Option Auctions*

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Abstract

All option trades must occur on exchanges, which typically offer auctions that improve prices over existing quotes. Wholesalers purchasing orders from brokers and initiating auctions must be willing to trade at the existing best quote or better. For S&P500 stocks, auctions are 23% of options volume and offer substantial price improvement of 50% of the quoted half-spread. Consistent with wholesalers cream skimming less informed trades into auctions, auctions have lower price impact and occur when arbitrage is less likely. This suggests eliminating the cream-skimming auctions could lead to the 10 cents average quoted spreads narrowing by approximately 1 cent.

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Price improvement, payment for order flow (PFOF), and fragmentation across trading venues are topics much debated by academics, regulators, and practitioners. Most discussion of price improvement and PFOF focuses on stocks. However, price improvement and PFOF exists in both stocks and options, and PFOF for options is more important for some large retail brokers (e.g. Robinhood). PFOF is often linked to price improvement for trades, but price improvement works very differently in options as the SEC requires all listed options trades to occur on exchanges. There is little research on price improvement in options and the structure of the modern automated options markets. The U.S. Securities and Exchange Commission (SEC) has suggested implementing order-by-order auctions, similar to options markets, in equity markets.[1] We study price improvement auctions on options exchanges.

The options market structure is broadly similar to the market structure in equities with some notable exceptions. Similar to equity markets, options trade on numerous exchanges. Listed options trade on one of 16 exchanges operated by 5 exchange groups, Nasdaq, CBOE, NYSE, MIAX, and TMX. An important difference from equities is that listed options are *only* traded on these exchanges.[2] Brokers can sell option orders to wholesalers but, they cannot internalize those orders by taking the other side of the order as principals. Wholesalers in the options market must execute the orders they purchase on an exchange, typically via an affiliated market making part of the wholesalers.

Similar to equity markets, resting orders at the best price receive execution priority. On equity exchanges, the arrival time of an order is often the tie breaker for orders at the same price. Options exchanges offer wholesalers the "...ability to 'direct' orders to an affiliated market maker, and the market maker gets a guaranteed allocation (e.g., 40%) if they are quoting at the best price," (SEC Staff Report (2021)).[3] Similar to internalization in equities where orders are executed at better than posted prices, some options exchanges offer price improving auctions. Auctions allow wholesalers the opportunity to interact with the orders they bring to the exchange (Ernst and Spatt (2022)). Similar to limit order book priority rules orders at the best price are executed first in auctions.

[1] Remarks before the Piper Sandler global exchange conference. In 2009 the SEC proposed banning flash orders, an order type on stock exchanges that allowed for price improvement. The exchanges ceased offering flash orders before they were formally banned (Skjeltorp et al. (2016)).

[2] See Staff Report on Equity and Options Market Structure Conditions in Early 2021, for more detail.

[3] If wholesalers have priority in the limit order book, they receive a 100% allocation, if they do not have priority and at the best price they receive a partial allocation, and if the order less than 5 contracts or less, they receive 100% of the order.

Also similar to the limit order book wholesalers that bring the order to auctions are guaranteed at least 40% of the order if they are quoting the best price. Some exchanges allow wholesalers to auto-match the winning price in the auction such that they are not required to bid the best price to receive a guaranteed allocation.

The structure that allows wholesalers to execute client orders against their own orders in the limit order book or in a price improving auction affords them advantages.[4] Orders that are more likely to be informed can be routed to markets where the wholesalers do not have a resting limit order, imposing adverse selection costs on those market makers. Orders that are less likely to be informed and can be executed more profitably will either be executed against their own resting limit orders in a market where they have priority or in an auction with a guaranteed allocation.

Orders in auctions must trade at or better than the best limit orders, often resulting in substantial price improvement over posted prices.[5] In contrast to equity markets, price improvement can only occur on 1-cent price increments. In addition to preferential allocation rules, wholesalers' also have the ability to initiate an auction or to direct an order to an affiliated market maker in the limit order book, facilitating cream-skimming. When wholesalers initiate auctions all bidders receive a flag as to whether or not the order originates from a non-professional traders.[6] However, the possibility to direct non-professional orders to an affiliated market-maker in the limit order book and professional orders to other market-makers may provide wholesalers with an informational advantage, potentially worsening execution. Therefore, removing cream-skimming auctions and the ability to direct orders to affiliated market makers could reduce liquidity costs.

We provide evidence on liquidity in options auction and non-auction (limit order book) trades. We use Options Price Reporting Authority (OPRA) data and focus on single leg trades in S&P 500 stocks that make up 77.87% of total option trades in these stock, more than 744 thousand trades per day. Single leg options trade similarly to equities and do not require negotiations and coordination

[4]Ernst and Spatt (2022) document that PFOF and price improvement is larger in options markets than in equity markets. They suggest that this could be because of the preferential treatment of wholesalers that makes spreads wide allowing for both large PFOF and price improvement. We study price improvement in options markets on an order-by-order basis, compare execution quality of limit order book and auction trades, provide evidence of cream-skimming by wholesalers and some evidence consistent with liquidity provision in auctions and the limit order book being less than fully competitive. Bryzgalova et al. (2022) use the auction flag to show that retail traders lose money when trading options.

[5]See the CBOE Automated Improvement Mechanism rules for more detail.

[6]SEC Rule 1000(14)(b) identifies traders that submit fewer than 390 orders per day in the prior month as non-professional. Our data does not include this flag.

to trade multiple option contracts simultaneously as for complex option trades. We focus on S&P 500 stocks because options in non S&P 500 stocks trade infrequently. We study electronic trades in electronic limit order markets and in automated auctions.[7] These electronic trades make up 99.86% of all single leg trades. Approximately 23% of all single leg trades execute in electronic price improving auctions, 168 thousand per day. Options markets are generally viewed as illiquid and the average quoted half-spread in our sample is 2.57% of the option price, or roughly 10 cents. Orders in these auctions receive price improvement of 50.42% of the quoted bid-ask (half) spread. A simple back-of-the-envelope calculation suggests that if eliminating auctions led to the price improvement being incorporated in the quoted spreads then these could narrow by approximately 1 cent, or 10% of the current bid-ask spread.[8] However, this narrower quoted spread would be greater than the existing costs in auctions, potentially making orders currently being executed in auctions worse off.

To better understand the economics of price improvement auctions we formulate a stylized, fully competitive model of auctions in which wholesalers can cream-skim uninformed orders. As in many information-based models, some traders have information, and other traders have liquidity and hedging needs unrelated to the future value of the security. Informed traders possess private information and trade to profit from the difference between the fundamental value known only to them and the execution price. The uninformed trade to capture private gains from trade. Wholesalers receive an informative signal about whether the trader is informed. In this sense wholesalers can cream-skim uninformed orders.[9] Wholesalers can trade with these clients in price improving auctions or route orders to a market maker in a limit order book. Informed traders impose adverse selections costs on wholesalers. Uninformed traders have no information about fundamental value and, consequently, their trading has no impact on prices. Using their signal wholesalers screen traders to avoid being adversely selected by informed traders.

Wholesalers also have non-informational reasons to internalize orders in auctions that are not modeled. Wholesalers compete for order flow by offering PFOF and price improvement.

[7] These trades are reported in OPRA using Trade Flag "I" - Auto, and "a" - SLAN (Single Leg Auction Non-ISO).

[8] This calculation makes a number of assumptions; i) the relative amounts of retail and professional trading would not change; and ii) market makers would quote the volume-weighted average spread of the current quoted spread and the spread in auctions. Given 23% of trades are in auctions, quoted spreads are 10 cents, and auction price improvement is 50%, this yields 10*0.77+5*0.25=8.85 cents, which is approximately 10% less than the 10 cent quoted spread.

[9] In our data we cannot distinguish between professional and non-professional trades and rely on the informed and uninformed distinctions.

Wholesalers can impact price improvement via auctions. Wholesalers have lower fees and a guaranteed participation at the winning price. Wholesalers compete in the auction through a publicly announced starting price and a non pre-trade transparent auto-match of the winning price. If the winning auction price is better than their initial price but not better than their match price, they receive an allocation. Because wholesalers must guarantee execution at their initial price, they are disadvantaged by exposure to adverse market movements during the 100 millisecond auction period.

Because traditionally, off-exchange market makers matched the best exchange price prior theoretical literature focused on PFOF rather than price improvement. Chordia and Subrahmanyam (1995) suggests that PFOF exists because the minimum tick-size is larger than the marginal costs of market making. Battalio and Holden (2001) show screening can lead to PFOF without discrete prices. Parlour and Rajan (2003) extends these models to include market and limit orders in a market without asymmetric information and shows that PFOF also exists in their setting. If PFOF and competition among brokers lowers commissions, then commissions and price improvement can be viewed as fungible. In these models price improvement is often infinitesimal and PFOF is thought to be transferred, at least partially, to customers through reduced commissions or increased service quality. Our model is similar to Battalio and Holden (2001) and can generate large price improvement, consistent with our empirical results on price improvement in options markets.

The model formalizes hypotheses to address a number of questions. Can wholesalers screen traders? And if so, can wholesalers perfectly screen traders? There is empirical evidence of the screening of uninformed orders in equity markets beginning with Chordia and Subrahmanyam (1995) and Easley et al. (1996). These papers find evidence that order-flow executed off-exchange is from less informed traders. Consistent with the evidence of screening in equity markets, in options markets the price impact of trades on exchanges is four times larger than for auction trades. Another way to test for wholesaler screening is to identify information-motivated trades. We identify 'arbitrage' trades that try to exploit changes in the underlying stock price that may not yet be reflected in option prices. We estimate a probit regression that shows that wholesalers are less likely to initiate auctions when arbitrage is more likely. Instead, these trades go to the limit order book, reducing adverse selection costs in auctions.

Price impacts and the probit regression suggest that uninformed orders are cream-skimmed into auctions. To test this more formally in our model, we study a number of screening predictions with respect to volatility. Higher volatility increases the informational advantage of informed traders and widens the quoted spread set by market makers. Volatility also increases the value of screening. If wholesalers can *screen*, then price improvement should increase with volatility and price impacts should be lower in auctions than in the limit order book. If wholesalers can *perfectly screen* then auction price impacts are independent of volatility. However, if wholesalers can only *imperfectly screen* then price impacts in auctions should be increasing in volatility. These predictions are tested by regressing quoted spread, price improvement, and price impacts on a measure of volatility. The results show that quoted spreads, price improvement, and price impacts are all increasing in volatility, consistent with wholesalers being able to *imperfectly screen* trades.

Our empirical results show that quoted bid-ask half spreads are wide in options (9.71 cents) and considerably wider than in equity markets (often 1/2 cent; Hagströmer (2021)). Griffith and Van Ness (2020) show a widening of options bid-ask spreads due to the introduction of order cancellation fees. Battalio et al. (2016) document wider bid-ask spreads at option venues that pay for order flow. Quoted spreads capture execution costs when using a market order in a limit order book but options markets also offer price improvement. To characterize liquidity costs, we document price improvement, effective spreads, price impacts, and realized spreads. Price improvement is roughly 2.88 cents, effective spreads are 6.49 cents, and price impacts are 1.65 cents. Realized spreads, the execution price minus the 1-minute price impact, are large at 4.85 cents, or 1.55% of the option price.[10]

Large quoted and realized spreads may arise from the more than 1,000,000 tradable options, versus roughly 4,000 equities, necessitating larger investments in technology, data, and operations to make markets in options. In addition, infrequent trading in some options means that market makers may have high hedging costs as they must hold inventory positions for multiple days or even to expiry. The implicit leverage in options may also attract more informed trading (Chakravarty et al. (2004)) and options market makers quoting across many options series on the same underlying could be exposed to significant adverse selection.

[10] Muravyev and Pearson (2020) find that quoted and effective spreads overstate trading costs if the quotes are not centered around the fundamental option value and informed trader execute on the side closer to fundamental value. Our realized spreads use future quote midpoints and are, therefore, only subject to this bias if the quotes continue to not reflect the correct fundamental value even after the trade occurs.

Payment for order flow is large and quoted spreads are wide in options markets. This could be evidence of a lack of competition, but is not dispositive. Market makers in auctions and limit orders could quote competitive (zero profit) prices conditional on execution, but because wholesalers may be able to direct less informed orders to their own resting limit orders they can earn profits supporting large payment-for-order-flow while other limit orders earn zero profits. The large and positive realized spreads in options could be driven by other features of the options market. While our data are not sufficiently detailed to test this, if wholesalers possess knowledge of how likely customers are to be informed, then wholesalers have an informational advantage in auctions that can result in market power. Wholesalers also benefit from preferential allocations, lower fees, and price auto-matching facilities that are likely to increase their advantages. To examine this, we extend the simple competitive model to include a monopolist wholesaler that maximizes revenues. Volatility widens the quoted spread, and, if wholesalers can screen, this increases their ability to profit in the auction. Higher volatility thereby increases the value of broker screening by increasing their potential profit. This provides an additional test that wholesaler revenues, proxied by realized spreads, should be increasing in volatility.[11] We find that this is true in our data.

We examine another prediction of the model that the price improvement is infinitesimal for monopolist wholesaler, similar to the prediction in Battalio and Holden (2001), to provide a test of competition. To proxy for infinitesimal price improvement we identify auctions with either 0 or 1-cent of price improvement. We find that roughly 45% of all auctions have minimal price improvement.[12] Minimal price improvement may also be a competitive outcome driven by wholesalers attempting to improve the price of an order. Wholesalers may still initiate auctions when they are unable to improve on the quoted price because market conditions or risk limits make providing more price improvement unprofitable.

We also find that the tick size is less binding in options markets as compared to equity markets. In S&P 500 stocks the quoted spread is predominantly the tick size, suggesting that market makers would quote a tighter spread if quoting on sub-penny ticks was allowed (Hagströmer (2021)). The tick size binds in the options market for less than 25% of all trades and less than 15% of auction trades. The market features that can give wholesalers advantages in auctions are also present in

[11] Realized spreads in the competitive model are zero so they do not vary with volatility.

[12] Depending on the options series, market conditions, trade participants, and market features minimum price improvement can be 0 or 1-cent.

the limit order book.[13] Similar to the predictions for monopolist wholesalers and consistent with imperfect competition, we find that the realized spreads also increase with volatility in the limit order book. Taken together, the structure of the options market appears to provide advantages to wholesalers' affiliated market makers by allowing them to preferentially interact with more profitable order flow at a lower cost than non-affiliated market makers.

1 Stylized Model

To guide our empirical work, we formulate and solve a stylized model with wholesalers that trade in auctions, and market makers that trade in the limit order book, and informed and uninformed traders. The setup is similar to Glosten and Milgrom (1985) with the addition of screening and auctions. The model is solved via backwards induction. There is a single risky asset with an unconditional expected value μ that is publicly observable and an innovation $\tilde{\sigma}$ that is only observable by informed traders. Volatility increases the size of the private information of informed traders. The risk-free rate is normalized to zero. Without loss of generality, we model traders seeking to purchase the asset; the sell side is analogous.[14] Uninformed buy and sell orders have equal probability and the arrival probability of informed and uninformed traders are equal. Competitive market makers set the ask price in a limit order market. Wholesalers receive a signal about trader type that they can use to screen traders. Wholesalers offer competitive price improvement over the ask price in an internalizing auction. Figure 1 illustrates the model setup visually.

FIGURE 1 HERE

First in the model, nature draws a realization of the fundamental value $v = \mu + \tilde{\sigma}$, where $\tilde{\sigma}$ can take on values $+\sigma$ or $-\sigma$ with equal probabilities. Next, the wholesaler chooses an auction policy which consists of a routing (auction or limit order book) decision rule s and price improvement pi. Then the market maker sets the ask price in the limit order book (LOB). Next, a trader arrives and submits their order. Uninformed traders are equally likely to buy or sell while the informed

[13] Asymmetric marketing and contra fees, preferential allocations, and specialist allocations granted primarily to affiliated market makers, wholesalers in our model, give affiliated market-makers significant advantages over non-affiliated market makers.

[14] We assume that the distribution of the risky asset is symmetric.

traders only buy (sell) when the realization of $\tilde{\sigma}$ is $+\sigma(-\sigma)$. When an arriving trader submits an order, the wholesaler observes a signal θ of trader type with $\theta \in \{-1, +1\}$. The informativeness of the wholesalers' signal is measured by $\mathcal{P}(\theta = +1|\text{U}) = \pi$; if the signal is perfectly informative then $\pi = 1$ and if the signal has no information $\pi = 1/2$.[15] The wholesaler executes the order in an auction with price improvement pi if $\theta = s$, and routes the order to the LOB otherwise. Figure 2 illustrates the model timeline.

FIGURE 2 HERE

We model wholesalers and market makers as competitive. Competitive market makers' zero profit condition implies that LOB quoted spread is identical to LOB price impact. Wholesalers compete on price improvement such that wholesalers make zero profits. A unique closed form solution exists and is given in Proposition 1 and shown in Figure 1.

1 Proposition. *When the wholesalers and market makers are competitive, and wholesalers screen clients, a unique closed form solution exist. Equilibrium price improvement is as follows:* $pi^* = \sigma(2\pi - 1)$, *market makers set ask price* $a^* = \mu + \pi\sigma$ *and auction price impact is* $\sigma(1 - \pi)$.

Proof: See appendix

1.1 Volatility

Price volatility, σ, is an important parameter in the model. Volatility increases market makers' adverse selection costs and widens the quoted spread. Price improvement over the quoted half-spread in the LOB is defined as $pi = \text{QS} - \Big(\mathbb{E}(\text{price impact} \mid \text{auction}\ )\Big)$. Volatility can have two effects on price improvement. If informed orders also execute in the auction, volatility increases the wholesalers' adverse selection cost. More adverse selection in auctions ceteris paribus means less price improvement because the difference between the expected price impact in the auction and the quoted spread is smaller. But, volatility also widens the quoted spread in the limit order market and ceteris paribus increases the amount of potential price improvement. By the same logic a wider quoted spread with the same price impact allows for more price improvement. The net effect of volatility on price improvement is the difference between the two.

[15]Without loss of generality, we assume that $\pi \geq 1/2$.

1.2 Model Results

The model can be used to address two important questions about wholesalers and uninformed traders. *Do wholesalers screen their clients? If so, is this screening imperfect?* The model generates three simple predictions to test these hypotheses.

1 Corollary. *When wholesalers can perfectly screen their clients, the auction price impact is identical to the valuation of the asset conditional on an uninformed trader's arrival and therefore independent of σ.*

Proof: See appendix.

2 Corollary. *When wholesalers* imperfectly *screen their clients and the wholesalers' signal is informative: (i) price improvement is increasing in σ, (ii) price impacts are lower in auctions as compared to the LOB and (iii) auction price impacts are increasing in σ.*

Proof: See appendix.

3 Corollary. *When wholesalers do not screen clients: (i) price improvement is zero and and therefore independent of σ, and (ii) price impact in auctions is identical to in the LOB.*

Proof: See appendix.

These Corollaries can be summarized as, if wholesalers can screen then:

Result 1: Price improvement is increasing in σ.

Result 2: Price impacts are lower in the auction than in the limit order book.

If wholesalers can *perfectly* screen then:

Result 3: Auction price impacts are independent of σ.

If wholesalers can *imperfectly* screen then:

Result 4: Auction price impacts are increasing in σ.

An additional testable feature of the model is as follows:

Result 5: Quoted spreads are increasing in σ.

Proof: Follows directly from corollaries 1, 2 and 3.

Price improvement in auctions increase in the model because the market makers widen the spread (increase the ask) in anticipation of the arrival of orders with higher price impacts. While this increases the price impact in auctions because wholesalers can only imperfectly screen, it also allows them to offer more price improvement. Lower price impacts in auctions are consistent with internalization results in equity markets in Chordia and Subrahmanyam (1995) and Battalio (1997).

1.3 Model Results and Empirical Results

We estimate regressions to test the predictions of the model on quoted spreads, price improvement, and price impacts in auctions with respect to σ. Table 1 provides a summary of our model results (comparative statics).

TABLE 1 HERE

In Panel A of Table 1 we report the model generated results for the competitive model. Panel C reports the empirical estimates from our regressions. Our empirical results match the results for wholesalers that *imperfectly screen*. We find that the quoted spread, price improvement, and the auction price impact all increase with volatility. In Section 3 we extend our model to include a monopolist wholesaler and a monopolist market maker, which does not have a simple closed-form solution. Panel B shows the comparative statics discussed above are the same in the monopolist model.

2 Institutional Details and Empirical Analysis

In equity markets orders can execute on-exchange or off-exchange with broker-dealers, wholesalers, or on alternative trading systems. In options markets all trades must execute on an NMS exchange if they are to be cleared by the SEC regulated Options Clearing Corporation. There are 16 National Market System (NMS) option exchanges, operated by 5 exchange groups (CBOE, ICE, MIAX, Nasdaq, TMX). Andersen et al. (2021) present descriptive statistics for these exchanges. We focus on two trade types reported in the OPRA data feed; (1) auto - electronic (code I) and: (2) electronic auctions (code a).[16] These two trade types correspond to our theoretical limit order book and internalizing wholesaler auctions. These trade types make up roughly 77% and 23% of all single leg trading respectively. Auto-electronic trades execute in limit order books. Electronic auctions must improve upon, or in some cases match the best available price in the limit order book. Auctions include a number of features that provide advantages to participants that bring an order to the auction. For instance, if a wholesaler brings an order to an auction they are guaranteed at least 40% or 50% of the order if they are quoting at the best price in the auction.[17] Wholesalers can also auto-match the best prices submitted by other auction participants.[18] Auto-matching allows wholesalers guaranteed participation in the auction without them competing on price.

2.1 Data

Our data are from OPRA include exchange, trade price, quoted spread, contract size, option underlying, strike, call or put, and other data. We focus on single leg equity options with S&P 500 stocks as the underlying. We match OPRA to the underlying stock data using the Trade and Quotation (TAQ) database. We split the trading data into 5-second increments and place each option trade within an increment. For instance, an option trade that occurs at 9:30:43 is associated with the 9:30:45 increment that covers the 5-second span between 9:30:40 to 9:30:45. To match the option trade with the underlying stock price we match the option trade to the stock price in the preceding 5-second increment. The option trade that occurred at 9:30:43 would be associated with the stock price from the 9:30:40 time increment. While the latency between OPRA and TAQ is likely fewer than 5 seconds this method ensures that we are using stock prices, quotes, and volumes, before the option trade. We use the methods outlined in Holden and Jacobsen (2014) to process TAQ. Andersen et al. (2021) provide a descriptive overview of the OPRA data.

Our sample period is the second half of 2020: August 2020 through December 2020. This period is after the market dislocations of March and April of 2020 and the floor closure and

[16]We are grateful to Citadel Securities for providing OPRA data and helpful conversations.

[17]Wholesalers are guaranteed 50% if there is one other bidder in the auction and 40% if there is more than 1 additional bidder.

[18]See CBOE Crossing Order Type for a description of guaranteed allocations and auto-matching rules. Other exchange groups have similar features and Ernst and Spatt (2022) state that these features are the same on NASDAQ PHLX.

re-opening periods. This provides a recent sample period without major market movements to examine normal and recent option market trading.

Each trade in our sample is matched to the prevailing option midpoint computed from the best bid and ask prices across option markets. Using the Lee and Ready (1991) tick test we sign all trades as either buyer or seller initiated. Defining D as the signed trade direction we compute (half) dollar effective spreads as follows:

$$ES = D \times (p - m) \tag{1}$$

where p is option price and m is the prevailing midpoint. Price improvement is the difference of the half quoted and effective spread.

$$pi = \text{QS} - \text{ES} \tag{2}$$

We compute price impact as the difference between the prevailing option midpoint at the time of trade and the synthetic option midpoint one minute after the given trade. We use the Black and Scholes (BS) model and the price of the underlying to compute the synthetic option midpoint one minute in the future. Muravyev and Pearson (2020) use a similar technique to calculate a contemporaneous synthetic option price with lagged implied volatility computed from quoted option midpoints and the BS model. We use the BS model to create a *future* option price assuming that the implied volatility is the same at trade time and in the future and using the *underlying* price one minute in the future to calculate a future option price. Realized spread is the difference between effective spread and price impact.

Table 2 reports summary statistics. Quoted bid-ask half spreads are wide in options markets at slightly less than 10 cents. Trade prices are low making quoted spread in relative terms even wider at 2.57% of the midpoint. Spreads in equity markets and particularly in S&P 500 stocks, are typically one cent wide. In a recent study, Hagströmer (2021) reports quoted bid-ask spreads in U.S. equities of roughly 3.55 basis point versus 257 basis point in our sample of options. Both in absolute and relative terms the quoted bid-ask spread in options market is wide. Muravyev and Pearson (2020) presents evidence that the quoted spread may over estimate actual liquidity costs for informed traders. Our results suggests that the quoted bid-ask spread may also over estimate execution costs for uninformed traders due to price improvement in auctions.

On average, price impacts represent 1.65 cents or 28 basis points of the option price. These relatively small price impacts leave room for ample price improvement and realized spreads. Realized spreads, the revenue earned by liquidity suppliers, are roughly 4.85 cents or 1.55% of the option price. The remainder is returned in the form of price improvement of 2.88 cents or 77 basis points of the option price.

On average there are 168 thousand auctions per day and more than 744 thousand trades. Slightly less than 5,000 different options trade with an average price of $8.66. Trades are small on average at 4.51 contracts or $2,420. Traded options have deltas less than 0.50 suggesting that more out-of-the-money options are traded than in-the-money options. Calls are traded 75% of the time and the average days-to-expiration of traded options is 25.

TABLE 2 HERE

Table 3 reports summary statistics for auctions, for the LOB and differences between auctions and limit order book trades. When auctions are initiated the quoted spread is statistically significantly wider, both in cents and in percent of the option price. This could be the case because it is easier to improve prices when the quoted spread is wide but also because internalizing orders when the spread is wide may be more profitable. The realized spread is slightly lower in the auction market in cents and relative to the option price but larger as a fraction of the effective spread by roughly 21%. The large realized spreads in both auctions and the limit order book suggest that these markets are not fully competitive. The realized spread is calculated after price improvement and the price impact have been subtracted from the quoted spread. Price impacts in the auction markets are roughly three times smaller in cents, and four times smaller relative to the option midpoint as compared to the LOB.

TABLE 3 HERE

The results comparing auctions to LOB trades are consistent with our theoretical model that predicts that more informed orders are more likely to be routed to the LOB than to the auction. This is also consistent with the idea that wholesalers screen client orders and route less informed orders to the auction and more informed orders to the limit order book. Price improvement in auctions is 6.41 cents and roughly 1.75% of the option price midpoint. While price improvement is not absent in the LOB, it is much smaller at only 1.85 cents or 0.49% of the option price.[19] Because of the larger amount of price improvement in auctions the effective spread is lower than in the LOB. This suggests that some of the benefits from wholesalers screening are passed on to traders that end up in an auction. Trades in auctions are larger in terms of the number of contracts and dollar volume.[20] Roughly 23% of trading volume occurs in auctions.

Table 3 reports the averages and statistical significance of the auction variable from the regressions reported in Tables 4 and 5. We regress quoted spreads and realized spreads in cents and in percent relative to the midpoint on an auction dummy and a number of controls. Quoted spreads are roughly 2.4 cents or 73 basis points wider when auctions are initiated versus when trades are routed to the limit order book. At-the-money options also trade with lower spreads. Hedging costs are an important component of option spreads and we show that the quoted spread in the option is positively correlated with the quoted spread in the underlying. We find that the realized spread is larger in the limit order book than in auctions. This could be for a number of reasons. While the tick-size in the limit order market can be 1-cent, 5-cents, or 10-cents, auctions can occur for all options in 1-cent increments.[21] This is consistent with the theoretical and empirical results presented in Chordia and Subrahmanyam (1995). Auctions relax the tick-size constraint for some options. We control for this by including a variable that takes the value 1 when the tick-size is 5 or 10 cents, and 0 when the tick-size is 1 cent.

TABLE 4 HERE

Table 5 reports similar regressions as in Table 4 for the price impact and price improvement. Consistent with our model we find that price impacts are lower in auctions. Price impacts are 1.3 cents and 30 basis point lower in auctions. There is some price improvement, in the form of hidden

[19]Price improvement outside of auctions can arise from hidden order types. For example, Nasdaq Options Market offers hidden orders in the limit order book described as follows: "Price Improvement: NOM accepts orders in penny increments in all series, which are displayed at the allowable quoting increment. NOM provides automatic and instantaneous price improvement to incoming orders." See `https://www.nasdaq.com/docs/NOM_faqs.pdf` FAQ # 7 for an example.

[20]Large trades occurring more often in auctions could result from more sophisticated investors routing to wholesalers that are more likely to hold auctions overall or on a specific trade. Table 8 shows that larger trades receive less price improvement and Table 10 shows that market maker trading revenues in auctions are larger for larger trade sizes.

[21]The tick size binds for roughly 25% of trades in our sample. Hagströmer (2021) does not report the exact statistics but notes that S&P 500 stocks trade at predominantly 1-cent (the tick size) quotes.

orders, in the limit order book. However, price improvement is considerably greater in the auction market. On average auction orders receive almost 5 cents or 1.3 percent larger price improvement.

TABLE 5 HERE

Price impacts are lower for at-the-money and out-of-the-money options, larger trades, and for higher underlying stock prices. Price impacts are higher when the underlying quoted spread is wider, for call options, for buys, and when the lagged option volume is high. While not the focus of this paper, the results for price impact suggest that informed traders may prefer in-the-money options and are perhaps more likely to buy calls in stocks and during times, when the underlying stock quoted spread is wide.

Price improvement is lower in at-the-money and out-of-the-money options, for large trades, for calls, when the lagged option volume is high, and when the underlying stock price is low. Price improvement is higher when the underlying stock price quoted spread is wide and when the option price is low. While these results tell us something about auctions in general and price impacts and price improvement overall, they do not shed light on how volatility affects auction outcomes.

3 Wholesaler Screening

The above results show differences between auctions and limit order trades. In our model wholesalers screen in order to avoid trading with informed investors. A simple way to test for wholesaler screening is to identify when informationally motivated trades are more likely.[22] Arbitrage-motivated trades are trades in the option in the same direction as the 5-second return in the underlying. For instance, if the price of the underlying moves up in the previous 5-seconds and we observe a subsequent buy for a call, we would classify that trade as an arbitrage trade. These orders are more likely to be informed and hence wholesalers are likely to screen these types of orders out of auctions. This type of test is relatively unambiguous in that the identity of the trader is irrelevant because regardless of the trader identity the wholesaler may suffer losses if they trade against the order. We find that wholesalers are more likely to route these types of orders to the

[22]In our model volatility does not impact the likelihood of auctions because the informed and uninformed always trade. If the uninformed and informed participation decisions are equally sensitive to costs then higher volatility will lead to more frequent auctions. This is because higher volatility causes costs to increase faster for the informed, who are less likely to get price improvement in an auction, than for the uninformed.

limit order book. We also include a number of variables that are likely to control for other informed trader characteristics or may otherwise influence the probability of an auction.

To study these questions we estimate a probit model as follows:

$$\mathcal{P}(\text{Auc}_t = 1|\sigma_{t-1}, \text{Controls}_t) = \Phi(\beta \text{ Arbitrage}_{t-1} + \gamma \text{Controls}_t), \tag{3}$$

where Auc is a binary response variable which equals one if the trade is executed in an auction and zero otherwise. Φ is the cumulative density function of the normal distribution. The probit regresses an auction dummy variable on a variable that captures arbitrage opportunities that should be correlated with informed trading and a list of controls that include moneyness, trade size, quoted spread of the option and the underlying, call/put indicator, buy/sell indicator, days to expiration and the inverse of option and underlying quote midpoints.

The probit results are reported in Table 6. The coefficient on arbitrage is negative and significant. This suggests that wholesalers screen for informed trades and route those trades to the limit order book. The probit also provides evidence on other variables that affect the probability of an auction. The probability of an auction is higher for at-the-money, and out-of-the-money options, large trades, calls, when the lagged option volumes are high, and when underlying stock prices are higher. The probability is lower when the stock quoted spread is wide, for buys, and when the days to expiry of the option is higher.

TABLE 6 HERE

3.1 Auctions and volatility

The probit regressions provide some evidence that wholesalers screen clients. The theoretical model provides three further predictions in terms of the relation between σ and the quoted spread, auction price improvement, and price impact. In order to translate the theoretical model into empirically testable predictions we first focus on an empirical estimate of σ. In the model σ is the volatility of the asset. We use the lagged absolute value of the 5-second return of the underlying stock return as our estimate of σ.[23]

[23] In Table A2 in the Appendix we show that the results are the similar when using a 1-minute lagged absolute value of the return.

To better understand the relations between volatility and quoted spread, price improvement and price impacts we run the following regressions:

$$X_t = \beta\sigma_{t-1} + \gamma \text{Controls}_t \tag{4}$$

where X_t is one of our dependent variables listed above. Control variables are as follows: moneyness, trade size, quoted spread of the option (except in the quoted spread regression) and the underlying, call/put indicator, buy/sell indicator, days to expiration and the inverse of option and the underlying midpoints. Our main parameter of interest from the regression model is β which measures the effect of a one percent change in volatility on the dependent variable. As in the previous tables we report results in cents and as a percentage of the midpoint. The first column for cents and the first column for percent reports the coefficient for volatility without controls, the second column of each specifications reports coefficients for the full model.

Our model predicts a positive relationship between quoted spread and σ. Table 4 shows that auctions are more likely when quoted spreads are large. We regress the quoted spread on the absolute stock return in one specification, and on absolute stock return with a number of other variables of interest in a second specification. A 1% increase in the lagged absolute stock return leads to an increase in the quoted bid-ask spread of 15.7 cents and 3.74 percent for the model with only volatility and 11.54 cents or 2.25% relative to the midpoint for the full model. The quoted spreads are also wider when arbitrage is more likely.

TABLE 7 HERE

Note that Table 7 is for the quoted spread in the limit order market and the remaining regressions are for auctions only. We show that the spread in the limit order market is lower for ATM and OTM options, for large trades, and when lagged trading volume is high. The quoted spread is consistently wider when the underlying stock's quoted spread is wide.

Table 8 reports the regression of price improvement in auctions on volatility and our control variables.

TABLE 8 HERE

The model predicts that wholesalers offer more price improvement when σ is large. Consistent with this, we find that a one percent increase in volatility is associated with a 6.56 cent or 1.31 percent (relative to midpoint) increase in price improvement, in the specification with all of the controls. Without controls a 1% increase is associated with a roughly 9.5 cent and a 2.6% increase in price improvement. Price improvement is consistently lower for at-the-money options, for larger trades, and when lagged volume is higher. Price improvement is higher when the underlying stock quoted spread is wider.

The model predicts that price impacts are increasing in σ. We test this in Table 9.

TABLE 9 HERE

Consistent with wholesaler screening, a one percent increase in lagged absolute stock return is associated with a 2.73 cents or 32.08 basis point (relative to midpoint) increase in price impact for the fully specified model and 3.2 cents and 45 basis points for the model with only volatility. Price impacts are lower for at-the-money and out-of-the-money options. Price impacts are higher for larger trades, when stock quoted spreads are wider, calls, and buys, and when lagged volume is higher. Price impacts are also higher in auctions when arbitrage is more likely.

Overall, our regression results are consistent with the results of the theoretical model. Volatility increases the quoted bid-ask spread in the limit order market, price improvement in auctions, and price impact in auctions.

4 Imperfect market maker and wholesaler competition

Large payments for order flow and wide spreads suggest that options markets may not be competitive. However, wide spreads and large payment for order flow do not necessarily indicate that the auction, or the limit order book are not competitive. Market makers bring retail orders to the auction to receive price improvement, and may periodically profitably direct retail orders to their resting limit orders. The profitable limit order executions can generate large payments for order flow. Conditional on not being able to trade with specific orders each market is competitive. However, auctions, and the limit order book, could also be not fully competitive. Our data do not allow us to answer this question directly. Our model extension does provide indirect evidence that we present below.

4.1 Model Results

The descriptive results in Table 3 shows that realized spreads (market maker revenues) are positive in auctions and in the limit order book. In the Appendix we add a simple extension of the competitive model to include monopolist wholesalers and monopolist market makers in the LOB that maximize trading revenues. The extension shows that revenues are positively correlated with volatility. The intuition behind this results is simple. Volatility increases the spread and thereby the value of screening. A wider spread leaves wholesalers more scope to offer de minimis price improvement and increase revenues. The monopolist market maker's revenues will also increase in volatility and the quoted spread will be considerably wider than under the competitive case.[24] The intuition here is also simple. The market maker will quote $\mu + \sigma$ and earn larger profits from the uninformed when volatility is high. The extension is presented and solved in Appendix Proposition 2.

4.1.1 Wholesalers

To proxy for wholesaler revenues we use the realized spread. The realized spread is portion of the quoted spread that remains after price impacts and price improvements are subtracted. Figure 3 presents a visual breakdown of the quoted spread into price improvement, realized spread and price impact in auctions for high and low volatility. Figure 3 plots the average of the variables for a single high volume option with Tesla as the underlying. The option has a strike price of \$500 and expired on November 11^{th} 2020. We split observations into below and above median volatility on the x-axis and the variables in cents on the y-axis. All three variables increasing in volatility is consistent with a monopolist wholesaler.

FIGURE 3 HERE

To further examine the model results we estimate a regression similar to Equation 4. Positive realized spreads in auctions could be positive because they represent revenues before hedge costs.

[24] We have also solved the model for monopolist wholesalers and competitive market makers and vice versa. The comparative statistics with respect to σ are identical for quoted spread, price impact and price improvement, while expected revenues (realized spread) is increasing for the monopolist type.

First, we assume that hedge costs are fixed and not directly correlated with volatility. To control for the initial hedge costs of a trade we include the absolute value of the delta of the traded option and the underlying stock spread. We report the results of the auction realized spread regression in Table 10.

TABLE 10 HERE

Consistent with the monopolist model we find that wholesaler realized spreads are positively correlated with volatility. A 1% increase in volatility increases the realized spread by 2.72 cents and 0.65% in the fully specified model and 4 cents and 1% in the model that only includes volatility. Realized spread are larger for large trades and for underlying stocks with wide quoted spreads. Realized spreads are consistently smaller for ATM and OTM options, for buys, and when lagged option volume is high. Realized spread increasing in volatility could potentially also be driven by hedging costs that increase with volatility. As the price of the underlying changes the optimal hedge for the option changes. Muravyev and Pearson (2020) notes that dynamic hedging costs are likely to be lower for in-the-money options as they infrequently need to be re-balanced. This is true for both in and out-of-the-money options. At-the-money options need to be rebalanced most frequently. To account for dynamic hedging costs we estimate a third regression that includes an interaction between volatility and a dummy variable for at-the-money options as column three in each specification. If hedge costs vary with volatility they should vary most strongly with ATM options. The regression coefficient on the interaction between volatility and the ATM dummy is negative and significant. The regression coefficient of volatility remains positive and significant across all regressions.

In the monopolist model, wholesalers offer the minimum amount of price improvement to internalize profitable orders, this is similar to the results presented in Battalio and Holden (2001). In option auctions, the minimum price improvement can be either 0 or 1 cent depending on the trader, market, trade size, and quoted spread. Figure 4 plots the frequency of price improvement in cents.

FIGURE 4 HERE

In our data minimum price improvement occurs for roughly 45% of auctions. This suggests that while price improvement may be large on average, close to half of all auctions occur with the minimum price improvement. The next most frequent amount of price improvement is 2-cents, followed by 5-cents. Less than 20% of price improvement is greater than 10-cents. These results suggest that for slightly less than half of all auctions zero or small price improvement is the competitive outcome or wholesalers face limited competition.

4.1.2 Market Makers

Some of the same forces that may allow wholesalers to not be fully competitive in auctions exist in limit order markets. Market makers receive advantages in the form of order preferencing and lower fees and are often the same as the market makers in auctions. We report the results of the limit order book realized spread regression in Table 11.

TABLE 11 HERE

Similar to the realized spread results for the auction market we find a positive relationship between volatility and realized spreads. In addition, our variables that capture static or dynamic hedge costs cannot explain the findings.

4.2 Discussion

Quoted spreads in options market are considerably wider than in the underlying equities. There are over 1,000,000 tradable options, versus roughly 4,000 equities, necessitating a large investment in technology, data, and operations to make markets in options. In particular computing option sensitivity to the volatility surface in near real-time is expensive. The higher costs could lead to less competition. Infrequent trading in some options means that market makers may also hold inventory positions for multiple days. The leverage in options may also attract more informed traders. Taken together these difference could explain wider spreads in options than in equities. Wide spreads and large payment for order flow could be a competitive outcome conditional on the market structure. Market makers can quote zero-profit prices in the auction and in the limit order book. When wholesalers can direct uninformed orders to their own orders in the limit order book, this can generate revenues and payment for order flow.

Our results provide some suggestive evidence against perfect competition in liquidity supply in options. If market makers are competitive, spreads balance the losses to trading against informed traders and gains associated with trading against uninformed investors. If the limit order book is populated by a monopolist marker maker the spread will be wider than in the competitive case. Is there evidence that options markets are less competitive than equity markets? In equity markets, because of competition, the spread is often constrained to the size of the tick whereas options markets are often not tick-constrained. To illustrate this point, in Figure 5 we plot the frequency with which trades occur when the quoted spread is 1, 2, ... 10+ ticks wide. Options are tick constrained for roughly 24% of trades. For over 15% of all trades spreads are more than 10 ticks wide. When auctions are initiated spreads are even less likely to be tick constrained. Roughly 16% of auctions happen when spreads are 1-tick wide. Spreads are more likely to be 2-ticks, 3-ticks or greater than 10-ticks wide than they are 1-tick wide when auctions are initiated. If auctions were competitive and the tick size was binding, then one would expect more auctions when the tick size binds. And, if the tick-size was hindering competition in the limit order book one would expect the spread to be one tick wide more often. That neither appear to be true suggests that auctions are not fully competitive and that it is unlikely that the tick size being too large is an explanation for the limited competition.

FIGURE 5 HERE

Why are equity markets competitive? Wholesalers, or their affiliated market makers, in options markets are afforded advantages relative to equity markets. Marketing fees are paid by market makers when interacting with customer orders on most exchanges. These marketing fees are then paid out to the wholesalers, that can also be market makers on the exchanges.[25] Options exchanges also often appoint specialists that are wholesalers.[26] Similar to auctions where wholesaler-affiliated market makers have priority, wholesaler-affiliated market makers at options exchanges are given preferential allocations to incoming order flow.[27] While it may be beneficial to give specialist preferential treatment to compensate specialist firms for quoting in low trading-volume options, this practice may also widen spreads overall.

[25] CBOE fee schedule Page 3.

[26] On the CBOE Susquehanna, Citadel, and Wolverine are the top-3 specialists in terms of number of number of securities and are also the top-3 wholesalers for Robinhood and Schwab.

[27] CBOE C1 Rule Book Page 253.

5 Conclusion

The literature on the structure of electronic trading in the options market is limited. We examine single leg option trades where the underlying stock is part of the S&P 500. Trading occurs predominantly in electronic limit order markets but, in contrast to equity markets, wholesalers can choose to run electronic price improvement auctions. This stems from regulations requiring equity options to trade on an exchange. Auctions allow wholesalers to internalize on exchanges.

We develop and test a simple model with cream-skimming, internalization and price improvement to address a series of questions. Can wholesalers screen clients? Can wholesalers screen clients perfectly? The empirical results suggest that wholesalers can screen their clients, but not perfectly. Are auctions fully competitive? We extend the model to include monopolist wholesalers and find suggestive evidence that the market for options is not perfectly competitive and that the tick size is not the only impediment to competition. While our model suggests that auctions and the limit order book may not be fully competitive, further study is required to answer the question more definitively.

Price improvement and price improving auctions have been presented as beneficial for retail investors. Wholesalers regularly promote the amount of price improvement investors can expect to receive when trading through their platform.[28] The assumption is that retail investors are therefore getting good prices because price improvement is high. We show that while some trades receive significant price improvement, roughly 45% receive the minimum price improvement.

If wholesalers in auctions and market makers on exchanges are not fully competitive then it is not clear that the price improvement received in auctions generates prices that are better than under alternative market structures. While price improvement appears large at 6 cents, almost half of trades only receive the minimum price improvement. In addition, the realized half spread after price impacts in auctions is 3 cents, is much larger than the entire quoted spread in equity markets. The realized spread in the limit order book is even larger.

The presence of auctions allows wholesalers to offer price improvement to uninformed orders. If removing auctions led to quotes reflecting the average price offered to all trades, both auction and non-auction, and did not affect the market in other ways, then the bid-ask spread would fall by

[28]For example, Fidelity Price Improvement.

roughly 1 cent, or 10%.[29] This would benefit the 77% of orders that trade in the limit order book, but could cause orders currently executing in auctions to receive worse prices.

Is it possible for regulators to increase competition in options markets? Some potential changes may be able to increase competitiveness in options markets. For instance, the removal of guaranteed participation rights and auto-match provisions in auctions could increase incentives to bid more aggressively. In addition, limiting asymmetric fees for wholesalers initiating auctions and constraining routing options for which wholesalers are also specialists could limit potential agency issues in order routing. Additional measures could limit the ability of wholesalers to decide whether to initiate an auction and to direct orders to affiliated market makers on exchanges.

Future work should focus on whether or not the advantages afforded to wholesalers have benefits such as ensuring liquidity across the entire market and in thinly traded riskier options in particular. Best execution may need to consider taking into account that the NBBO may not be set by perfectly competitive market makers. If the options market structure results in a wide bid-ask spread, then measuring best execution against the NBBO may be insufficient.

Additional data is required to better understand competition in options execution. Data could include exchange level data with the identities of the wholesaler, non-affiliated market makers in the auction and the limit order book, trader identities, and the non-professional trading flag in auctions and the limit order book. Data showing the initial bid, reserve bid, and all auctions responses could be used to better understand wholesalers' informational advantage. Auction, routing, and limit order book identities would allow researchers to understand how the ability to internalize an order on a limit order market affects wholesalers bidding and routing decisions.

[29] While theoretically straightforward, whether changing the amount of cream skimming impacts quoted spreads has yet to be shown empirically, see, for example, Battalio (1997).

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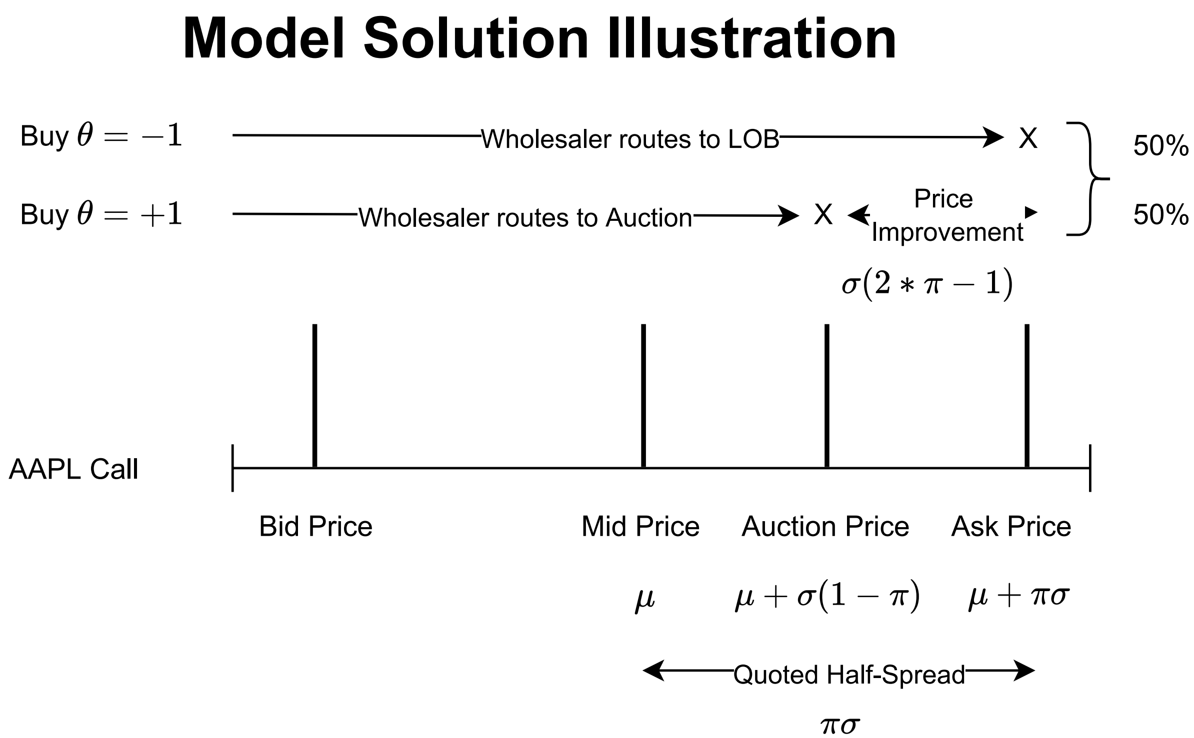

Figure 1: Illustration of the model
This figures illustrates our model visually. The option midpoint μ, denotes the valuation of the uninformed trader type and σ denotes volatility. The wholesalers signal is symmetrically defined on the discrete support set $\theta \in \{+1, -1\}$ with $\mathcal{P}(\theta = +1|\mathrm{U}) = \pi$. The event U denotes an arrival of the uninformed trader type. WLOG we assume $\pi \geq \frac{1}{2}$.

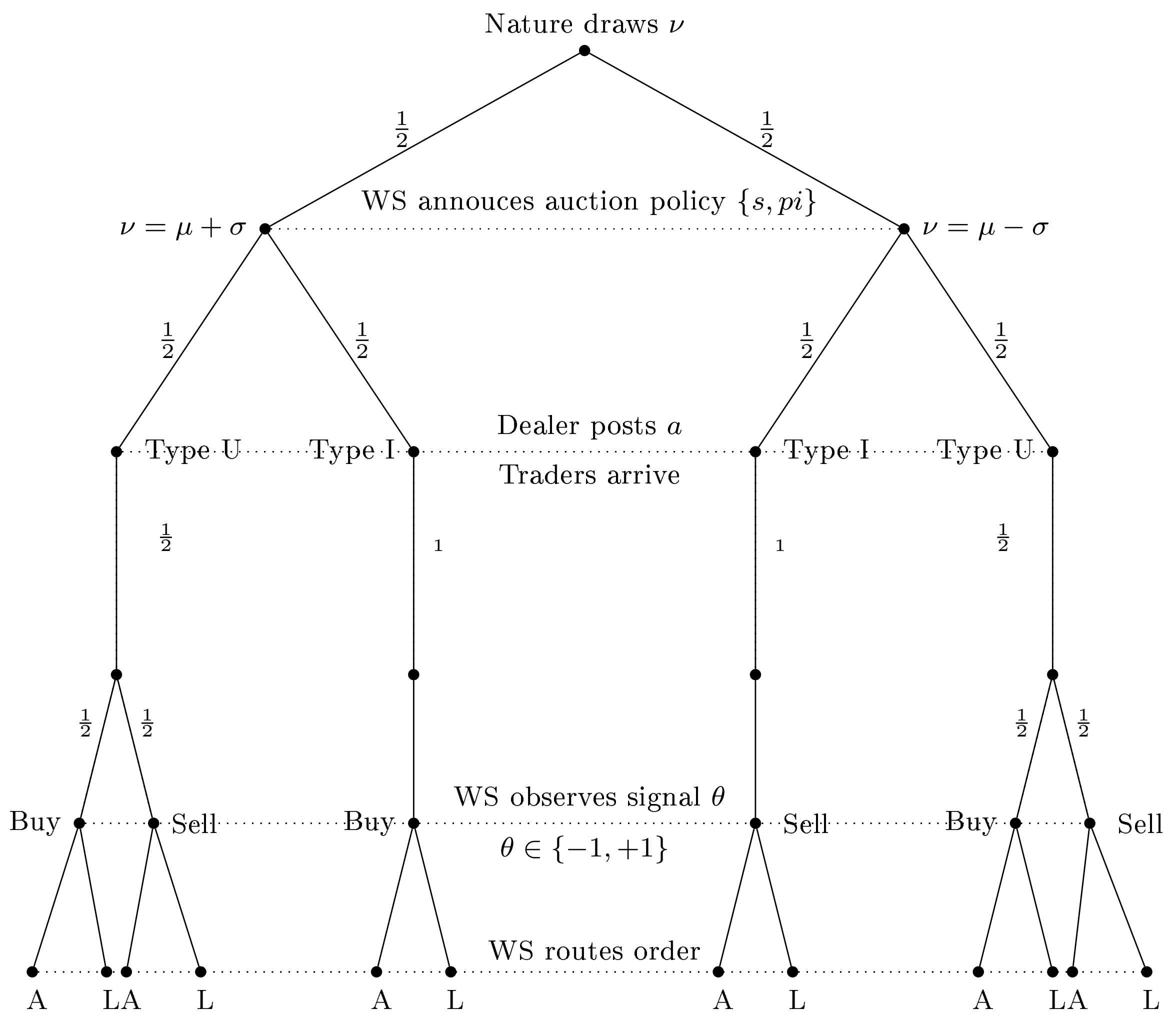

Figure 2: Model timeline
This figure shows the model timeline. WS denotes wholesaler. Type U (Type I) denotes uninformed (informed) trader types. In the wholesalers' routing decision node, A denotes order is executed in an auction and L denotes order is routed to LOB.

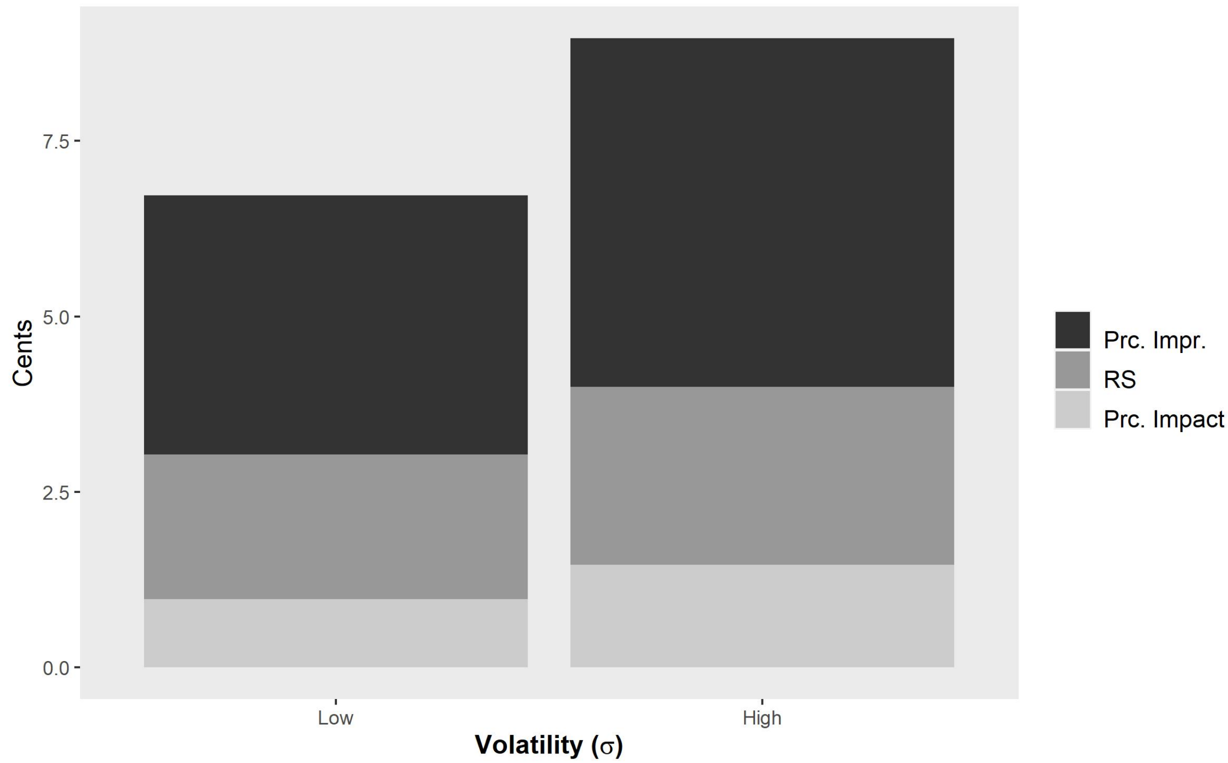

Figure 3: High versus low volatility auction trades
This figures plots average price impact (Prc. Impact), realized spread (RS) and price improvement (Prc. Impr.) across all auction trades, for a 100 contract call option on Tesla (TSLA) stock with a strike price of 500 and expiration date of 11th, November 2020. Volatility is defined as high (low) if the 5-second prior absolute value of stock return is higher (lower) than its median value across option trades.

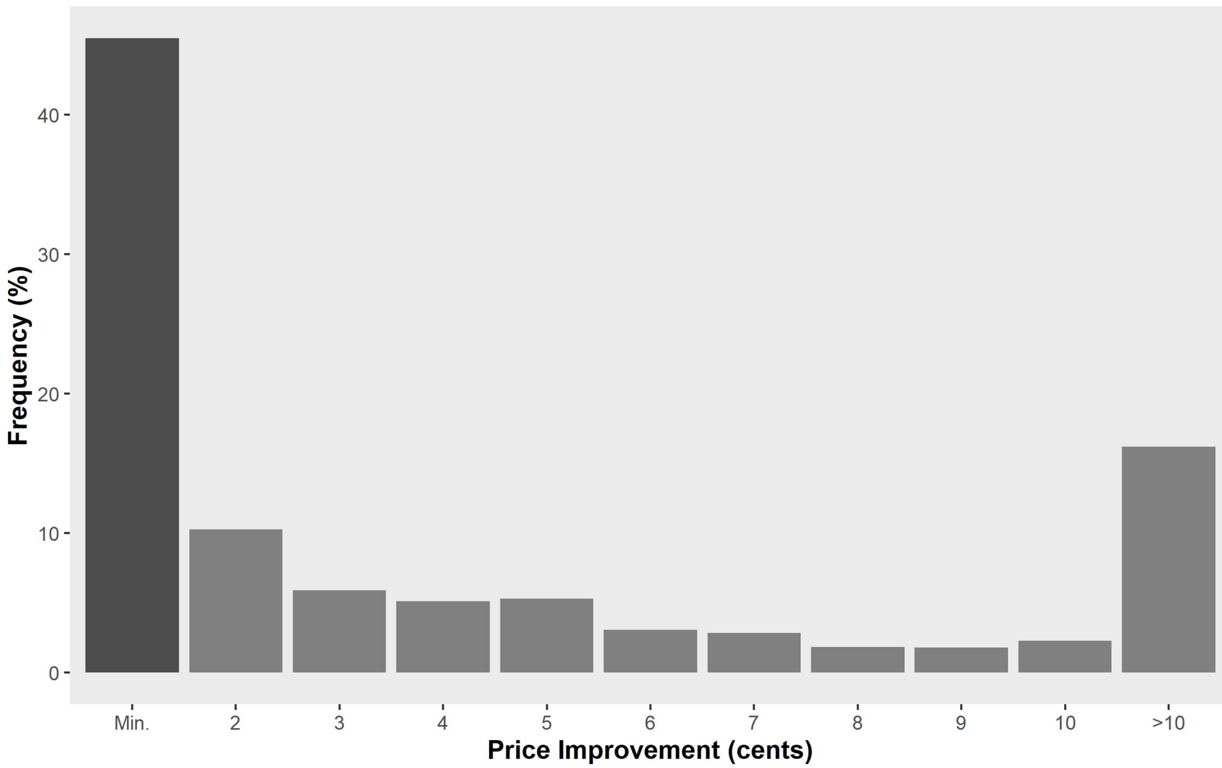

Figure 4: Auction frequency by price improvement
This figures plots trade frequency for auctions versus auction price improvement measured in cents. Minimum price improvement is 0 and 1-cent. Our sample period is the second half of 2020: August 2020 through December 2020.

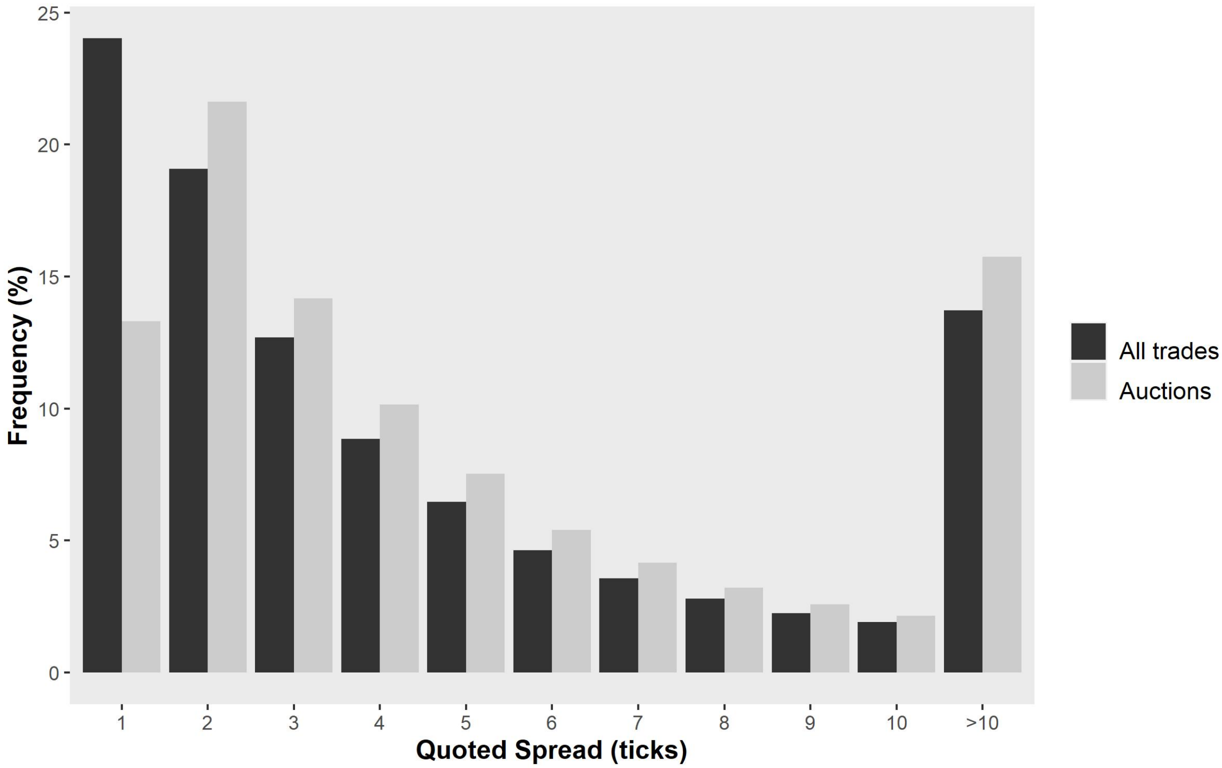

Figure 5: Trade frequency by quoted spreads in ticks
This figures plots trade frequency versus quoted spreads measured in tick-size, prevailing at the time of trade. Our sample period is the second half of 2020: August 2020 through December 2020. Our sample consist of all single leg trades in the S&P 500 option trades.

Table 1: Comparative statistics
This table presents comparative statistics for the competitive brokers and market makers model (panel A) and monopolist broker and market maker model (panel B). Panel C presents empirical estimates from the regression models. Auc. Prc. Impr. denotes auction price improvement, Auc. PImp. denotes auction price impact, Auc. RS (LOB) RS denotes broker (market maker) realized spread. Panel C presents empirical estimates from our regression models.

Panel A: Competitive brokers and market makers

Parameter	Correlation				
	QS	Auc. Prc. Impr.	Auc. Prc. Imp.	Auc. RS	LOB RS
σ	+	+	+	0	0

Panel B: Monopolist broker and market maker

Parameter	Correlation				
	QS	Auc. Prc. Impr.	Auc. Prc. Imp.	Auc. RS	LOB RS
σ	+	0[30]	+	+	+

Panel C: Empirical Estimates

Parameter	Regression Coefficient				
	QS	Auc. Prc. Impr.	Auc. Prc. Imp.	Auc. RS	LOB RS
σ	11.54	6.56	2.73	2.72	6.42

[30]The monopolist broker offers minimum price improvement required to initiate an auction independent of σ. Roughly 45% of auctions in our sample recieve minimum price improvement.

Table 2: Descriptive statistics
This table presents sample descriptive statistics computed from daily averages. Quoted spread is the difference of option ask and bid prices prevailing at the time of trade. Realized spread is the difference between effective spread and price impact. Price impact is the difference between the option midpoint prevailing at the time of trade and the synthetic midpoint prevailing one minute after the trade, times trade direction. We compute synthetic option midpoint using the Black-Scholes model. Price improvement is the difference between option quoted spread and effective spread. Effective spread is the difference between option price and midpoint, times trade direction. Market capitalization is price time shares outstanding from the end of the previous month. Stock midpoint is the prevailing stock midpoint at the time of option trade. Option depth is the average offered option contracts on the ask and bid side. Call (put) volume is daily call (put) traded volume as a percentage of total traded volume. All percents are relative to option midpoint except price improvement which is relative to option quoted spread. Our sample period is the second half of 2020: August 2020 through December 2020. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

				Percentiles				
	Unit	Mean	St.Dev	5%	25%	50%	75%	95%
Quoted half Spr.	cents	9.71	1.80	7.70	8.45	9.16	10.75	13.24
Quoted half Spr.	%	2.57	0.38	2.01	2.30	2.55	2.82	3.27
Realized half Spr.	cents	4.85	1.12	3.45	4.01	4.64	5.43	7.28
Realized half Spr.	%	1.55	0.25	1.15	1.37	1.55	1.71	2.01
Price Improvement	cents	2.88	0.52	2.29	2.55	2.73	3.05	4.04
Price Improvement	/QS%	22.25	1.19	20.50	21.64	22.20	22.95	23.97
Price Improvement	/Mid.%	0.77	0.12	0.60	0.69	0.77	0.85	0.97
Price Impact	cents	1.65	0.41	0.99	1.35	1.63	1.94	2.32
Price Impact	bps.	28.85	6.83	19.41	24.06	28.40	32.88	40.49
Effective half Spr.	cents	6.49	1.19	5.07	5.61	6.17	7.40	8.65
Effective half Spr.	%	1.84	0.28	1.38	1.65	1.82	2.03	2.36
Hedge Cost	bps.	0.59	0.07	0.48	0.55	0.59	0.64	0.71
Number of auctions	1,000s/day	168.39	32.26	115.60	146.28	167.07	188.77	226.93
Trades	1,000s/day	744.28	147.82	540.10	635.02	726.76	837.72	1,016.64
Options traded	1,000s/day	4.99	0.44	4.37	4.71	4.96	5.24	5.69
Trade Price	$	8.66	1.64	6.43	7.45	8.56	9.42	11.72
Market capitalization	$ billion	58.43	150.91	4.56	12.40	23.18	52.00	203.48
Stock Midpoint	$	142.00	6.40	133.04	136.83	140.37	148.08	152.31
Trade size	contracts $	4.51	0.32	4.04	4.27	4.51	4.69	5.02
Trade size	1,000s $	2.42	0.38	1.88	2.12	2.40	2.61	3.20
Dollar volume	billions $/day	1.82	0.56	1.14	1.39	1.75	2.08	3.08
Depth	contracts	158.44	41.44	96.45	123.63	155.47	196.08	218.29
|Delta|		0.30	0.02	0.27	0.29	0.30	0.32	0.33
Call Volume	%	75.48	5.52	66.05	72.29	76.29	79.31	82.59
Put Volume	%	24.52	5.52	17.41	20.69	23.71	27.71	33.95
Days-to-expiration	days	25.22	3.09	20.27	23.28	24.94	27.11	30.24

Table 3: Auctions and limit order book trades
This table presents sample descriptive statistics computed from daily averages for trades which are executed as auctions versus trades executed at the LOB. Quoted half spread is half the difference of option ask and bid prices prevailing at the time of trade. Realized half spread is the difference between effective spread and price impact. Price impact is the difference between the option midpoint prevailing at the time of trade and the synthetic midpoint prevailing one minute after the trade, times trade direction. We compute synthetic option midpoint using the Black-Scholes model. Price improvement is the difference between option quoted spread and effective spread. Effective half spread is difference between option price and midpoint, times trade direction. Our sample period is the second half of 2020: August 2020 through December 2020. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$

	Units	Auctions	LOB	Auction minus LOB
Quoted Spr.	cents	10.72	9.42	1.30***
				(0.27)
Quoted Spr.	%	3.00	2.45	0.55***
				(0.06)
Realized Spr.	cents	3.28	5.30	−2.03***
				(0.14)
Realized Spr.	%	1.33	1.62	−0.28***
				(0.03)
Price Impacts	cents	0.69	1.92	−1.24***
				(0.05)
Price Impact	bps.	8.13	34.91	−26.77***
				(0.86)
Price Improvement	cents	6.41	1.85	4.56***
				(0.12)
Price Improvement	/QS%	50.42	13.99	36.43***
				(0.21)
Price Improvement	/Mid%	1.75	0.49	1.26***
				(0.03)
Effective Spr.	cents	3.96	7.23	−3.27***
				(0.15)
Effective Spr.	%	1.41	1.97	−0.55***
				(0.04)
Trade Size	contracts	5.14	4.33	0.82***
				(0.05)
Trade Size	thousand $	2.47	2.41	0.06
				(0.06)
Trading Volume	%	23.09	76.91	−53.83***
				(0.23)

Table 4: Spreads and auctions
This table presents results for spreads regressed on auction indicator. The dependent variable is quoted spreads and realized spreads in cents (columns 1 and 2) and in percents relative to the option midpoint (columns 3 and 4). Auction is an indicator variable which equals 1 if the trade is executed as an auction and zero otherwise. All dependent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number trades in our sample: 78,893,354. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	Cents		Percent	
	Quoted spread	Realized spread	Quoted spread	Realized spread
Auction	2.41^{***}	-1.19^{***}	0.73^{***}	-0.12^{***}
	(0.08)	(0.05)	(0.01)	(0.01)
Stock QS	0.15^{***}	0.08^{***}	0.21^{***}	0.11^{***}
	(0.01)	(0.00)	(0.01)	(0.00)
|Delta|	22.80^{***}	5.08^{***}	-4.35^{***}	-3.99^{***}
	(0.90)	(0.38)	(0.06)	(0.05)
ATM	-2.71^{***}	-2.47^{***}	-1.43^{***}	-1.19^{***}
	(0.24)	(0.15)	(0.02)	(0.02)
OTM	-0.73^{**}	-1.66^{***}	-1.74^{***}	-1.54^{***}
	(0.35)	(0.21)	(0.03)	(0.02)
Option Volume$_{t-1}$	-0.27^{**}	-0.46^{***}	-0.06^{***}	-0.08^{***}
	(0.11)	(0.07)	(0.01)	(0.01)
Trade size	-0.07^{***}	0.03^{***}	0.05^{***}	0.05^{***}
	(0.01)	(0.01)	(0.00)	(0.00)
Call	-4.00^{***}	-2.17^{***}	0.52^{***}	0.22^{***}
	(0.15)	(0.08)	(0.02)	(0.01)
Buy	-0.00	-0.45^{***}	-0.03^{***}	-0.12^{***}
	(0.01)	(0.07)	(0.00)	(0.01)
Tick Ind.	-3.16^{***}	-2.21^{***}	1.07^{***}	0.64^{***}
	(0.15)	(0.08)	(0.04)	(0.03)
Days Exp.	2.87^{***}	1.63^{***}	-0.22^{***}	-0.09^{***}
	(0.08)	(0.04)	(0.01)	(0.01)
1/Stock Midpoint	-114.37^{***}	-62.67^{***}	-3.12^{**}	1.35^{*}
	(7.09)	(3.88)	(1.25)	(0.83)
1/Option Midpoint	0.81^{***}	0.17^{***}		
	(0.04)	(0.01)		

Table 5: Price impact, price improvement and auctions

This table presents regression results for price impact and price improvement regressed on auction indicator. The dependent variable is price impact and price improvement (columns 1 and 3) in cents and in percents relative to the option midpoint (columns 2 and 4). Auction is an indicator variable which equals 1 if the trade is executed as an auction and zero otherwise. All dependent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number trades in our sample: 78,893,354. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	Cents		Percent	
	Prc Impact	Prc Improvement	Prc Impact	Prc Improvement
Auction	−1.36***	4.89***	−30.52***	1.32***
	(0.04)	(0.14)	(0.40)	(0.02)
Stock QS	0.01***	0.04***	2.98***	0.08***
	(0.00)	(0.00)	(0.10)	(0.00)
|Delta|	9.02***	6.36***	70.03***	−1.41***
	(0.35)	(0.26)	(1.37)	(0.03)
ATM	0.87***	−0.75***	18.11***	−0.53***
	(0.08)	(0.08)	(0.44)	(0.01)
OTM	1.23***	−0.14	28.25***	−0.66***
	(0.09)	(0.12)	(0.68)	(0.01)
Option Volume$_{t-1}$	0.25***	−0.04	2.85***	−0.01**
	(0.04)	(0.03)	(0.42)	(0.01)
Trade size	−0.05***	−0.04***	−0.14**	−0.00***
	(0.00)	(0.00)	(0.06)	(0.00)
Call	−0.50***	−0.98***	17.19***	0.15***
	(0.03)	(0.05)	(0.56)	(0.01)
Buy	0.36***	0.07***	9.32***	−0.01***
	(0.07)	(0.01)	(1.10)	(0.00)
Tick Ind.	0.00	−1.26***	13.46***	0.42***
	(0.03)	(0.04)	(0.37)	(0.01)
Days Exp.	0.11***	0.80***	−10.60***	−0.02***
	(0.01)	(0.02)	(0.19)	(0.00)
1/Stock Midpoint	−11.44***	−27.81***	−122.27***	−4.29***
	(1.88)	(1.89)	(27.69)	(0.81)
1/Option Midpoint	0.29***	0.20***		
	(0.01)	(0.01)		

Table 6: Probit model for auctions

This table presents probit results for auctions. The dependent variable is a binary response variable which equals one if the trade is executed as an auction and zero otherwise. Arbitrage is the product of call/put direction indicator, option buy/sell direction indicator and underlying stock return prior to option trade. All dependent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each probit specification is the total number trades in our sample: 78,893,354. * $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

Arbitrage_{t-1}	-1.018^{***}	-0.999^{***}
	(0.003)	(0.003)
Stock QS		-0.011^{***}
		(0.000)
|Delta|		-0.036^{***}
		(0.002)
ATM		0.083^{***}
		(0.001)
OTM		0.027^{***}
		(0.001)
Option QS		0.003^{***}
		(0.000)
$\text{Option Volume}_{t-1}$		0.042^{***}
		(0.000)
Trade size		0.038^{***}
		(0.000)
Call		0.169^{***}
		(0.000)
Buy		-0.036^{***}
		(0.000)
Tick Ind.		0.044^{***}
		(0.000)
Days Exp.		-0.075^{***}
		(0.000)
1/Stock Midpoint		2.453^{***}
		(0.011)
1/Option Midpoint		-0.005^{***}
		(0.000)
Intercept	-0.746^{***}	-1.283^{***}
	(0.000)	(0.002)

Table 7: Quoted spread and volatility

This table presents regression results for quoted spread in cents (columns 1 and 2) and in percent (columns 3 and 2). Absolute stock return (|Stock Ret|) is the size of underlying stock return from the previous 5 second, computed as the absolute value. All independent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number of trades in our sample: 78,893,354. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	cents		percent	
$\lvert\text{Stock Ret}\rvert_{t-1}(\sigma)$	15.70***	11.54***	3.74***	2.25***
	(1.11)	(0.92)	(0.21)	(0.15)
Arbitrage_{t-1}		5.06***		0.24***
		(0.32)		(0.03)
Stock QS		0.15***		0.20***
		(0.01)		(0.01)
|Delta|		22.80***		−4.34***
		(0.90)		(0.06)
ATM		−2.65***		−1.41***
		(0.24)		(0.02)
OTM		−0.70**		−1.73***
		(0.35)		(0.03)
$\text{Option Volume}_{t-1}$		−0.36***		−0.08***
		(0.11)		(0.01)
Trade size		−0.05***		0.06***
		(0.01)		(0.00)
Call		−3.90***		0.55***
		(0.15)		(0.02)
Buy		−0.04***		−0.03***
		(0.01)		(0.00)
Tick Ind.		−3.15***		1.07***
		(0.15)		(0.04)
Days Exp.		2.82***		−0.23***
		(0.08)		(0.01)
1/Stock Midpoint		−111.58***		−1.49
		(6.94)		(1.26)
1/Option Midpoint		0.81***		
		(0.04)		

Table 8: Auction price improvement and volatility
This table presents regression results for auction price improvement cents (columns 1 and 2) and in percent (columns 3 and 2). Absolute stock return (|Stock Ret|) is the size of underlying stock return from the previous 5 second, computed as the absolute value. All independent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number of auction in our sample: 17,849,031. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	cents		percent	
$\lvert$Stock Ret$\rvert_{t-1}(\sigma)$	9.49***	6.56***	2.60***	1.31***
	(0.72)	(0.58)	(0.17)	(0.11)
Arbitrage$_{t-1}$		0.80***		0.08***
		(0.14)		(0.03)
Stock QS		0.10***		0.19***
		(0.00)		(0.01)
$\lvert$Delta$\rvert$		16.17***		−3.61***
		(0.66)		(0.07)
ATM		−1.26***		−1.20***
		(0.19)		(0.03)
OTM		0.38		−1.68***
		(0.29)		(0.04)
Option Volume$_{t-1}$		−0.31***		−0.09***
		(0.09)		(0.01)
Trade size		−0.14***		−0.05***
		(0.01)		(0.00)
Call		−3.07***		0.18***
		(0.12)		(0.02)
Buy		0.03***		−0.02***
		(0.01)		(0.00)
Tick Ind.		−2.89***		0.96***
		(0.12)		(0.04)
Days Exp.		1.76***		−0.01**
		(0.05)		(0.01)
1/Stock Midpoint		−65.86***		−11.58***
		(4.42)		(2.60)
1/Option Midpoint		0.40***		
		(0.02)		

Table 9: Auction price impact and volatility
This table presents regression results for auction price impact in cents (columns 1 and 2) and in basis points (columns 3 and 2). Absolute stock return (|Stock Ret|) is the size of underlying stock return from the previous 5 second, computed as the absolute value. All independent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number of auction in our sample: 17,849,031. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	cents		Bps	
$\lvert\text{Stock Ret}\rvert_{t-1}(\sigma)$	3.24***	2.73***	45.63***	32.08***
	(0.36)	(0.35)	(4.18)	(3.88)
Arbitrage_{t-1}		3.67***		64.47***
		(0.76)		(11.76)
Stock QS		0.01***		1.34***
		(0.00)		(0.10)
|Delta|		4.22***		19.13***
		(0.26)		(1.54)
ATM		0.57***		4.53***
		(0.07)		(0.59)
OTM		0.65***		5.47***
		(0.09)		(0.93)
$\text{Option Volume}_{t-1}$		0.15***		1.92***
		(0.03)		(0.30)
Trade size		0.04***		1.26***
		(0.00)		(0.09)
Call		−0.30***		4.72***
		(0.03)		(0.40)
Buy		0.44***		8.88***
		(0.08)		(1.39)
Tick Ind.		−0.00		2.14***
		(0.03)		(0.41)
Days Exp.		0.04***		−3.75***
		(0.01)		(0.15)
1/Stock Midpoint		0.17		−6.64
		(1.48)		(24.53)
1/Option Midpoint		0.16***		
		(0.01)		

Table 10: Auction realized spread and volatility

This table presents regression results for realized spread in cents (columns 1 and 2) and in percent (columns 3 and 2). Absolute stock return (|Stock Ret|) is the size of underlying stock return from the previous 5 second, computed as the absolute value. All independent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number of auction in our sample: 17,849,031. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	cents			percent		
$\lvert\text{Stock Ret}\rvert_{t-1}(\sigma)$	4.10***	2.72***	4.17***	1.03***	0.65***	0.61***
	(0.53)	(0.45)	(0.47)	(0.09)	(0.07)	(0.08)
Arbitrage_{t-1}		−0.54	−0.52		−0.29**	−0.29**
		(0.82)	(0.82)		(0.12)	(0.12)
Stock QS		0.06***	0.06***		0.07***	0.07***
		(0.00)	(0.00)		(0.00)	(0.00)
|Delta|		4.02***	3.61***		−3.55***	−3.55***
		(0.31)	(0.31)		(0.06)	(0.06)
ATM		−1.44***	−1.43***		−0.97***	−0.98***
		(0.11)	(0.11)		(0.02)	(0.02)
OTM		−0.74***	−0.76***		−1.27***	−1.27***
		(0.16)	(0.16)		(0.03)	(0.03)
$\text{Option Volume}_{t-1}$		−0.34***	−0.23***		−0.05***	−0.05***
		(0.06)	(0.06)		(0.01)	(0.01)
Trade size		0.09***	0.08***		0.05***	0.05***
		(0.01)	(0.01)		(0.00)	(0.00)
Call		−1.15***	−1.08***		0.29***	0.29***
		(0.05)	(0.05)		(0.01)	(0.01)
Buy		−0.58***	−0.59***		−0.20***	−0.20***
		(0.08)	(0.08)		(0.01)	(0.01)
Tick Ind.		−1.14***	−1.34***		0.70***	0.70***
		(0.06)	(0.06)		(0.03)	(0.03)
Days Exp.		0.92***	0.82***		−0.11***	−0.11***
		(0.03)	(0.03)		(0.01)	(0.01)
1/Stock Midpoint		−44.82***	−1.33***		4.12***	4.24***
		(3.24)	(3.24)		(0.96)	(0.96)
1/Option Midpoint		0.03***	0.01***			
		(0.01)	(0.01)			
$\lvert\text{Stock Ret}\rvert_{t-1}(\sigma)\times$ATM			−2.56***			0.12
			(0.65)			(0.11)

Table 11: LOB realized spread and volatility

This table presents regression results for LOB realized spread in cents (columns 1 and 2) and in percent (columns 3 and 2). Absolute stock return (|Stock Ret|) is the size of underlying stock return from the previous 5 second, computed as the absolute value. All independent variables are defined in table A1. Our sample period is the second half of 2020: August 2020 through December 2020. Sample size in each regression specification is the total number of LOB trades in our sample: 61,044,323. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	cents			percent		
$\lvert$Stock Ret$\rvert_{t-1}(\sigma)$	8.45***	6.42***	7.04***	2.28***	1.50***	1.53***
	(0.68)	(0.61)	(0.60)	(0.14)	(0.11)	(0.12)
Arbitrage$_{t-1}$		1.25*	1.60*		−0.24**	−0.19**
		(0.71)	(0.71)		(0.10)	(0.10)
Stock QS		0.09***	0.10***		0.12***	0.12***
		(0.00)	(0.00)		(0.00)	(0.00)
$\lvert$Delta$\rvert$		5.33***	4.84***		−4.12***	−4.15***
		(0.40)	(0.40)		(0.05)	(0.05)
ATM		−2.79***	−2.87***		−1.27***	−1.28***
		(0.16)	(0.15)		(0.02)	(0.02)
OTM		−1.94***	−1.96***		−1.61***	−1.62***
		(0.23)	(0.23)		(0.02)	(0.02)
Option Volume$_{t-1}$		−0.53***	−0.36***		−0.10***	−0.08***
		(0.08)	(0.08)		(0.01)	(0.01)
Trade size		0.01*	0.01*		0.05***	0.05***
		(0.01)	(0.01)		(0.00)	(0.00)
Call		−2.39***	−2.29***		0.22***	0.22***
		(0.08)	(0.08)		(0.01)	(0.01)
Buy		−0.40***	−0.41***		−0.10***	−0.10***
		(0.07)	(0.07)		(0.01)	(0.01)
Tick Ind.		−2.47***	−2.74***		0.63***	0.60***
		(0.09)	(0.09)		(0.03)	(0.03)
Days Exp.		1.83***	1.69***		−0.08***	−0.10***
		(0.05)	(0.05)		(0.01)	(0.01)
1/Stock Midpoint		−68.27***	−7.57***		1.32*	7.78*
		(4.12)	(4.12)		(0.89)	(0.89)
1/Option Midpoint		0.23***	0.19***			
		(0.01)	(0.01)			
$\lvert$Stock Ret$\rvert_{t-1}(\sigma)\times$ATM			0.48			0.16
			(0.61)			(0.09)

Empirical Appendix

Table A1: Definition of the variables
This table presents description of variables used in our regression and probit models.

Variable	Definition	Source
Auction	Indicator variable which equals 1 if trade is executed as an auction.	OPRA
$\lvert\text{Stock Ret}\rvert_{t-1}(\sigma)$	Size of underlying stock return from the previous 5 second.	TAQ
Arbitrage_{t-1}	Product of call/put direction indicator, option buy/sell direction indicator and underlying stock return prior to option trade. Call/put direction indicator equals 1 (-1) if the option traded is a call (put). Buy/sell direction indicator equals 1 (-1) if the option trade is initiated by a buyer (seller).	OPRA & TAQ
|Delta|	Absolute value of the option's delta.	OPRA
ATM	Indicator variable which equals 1 if the option traded is an ATM.	OPRA
ITM	Indicator variable which equals 1 if the option traded is an ITM.	OPRA
Stock QS	Average quoted spread of the underlying stock computed from 5 seconds prior to option trade.	TAQ
$\text{Option Volume}_{t-1}$	Logarithmic of daily option volume (in contracts) from the previous day.	OPRA
Trade size	Logarithmic of option trade size (in contracts)	OPRA
Call	Indicator variable which equals 1 if the option traded is a call option.	OPRA
Days Exp.	Logarithmic of number of days to option expiration.	OPRA
1/Stock Midpoint	Reciprocal of underlying stock midpoint prevailing prior to option trade.	TAQ
1/Option Midpoint	Reciprocal of option midpoint prevailing at the time of option trade.	OPRA
Tick Ind.	Indicator variable which equals 1 if the option price is less than \$3. Option tick size changes when an option is trading above \$3.	OPRA

Table A2: Robustness: 1 minute volatility
This table presents empirical results using 1 minute volatility of underlying stock. The dependent variables in cents are as follows: QS denotes quoted spread, Auc. PImpr denotes auction price improvement, Auc. PImpact denotes auction price impact, RS Auc. (RS LOB) denotes auction (LOB) realized spread. All independent variables are defined in table A1. All regression include stock and time (day) fixed effects. Standard errors are double clustered at the option and day level. Spreads are winsorized at the 1% level on each tail.* $p < 0.01$; ** $p < 0.05$; *** $p < 0.001$.

	QS	PImpr	PImpact	RS Auc.	RS LOB
$\lvert$Stock Ret$\rvert_{t-1}(\sigma)$	7.03***	3.79***	1.35***	2.39***	4.57***
	(0.54)	(0.29)	(0.16)	(0.23)	(0.36)
Arbitrage$_{t-1}$	4.91***	0.73***	3.34***	−0.14	1.51*
	(0.31)	(0.14)	(0.77)	(0.83)	(0.72)
Stock QS	0.14***	0.10***	0.01***	0.06***	0.09***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$\lvert$Delta$\rvert$	22.70***	16.10***	4.17***	3.58***	4.80***
	(0.90)	(0.66)	(0.26)	(0.31)	(0.40)
ATM	−2.65***	−1.28***	0.57***	−1.44***	−2.83***
	(0.24)	(0.19)	(0.07)	(0.10)	(0.14)
OTM	−0.70**	0.37	0.66***	−0.79***	−1.95***
	(0.34)	(0.29)	(0.08)	(0.16)	(0.23)
Option Volume$_{t-1}$	−0.52***	−0.40***	0.12***	−0.29***	−0.48***
	(0.11)	(0.09)	(0.03)	(0.06)	(0.08)
Trade size	−0.04***	−0.14***	0.04***	0.08***	0.02**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Call	−3.92***	−3.07***	−0.30***	−1.07***	−2.30***
	(0.15)	(0.12)	(0.03)	(0.05)	(0.08)
Buy	−0.05***	0.03***	0.43***	−0.58***	−0.41***
	(0.01)	(0.01)	(0.08)	(0.08)	(0.07)
Tick Ind.	−3.10***	−2.86***	0.01	−1.33***	−2.71***
	(0.15)	(0.12)	(0.03)	(0.06)	(0.09)
Days Exp.	2.83***	1.77***	0.05***	0.82***	1.70***
	(0.08)	(0.05)	(0.01)	(0.03)	(0.05)
1/Stock Midpoint	−111.49***	−65.51***	0.26	−2.28***	−9.86***
	(6.85)	(4.37)	(1.46)	(3.23)	(4.10)
1/Option Midpoint	0.81***	0.40***	0.16***	0.01***	0.20***
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
$\lvert$Stock Ret$\rvert_{t-1}$×ATM				−0.80***	−0.12
				(0.24)	(0.28)

Theory Appendix

Proof of proposition 1.

Using backward induction we start with the wholesalers' routing decision. At this stage the wholesaler has already announced his auction policy and simply implements this policy. Next we solve for the informed trader type's trading decision. The informed trader will choose to buy (sell) whenever the realization of σ is $+\sigma(-\sigma)$. The uninformed traders will choose to buy or sell with equal probability and therefore independent of the realization of σ.

The next step is to solve for the competitive market makers' ask price. The zero profit condition yields the following solution:

$$\begin{aligned} a^* &= \mu + \sigma \mathcal{P}(\mathrm{I}|\mathrm{LOB}) \\ &= \mu + \sigma \mathcal{P}(\mathrm{I}|\theta \neq s^*) \end{aligned} \tag{5}$$

where I denotes an informed trader arrival. The competitive wholesalers' objective is to maximize price improvement. Therefore, given an informative signal the wholesaler will execute orders with signal $\theta = +1$ in auctions and route orders with signal $\theta = -1$ to the market maker[31]. At the final step of backward induction the competitive wholesalers' price improvement follows from zero profit condition:

$$\begin{aligned} pi^* &= \mathbb{E}(\nu|\mathrm{Auc.}) - \mathbb{E}(\nu|\mathrm{LOB}) \\ &= \mathbb{E}(\nu|\theta = s^*) - \mathbb{E}(\nu|\theta \neq s^*) \end{aligned} \tag{6}$$

Substituting $s^* = +1$:

$$pi^* = \sigma(2\pi - 1) \tag{7}$$

Proof of corollary 1.

When wholesalers can perfectly screen, the equilibrium auction price impact is the valuation of the uninformed trader μ, and therefore auction price improvement is independent of σ.

Proof of corollary 2.

(i) Differentiating equilibrium price improvement given in equation 7 with respect to σ completes the proof.

(ii) The difference in LOB versus auction price impact is wholesaler surplus given in equation . Competitive wholesalers equilibrium price improvement is strictly positive and therefore price impact is smaller in auctions as compared to the limit order book.

[31] The two realization of the signal are perfectly symmetric, hence WLOG $\pi \geq \frac{1}{2}$. An informative signal is one with $\pi > \frac{1}{2}$.

(iii) Differentiating auction price impact from proposition 1 with respect to σ completes the proof.

Proof of corollary 3.
When wholesalers do not screen clients the zero profit condition for wholesalers implies zero price improvement. And, therefore equilibrium price improvement is necessarily independent of σ. In addition, given competitive wholesalers and market makers, zero price improvement implies identical price impacts in auctions and LOB.

2 Proposition. *When both the wholesaler and market maker are monopolist a unique closed form solution exists. Equilibrium price improvement is the minimal price improvement required for an auction at an exchange, denoted by ϵ. Market maker sets ask price $a^* = \mu + \sigma$*

Proof: All backward induction steps are identical to proposition 1 except for the wholesalers' and market maker's decisions that are now modified to profit maximization problems. The monopolist market maker chooses an ask price to maximize expected profits[32]:

$$a^* := \max_a \left\{ \mathcal{P}(\theta = -1) \Big[a - \mathbb{E}(\nu | \theta = -1) \Big] \right\} \tag{8}$$

The monopolist market maker's expected profits are strictly decreasing in LOB ask. Hence the optimal ask price is the valuation of the risky asset μ conditional on an informed trader arrival, which is $\mu + \sigma$.[33]

In the final step of backward induction the monopolist wholesaler chooses price improvement to maximize expected profits:

$$pi^* := \max_{pi} \left\{ \mathcal{P}(\theta = +1) \Big[a^* - pi - \mathbb{E}(\nu | \theta = +1) \Big] \right\} \tag{9}$$

The monopolist wholesaler's expected profits are strictly decreasing in price improvement. Hence the optimal price improvement is the minimal price improvement required by the exchange to execute an order as an auction.

4 Corollary. *When both broker's and market maker's are monopolists, expected profits (realized spreads) are increasing in σ in auctions and LOB.*

Proof: Monopolist broker's equilibrium expected profit is as follows: $\frac{1}{2}\Big((\pi\sigma - \epsilon)\Big)$ and is strictly increasing in σ for all informative signals.

Correspondingly the monopolist market maker's expected profit is as follow: $\frac{1}{2}(1 - \pi)\sigma$ and is also strictly increasing in σ.

[32]Price impact is strictly smaller for signal $\theta = +1$. Therefore, consistent with profits maximization, the monopolist wholesaler will internalize all orders with $\theta = +1$ in auctions and route all orders with signal $\theta = -1$ to the LOB.

[33]An ask price larger than $\mu + \sigma$ cannot be an equilibrium since in this case the monopolist wholesaler will execute all trades in an auction and the market maker will make zero profits.