session-period fixed effects).

	EPMO	SPREAD	TIME	Pseudo R^2	N
All signal types All sessions (1–19)	−0.102*** (−3.22)	0.389*** (9.16)	0.0008 (0.79)	0.088	9624
Moderate signal Inexperienced sessions (1–10)	−0.107 (−1.41)	0.303*** (4.92)	0.0014 (0.13)	0.064	2644
Moderate signal Experienced sessions (11–19)	−0.022 (−0.33)	0.493*** (7.14)	−0.0018 (1.06)	0.104	2140
Extreme signal Inexperienced sessions (1–10)	−0.164*** (−4.61)	0.341*** (4.97)	0.0020 (1.09)	0.112	2434
Extreme signal Experienced sessions (11–19)	−0.092* (−1.76)	0.495*** (4.78)	0.0031 (0.95)	0.106	2406

Note: We report the results of logit regressions analysing the order choice of informed traders, for all sessions, separately for sub-sample combinations of sessions with inexperienced and experienced traders and traders with either a moderate signal or extreme signal. We analyse the choice between a limit order and a market order when there is a standing bid and ask at the time of order submission. The first explanatory variable is the difference between the inside bid and the informed trader's signal if the signal is below the midpoint of the bid-ask spread, or the difference between the signal and the inside ask if the signal is above the midpoint of the spread. This measures the difference between the informed trader's signal and the information in the market quotes and is the expected profit from a market order conditional on the trader's signal (EPMO). The second variable is the size of the inside spread at the time of the order submission (SPREAD). This captures the difference in expected profit (conditional on the signal) between submitting a limit order that is just exposed to the market and a market order. The third variable (TIME) is the number of seconds that have elapsed in the trading period. We additionally include fixed effects to control for dependencies across sessions. We also include a variable that is the signed net required position of the liquidity traders, positive if they are net buying [selling] and the asset value is above [below] the conditional mean, and negative otherwise. We account for the possible autocorrelation in the residuals due to each trader making multiple decisions by estimating robust Z-statistics, clustering on each trader. Significance for a two-tailed test relative to zero at the 10%, 5% and 1% level are indicated with *, ** and *** respectively with t-statistics in parentheses. N is the number of observations.

TABLE A6 | Order choice: Limit order versus market order by subject location.

	EPMO	SPREAD	TIME	Pseudo R^2	*N*
Country A					
All signal types All sessions	−0.090** (−2.33)	0.405*** (7.86)	0.0016 (1.19)	0.083	6898
Moderate signal Inexperienced sessions	−0.084 (−0.97)	0.306*** (3.98)	−0.0003 (0.15)	0.060	1841
Moderate signal Experienced sessions	−0.005 (−0.06)	0.477*** (5.04)	−0.0007 (−0.29)	0.092	1564
Extreme signal Inexperienced sessions	−0.123*** (−3.29)	0.361*** (4.63)	0.0021 (0.94)	0.102	1847
Extreme signal Experienced sessions	−0.100* (−1.66)	0.540*** (4.38)	0.0048 (1.64)	0.119	1646
Country B					
All signal types All sessions	−0.151*** (−3.57)	0.351*** (4.77)	−0.0011 (−0.74)	0.103	2726
Moderate signal Inexperienced sessions	−0.211 (−1.62)	0.311*** (2.76)	0.0014 (0.89)	0.076	803
Moderate signal Experienced sessions	−0.147 (−1.10)	0.491*** (4.36)	0.0067** (−2.02)	0.184	576
Extreme signal Inexperienced sessions	−0.358*** (−3.07)	0.249** (2.32)	0.00210 (0.31)	0.193	587
Extreme signal Experienced sessions	−0.074 (−0.78)	0.447** (2.19)	−0.0015 (−0.49)	0.085	760

Note: We report the results of logit regressions analysing the order choice of informed traders, for all sessions, separately for sub-sample combinations of sessions with inexperienced and experienced traders and traders with either a moderate signal or extreme signal. We analyse the choice between a limit order and a market order when there is a standing bid and ask at the time of order submission. The first explanatory variable is the difference between the inside bid and the informed trader's signal if the signal is below the midpoint of the bid-ask spread, or the difference between the signal and the inside ask if the signal is above the midpoint of the spread. This measures the difference between the informed trader's signal and the information in the market quotes and is the expected profit from a market order conditional on the trader's signal (EPMO). The second variable is the size of the inside spread at the time of the order submission (SPREAD). This captures the difference in expected profit (conditional on the signal) between submitting a limit order that is just exposed to the market and a market order. The third variable (TIME) is the number of seconds that have elapsed in the trading period. We additionally include fixed effects to control for dependencies across sessions. We also include a variable that is the signed net required position of the liquidity traders, positive if they are net buying [selling] and the asset value is above [below] the conditional mean, and negative otherwise. We account for the possible autocorrelation in the residuals due to each trader making multiple decisions by estimating robust Z-statistics, clustering on each trader. Significance for a two-tailed test relative to zero at the 10%, 5% and 1% level are indicated with *, ** and *** respectively with t-statistics in parentheses. N is the number of observations.

Appendix B

Experimental Instructions

This is an experiment in economic decision making. These are the instructions, and if you follow them carefully you can earn money. Everything you need to know about this experiment is included in these instructions. Everything contained in these instructions and everything you hear in this session is an accurate representation of this experiment. Be sure to ask any questions that you may have during this instruction period, and ask for assistance, if needed, at any time.

All Participants Receive the Same Instructions

There are four parts in today's experiment:

1. These instructions;
2. Twelve trading periods. The amount of money you earn is based on your decisions and the decisions of other participants;
3. A questionnaire;
4. The (private) payment of earnings.

This experiment involves the trading of units of an asset among the participants. The single risky asset's value is determined randomly each trading period. All trading of the asset will be conducted via networked computers. Just prior to the start of the first trading period, you will be assigned randomly to be either one of six INFORMED TRADERS or one of two TRADERS. You will remain in the same role for the entire session. More details about these roles will be provided later in these instructions.

Just prior to the start of each trading period, INFORMED TRADERS will learn information about the end-of-period value of the asset and you may use this information in an attempt to earn trading profits. TRADERS will learn the number of units of the asset that they will be required to buy or sell over the trading interval. For both INFORMED TRADERS and TRADERS, your earnings for participating in the experiment will be in part determined by the profits and losses you incur through your trading activity.

Computation of Payments

All participants will be paid in cash at the end of the experiment. Balances during the experiment are denominated in lab dollars (L$). At the end of today's trading, you will be paid in cash your balance of lab dollars at the end of the final trading period multiplied by 0.10.

Trader Types

There are two types of traders in this experiment. You will be randomly assigned to one of these two roles at the beginning of the experiment, and you will remain in that role for the entire session.

INFORMED TRADERS: Each INFORMED TRADER begins the first trading period with an endowment of L$200. At the beginning of each trading period, each INFORMED TRADER receives information about the end-of-period value of the asset. Different INFORMED TRADERS will usually receive different information, but all information is of use in determining the value of the asset since each piece of information is used to determine the asset's end-of-period value. More about the information will be explained below. Each INFORMED TRADER is free to use this information in pursuit of trading profits. At the end of each period, the trading profits or losses of each INFORMED TRADER are added to his/her beginning-of-period cash balance and carried forward to the next period. After the last trading period, each INFORMED TRADER will be paid his/her final balance multiplied by 0.10 in cash.

TRADERS: Each TRADER begins the first trading period with an endowment of L$300. Each TRADER will be required, in net, to buy or sell a specified number of units of the asset. The required position for each trader is independent of the asset's end-of-period value. If a TRADER does not meet this requirement, there will be a penalty assessed at the end of the period, as is explained below. The penalty is large enough so that making the required number of trades will never result in a lower end-of-period cash balance than not trading and incurring the penalty. At the end of each period, the trading profits or losses of each TRADER are added to his/her beginning-of-period cash balance and carried forward to the next period. After the last trading period, each TRADER will be paid his/her final balance multiplied by 0.10 in cash.

Prior to the Start of Each Trading Period

Before the beginning of each trading period, each INFORMED TRADER receives information about the end-of-period value of the asset. Each INFORMED TRADER's information will be disclosed on his/her computer screen and will be known only to that INFORMED TRADER. Different INFORMED TRADERS may receive different information. More information on the distribution of the asset value will be given later in these instructions.

Before the beginning of each trading period, each TRADER learns the number of units of the asset he/she is required to buy or sell (in net) for that period. This is determined by the computer and will range between −5 and +5. For example, if a TRADER has a required position of +3, that TRADER must have bought, in net, 3 units of the asset at the end of the period. If a TRADER has a required position of −2, that TRADER must have sold, in net, two assets by the end of the period. Only the TRADER learns the number of units that must be bought or sold by the end of the period. Different TRADERS will receive different required positions and the positions of the liquidity traders will at least partially offset each trading period. This means that if Trader 1 needs to buy assets in order to meet his required position, Trader 2 will need to sell assets in order to meet her required position. The magnitude of the required positions will typically differ; however, there is no relationship between the TRADERS' required positions and the end-of period asset value.

Each INFORMED TRADER and each TRADER begins each trading period without an inventory of assets. Over the course of the trading period, a trader can buy or sell as many units of the asset as desired. At the end of each trading period, the computer will automatically reset the inventory to zero as follows: positive inventories are 'sold' at the end-of-period asset value, and negative inventories are 'covered' by buying at the end-of-period asset value the number of units of the asset necessary to return the inventory to zero. More information on the calculation of trading profits will follow below.

The Trading Period

After each trader receives information about the asset value, the trading period begins. During the trading period, each INFORMED TRADER and each TRADER may post a bid price and/or an ask price at any time. A bid price indicates the price at which the trader is willing to buy a single unit of the risky asset while an ask price indicates the price at which he/she is willing to sell a single unit of the risky asset. An INFORMED TRADER or a TRADER may only have one bid and one ask outstanding at one point in time, but they can be changed at any time by removing the bid or ask and replacing it with a new bid or ask. In addition, both types of traders can trade at any time by trading against a posted bid or ask. More information on how to post bids and asks and how to trade against posted bids and asks will be given below. Each time a trade is completed, the trading interval clock is paused and all participants learn of the trade. Over the trading period, there is no limit on the number of transactions either type of trader may participate in. If there are multiple bids and/or asks posted, only the highest bid or lowest ask is available for trade. Each trading period will be 3 min, but because of pauses after transactions, each trading period may take more time.

Assume that after the trading period begins, T1 submits an ‘ask’ at a price of 105 and T5 submits a ‘bid’ at a price of 99. T2 then double clicks on the ‘ask’ at a price of 105. T2 therefore buys from T1 at a price of 105. This will be indicated on the ticker at the bottom of your screen by +1 (the + indicates the trade was initiated by a buyer). If the end-of-period asset value is below 105, T1 earns profits on the trade and T2 incurs a loss. If the end-of-period asset value is above 105, T1 incurs a loss and T2 earns a profit.

Assume that with 50 s remaining in a trading period, the posted bids are 99, 98.5 and 97. T4 submits a sell order and therefore sells one unit at a price of 99. If the end-of-period asset value is revealed to be 97, then T4 earns a profit of 2 on the trade, and the trader that posted the bid loses 2.

After Each Trading Period

1. After the trading period ends, the value of the asset is revealed to all participants.
2. Trading profits for each type of trader are calculated as follows: For each trade, the buyer's profit is equal to the end-of-period asset value less the trading price. The seller's profit is equal to the trading price less the end-of-period value.

The end-of-period value is the ‘true’ asset value that is revealed to all at the end of the trading period. It is *not* the last transaction price.

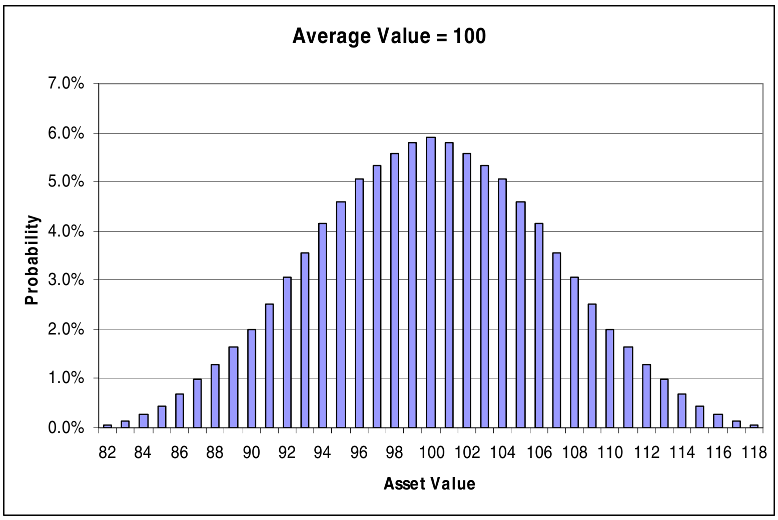
If a TRADER does not meet his/her required position by the end of the period, he/she will incur a penalty of L$36 times the difference (in absolute value) between the required position and the actual position. For example, if a TRADER is required to have an ending inventory of −2, but does not trade, then the TRADER will have L$72 deducted from his/her cash balance.

Again, end-of-period cash balances are carried forward to the next trading period.

The End-Of-Period Asset Value

Before receiving information, all traders know the following distribution determines the asset value at the end of each trading period: the asset value's mean is 100 and its standard deviation is 6.5.

Asset value	Within range	Outside range	Asset value distribution
82–118	100%	0.0%	
83–117	99.99%	0.01%	
84–116	99.7%	0.3%	
85–115	99.2%	0.8%	
86–114	98.3%	1.7%	
87–113	97.0%	3.0%	
88–112	95.0%	5.0%	
89–111	92.4%	7.6%	
90–110	89.1%	10.9%	
91–109	85.1%	14.9%	
82–108	80.1%	19.9%	
93–107	74.0%	26.0%	
94–106	66.9%	33.1%	
95–105	58.6%	41.4%	
96–104	49.4%	50.6%	
97–103	39.3%	60.7%	
98–102	28.6%	71.4%	
99–101	17.5%	82.5%	
100	5.9%	94.1%	



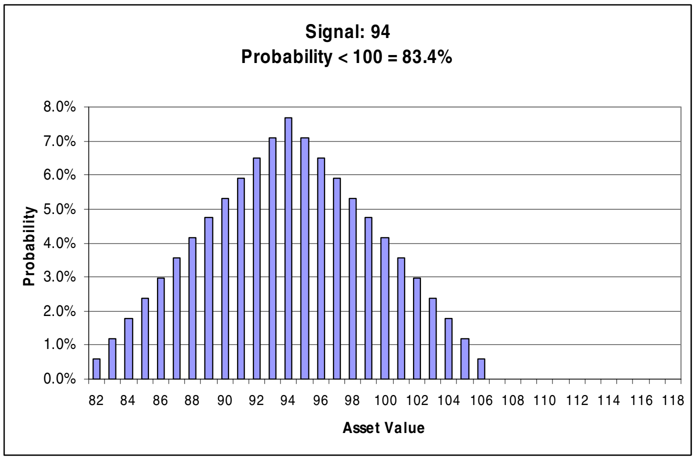
Each trading period, each INFORMED TRADER will receive information that will helps narrow the range of possible asset values, and predict the value with more accuracy. Different INFORMED TRADERS may receive different information, but all information will be of some use in determining the end-of-period asset value. Given this, it may be possible to gain some information about the information of others by the trades that are completed and the bids and asks that are posted, but remember that the trades of the TRADERS will be unrelated to the end-of-period value. An example of how the asset value is determined is included at the end of these instructions.

On the following pages, INFORMED TRADERS have information for each possible signal they may receive. Feel free to refer to the page corresponding to your information for each period.

Remember: Each period, a new random draw determines the asset values.

A chart and table similar to the following for each possible signal (94–106) is given to each informed trader as part of the experimental instructions. Subjects are permitted to refer to these during the experiment.

	Within	outside
Asset value	Range	Range
82–106	100.0%	0.0%
83–105	98.8%	1.2%
84–104	96.4%	3.6%
85–103	92.9%	7.1%
86–102	88.2%	11.8%
87–101	82.2%	17.8%
88–100	75.1%	24.9%
89–99	66.9%	33.1%
90–98	57.4%	42.6%
91–97	46.7%	53.3%
92–96	34.9%	65.1%
93–95	21.9%	78.1%
94	7.7%	92.3%



How the Asset Value Is Determined Each Trading Period

The resale value each trading period depends on the information received by the bidders. Each trading period there are three random draws to determine three independent information signals. Each of the six INFORMED TRADERS receives an information signal, so each trading period there are two INFORMED TRADERS that receive the same signal. Each information signal is an integer in the range from 94 to 106. The probability of each information signal is equal to (7.7%). The end-of-period asset value is determined from the signals as follows. First the difference between each unique signal and the average asset value (100) is calculated. The signals are then added together. The end-of-period asset value is the sum of the signals added to 100.

Example: Assume the signals received by the INFORMED TRADERS are as follows:

Bidder:	1	2	3	4	5	6
Signal:	105	105	102	102	97	97

The three unique signals are therefore 105, 102 and 97 (note since each signal is determined by a random draw, it is possible for the same signal to be drawn twice, or even three times in a single trading period; although this would be very unlikely).

Unique information signal	A	B	C
Information signal	105	102	97
Difference between signal and 100	+5	+2	−3
End-of-period value:		$(5+2-3)+100=104$	

Quiz:

Assume the INFORMED TRADERS receive the following information signals:

Bidder:	1	2	3	4	5	6
Signal:	103	103	98	98	95	95

What Is the End-Of-Period Asset Value?

Now assume the INFORMED TRADERS receive the following information signals:

Bidder:	1	2	3	4	5	6
Signal:	101	101	102	102	105	105

What Is the End-Of-Period Asset Value?

Remember: Each INFORMED TRADER only observes his/her own signal, and TRADERS do not observe information signals.

Appendix C

Trading Instructions

Submitting, Removing and Changing an ASK

If you submit an ask, it commits you to sell at that price if your ask is (or becomes) the lowest ask and it is double clicked on by another trader.

1. Submitting an ask price

   Place the cursor in the rectangle just below and to the right of ASK. After you enter a price between 75 and 125, 'SUBMIT ASK' will appear in the bottom rectangle. After you click on this rectangle, your ask will be displayed and seen by all the participants.

2. Removing an ask price

   In order to remove an ask, simply double click on it.

3. Changing an ask price

   Change an ask price by removing it, and then submitting a new ask. You may only have one ask price at any time.

Submitting, Removing and Changing a BID

If you submit a bid, it commits you to buy at that price if your bid is (or becomes) the highest bid and it is double clicked on by another trader.

1. Submitting a bid price

   Place the cursor in the rectangle just above and to the right of BID. After you enter a price between 75 and 125, 'SUBMIT BID' will appear in the bottom rectangle. After you click on this rectangle, your bid will be displayed and seen by all the participants.

2. Removing a bid price

   In order to remove a bid, simply double click on it.

3. Changing a bid price

   Change a bid price by removing it, and then submitting a new bid. You may only have one bid price at any time.

Transacting Against an Existing Bid or Ask

If you wish to buy at the lowest ask price, double click on it.

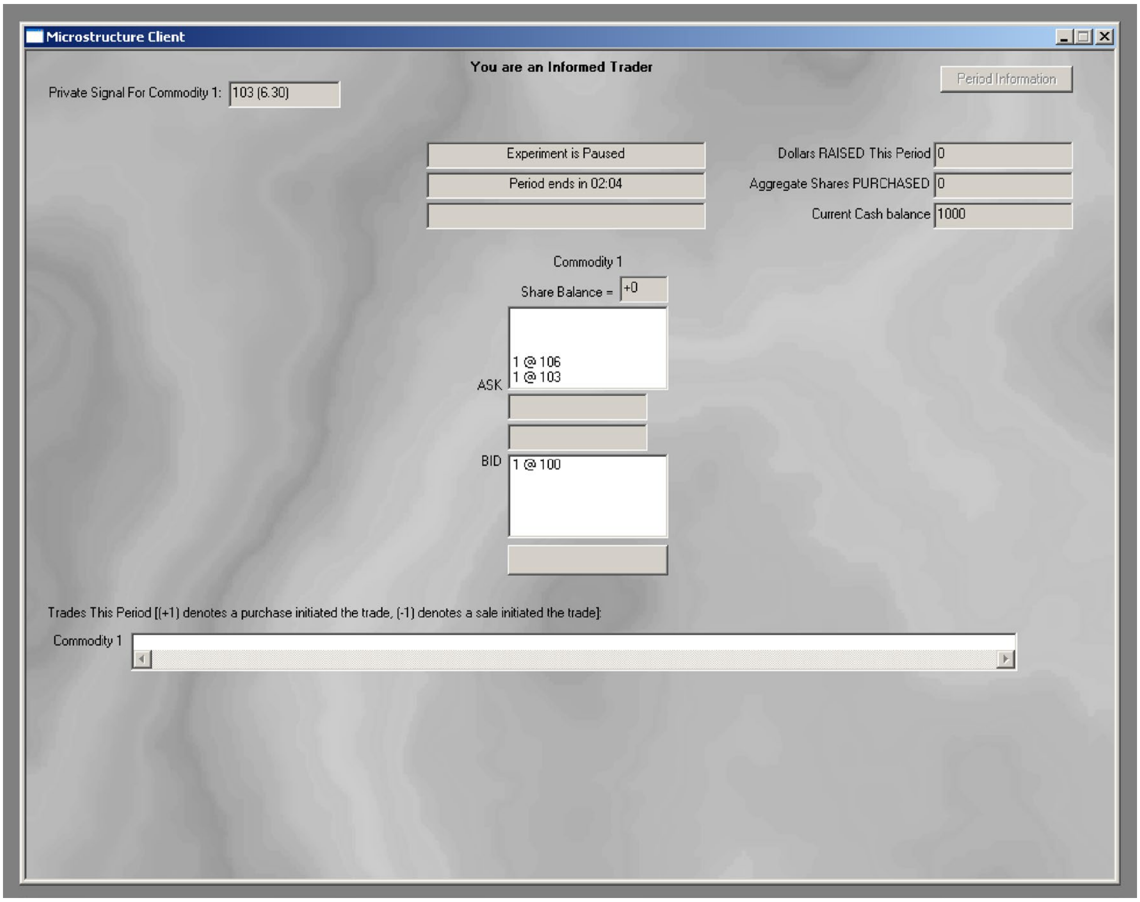
If you wish to sell at the highest bid price, double click on it.

Remember

1. All trades are for one unit.
2. You earn a profit when you buy for less than the end-of-period value of the asset or sell for more than the end-of-period value of the asset.
3. You incur a loss when you buy for more than the end-of-period value of the asset or sell for less than the end-of-period value of the asset.
4. If you make trades at different prices, your profits or losses on each trade will differ.
5. Your bids, asks and trades that you participated in are indicated with an asterisk on the trading screen.

Trading Screens

Below is an example of the trading interface for an INFORMED TRADER. Your private information about the value of the asset is indicated in the top left corner (in this case 103). The (6.30) is the standard deviation of the stock distribution around your expected value. The parameters in today's session may be different than those indicated on these sample screens.



Transacting Against an Existing Bid or Ask

If you wish to buy at the lowest ask price, double click on it.

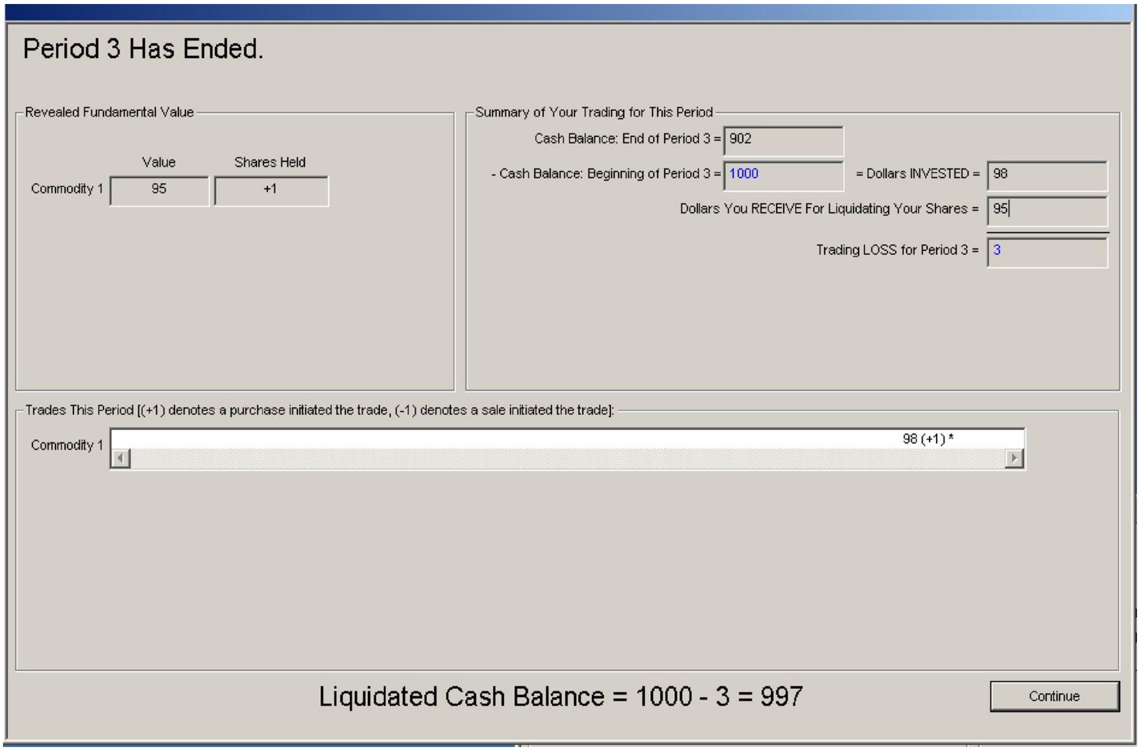
If you wish to sell at the highest bid price, double click on it.

You may remove a limit order at any time by double clicking on it.

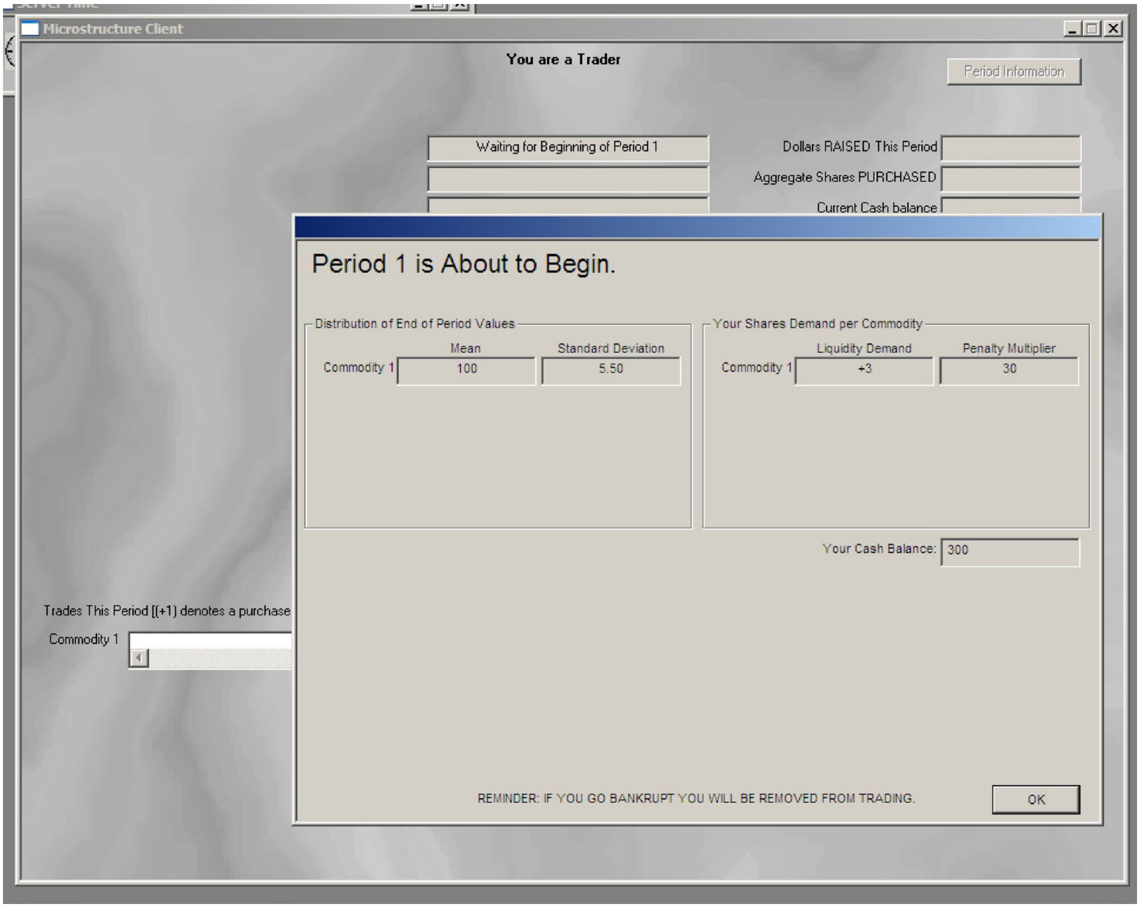
If you wish to transact against someone else's limit order simply double click on it. In the example above you can buy at a price of 103 by double clicking on the 103. If you double click on the bid at 100 you will sell one share at a price of 100.

Completed trades will be indicated in the ticker as they are completed. A + 1 indicates the market order was a buy (it was executed against an ask). A − 1 indicates the market order was a sell order (it was executed against a bid).

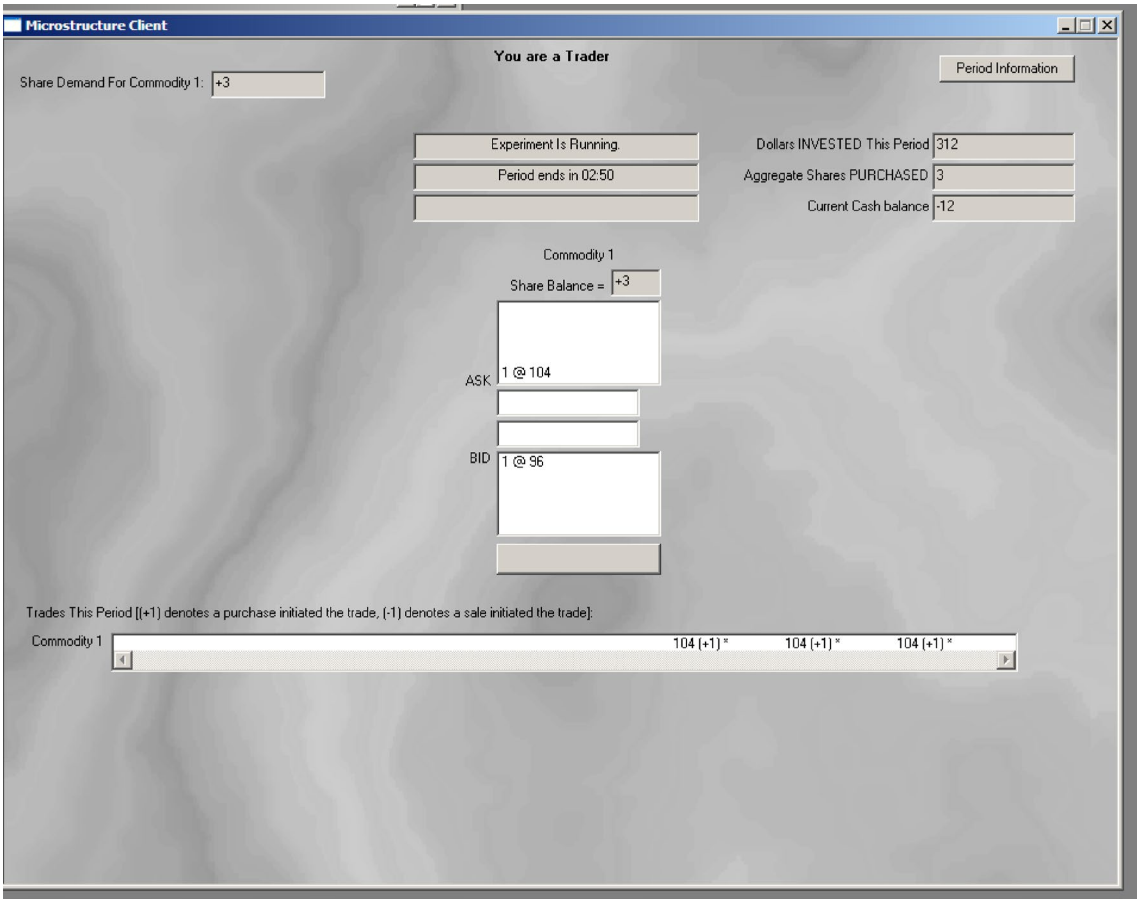
After the period has ended you will learn the actual asset value. Your profits for the trading period will depend on the prices at which you transacted relative to the actual asset value. In general, if you tended to buy for less than the actual value or tended to sell for more, you will earn profits.



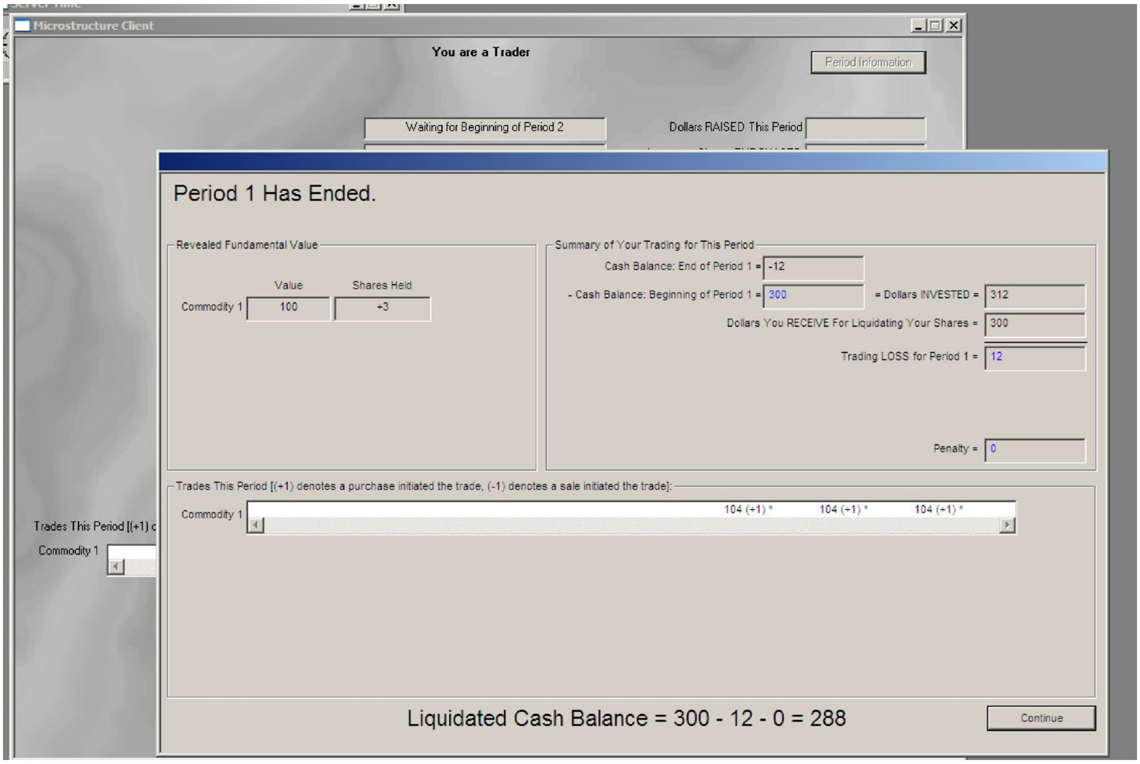
Below is an example of the TRADER's screen prior to the beginning of the first trading period. In this period, this TRADER will be required to have a balance of 3 units of the asset by the end of the period to avoid incurring a penalty. The parameters in today's session may be different than those indicated on these sample screens.



Following is the TRADER'S screen during the trading period. Note the required position (Share Demand) is located in the top left corner of the screen. This trader has completed 3 purchases, so the required trading for this period is completed.



At the end of the period, each TRADER will receive a screen that summarises his/her trading activity for the period, indicates whether the required end-of-period share balance was attained, calculates trading profits or losses, and reports the end-of-period cash balance. Remember, if a TRADER does not exactly attain the required end-of-period share balance, a penalty will be incurred equal to L$36 times the absolute value of the difference between the required share balance and the actual ending share balance.



Trading Summary

If you wish to buy a unit of the asset:

1. Double click on the lowest ask, OR.
2. Submit a 'bid' and wait for another participant to double click on it (remember that only the highest bid at any time is available for trade).

If you wish to sell:

1. Double click on the highest bid, OR.
2. Submit an 'ask' and wait for another participant to double click on it (remember that only the lowest ask at any time is available for trade).