Options Market Makers*

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Abstract

Options market makers (OMMs) facilitate most option trades, yet little is known about how they perform and manage risk. Using unique account-level data for KOSPI 200 index options and futures, we conduct the first study of individual OMMs. OMMs earn high Sharpe ratios, with positive profits on 74% of days. They reduce risk primarily by rebalancing inventory within minutes, rather than relying on costly delta hedging. Indeed, only four of 43 market makers in our sample consistently delta hedge. Consistent with KOSPI 200 results, S&P 500 OMMs turn over positions rapidly, as their daily trading volume exceeds net position changes by a factor of 32. Our findings support classic microstructure theories emphasizing inventory management and challenge the widespread belief that OMMs always fully delta hedge.

Keywords: market makers, options, inventory, delta hedging, risk management

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1. Introduction

Hedging is a core risk management strategy. For instance, systematic beta exposure in an equity portfolio can be hedged by selling index futures, while the directional risk of a long call option can be "delta-hedged" by selling the underlying asset. However, the microstructure and options literatures disagree on the role of hedging. Microstructure theories are mostly silent about hedging, focusing instead on how liquidity providers actively manage inventory and adverse selection risks (e.g., Stoll, 1978; Ho and Stoll, 1983). In contrast, the options literature and textbooks focus on hedging, neglecting other risk reduction strategies (e.g., Black and Scholes, 1972; Leland, 1985; Hull, 2018).[5] Have microstructure theories missed a crucial aspect of risk management?

To address this question, we study options market makers (OMMs), an important class of market participants predisposed to prioritize hedging among risk management techniques. The Futures Industry Association estimates that 108 billion options contracts were traded worldwide in 2023, with 1.35 million distinct option contracts listed in the U.S. alone. OMMs usually serve as the sole providers of price quotes for most of these option contracts, ensuring continuous two-sided quotes and facilitating most trades. Without OMMs, most option contracts would lack liquidity and quoted prices, impeding market function. Despite their importance, surprisingly little is known about options market makers. How profitable are they, and do they primarily manage risk through delta hedging or active inventory management? Answering these questions requires detailed account-level data, generally unavailable to researchers.

This paper is the first to directly study how individual OMMs trade and manage risk. Our main analysis relies on unique account-level data from KOSPI 200 index options and futures, capturing all transactions in options and the underlying asset. Later, we assess how some of our

[5] E.g., Hull (2018), pp. 431: "Derivatives dealers usually rebalance their positions once a day to maintain delta neutrality."; Hull and White (2017): "Ever since the birth of exchange-traded options markets in 1973, delta hedging has played a major role in the management of portfolios of options. Option traders adjust delta frequently, making it close to zero, by trading the underlying asset."; Sinclair (2010), pp.217: "Many customers trade options to obtain directional exposure so they will not hedge, or will at least hedge less frequently than the market maker who will be actively delta hedging his position."

KOSPI results generalize to the S&P 500 index options by studying aggregate market-maker positions. Specifically, we observe each investor's trades and quotes in KOSPI 200 index options and futures from January 2010 to June 2014, including over one billion option transactions. We identify market maker accounts based on their trading behavior since any firm can act as a market maker in KOSPI 200 options. Out of 161,010 accounts that trade options, we identify 43 accounts that engage exclusively in market making, selected based on their consistent two-sided BBO quoting and high passive trading volume.

Several features make this market well-suited for studying OMMs. First, the KOSPI 200 index futures and options are among the world's most actively traded.[6] During our sample period, about one billion U.S. dollars' worth of KOSPI 200 options was traded daily, only slightly less than the volume of S&P 500 options. Second, the KOSPI 200 options market structure is similar to other major options markets, featuring an electronic limit order book and participation from leading global OMMs such as Optiver, SIG, IMC, and Virtu.[7] Indeed, 39 of the 43 OMMs that we identify are foreign firms, which likely employ similar strategies worldwide. While these similarities suggest our findings could generalize to other active options markets, further research is needed into OMMs' strategies across different markets. Finally, KOSPI 200 options can *only* be effectively hedged using futures. Thus, we observe the entire market for options and the underlying asset. Such comprehensive data is not available in the U.S., where multiple index, equity, and futures options exist on the S&P 500. Despite this limitation, we confirm some of our KOSPI results for the S&P 500 index options using aggregate market maker positions in options (but not the underlying) over the extended 1996-2018 period.

We document several main results. First, options market makers earn consistently high profits. An average OMM makes 521 million Korean won (KRW) per month from options trading, or about half a million U.S. dollars, while incurring small losses from futures trading. These profits

[6] The World Federation of Exchanges ranked Korea Exchange as the leading market globally for stock index options trading in 2011, with 3.67 billion contracts traded, which exceeded the combined volume of the next three largest markets - NSE India (0.87 billion), EUREX (0.47 billion), and Cboe (0.32 billion). https://www.world-exchanges.org/storage/app/media/2011%20WFE%20Market%20Highlights.pdf

[7] E.g., "A Knight in the Kospi" (https://amsterdamtrader1.rssing.com/chan-5818139/article65.html#c5818139a65).

include exchange fees but exclude hard-to-estimate fixed costs. OMMs earn positive profits on 74% of days – better than discretionary traders who profit on just over half of days, but below equity HFTs who rarely experience losses (Baron et al., 2019). In theory, market makers can earn half of the bid-ask spread per trade; however, the OMMs in our sample earn 12% of the half-spread on average. Small per-trade profits accumulate over many weakly correlated trades into annualized Sharpe ratios of 5.8 to 11.3, comparable to U.S. equity HFTs. Consistent with microstructure theories, OMMs' profits increase with volatility, trading volume, and bid-ask spreads.

Second, options market makers' decisions to enter or exit the market are driven mostly by competitive pressure rather than severe losses. Only six out of 43 OMMs are active at any given time, suggesting high turnover in this competitive space. While OMMs can have occasional bad days, their losses remain modest, averaging -2.7% on their worst trading days, compared to -28.5% for non-market makers. OMMs typically exit the market when their daily profits approach zero and cannot cover fixed costs.

Third, KOSPI 200 options market makers rarely delta hedge. Out of 43 OMMs, only 35 ever trade futures, and only 18 hold both options and futures positions overnight and thus might hedge. For these 18 OMMs, a regression analysis of end-of-day futures delta against options delta positions reveals that only *four* market makers consistently delta hedge. Nonparametric tests further confirm that delta hedging is *not* common: the futures position delta falls within a 50% band around the target hedge ratio on only 9.1% of days for an average account.

Given the importance of delta hedging, we further examine the four OMMs who delta hedge. Their futures positions typically offset less than half of their option delta exposure. They frequently use limit orders for futures trades to minimize hedging costs. Intraday, their positions are most hedged near market close and least hedged around noon. Finally, they hedge more intensively after inventory shocks and volatility spikes, consistent with models of inventory risk.

The OMMs in our sample manage risk primarily through active inventory management rather than delta hedging. They follow the universal market-making principle of setting bid-ask prices to maintain a balanced order flow and avoid systematic imbalances. When inventory shocks occur, consistent with models such as Amihud and Mendelson (1980), they adjust quotes higher when long and lower when short to attract offsetting trades and return to target inventory. OMMs rebalance inventory rapidly, with 38-48% of the inventory reversing within five minutes, primarily through options limit orders (28%), supplemented by options market orders (9.5%) and minimal futures trading (0.5%). Even the four delta hedgers primarily rely on rapid inventory management rather than hedging in the underlying. Since OMMs can rotate positions within minutes, delta hedging becomes less appealing due to the transaction costs of repeatedly establishing and unwinding hedge positions.

We validate our key finding that OMMs rapidly rebalance positions beyond the Korean market by examining S&P 500 index options. For this analysis, we use Cboe's Open-Close data, which classifies OMM volume as opening or closing positions for each option contract and date. As S&P 500 options trade only on Cboe, we observe complete OMM positions over 23 years from 1996 to 2018. While this dataset lacks the underlying trading and account-level detail of our KOSPI data, it shows how OMMs' volume relates to end-of-day position changes, which may require hedging. On an average day, their delta-adjusted volume exceeds the net delta position change by a factor of 32. This striking difference suggests that S&P 500 OMMs, like their KOSPI 200 counterparts, actively rotate positions intraday rather than accumulate positions that may require delta hedging.

Overall, our study provides the first direct evidence on the strategies and performance of OMMs. While the prevailing view holds that OMMs *always fully* delta hedge their positions (e.g., Hull and White, 2017), we find that delta hedging is less universal than commonly assumed. Rather than challenging this view entirely, our evidence suggests that hedging depends on market conditions. Theoretically (e.g., Leland, 1985), the optimal hedging frequency depends on the underlying trading costs and the expected holding horizon. Consistent with this framework, KOSPI 200 OMMs who delta hedge tend to quote more illiquid contracts and hold inventory for longer.

We contribute to several strands of literature. First, the derivatives literature assumes that market makers consistently delta hedge. Building on this assumption, many studies argue that delta hedging affects various outcomes including option prices (e.g., Hodges and Neuberger 1989; Boyle and Vorst, 1992), option bid-ask spreads (e.g., Jameson and Wilhelm, 1992), option returns

(Christoffersen et al., 2018), and underlying stock returns (Hu, 2014; Baltussen et al. 2021).[8] Unlike these studies, we *directly* observe OMMs' trading in options and the underlying.[9] Our results challenge the assumption that OMMs *always fully* delta hedge by providing an example of an active options market where OMMs manage risk primarily through rapid inventory rebalancing rather than hedging, as hedging costs often outweigh benefits. We also document the hedging strategies of the minority of OMMs who delta hedge. Overall, our findings provide a starting point for further research into OMMs' hedging and non-hedging strategies.

Recent growth in 0DTE S&P 500 options trading has raised concerns about market stability, as these near-expiry options' high delta sensitivity could trigger destabilizing hedging activity. Prior research documents how delta hedging affects underlying prices and volatility (Ni et al., 2005; Ni et al., 2020), with recent work examining this mechanism in 0DTE options (Brogaard et al., 2024; Dim et al., 2024; Adams et al., 2024). While we do not focus on 0DTE options, our evidence from both KOSPI 200 and S&P 500 markets suggests that OMMs can effectively manage risk through rapid rotation of positions rather than continuous hedging. Thus, actual hedging demand for 0DTE options may be lower than their large trading volume suggests.

We also contribute to the microstructure literature by assessing the role of hedging for market makers. While traditional microstructure theories (e.g., Ho and Stoll, 1983; Kyle, 1985) focus on inventory and adverse selection risks, the options literature emphasizes delta hedging as crucial for risk management. Our evidence helps to reconcile these views: in active markets like KOSPI 200 options, OMMs primarily mitigate risk through rapid inventory management rather than costly hedging, consistent with microstructure models. Finally, several studies examine equity HFTs and market makers using account-level data (e.g., Menkveld, 2013; Baron et al., 2019), while we provide the first such analysis of options market makers.

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[8] Many studies explore the indirect effect of OMMs including Ho and Macris (1984), Figlewski (1989), Cho and Engle (1999), Battalio, Hatch, and Jennings (2004), Bollen and Whaley (2004), Lakonishok, et al. (2007), Garleanu, Pedersen, and Poteshman (2008), Huh, Lin, and Mello (2015), Muravyev (2016), Fournier and Jacobs (2020), Eraker and Osterrieder (2023), Nimalendran, Rzayev, and Sagade (2024).

[9] KOSPI 200 options have been studied before (e.g., Hu et al. (2023) and Ahn, Kang, and Ryu (2008)) but we are the first to study individual market makers.

The paper is organized as follows. Section 2 describes the data, institutional details, and market maker identification. Sections 3 and 4 study profitability and position management. Section 5 examines S&P 500 index options. Section 6 concludes.

2. Institutional details and data

In this section, we describe the market structure and contract specifications of KOSPI 200 index options and futures. We then describe our unique account-level data and explain how we identify OMMs.

2.1 KOSPI 200 options and futures markets

The KOSPI 200, South Korea's benchmark index tracking its 200 largest stocks, underlies one of the world's most actively traded options markets. During our sample period from January 2010 to June 2014, KOSPI 200 options had 8.6 billion contracts traded with a total premium of KRW 1,324 trillion (around USD 1.2 trillion). The Korea Exchange (KRX) led all derivatives exchanges globally in options trading volume over this period according to the Futures Industry Association.[10]

Investors primarily use KOSPI 200 index futures to make directional bets on the KOSPI 200 index because other KOSPI 200-linked products are much less liquid. The total trading volume of all the KOSPI 200 ETFs is KRW 0.354 trillion per day during the same period, while the futures trading volume reaches almost KRW 28 trillion per day according to the Korea Securities Computing Corporation. The KOSPI 200 constituent stocks were even less active, averaging KRW 9.3 billion per stock-day. Both KOSPI 200 options and futures are traded on the Korea Exchange, ensuring compatible technology and facilitating cross-market strategies like delta hedging.

[10] See for example page 24 of https://www.fia.org/sites/default/files/2019-05/FI-2012-Volume-Survey.pdf.

Next, we describe the option contract specifications.[11] Similar to other equity index options traded globally, KOSPI 200 options are cash-settled European-style options; that is, they can only be exercised at expiration and are settled in cash based on the index level. Originally, each KOSPI 200 option contract had a multiplier of KRW 100,000, equating to a contract size of about 22,714 USD. In June 2012, this multiplier increased fivefold to KRW 500,000, raising the contract size to levels comparable to E-mini S&P 500 options (but lower than S&P 500 index options). KOSPI 200 options provide a broad selection of maturities and strike prices. Expirations include the next three months and nearest quarterly month (March, June, September, December). Near-term contracts have nine strikes while quarterly ones have five. KOSPI 200 options have a tiered tick size structure: 0.05 points (KRW 5,000) for options priced at or above three points, and 0.01 points (KRW 1,000) for options below three points. This design balances price precision with liquidity across different price levels, accommodating both retail and institutional trading needs.

A trading day in the KOSPI 200 derivatives market begins with an opening call auction at 08:00 local time, setting the day's opening prices. Post-auction, a regular continuous trading session runs from 09:00 until 15:05, ending with a closing auction at 15:15. A night session facilitated by the Eurex/KRX Link operates from 18:00 to 5:00, although it is far less active than the main session.

The market structure for KOSPI 200 derivatives shares similarities with other modern markets, operating as a pure order-driven electronic market. All limit orders are consolidated into a central limit order book and are matched with incoming marketable orders, facilitating price discovery. Unlike some derivatives markets, the KOSPI 200 options and futures markets do not have incentive schemes for liquidity provision. Both liquidity providers and takers face the same fees during our sample period. While anyone can provide liquidity through limit orders, we study professional traders who actively quote two-sided markets.

[11] Detailed specifications can be found at http://web.archive.org/web/20111029093810/http://eng.krx.co.kr:80/m3/m3_3/m3_3_1/m3_3_1_2/UHPENG03003_01_02.html.

In KOSPI 200 options, liquidity provision relies on self-appointed market makers who face no quoting requirements, unlike their Cboe counterparts. KOSPI 200 market makers only quote options they intend to trade, while Cboe market makers often post extremely wide spreads (25% or more) for options they prefer to avoid (Muravyev and Pearson, 2020). Both approaches effectively limit trading in options where market makers are inactive. KOSPI 200 options exhibit similar liquidity properties to S&P 500 options. Trading concentrates in at-the-money and slightly out-of-the-money options, with active trading in both calls and puts. The average effective bid-ask spread for KOSPI 200 options is 0.015 points (KRW 1,500), or 2.55% of option prices. For comparison, the S&P 500 index (SPX) and SPY ETF options have spreads of roughly 6% and 2% respectively over the same period. The high liquidity and tight bid-ask spreads of the KOSPI 200 options market make it a useful setting for studying market maker behavior, with implications for global options markets.

The KOSPI 200 options market requires trading expertise similar to major global markets. Market makers sometimes move between Korea and other major markets, as implied by LinkedIn profiles of traders at firms like Optiver, IMC, and Getco that we identify. For example, George Karcevski served as an "options market-maker in SPX/ES/SPY" from 2012 to 2015 before moving to a market-making and low-latency trading role in KOSPI derivatives from 2015 to 2018.[12] This suggests our findings have broader relevance for understanding global derivatives markets.

2.2 Account-level data

We obtain administrative data from the KRX that includes anonymized account identities, reflecting investor behavior at the account level across both options and futures markets. These anonymous but consistent account IDs allow us to track trading actions across markets, providing a unique advantage for studying individual behavior. Our dataset spans 161,010 accounts with a complete record of KOSPI 200 derivatives trading activity.

[12] https://www.linkedin.com/in/georgekarcevski/details/experience/

We construct investor positions using trades from all sessions, while our primary analyses focus on the regular trading session, which constitutes 99.1% of the total trading volume. The dataset records all trader actions with millisecond timestamps, including order placements, modifications, cancellations, and executed trades. For each trade, we determine the liquidity provider by comparing the order arrival and execution times. The participant who placed their order first serves as the liquidity provider, while the counterparty who later submitted the matching order acts as the taker. We reconstruct the limit order book and trace each account's activity.

The exchange identifies account domicile (domestic or foreign) and investor type (individual or institution). Foreign investors represent 35% of the total trading volume, while institutions account for 69%.[13] While Hu et al. (2023) use and describe the same KRX data to study retail option trading patterns, we focus specifically on market makers' strategies.

2.3 Market maker identification

The KRX dataset does not explicitly label accounts as market makers, so we identify OMMs based on their distinctive quoting and trading patterns. Harris (2002, pp. 401) describes market makers as "dealers who allow their impatient customers to trade at bid and ask prices that the market makers quote. Market makers often trade very frequently. They try to buy after they sell, and vice versa. They avoid large inventory positions ... and simply try to discover the prices that produce balanced two-sided order flow." Guided by this definition, we characterize OMMs as accounts that trade actively and provide two-sided quotes.

Given the size of our data, we implement two preliminary filters to efficiently identify likely OMM accounts. First, we shortlist accounts based on high passive trading volume, as market makers primarily provide liquidity. Specifically, we select the 30 accounts with the highest passive (liquidity-providing) dollar volume for each day, obtaining 959 unique accounts that meet this criterion at least once during the sample period. Then, to refine our selection further, we identify

[13] Similarly, KRX estimates that global customers represented about 33% of total market capitalization in 2011 (https://global.krx.co.kr/board/GLB0205020100/bbs#view=19789).

accounts that provide two-sided quotes. For the 959 shortlisted accounts, we analyze their most active contract daily. After reconstructing each account's limit order book, we track its quoting behavior to determine whether it provides two-sided quotes, one-sided quotes, or no quotes in its primary contract each day. We select accounts that provide two-sided quotes at least 80% of the time on at least 10 days during the sample period. This filter narrows our set from 959 to 90 candidate accounts, which display consistent two-sided quoting indicative of market making.

After reducing the sample size to 90 potential market makers, we examine their full activity in all contracts that they trade. We apply three further criteria outlined in Table A1 of the Appendix to confirm OMM status. Some smaller accounts may have passed the initial filters by chance, so our first criterion focuses on total trading volume to distinguish genuine OMMs. Recognizing that OMMs may enter and exit the market at different times, we measure volume monthly rather than over the full sample period. For each account-month, we calculate the total options contract volume, identifying accounts above the bottom quintile of the volume distribution (over 80,083 lots per month) as potential OMMs.

Our second and most important criterion evaluates quote competitiveness at the best bid and offer (BBO). We reconstruct each account's continuous-time quotes and measure how often they are at both sides of the BBO. For each option contract, we compute the percentage of trading hours with competitive two-sided quotes, and we take the volume-weighted average across contracts to get daily scores. These daily scores are then averaged into monthly metrics of quote competitiveness. Accounts must reach the top 30th percentile, maintaining BBO quotes at least 14% of the time, to qualify as OMMs in our sample.

The third criterion tries to separate pure market-maker accounts from those that mix market making with other strategies, as our data cannot distinguish between sub-strategies within each account. Other strategies typically carry large directional exposure over time. In contrast, market makers trade a lot but limit overnight risk. We quantify this by calculating each account's total delta exposure, incorporating both options and futures positions at the close. We then take the average absolute delta exposure and scale it by the account's average daily options volume (which is typically large), requiring a value below the 80th percentile (0.0035) to qualify as an OMM.

This ensures that we exclude accounts holding substantial directional exposure overnight, typical of speculative trading.

We identify 43 unique OMM accounts meeting all three criteria. Those 43 market makers correspond to 294 account-months, with an average of six active market makers per month. To confirm that the selected accounts consistently exhibit market maker behavior, Table 1 presents summary statistics for their trading activity. For each account-month, we first compute daily averages for all key descriptive variables, then report summary statistics of these daily averages across all OMM account-months.

[Table 1 is here]

As expected, the first two rows show that OMMs' trading volumes significantly exceed their overnight inventories. On average, a market maker executes 206,864 option contracts per day but retains only 4,431 contracts overnight. There is considerable variation across account-months, with a daily volume minimum of 1,857 contracts and a maximum of 2,440,595. This distribution skews toward the right tail, as the median daily volume of 86,951 contracts is substantially lower than the mean. Overnight inventory varies little, but even the median inventory is only 190 contracts, indicating that many account-months maintain close-to-zero overnight positions, consistent with typical market-making practices.

On average, OMMs maintain two-sided quotes 78% of the time throughout the trading day, with little variation across account-months: the bottom quartile is 72.6%, and the top quartile is 88.7%. These quotes are competitive, aligning with both the best bid and offer 32.4% of the time and matching at least one side of the BBO 47.4% of the time on average. Even among the least active account-months, quotes match both sides of the BBO 12.9% of the time and one side 16.8% of the time, underscoring the consistency and competitive positioning of OMMs within the market.

OMMs maintain relatively little end-of-day Greek exposure. We examine delta exposure in three forms – raw, scaled by position size, and scaled by daily options volume – with similar results. The average delta for OMM account-months is 36, with scaled delta imbalance at −2 bps of inventory and absolute delta at 7 bps of daily options volume. Other Greek exposures are similarly modest: vega and gamma imbalances average just 1 bp and 0 bps of daily options volume, respectively. The median for all of these variables is zero.

Overall, the statistics in Table 1 confirm that our identified OMMs match typical market maker characteristics: providing liquidity through active and competitive two-sided quoting and generating high trading volumes relative to overnight exposure. These patterns validate our identification of genuine market makers in KOSPI 200 options.

3. Profitability

How profitable is options market making? Despite the success of firms like Citadel Securities suggesting high returns, researchers have lacked direct evidence. We conduct the first systematic analysis of options market maker profits using detailed KOSPI 200 options data.

3.1 Profitability measure

In this section, we define our primary performance measure: return on capital invested, adapted for margin derivatives trading. Unlike stocks and bonds, derivatives require posting margin rather than full position value, with dynamic daily adjustments through mark-to-market settlements. For option buyers, returns are calculated traditionally using the contract premium as the measure of invested capital. However, option sellers face stricter capital requirements, posting margins to maintain open positions rather than receiving sale proceeds upfront. Our return measure for short positions thus incorporates these dynamic margin requirements, better reflecting the capital efficiency of options market making.[14]

We trace each account's trading record to construct positions and calculate trading Profit and Loss (PNL). We use the "first-in, first-out" (FIFO) method for positions with varying entry and exit sizes. Overnight positions are marked to market using closing mid-quotes, while positions

[14] The KRX applies a uniform margin rate to options positions regardless of moneyness and maturity. Short trade margin rates range from 10.5% to 15% of contract value during our sample period, with exact rates obtained from exchange archives (http://global.krx.co.kr/contents/GLB/06/0608/0608030700/GLB0608030700.jsp).

at expiration are valued based on the underlying index's closing price. We deduct exchange fees (1.2 bps of premium) per trade but exclude brokerage fees given market makers' direct exchange access. Our PNL excludes unobservable fixed costs such as exchange membership and IT infrastructure, so a positive PNL may not guarantee overall profitability.

Once daily PNL is determined for each account, we scale it by the account's maximum margin requirement over the full sample period, following the approach of Baron et al. (2019):

$$\text{Daily return} = \text{Daily PNL} / \text{Maximum margin requirement}.$$

The maximum margin requirement represents each account's peak capital need during our sample, indicating the minimum capital required to support trading. We assume investors commit this capital upfront since actual commitments are unobservable. Alternative approaches, like daily margin recalculation, yield similar results, confirming our return measure's robustness.

To facilitate cross-account comparison, we first compute each account's mean daily return over the full period. We then calculate the Sharpe ratio by dividing the average daily return by the standard deviation of daily returns, annualizing it based on 252 trading days in a year. This standardized performance metric enables meaningful risk-adjusted return comparisons.

A common concern with margin-adjusted returns and Sharpe ratios for options strategies is the potential outliers due to embedded leverage. However, this issue is less relevant for our analysis. The OMMs in our sample hold positions briefly, limiting exposure to extreme outcomes and avoiding the skewed payoff distributions typical of strategies holding options to expiration. Indeed, we find OMM returns are symmetrically distributed, validating our use of standard performance measures like the Sharpe ratio.

3.2 Profitability results

We analyze OMMs' performance in Table 2, beginning with account-month statistics in Panel A and continuing with account statistics in Panel B. On average, an OMM earns 521.3 million KRW per month from options trading, equivalent to approximately half a million USD. Monthly PNL exhibits substantial variability, with a standard deviation of 1,224 million KRW—

around 2.3 times the average profit. The median monthly PNL is 285.2 million KRW, lower than the mean, indicating a right-skewed distribution where large gains are more likely than large losses. Consistent profitability is evident, as shown by a positive 25th percentile cutoff of 74.8 million KRW, suggesting that OMMs profit from options trading on most days.

[Table 2 is here]

OMMs incur slight losses from trading futures, averaging -159.4 million KRW per month. These losses appear consistent, as shown by the negative 3rd quintile cutoff of -11.6 million KRW. Despite this, the combined performance from both options and futures trading remains positive, with the average OMM earning 437 million KRW per month.

In a typical month, OMMs are profitable on 74% of trading days, with a mean daily return of 1.39%. The average worst-day return within a month is –0.39%. Due to the persistence of trading profits, OMMs' Sharpe ratios annualize to above 10 in the account-month sample, underscoring that liquidity provision in the options market offers a strong risk-return tradeoff.

Panel B of Table 2 presents performance metrics aggregated by account rather than by account-month. For each account, we compute performance over the entire sample period and then report the summary statistics across all accounts. The average total PNL from options trading per account is 3.6 billion KRW (approximately 3.3 million USD), with a median total PNL of 1.5 billion KRW. Consistent with the account-month analysis, futures trading yields negative returns for most accounts, averaging –749 million KRW.

The proportion of profitable trading days remains high at the account level, with accounts showing an average of 70% positive PNL days, reinforcing the persistent profitability observed in Panel A. The average daily return across accounts is 1.7%, with an average worst-day return of –2.69%. The Sharpe ratio from options trading alone averages 9.5 across accounts, and 5.8 when combined with futures trading PNL.

For comparison, Hu et al. (2023) report that the best-performing directional strategy in this market – selling volatility – generates an average PNL of 41.5 million KRW and a Sharpe ratio of

1.90. This comparison highlights market making's superior risk-return performance in KOSPI 200 options, delivering both higher returns and better investment efficiency than directional strategies.

We also analyze OMMs' trade profits relative to the bid-ask spread. Ideally, market makers aim to capture half of the bid-ask spread on each trade. To measure this, we calculate the ratio of an OMM's total dollar profits from all trades to the sum of half bid-ask spreads at the time of each trade. Table 3 presents this profit-to-spread ratio across accounts and account-months, measuring how effectively OMMs capture profits relative to the theoretical half-spread benchmark.

[Table 3 is here]

OMMs capture 12% of the half-spread per trade on average, with a median of 11.9%, showing a symmetric distribution. Typical performance falls between 7.3% and 16.5% of the half-spread, as indicated by the interquartile range. An alternative measure using daily average spreads yields similar results. For liquidity-providing trades, OMMs' performance improves substantially, capturing 43.6% of the half-spread on average. In the most liquid contracts, OMMs earn 12.7% of the half-spread, consistent with the overall average. These findings remain stable when analyzing at the account level rather than account-month level in Panel B, with nearly identical mean values across both panels. This evidence suggests OMMs build profitability through numerous small, mostly uncorrelated trades, ultimately generating high returns and strong Sharpe ratios.

3.3 Determinants of OMM performance

Options market makers play a critical role in providing liquidity for other market participants, and the profitability of their service naturally depends on market conditions related to liquidity. After establishing the strong overall performance of OMMs, we explore how their performance varies with market and account factors. In Table 4, we regress OMMs' daily returns on a range of explanatory variables.

[Table 4 is here]

Column (1) focuses on market-level conditions, with independent variables including the daily KOSPI 200 index return, index volatility (calculated using 5-minute index returns), the logarithm of aggregate market trading volume, volume-weighted average percentage bid-ask spread, OMM competition (measured as the number of active market makers each day), and a time trend variable. Account fixed effects are included to account for individual market-maker characteristics. The results in Column (1) show that OMM returns are not significantly correlated with the index return, supporting the idea that market makers generally avoid large directional exposure. However, OMM performance is significantly and positively related to index volatility, market trading volume, and bid-ask spreads, with *t*-statistics above 3. These findings indicate that market making becomes more profitable during periods of higher volatility (when options premiums are high), increased trading volume (indicating strong demand), and wider spreads (higher trading costs)—conditions that likely maximize the value of liquidity provision. Neither OMM competition nor the time trend significantly affects performance.

In Column (2), we investigate how account-specific characteristics relate to OMM performance. We include a measure of account activity defined as the logarithm of daily trading volume, given that high turnover and efficient capital use are essential skills for OMMs. A successful OMM, therefore, is expected to generate both high trading volume and high profits. We also include the proportion of passive trades to measure liquidity provision versus liquidity taking, an account-specific time trend capturing tenure duration, and a foreign investor indicator. Given the persistence in OMM characteristics, this specification relies solely on time fixed effects.

The results in Column (2) support our hypotheses regarding the first two OMM characteristics. Higher trading volumes are indeed associated with better performance (coefficient = 0.010, *t*-statistic = 18.34). Similarly, performance increases with the proportion of passive trades (coefficient = 0.070, *t*-statistic = 18.30), highlighting the crucial role of passive liquidity provision. Since the market-making model limits per-trade profits to the spread, which can be small, OMMs need high trading volumes in passive trades to achieve meaningful overall profits. The account time trend variable has a negative coefficient (–0.009, *t*-statistic = –6.62), suggesting declining performance over time, possibly due to new competitor entry. Lastly, foreign OMMs demonstrate superior performance (0.022, *t*-statistic = 10.26), indicating a competitive advantage likely stemming from their broader expertise and resources.

When we estimate the full model in Column (3), the results remain consistent with those in Columns (1) and (2). Overall, the evidence in Table 4 suggests that OMM performance is strongly influenced by both market conditions and account-specific skills. Profitability tends to increase during periods of market stress, characterized by heightened volatility, wider bid-ask spreads, and higher trading volumes. Additionally, an OMM's trading volume and the proportion of trades attributed to liquidity provision positively impact performance, underscoring the importance of both market dynamics and trading efficiency in driving profitability.

3.4 Market entry and exit

Understanding when and why OMMs enter and exit the market provides valuable insights into the sustainability and tail risks of their trading strategies. By analyzing OMM profitability around their entry and exit points, we can assess how market conditions and strategic adjustments influence their long-term performance.

Figure 1 shows that OMMs achieve stable profitability shortly after entry, with daily averages of 30 million KRW and a cross-account median of 7 million KRW. This gap between mean and median reflects the influence of large OMMs with high trading volumes. Profitability deteriorates before market exit, declining to 20 million KRW daily about 10 days prior, with increased performance volatility. The final three days before exit show negative average profits, while median profitability approaches but remains above zero. However, when accounting for fixed costs like IT infrastructure, data, and personnel, even positive median profits likely translate to net losses. This pattern suggests OMMs exit due to gradual competitive decline rather than sudden losses.

[Figure 1 is here]

Overall, these findings show that OMMs generate consistent daily profits. While they incur futures trading losses, their primary activity—options trading—yields profits that more than offset these losses. This performance validates market making's reputation as an effective strategy. We next examine how OMMs' risk management practices support this sustained profitability.

4. Risk management

In this section, we analyze how OMMs manage risk to maintain their performance. We begin by examining their delta-hedging activities in the underlying futures market, a key strategy for offsetting directional exposure according to the derivatives literature. We then explore their option order placement strategies, which aim to minimize unwanted inventory positions and further control risk.

4.1 Delta hedging

Options investors often trade the underlying asset to hedge the directional risks of their option positions, as measured by the option delta—the sensitivity of the option price to changes in the underlying asset price. Delta hedging is a fundamental risk management practice in derivatives markets, and OMMs are widely believed to delta hedge their positions frequently. For example, Hull and White (2017) note that "Ever since the birth of exchange-traded options markets in 1973, delta hedging has played a major role in the management of portfolios of options. Option traders adjust delta frequently, making it close to zero, by trading the underlying asset." A substantial body of literature, e.g. Leland (1985), and Hodges and Neuberger (1989), focus on optimal delta-hedging strategies. However, these studies lack direct observations of both options and underlying positions, leaving uncertainty about how investors implement delta hedging in practice. Our study fills this gap by analyzing OMMs' actual hedging behavior using comprehensive position data.

Our account-level data offers the first direct evidence of OMM delta-hedging practices. We focus initially on end-of-day hedging, when managing exposure is particularly critical due to overnight risks from market-moving news.

Of the 43 accounts we identify as market makers, only 18 hold both options and futures positions at the end of a trading day, indicating limited end-of-day hedging among OMMs.

Surprisingly, 8 accounts never trade futures throughout the sample period, 7 accounts trade both options and futures only intraday, and 12 accounts leave overnight options positions unhedged by futures. As an initial analysis of OMMs' delta-hedging behavior, we focus on the 18 accounts with potential end-of-day hedging activity in Table 5.

[Table 5 is here]

We begin by examining descriptive statistics on the frequency with which options and futures positions have opposite signs, as would be expected in delta hedging. For each account, we calculate the percentage of days on which the end-of-day delta exposures from options and futures have opposing signs. As shown in Table 5, OMMs have opposite signs for options and futures positions on 53.5% of days on average, ranging from 12.3% to 91.5% across accounts. Since random positioning would yield about 50%, these results suggest limited systematic delta hedging. Indeed, some accounts frequently hold positions with matching signs, contrary to classical hedging practice.

Next, we assess how often the sizes of options and futures deltas align to facilitate a meaningful hedge, given opposing signs. The second row of Table 5 shows the percentage of days when the end-of-day futures delta is close to the optimal hedge. We consider a hedge 'meaningful' if the futures delta has the opposite sign and falls within 0.5 to 1.5 times the size of the options delta. On average, OMMs' positions are meaningfully hedged on only 9% of days, ranging from 0% (minimum) to 42.6% (maximum) across accounts.

To formally quantify delta hedging, we estimate the average hedge ratio for each account by regressing end-of-day futures delta on options delta. The bottom panel of Table 5 presents the summary statistics of the slope coefficients (hedge ratios), *t*-statistics, and R-squared values from individual regressions for the 18 OMMs. The mean and median slope coefficients, representing the average hedge ratio, are −0.2 and −0.1, respectively. Although these hedge ratios are statistically significant, their magnitudes are far smaller than −1.0, which would indicate a full hedge of delta risk. The minimum hedge ratio observed is −0.9, suggesting that at least one OMM closely follows traditional delta-hedging practices. However, the overall low average R-squared of 21.8% implies that these hedge ratios are not consistently applied, further indicating that full delta hedging is uncommon among the OMMs in our sample.

To explore hedge ratio variation across OMMs, Figure 2 shows the hedge ratio for each OMM in Panel A and the corresponding R-squared values in Panel B. While all hedge ratios are negative, only six accounts show meaningful hedging (ratios below −0.2). Among these, two accounts have R-squared values below 10%, suggesting their large coefficients likely reflect outliers rather than systematic hedging. This leaves only four accounts demonstrating consistent delta-hedging behavior. Similar patterns emerge when analyzing midday positions (Figure A1 in the Appendix).

[Figure 2 is here]

Overall, delta hedging is less prevalent than expected in our sample, contradicting the view that market makers primarily manage risk through hedging in the underlying. Most market makers in our sample primarily rely on other risk management techniques, particularly active inventory management. While we discuss the broader implications of this unexpected finding in Section 4.4, we identify a few accounts that consistently delta hedge and analyze their strategies in Section 4.3.

4.2 Determinants of OMMs' hedging

Our analysis shows that delta hedging is not common among OMMs, even for overnight risk management. We next examine how market conditions influence delta-hedging decisions, following a similar approach to our performance analysis in Section 3.3.

We introduce a dynamic measure called *hedge intensity* to capture the extent of delta hedging. At day's end, we assign zero intensity when an OMM holds only options or when options and futures deltas share the same sign. When deltas have opposite signs, we calculate hedge intensity as: 1 − abs[(options delta + futures delta)/options delta]. This measure increases with hedging effectiveness, approaching one as the combined delta nears zero. We cap over-hedged positions at intensity of one, creating a bounded [0,1] measure that allows us to evaluate hedging behavior across market conditions.

Table 6 presents regressions of OMM delta-hedging intensity on market conditions, including index returns, volatility, trading volumes, bid-ask spreads, market maker competition, and time trends in Column (1), and with additional account fixed effects in Column (2). The results are largely the same in both columns. Hedging decisions strongly relate to market liquidity. For example, Column (2) shows hedging intensity decreases with higher options market volume (coefficient = −0.075, *t*-statistic = −5.36), likely because an active options market enables direct position management, reducing the need for costly hedging in the underlying. Consistent with transaction cost effects, hedging intensity increases with futures market trading volume (coefficient = 0.204, *t*-statistic = 5.79) and decreases with futures bid-ask spreads (coefficient = −20.279, *t*-statistic = −3.57). OMM competition correlates negatively with hedging intensity (coefficient = −0.030, *t*-statistic = −3.44), possibly reflecting reduced profit margins. Finally, hedging intensity shows a positive time trend, and while it varies with index returns and volatility, these relationships are not statistically significant at the 5% level. Overall, the results indicate that hedging decisions primarily respond to market liquidity conditions.

[Table 6 is here]

To examine the economic tradeoffs of hedging, we compare delta hedgers and non-hedgers, focusing on inventory size and adverse selection costs from unhedged positions. OMMs who hold positions for longer face larger inventory risk and thus are more likely to benefit from delta hedging. We find evidence consistent with this hypothesis based on the typical holding period, which is reported in Panel A of Table 7. For intraday positions, the four delta hedgers in our sample have a longer average holding period than the non-delta hedgers (46.1 versus 27.5 minutes), and the difference in means is statistically significant (*t*-statistic = 3.60). The difference is even larger for the median holding times (50.6 versus 5.6 minutes).

Moreover, non-delta hedgers focus on actively traded options for quick inventory turnover, while delta hedgers cover a broader range of contracts. Consistent with this, Panel B shows that delta hedgers trade in less liquid options, with average daily market volume of 391,128 lots versus 647,811 lots for the contracts traded by non-hedgers (*t*-statistic = −3.93 on the difference), and median volumes of 245,043 versus 456,689 lots. Delta hedgers also trade a larger number of distinct contracts daily (mean: 33 vs. 28), though both groups share a median of 22 contracts.

Overall, these results suggest that delta-hedging decisions reflect broader strategic choices about holding periods and contract selection. Rather than serving as the default risk management tool described in classical textbooks, delta hedging appears to be one of several risk management options that OMMs evaluate based on costs and benefits.

[Table 7 is here]

4.3 Delta hedgers' strategies

While most OMMs in our sample rarely use futures for delta hedging, we identify four that consistently do so. This section analyzes their hedging strategies, focusing on days with both options and futures activity.

Figure 3 shows the relationship between futures and options net positions for each delta hedger. In this figure, each scatter plot depicts futures net positions (Y-axis) against options net positions (X-axis), expressed in end-of-day delta exposure for a given OMM. Each point represents a single trading day, while the trendline illustrates the relationship between futures and options positions. A negative slope of the trendline indicates a consistent effort to offset options exposure through futures, aligning with classic delta-hedging practices. We exclude account-days where no options or futures positions were present to focus solely on active hedging behavior.

[Figure 3 is here]

The four delta hedgers show significant heterogeneity. The first shows limited hedging, with futures and options positions typically opposing in sign but achieving only a −0.27 hedge ratio and 36% R-squared, indicating inconsistent implementation. The second exemplifies classical delta hedging with a −0.9 hedge ratio and 96% R-squared, showing consistent risk management. The third adopts a moderate approach in the middle of the two extremes, with a −0.49 hedge ratio and 52% R-squared. The fourth OMM resembles the third but appears to operate in two distinct regimes: this account initially added a negative futures position and then continued to adjust its hedging with additional trades. These variations suggest that even dedicated hedgers adapt their strategies to different market conditions and objectives.

In addition to the hedge ratio, Table A2 in the Appendix shows significant variation in delta hedgers' trading intensity and how they execute delta-hedging trades in the futures market. While Accounts 2 and 4 are highly active in options trading, each averaging over 300,000 contracts per day, Accounts 1 and 3 trade significantly less, with roughly 71,000 and 11,000 contracts per day, respectively. Across all four accounts, futures trading is far less frequent, ranging from an average of 393 to 1,894 contracts daily. The table also reveals differences in liquidity-taking behavior when executing hedging trades: on average, delta hedgers take liquidity in about half of their futures trades, but strategies vary widely. Account 1 prioritizes execution speed, taking liquidity in 93.1% of its futures trades and executing 83.7% aggressively, whereas Account 3 focuses on cost efficiency, initiating only 6.4% of its futures trades and trading aggressively in 12.5%. Accounts 2 and 4 adopt a balanced approach, initiating around 40-50% of their futures trades with about 47% of trades being aggressive. These differences further reinforce the heterogeneity in trading patterns even among the delta hedgers.

We examine intraday variation in delta-hedge ratios for the four delta hedgers by regressing futures delta on options delta at different times of the trading day. Table 8 shows an inverse U-shaped pattern: the hedge ratio starts high at market open (−0.291 at 9:05), drops to −0.205 by noon, then peaks at −0.317 at market close. This pattern suggests more active hedging during riskier periods at market open and close. The significant interaction between options delta and end-of-day indicator (−0.108, *t*-statistic = −6.86) confirms that increased hedging near market close is both economically and statistically significant.

[Table 8 is here]

4.4 Active inventory management

In this section, we examine how OMMs manage risk through rapid inventory management rather than delta hedging. According to standard market-making principles, they set bid-ask prices to maintain a balanced order flow across their options portfolio. When significant inventory shocks occur, they dynamically adjust their quotes in line with Amihud and Mendelson (1980) to attract offsetting trades, raising prices when their position becomes too long and lowering them when too short. Through this active quote management process, their inventory naturally reverses to the desired level.

To test this hypothesis, we analyze 5-minute changes in total delta inventory across all 43 OMMs, applying time-series regressions for each market maker and averaging the results to capture general patterns. Table 9 presents strong evidence of rapid inventory reversion. Column (1) reports an average first-order autocorrelation of −0.383 (t-statistic = −36.7), indicating that inventory positions revert quickly, typically within minutes. When we add a second lag of inventory change in Column (2), the first-order autocorrelation (AR1) becomes even stronger at −0.479, while the average second-order autocorrelation (AR2) is also negative at −0.219, and both are statistically significant. These coefficients sum to around −0.7, suggesting that about 70% of an OMM's delta imbalance is offset within 10 minutes. This fast reversion remains consistent even after controlling for concurrent and lagged index returns in Column (3).

To further dissect how OMMs manage these rapid adjustments, we decompose inventory change into three distinct components: (1) aggressive options trades, where OMMs actively offload positions using market orders; (2) passive options trades, where OMMs adjust inventory by providing liquidity to natural order flows; and (3) futures trades, where they use the underlying asset to hedge. Columns (4) through (6) report the effectiveness of each mechanism in responding to inventory shocks. Passive options trades emerge as the most important, reducing 28.3% of the initial delta imbalance within a given 5-minute interval. This finding suggests that OMMs primarily manage risk by adjusting their quotes to attract offsetting order flow.

In contrast, aggressive options trades account for only 9.5% of the delta reversion, indicating that while OMMs occasionally cross the spread, this is less common and likely reserved for situations where inventory reaches critical levels. Futures trades contribute the least to inventory adjustment, offsetting a mere 0.5% of the imbalance. This minimal reliance on futures supports the broader conclusion that OMMs in this sample prioritize inventory management through options trades rather than through hedging with the underlying.

Overall, these results underscore a nuanced approach to risk management. Rather than continuously hedging through futures, OMMs adjust their inventory mainly through passive trading in the options market, with selective use of aggressive trades for urgent rebalancing. This strategy reflects an effort to minimize transaction costs while maintaining flexible risk exposure, allowing OMMs to efficiently adapt to fluctuations in order flow and inventory levels.

[Table 9 is here]

We also conduct an equivalent analysis focused on the four delta hedgers to examine how their intraday inventory management—through active order management versus delta hedging—compares with the full OMM sample. Table 10 presents the results. The baseline regression in Column (1) shows an average AR1 coefficient of −0.34 with a *t*-statistic of −42.09, consistent with the direction and magnitude observed in the full OMM sample in Column (1) of Table 9. This indicates that delta hedgers, like the broader group, revert their inventory imbalances rapidly. Columns (2) and (3) of Table 10 show that the average response to delta imbalance through both aggressive (−5.7%) and passive (−27%) options trading for the four delta hedgers is similar to the inventory management patterns of the full sample, highlighting a reliance on options markets for rebalancing. However, Column (4) reveals that these delta hedgers exhibit a larger response in futures trading, with a delta-hedging adjustment of −1.4%, almost three times greater than the average across all OMMs (−0.5%). This finding confirms that delta hedgers utilize the underlying asset more actively than other OMMs for inventory control, although futures still play a limited role compared to options trading.

[Table 10 is here]

Microstructure theories suggest that risk management intensifies under high-risk conditions, such as spikes in inventory exposure or market volatility. To test this, we examine how delta hedgers respond to extreme market conditions by creating indicator variables for 5-minute intervals when the underlying volatility or the absolute delta inventory reaches the 90th percentile. Columns (5) through (8) in Table 10 report the results of regressions including interaction terms between lagged delta imbalance and these high-stress indicators.

Delta hedgers intensify risk management after volatility spikes across all inventory adjustment methods. The magnitudes of volatility shock interaction coefficients nearly match those of lagged inventory changes, indicating doubled rebalancing following high volatility. Inventory size shocks elicit a weaker response, significantly affecting only delta-hedging behavior. While lagged inventory changes predict both aggressive and passive options trading, they lose significance in predicting futures-based hedging adjustments. This suggests delta hedgers mainly rely on options trades for routine risk management, turning to futures hedging primarily during volatile periods or after extreme inventory shocks. Delta hedging thus emerges as a stress-response strategy, reinforcing that options market makers primarily manage risk within the options market itself.

5. Evidence from S&P 500 index options

In this section, we examine whether some of our findings for KOSPI 200 options market makers generalize to the S&P 500 index options, the most studied options market. While our KOSPI 200 options analysis leverages comprehensive account-level transaction data for both options and futures, a similar granular analysis is not feasible for S&P 500 options. Despite this limitation, we explore the generalizability of our findings using available U.S. data. Essentially, we want to confirm for S&P 500 OMMs a basic point that market makers "simply try to discover the prices that produce balanced two-sided order flow." (Harris, 2002, pp. 401). By balancing the order flow market makers avoid large inventory positions and thus the need for costly heding.

For this analyhsis, we use the Chicago Board Options Exchange (Cboe) Open-Close Volume Summary database, which contains OMMs' daily trading volume imbalances in S&P 500 index (SPX) options over 23 years, from January 1996 to December 2018. Pan and Poteshman (2006) were the first to use and describe this data. Specifically, for each option contract and day, OMM volume is split into four categories: opening and closing trades for both buys and sells. Since S&P 500 index options trade exclusively on the Cboe, this database provides comprehensive coverage of all OMM positions in these options. To calculate OMM positions, we use the fact that options are in zero net supply and thus OMM positions must offset proprietary traders' and public customers' positions. Unlike KOSPI 200's granular data, the open-close data provides daily aggregate OMM activity and contains only options, so we cannot directly study delta hedging and intraday position rebalancing by individual OMMs.

We report daily volume statistics for S&P 500 OMMs in Table 11. In aggregate, they trade 415,840 (370,189) options contracts on an average (median) day, which is concentrated in ATM and slightly OTM options and has grown substantially over time. This high volume reflects OMMs' role as a counterparty to most option trades. If this volume were primarily one-sided, this would create a huge inventory problem for OMMs.

In theory, OMMs would adjust their delta exposure every time their inventory changes. To estimate their potential hedging needs, we assume that each option trade is hedged immediately and calculate a naïve hedge by summing the product of absolute delta and volume across option contracts, using deltas from OptionMetrics. This simple analysis suggests S&P 500 OMMs would need to hedge approximately 110,953 contract deltas daily. Given that each S&P 500 option provides 100 units of index exposure and the S&P 500 averaged 1,420 over our sample period, this translates to roughly 15.8 billion dollars in notional value per day. This hypothetical hedging volume estimate would represent a significant portion of S&P 500 e-mini futures volume, averaging at 128 billion dollars per day during the same period according to Bloomberg.

However, the main result from our KOSPI 200 options analysis suggests that OMMs may not require extensive delta hedging because they rotate inventory fast. Instead of relying heavily on delta hedging, OMMs tend to either rebalance inventory within the same contract or offset risk by trading similar option contracts. To investigate this hypothesis, we estimate the net change in end-of-day OMM positions, breaking it down into call and put positions (to account for their opposite delta signs). On average, absolute changes in call and put positions are 6,000 and 9,020 contracts respectively, which is small compared to the total trading volume—a 1-to-27 ratio relative to the average daily OMM volume of 415,840 contracts.

Furthermore, when adjusting for delta on these end-of-day position changes, we find that the average (median) absolute daily change in OMMs' delta positions is only 3,466 (2,260) contracts. This change represents a 1-to-32 ratio relative to the naïve delta-hedge volume of 110,953 contracts on an average day, or a 1-to-40 ratio on a median day. The factor by which daily OMM trading volume exceeds net position changes remains consistently high throughout our sample period. These estimates suggest that, at the end of the trading day, an OMM has only a minor delta imbalance to manage that can be either hedged or carried overnight.

[Table 11 is here]

Overall, our estimates show that S&P 500 OMMs maintain two-sided quotes, successfully attracting balanced order flow and keeping their net delta exposure small relative to trading volume. The pattern suggests that, similarly to KOSPI 200 OMMs, S&P 500 OMMs focus on rapid inventory turnover, instead of relying heavily on continuous delta hedging in the underlying market.

This result also has broader implications. For instance, some studies emphasize options market makers' challenges with end-of-day inventory management; however, our evidence suggests these exposures are modest relative to intraday trading activity. For example, Baltussen et al. (2021) attribute intraday momentum in the S&P 500 index to end-of-day delta hedging by OMMs, arguing that "the bulk of the hedge seems to take place towards the end of the day." They propose but do not test five reasons for concentrated hedging at the close, including lower trading costs, overnight risk management, and margin requirements. However, their analysis relies on indirect evidence, as they do not directly observe delta-hedging activity to verify this assumption.

6. Conclusion

In this study, we provide the first direct insights into the trading strategies of options market makers. Using unique account-level data that captures complete activity in KOSPI 200 index options and futures, we identify 43 OMMs over a four-and-a-half-year period. Despite their diverse strategies, we observe several common features. First, market making is highly profitable, providing positive returns on most trading days and high Sharpe ratios. Second, while OMMs exhibit high turnover with frequent market entries and exits, their exits are preceded by gradual declines in profitability rather than catastrophic losses.

We especially focus on delta hedging, given its perceived importance. Surprisingly, few market makers delta hedge. Instead, OMMs adjust their inventory within minutes after an inventory shock, primarily using option limit orders rather than taking liquidity. Thus, OMMs behave similarly to equity market makers (which have been extensively studied). We hypothesize that in the liquid KOSPI 200 options market, the delta-hedging costs exceed the risk reduction benefits. Evidence from the S&P 500 options market (using less granular data) further indicates that rapid position rebalancing dominates delta hedging for U.S. market makers.

We identify four OMMs who consistently delta hedge and analyze their strategies. They hedge more towards the market close, hedge more aggressively following volatility or inventory spikes, and mostly provide liquidity in their futures trades. However, even these delta hedgers primarily rely on rapid inventory management rather than hedging.

Our findings suggest that while OMMs rarely delta hedge in this highly active market, this may not be universal. Market makers in less liquid markets, such as U.S. equity options outside of the most traded names, likely hold option positions for longer and thus may rely more heavily on delta hedging. While this hypothesis presents a promising direction for future research, testing it in the U.S. market is challenging due to the lack of account-level data on joint trading in options and the underlying.

References

Ahn H., Kang, J., and Ryu, D., 2008. Informed trading in the index option market: The case of KOSPI 200 options. Journal of Futures Markets, 28(12), pp. 1118-1146.

Amihud, Y. and Mendelson, H., 1980. Dealership market: Market-making with inventory. Journal of Financial Economics, 8(1), pp.31-53.

Baltussen, G., Da, Z., Lammers, S. and Martens, M., 2021. Hedging demand and market intraday momentum. Journal of Financial Economics, 142(1), pp.377-403.

Baron, M., Brogaard, J., Hagströmer, B., Kirilenko, A. A., 2019. Risk and Return in High-Frequency Trading. Journal of Financial and Quantitative Analysis, 54(3), pp.993-1024.

Battalio, R., Hatch, B. and Jennings, R., 2004. Toward a national market system for US exchange–listed equity options. The Journal of Finance, 59(2), pp.933-962.

Baltussen, G., Da, Z., Lammers, S. and Martens, M., 2021. Hedging demand and market intraday momentum. Journal of Financial Economics, 142(1), pp.377-403.

Black, F. and Scholes, M., 1972. The valuation of option contracts and a test of market efficiency. The Journal of Finance, 27(2), pp.399-417.

Bollen, N.P. and Whaley, R.E., 2004. Does net buying pressure affect the shape of implied volatility functions?. The Journal of Finance, 59(2), pp.711-753.

Boyle, P.P. and Emanuel, D., 1980. Discretely adjusted option hedges. Journal of Financial Economics, 8(3), pp. 259-282.

Boyle, P.P. and Vorst, T., 1992. Option replication in discrete time with transaction costs. The Journal of Finance, 47(1), pp.271-293.

Cho, Y.H. and Engle, R.F., 1999. Modeling the impacts of market activity on bid-ask spreads in the options market.

Chordia, T., Kurov, A., Muravyev, D. and Subrahmanyam, A., 2021. Index option trading activity and market returns. Management Science, 67(3), pp.1758-1778.

Christoffersen, P., Goyenko, R., Jacobs, K. and Karoui, M., 2018. Illiquidity premia in the equity options market. The Review of Financial Studies, 31(3), pp.811-851.

Dim, C., Eraker, B. and Vilkov, G., 2024. 0DTEs: Trading, Gamma Risk and Volatility Propagation. Gamma Risk and Volatility Propagation (January 11, 2024).

Figlewski, S., 1989. Options arbitrage in imperfect markets. The Journal of Finance, 44(5), pp.1289-1311.

Foucault, T., Pagano, M., and Röell, A., 2013. Market liquidity: theory, evidence, and policy. Oxford University Press.

Fournier, M. and Jacobs, K., 2020. A tractable framework for option pricing with dynamic market maker inventory and wealth. Journal of Financial and Quantitative Analysis, 55(4), pp.1117-1162.

Garleanu, N., Pedersen, L.H. and Poteshman, A.M., 2008. Demand-based option pricing. The Review of Financial Studies, 22(10), pp.4259-4299.

George, T.J. and Longstaff, F.A., 1993. Bid-ask spreads and trading activity in the S&P 100 index options market. Journal of Financial and Quantitative Analysis, 28(3), pp.381-397.

Harris, L., 2002. Trading and exchanges: Market microstructure for practitioners. OUP USA.

Ho, T.S. and Macris, R.G., 1984. Dealer bid-ask quotes and transaction prices: An empirical study of some AMEX options. The Journal of Finance, 39(1), pp.23-45.

Ho, T.S. and Stoll, H.R., 1983. The dynamics of dealer markets under competition. The Journal of finance, 38(4), pp.1053-1074.

Hodges, S.D. and Neuberger, A., 1989. Optimal replication of contingent claims under transaction costs. Review of Futures Markets, 8, pp. 222-239.

Hu, J., 2014. Does option trading convey stock price information?. Journal of Financial Economics, 111(3), pp.625-645.

Hu, J., Kirilova, A., Park, S. G., Ryu, D., 2023. Who Profits From Trading Options? Management Science, forthcoming.

Huh, S.W., Lin, H. and Mello, A.S., 2015. Options market makers′ hedging and informed trading: Theory and evidence. Journal of Financial Markets, 23, pp.26-58.

Hull, J., 2018. Options, futures, and other derivatives/John C. Hull. Upper Saddle River, NJ: Prentice Hall.

Hull, J. and White, A., 2017. Optimal delta hedging for options. Journal of Banking & Finance, 82, pp.180-190.

Jameson, M. and Wilhelm, W., 1992. Market making in the options markets and the costs of discrete hedge rebalancing. The Journal of Finance, 47(2), pp. 765-779.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica, 53(6), pp. 1315-1335.

Leland, H.E., 1985. Option pricing and replication with transaction costs. The Journal of Finance, 40(5), pp.1283-1301.

Menkveld, A.J., 2013. High frequency trading and the new market makers. Journal of Financial Markets, 16(4), pp. 712-740.

Muravyev, D., 2016. Order flow and expected option returns. The Journal of Finance, 71(2), pp.673-708.

Muravyev, D., Pearson, N.D. 2020. Options trading costs are lower than you think. The Review of Financial Studies, 33(11), pp. 4973-5014.

Ni, S.X., Pearson, N.D., and Poteshman, A.M., 2005. Stock price clustering on option expiration dates. Journal of Financial Economics, 78(1), pp.49-87.

Ni, S.X., Pearson, N.D., Poteshman, A.M. and White, J., 2021. Does option trading have a pervasive impact on underlying stock prices? The Review of Financial Studies, 34(4), pp.1952-1986.

Nimalendran, M., Rzayev, K. and Sagade, S., 2024. High-frequency trading in the stock market and the costs of options market making. Journal of Financial Economics, 159, p.103900.

Pan, J., Poteshman, A.M., 2006. The Information in Option Volume for Future Stock Prices. The Review of Financial Studies, 19(3), pp.871-908.

Stoll, H.R., 1978. The supply of dealer services in securities markets. The Journal of Finance, 33(4), pp.1133-1151.

Figure 1

This figure illustrates the average and median daily profitability across options market makers (OMMs) immediately after they enter the market (left) and just before they exit the market (right). The horizontal axis represents the number of days following entry (for the left panels) or preceding exit (for the right panels). *Profit and Loss (PNL)* on the vertical axis is measured in millions of Korean won (KRW) per day (the average exchange rate during the sample period was 1,100 KRW per U.S. dollar).

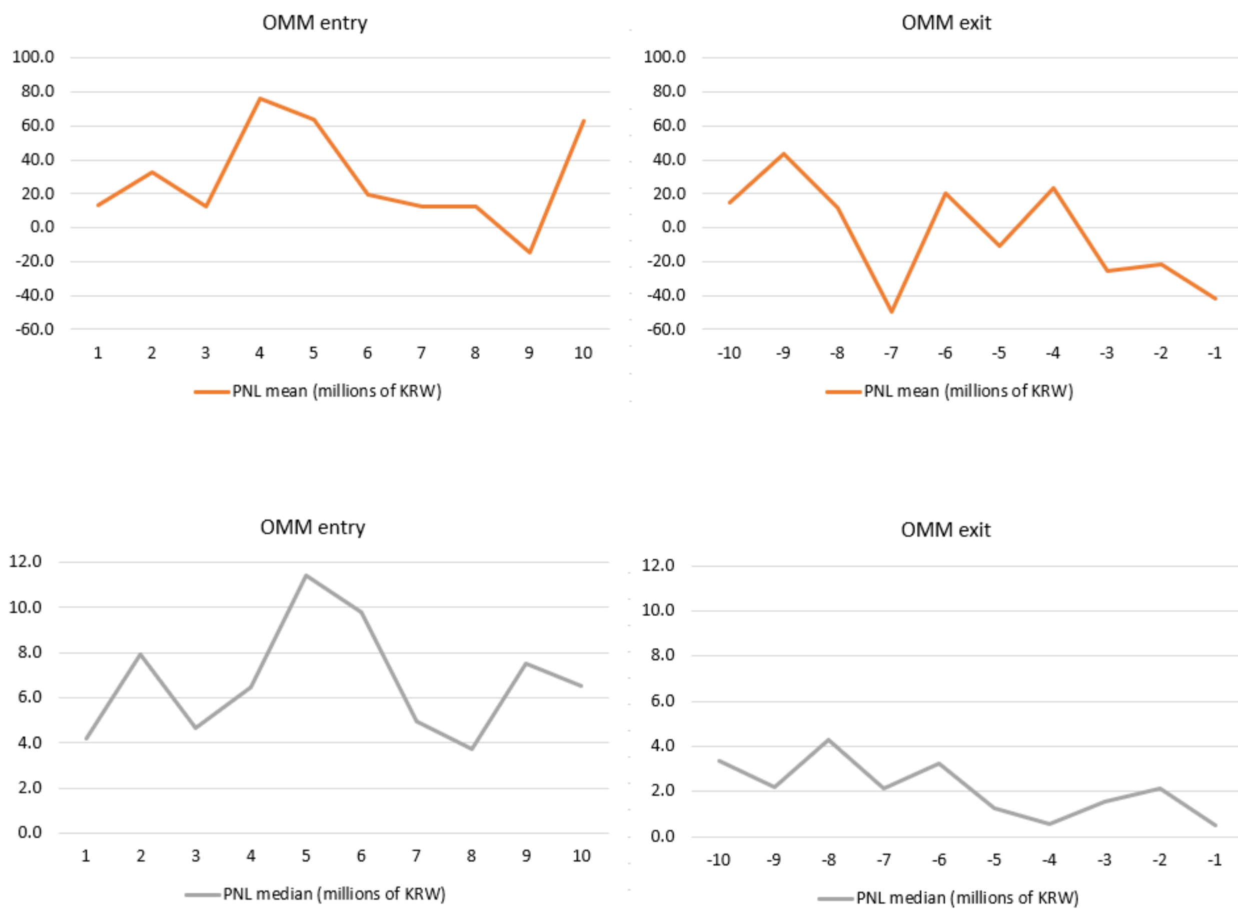
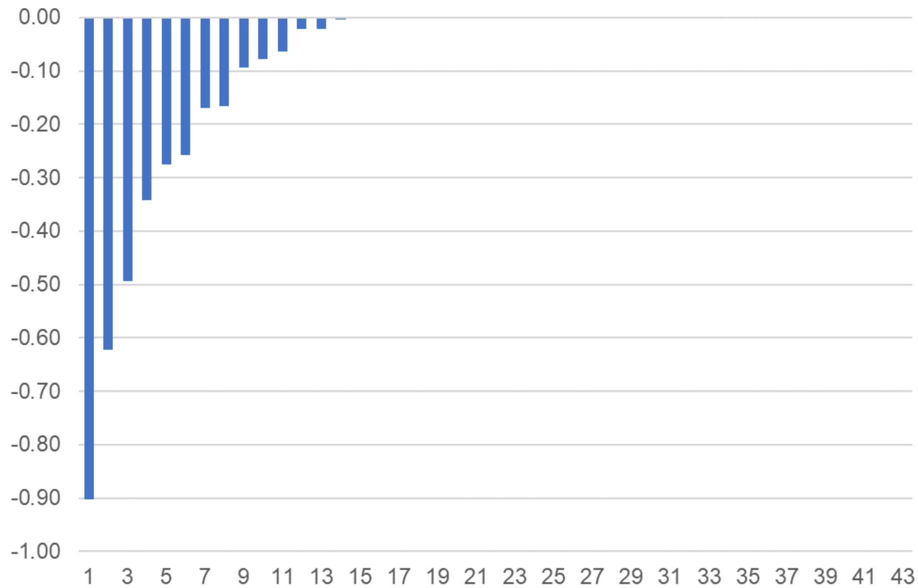


Figure 2

This figure illustrates the extent of delta hedging by the 43 market makers we identify. Panel A shows the hedge ratios, defined as the slope from the regression of end-of-day futures delta positions on options delta positions, estimated separately for each market maker. A hedge ratio of -1 indicates a perfect delta hedge. Hedge ratios are ordered from more negative values (indicating stronger delta hedging) to less negative values (indicating weaker delta hedging). Market makers ranked 19 to 43 hold no futures positions, resulting in a hedge ratio of zero. Panel B presents the corresponding R-squared values, indicating the consistency of the hedge ratio for each market maker.

Panel A: Hedge ratio



Panel B: R-squared for hedge ratio

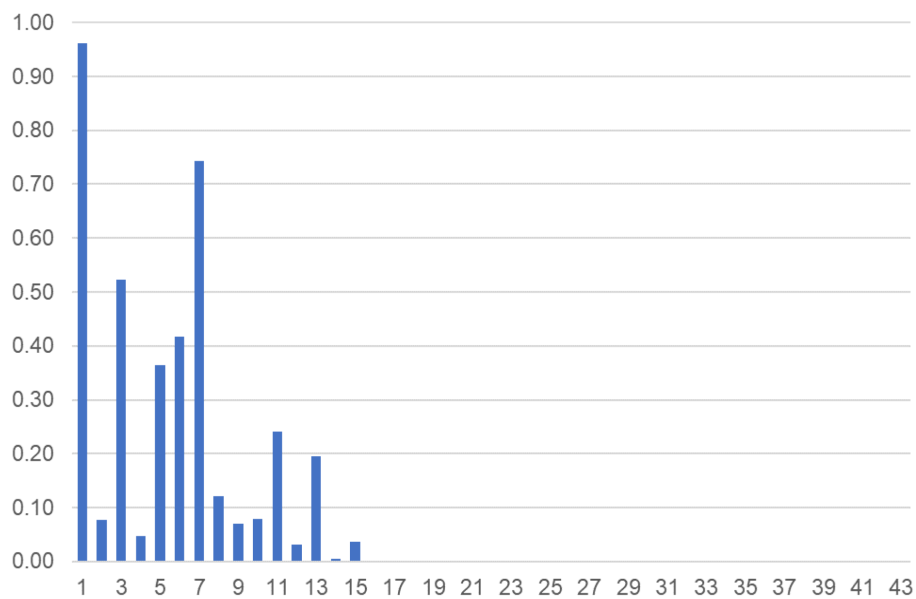
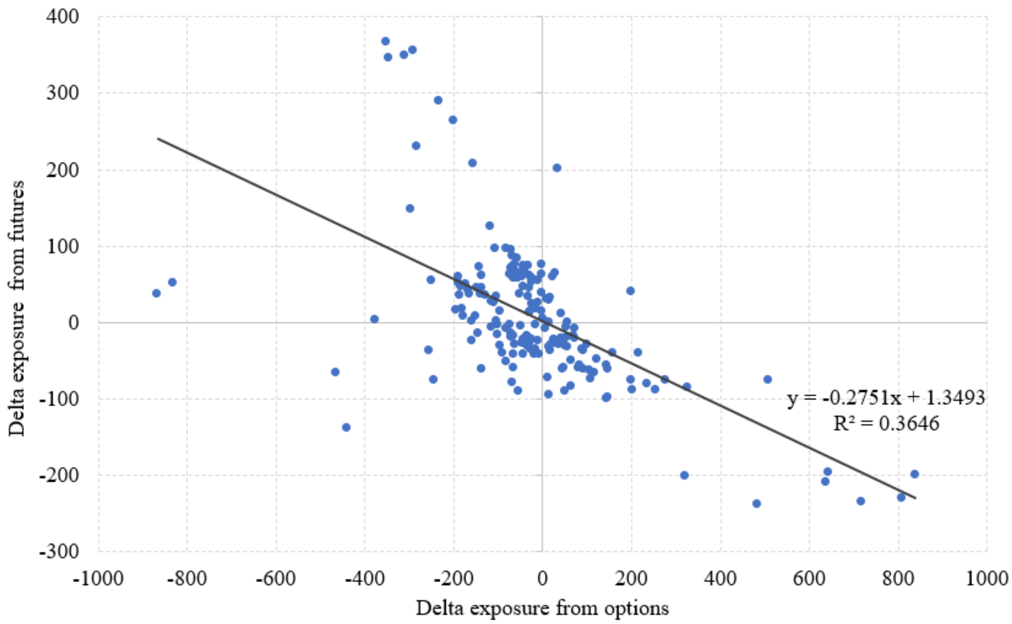
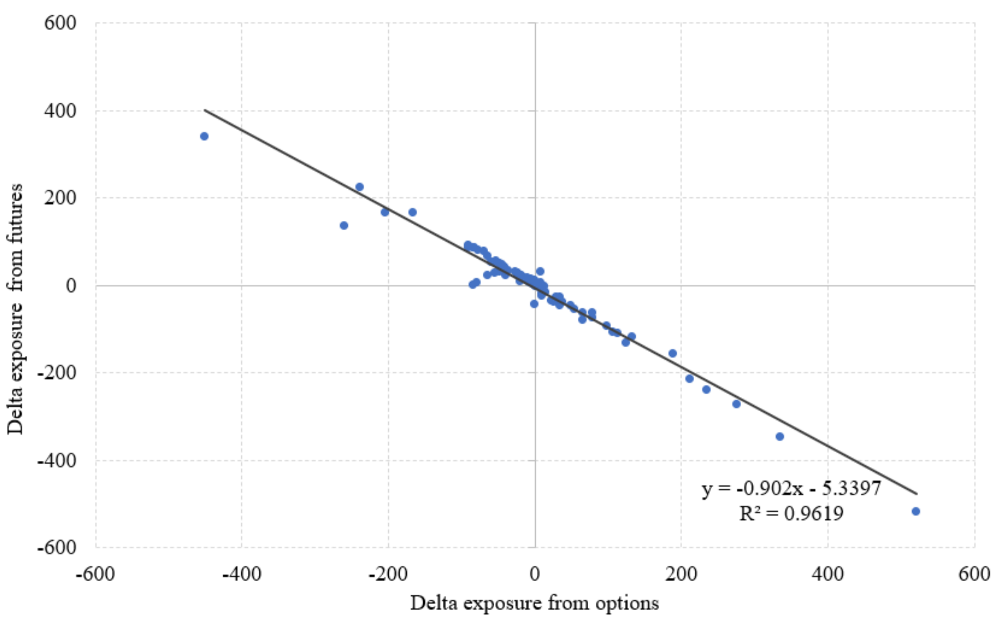
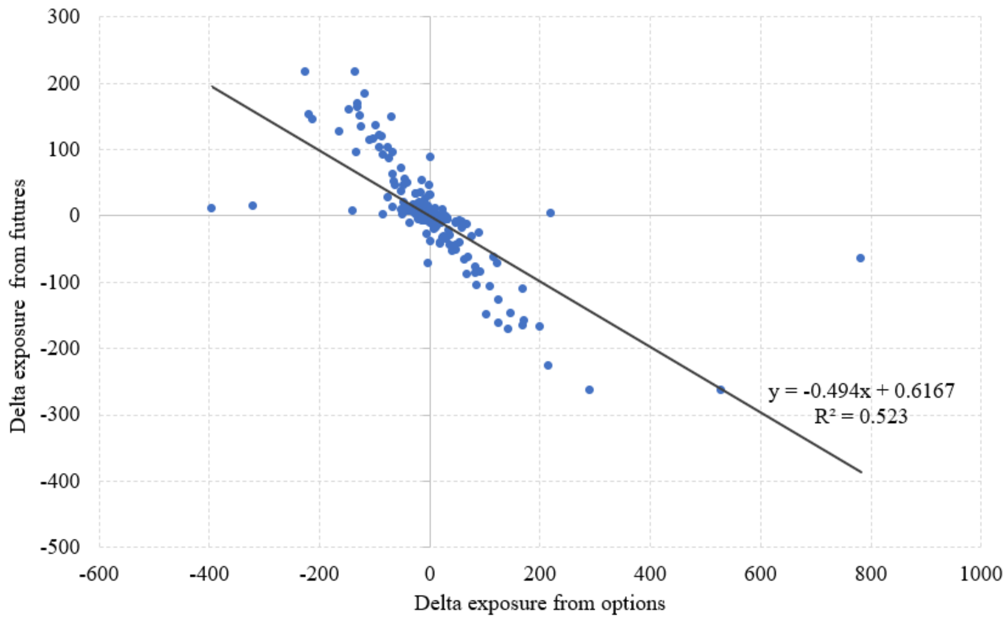


Figure 3

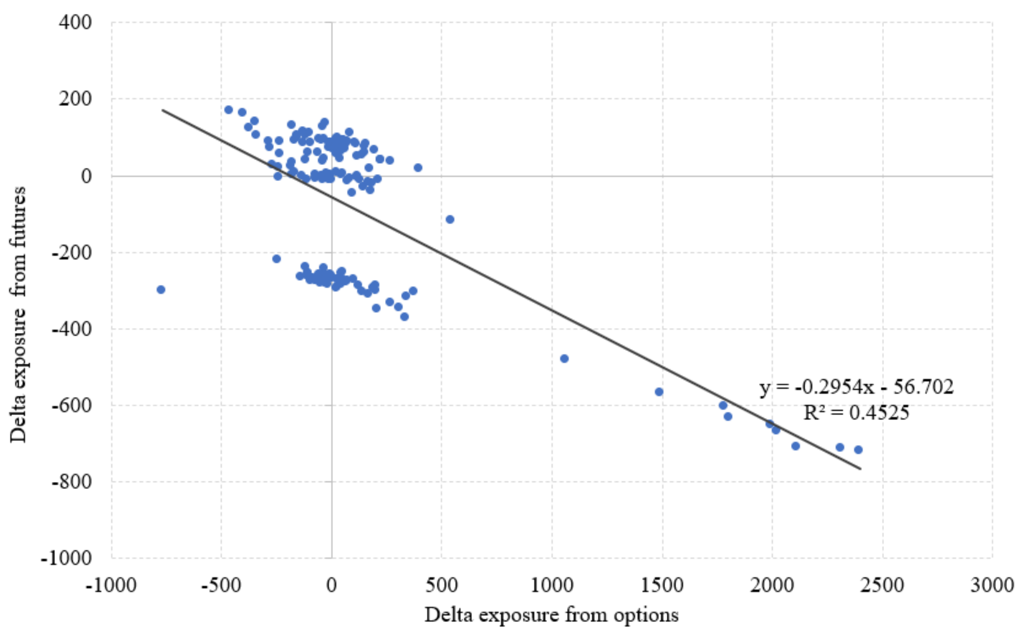
This figure compares futures and options net positions for each of the four delta-hedger accounts. The scatter plots display futures net positions (Y-axis) against options net positions (X-axis), both measured in end-of-day delta exposure for each account. Each point represents an account-day. A trendline in each plot illustrates the relationship between futures and options positions. If an account engages in delta hedging, we expect a negative relationship between options and futures positions, with a slope of -1 indicating a fully hedged option delta with futures. Account-days without options or futures positions are excluded from the analysis.







300
200
100
0
-100
-200
-300
-400
-500
-600
-400
-200
0
200
400
600
800
1000
Delta exposure from futures
Delta exposure from options
y = -0.494x + 0.6167
R² = 0.523



400
200
0
-200
-400
-600
-800
-1000
-1000
-500
0
500
1000
1500
2000
2500
3000
Delta exposure from futures
Delta exposure from options
y = -0.2954x - 56.702
R² = 0.4525

Table 1. Summary statistics

This table presents summary statistics for key metrics across options market maker (OMM) account-months, including the mean, standard deviation, minimum, first quartile, median, third quartile, and maximum values. *Trading Volume* represents the daily average of option contract volume per account-month. *Positions* refers to the average end-of-day position, measured in number of contracts held. The next four variables capture quoting activity. We report the average portion of the day an OMM maintains two-sided quotes and one-sided quotes, as well as the portion of the day with two-sided and one-sided quotes at the best bid and offer (BBO), respectively. Following this, we provide three delta measures: original delta exposure, delta exposure scaled by position size, and absolute delta exposure scaled by average daily options volume. Finally, we report vega and gamma exposures, both scaled by average daily options volume. All exposures are based on end-of-day positions.

Variable	**mean**	**std**	**min**	**q1**	**median**	**q3**	**max**
Trading Volume	206,864	323,550	1,857	31,816	86,951	234,429	2,440,595
Positions	4,431	7,936	0	0	190	6,970	52,423
2-sided Quotes	78.3%	14.4%	24.3%	72.6%	80.9%	88.7%	97.9%
1-sided Quotes	8.7%	12.9%	0.1%	0.6%	3.5%	11.9%	72.8%
2-sided Quotes at BBO	32.4%	13.2%	12.9%	23.3%	29.6%	36.3%	75.2%
1-sided Quotes at BBO	47.4%	10.6%	16.8%	41.8%	47.8%	53.9%	78.6%
Delta (original)	36.07	342.37	-603.84	-2.21	0.00	0.05	3,225.9
Delta (scaled)	-0.02%	2.87%	-21.67%	-0.13%	0.00%	0.05%	21.22%
Absolute Delta (scaled)	0.07%	0.12%	0.00%	0.00%	0.00%	0.09%	0.88%
Vega (scaled)	0.01%	0.09%	-0.16%	0.00%	0.00%	0.00%	0.95%
Gamma (scaled)	0.00%	0.01%	-0.05%	0.00%	0.00%	0.00%	0.07%

Table 2. Profitability

This table provides summary statistics on the performance of options market makers (OMMs). Panel A presents performance metrics by account-month, while Panel B aggregates the metrics by account. *Profit and Loss (PNL)* is measured in millions of KRW (1 USD ~ 1,100 KRW during the sample period). *Daily Return* is calculated as the daily PNL net of exchange fees, scaled by each account's maximum margin requirement over the sample period. The *Sharpe Ratio* is calculated as the mean daily return divided by the standard deviation of daily returns, and it is annualized by multiplying the ratio by the square root of 252.

Panel A: By account-month

	mean	std	min	q1	median	q3	max
Monthly PNL from options (millions of KRW)	521.3	1,224.1	-6,521	74.8	285.2	642.5	11,355
Monthly PNL from futures (millions of KRW)	-159.4	2,161.1	-7,813	-470.9	-166.5	-11.6	21,586
Total monthly PNL (millions of KRW)	437.2	2,059.0	-8,474	25.2	170.8	458.2	30,042
% of days with positive PNL	74%	24%	0%	55%	81%	95%	100%
Daily mean return	1.39%	3.01%	-2.74%	0.01%	0.10%	1.00%	17.58%
Std. Dev. of daily returns	1.13%	1.93%	0.01%	0.10%	0.35%	1.16%	13.53%
Worst daily return in the month	-0.39%	2.26%	-23.50%	-0.51%	-0.17%	-0.02%	10.35%
Monthly Sharpe ratio from options (annualized)	13.9	11.5	-6.8	5.8	12.2	19.2	66.0
Total monthly Sharpe ratio (annualized)	11.3	14.1	-43.1	1.5	10.2	18.8	66.0

Panel B: By account

	mean	std	min	q1	median	q3	max
Total PNL from options (millions of KRW)	3,564	6,244	-1,204	324.8	1,471	2,793	28,198
Total PNL from futures (millions of KRW)	-748.9	4,606.1	-9,995	-1,879	-496.0	-10.4	21,929
Total PNL (millions of KRW)	2,989	8,511	-9,016	74.5	669.9	2,302	50,126
% of days with positive PNL	69%	24%	0%	53%	70%	88%	99%
Daily mean return	1.70%	2.91%	-1.47%	0.01%	0.07%	1.76%	10.92%
Std. Dev. of daily returns	2.06%	2.69%	0.01%	0.19%	0.71%	2.98%	9.56%
Worst daily return in the sample	-2.69%	3.87%	-23.50%	-3.10%	-1.68%	-0.56%	-0.04%
Sharpe ratio from options (annualized)	9.5	6.5	-0.7	3.9	9.4	13.1	29.3
Total Sharpe ratio (annualized)	5.8	10.7	-34.5	0.2	5.7	12.8	29.3

Table 3. Per-trade profitability relative to the bid-ask spread

This table presents statistics for the ratio of total profits earned by OMMs ("Profit") to the sum of half bid-ask spreads ("Half-Spread"), where a 100% ratio indicates that an OMM earns half of the bid-ask spread per trade on average. The half-spread is calculated at the time of each trade, except in the second row ("average spread"), which uses the average half-spread across all trades by all investors in a given contract on a given day. We also report the profit-to-half-spread ratio specifically for liquidity-providing trades (based on order arrival times) and for the top 30% of option contracts by trading volume. Panels A and B display distributions of these metrics by account-month and by account, respectively.

Panel A: By account-month

	mean	std	min	q1	median	q3	max
Profit / Half-Spread	12.0%	15.4%	-142.0%	7.3%	11.9%	16.5%	82.5%
Profit / Half-Spread, average spread	12.3%	15.6%	-144.1%	7.4%	12.3%	17.4%	84.3%
Profit / Half-Spread, only provide liquidity	43.6%	53.8%	-387.7%	23.5%	35.0%	56.4%	345.3%
Profit / Half-Spread, most active contracts	12.7%	15.8%	-142.0%	7.5%	12.7%	18.0%	82.5%

Panel B: By account

	mean	std	min	q1	median	q3	max
Profit / Half-Spread	12.4%	5.0%	-1.5%	8.6%	13.3%	15.3%	25.0%
Profit / Half-Spread, average spread	12.7%	5.1%	-1.5%	9.8%	13.5%	15.6%	24.3%
Profit / Half-Spread, only provide liquidity	45.4%	32.5%	-5.6%	29.5%	37.1%	54.7%	163.6%
Profit / Half-Spread, most active contracts	12.8%	5.4%	-1.5%	8.6%	13.7%	15.8%	27.1%

Table 4. What explains OMMs' performance?

This table examines how OMMs' performance relates to market conditions and OMM characteristics. In column (1), we regress OMM daily return on market variables including the KOSPI 200 index daily return, the daily index volatility (calculated using 5-minute index returns), the logarithm of daily aggregate market trading volume, the daily volume-weighted average percentage bid-ask spread in the market, competition (number of active OMMs in the market on that day), and a general time trend variable (equal to 1 on the first day of the sample and incremented by 1 on each subsequent day, and divided by 252 trading days in a year). In column (2), we regress OMM daily return on account-level variables, including the logarithm of an OMM account's daily trading volume, the percentage of an account's trading volume that provides liquidity, an account-level time trend (equal to 1 on the first day when an account is active and incremented by 1 on each subsequent active day, and divided by 252 trading days in a year), and a dummy variable equal to 1 if the account is foreign. Finally, in column (3), we combine all the explanatory variables into one regression.

Dependent variable:	OMM daily return	OMM daily return	OMM daily return
	(1)	(2)	(3)
Intercept			-0.276***
			(-15.26)
Index return	-0.024		-0.038
	(-0.88)		(-1.02)
Index volatility	6.145***		9.153***
	(11.95)		(14.22)
Log(aggregate market trading volume)	0.002***		0.004***
	(3.04)		(5.06)
Average % bid-ask spread	0.055***		0.053***
	(5.41)		(3.94)
Competition	0.001		0.001
	(1.57)		(1.02)
General time trend	-0.001		-0.001
	(-0.55)		(-0.95)
Log(OMM account trading volume)		0.010***	0.009***
		(18.34)	(16.59)
% of account volume providing liquidity		0.070***	0.062***
		(18.30)	(16.85)
OMM account time trend		-0.009***	-0.006***
		(-6.62)	(-4.48)
Foreign account		0.022***	0.024***
		(10.26)	(11.97)
Account fixed effects	YES	NO	NO
Time fixed effects	NO	YES	NO
N observations	5,877	5,877	5,877
R^2	0.5714	0.3356	0.2028

Table 5. Extent of delta hedging by market makers

This table summarizes delta-hedging practices for 18 market makers that engage in end-of-day hedging. The first row shows the percentage of days when the option and futures deltas have opposite signs, while the second row indicates the percentage of days with an overnight position that is at least 50% hedged. This analysis is based on end-of-day positions. In the bottom panel, we report results from a regression of end-of-day futures delta on options delta for each market maker, including cross-account statistics for the regression coefficients, t-statistics, R-squared values, and the number of observations.

	mean	**std**	**min**	**q1**	**median**	**q3**	**max**
% of days when sign(option delta) * sign(futures delta) = -1	53.5%	20.3%	12.3%	39.6%	58.7%	67.0%	91.5%
% of days when (futures delta) = +/-50% of (-options delta)	9.1%	11.1%	0.0%	0.5%	5.6%	11.0%	42.6%
Regression of end-of-day futures delta on options delta							
Slope coefficient	-0.2	0.2	-0.9	-0.3	-0.1	0.0	0.0
T-statistic	-7.7	11.4	-48.2	-8.7	-3.6	-1.6	-0.1
R^2	21.8%	27.3%	0.0%	3.2%	7.8%	33.4%	96.2%
N observations used in regression	155	106	21	76	141	197	452

Table 6. What explains delta-hedging intensity?

The following regression examines OMMs' end-of-day hedge intensity, which is defined as: i) 0, if the OMM holds options but does not have any delta-hedge position in futures on the day; ii) 1, if the OMM over-hedges on the day; or iii) 1 - abs[(options delta + futures delta)/options delta] for the other cases. The market-level explanatory variables include the daily KOSPI 200 index return, index volatility (calculated using 5-minute index returns), logarithm of aggregate options market trading volume, volume-weighted average percentage bid-ask spread in the options market, logarithm of aggregate futures market trading volume, volume-weighted average percentage bid-ask spread in the futures market multiplied by 100, competition (number of active OMMs in the market on that day), and a general time trend variable (equal to 1 on the first day of the sample and incremented by 1 on each subsequent day, and divided by 252 trading days in a year).

Dependent variable:	Hedge intensity	Hedge intensity
	(1)	(2)
Intercept	-0.930**	
	(-2.06)	
Index return	0.987	1.077*
	(1.38)	(1.66)
Index volatility	0.689	-7.008
	(0.04)	(-0.48)
Log(aggregate options market trading volume)	-0.093***	-0.075***
	(-6.6)	(-5.36)
Average options % bid-ask spread	-0.154	-0.046
	(-0.66)	(-0.22)
Log(aggregate futures market trading volume)	0.283***	0.204***
	(7.68)	(5.79)
Average futures % bid-ask spread	-42.349***	-20.279***
	(-7.71)	(-3.57)
Competition	-0.030***	-0.030***
	(-3.33)	(-3.44)
General time trend	0.063***	0.226***
	(5.34)	(11.32)
Account fixed effects	NO	YES
N observations	2,946	2,946
R^2	0.1192	0.2903

Table 7. Differences between delta hedgers and non-delta hedgers

In this table we examine variables related to the decision of whether to hedge or not, and we compare them for the subsamples of delta hedgers and other OMMs. The means and medians are computed across account-months, and we include t-tests for difference in means across the two subsamples. Panel A shows a comparison of volume-weighted average position holding times. The first row includes overnight positions in the computation, while the second row includes only intraday positions. Panel B shows the average number of distinct option contracts traded per day, as well as the average liquidity of the traded option contracts, measured by the daily average of each contract's aggregate market volume.

Panel A: Position holding times

	Delta hedgers	Other OMMs			Delta hedgers	Other OMMs
	mean	**mean**	**diff**	**t-stat**	**median**	**median**
Average position holding time, including overnight positions	40.8 hrs	35.4 hrs	5.4 hrs	(0.53)	10.3 hrs	5.7 min
Average position holding time, only intraday positions	46.1 min	27.5 min	18.6 min	(3.60)	50.6 min	5.6 min

Panel B: Option contracts traded

	Delta hedgers	Other OMMs			Delta hedgers	Other OMMs
	mean	**mean**	**diff**	**t-stat**	**median**	**median**
Average number of distinct option contracts traded per day	33	28	5	(1.65)	22	22
Average liquidity (daily market volume) of traded option contracts	391,128	647,811	-256,684	(-3.93)	245,043	456,689

Table 8. Hedge ratios by time of day

This table shows how hedge ratios for delta hedgers vary throughout the trading day. The hedge ratio is calculated as the slope from a panel regression of futures delta on options delta at specific time intervals, from the start of the regular trading session at 9:05 to the end at 15:05, followed by the closing auction (labeled "EOD"). A hedge ratio of -1 indicates a fully hedged position. The last column combines the 12:05 and EOD samples, with the interaction term coefficient capturing the difference between midday and end-of-day hedge ratios (including the corresponding t-statistic). All panel regressions incorporate account fixed effects.

Dependent variable:	Futures delta						
Time of day:	9:05	10:35	12:05	13:35	15:05	EOD	12:05 & EOD
Options delta	-0.291***	-0.242***	-0.205***	-0.228***	-0.237***	-0.317***	-0.207***
	(-25.2)	(-21.05)	(-19.35)	(-21.39)	(-22.59)	(-27.17)	(-20.75)
Options delta * EOD indicator							-0.108***
							(-6.86)
Account fixed effects	YES	YES	YES	YES	YES	YES	YES
N of obs.	944	944	944	944	944	944	1,888
R^2	0.453	0.387	0.354	0.392	0.411	0.490	0.421

Table 9. How do market makers manage risk?

This table reports how market makers manage their overall inventory. For each market maker account, we estimate a regression of the 5-minute change in inventory on its lag(s). This regression quantifies the speed at which inventory reverts to its steady-state level. Inventory is measured as the total delta of options and futures positions held at the end of each 5-minute interval. The table reports cross-account averages of regression intercepts, coefficients, t-statistics, number of observations, and R-squared. The regression in column (1) includes only the first lag of inventory change as the independent variable. A negative coefficient indicates that inventory reverts to the mean. Column (2) adds the second lag of inventory change. Column (3) controls for the concurrent return of the underlying index as well as its two lags. In columns (4), (5) and (6), we decompose total inventory change into three components (that add up to total inventory change in column (1)): inventory change due to aggressive options orders, passive options orders, and futures orders. We compare coefficient magnitudes in columns (4)-(6) to identify which mechanism OMMs rely on the most to adjust their inventory.

Dependent variable:	Δ inventory	Δ inventory	Δ inventory	Δ inventory aggressive options orders	Δ inventory passive options orders	Δ inventory futures orders
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.111	0.166	0.148	-0.018	0.070	0.031
	(0.36)	(0.37)	(0.37)	(0.26)	(0.32)	(0.19)
Lag_1 of Δ inventory	-0.383	-0.479	-0.481	-0.095	-0.283	-0.005
	(-36.72)	(-42.89)	(-42.98)	(-27.18)	(-34.83)	(-4.77)
Lag_2 of Δ inventory		-0.219	-0.217			
		(-19.87)	(-19.79)			
Controls	NO	NO	YES	YES	YES	YES
N observations	9,120	9,120	9,120	9,120	9,120	9,120
R^2	0.1641	0.2130	0.2194	0.1121	0.1587	0.0108

Table 10. How do delta hedgers manage risk?

This table repeats the analysis in Table 9 for four delta hedgers instead of all market makers. We report the cross-account means of intercepts, coefficients, t-statistics, number of observations, and R-squared obtained from each account-level regression. All variables in regressions (1)-(4) are defined as in Table 9. Regressions in columns (5)-(8) include two interactions of the corresponding change in inventory with two indicator variables for volatility and inventory shocks. The *Volatility shock* indicator equals one if the underlying index experienced a large move in the previous 5 minutes (i.e., absolute 5-minute return was in the 90th percentile). The *Inventory shock* indicator equals one if the account experienced a large change in their inventory in the previous 5 minutes (i.e., absolute Δinventory was in the 90th percentile).

Dependent variable:	Δinventory	Δinventory aggressive options orders	Δinventory passive options orders	Δinventory futures orders	Δinventory	Δinventory aggressive options orders	Δinventory passive options orders	Δinventory futures orders
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.149	0.018	0.090	0.028	0.228	0.003	0.166	0.060
	(0.25)	(0.19)	(0.12)	(0.49)	(0.27)	(0.14)	(0.15)	(0.87)
Lag_1 of Δinventory	-0.340	-0.057	-0.270	-0.014	-0.260	-0.055	-0.210	0.005
	(-42.09)	(-22.73)	(-41.07)	(-10.78)	(-10.17)	(-6.35)	(-10.06)	(0.19)
Lag_1 of Δinventory * Volatility shock					-0.237	-0.045	-0.155	-0.037
					(-6.45)	(-4.95)	(-4.82)	(-4.49)
Lag_1 of Δinventory * Inventory shock					-0.076	0.002	-0.060	-0.018
					(-1.54)	(0.42)	(-1.45)	(-2.68)
Volatility shock					-0.155	0.260	-0.123	-0.292
					(0.03)	(0.31)	(-0.002)	(-1.08)
Inventory shock					-0.268	-0.070	-0.120	-0.078
					(-0.31)	(-0.30)	(-0.17)	(-0.22)
Controls	NO	YES	YES	YES	YES	YES	YES	YES
N observations	15,986	15,986	15,986	15,986	15,986	15,986	15,986	15,986
R^2	0.1252	0.0363	0.1284	0.0121	0.1376	0.0406	0.1347	0.0177

Table 11. Evidence from S&P 500 index options

This table reports summary statistics: mean, standard deviation, minimum, first quartile (q1), median, third quartile (q3), and maximum of OMM trading activity in the S&P 500 index options market from 1996 to 2018. We use data from the Cboe's Open-Close Volume Summary for SPX options. To calculate OMM positions, we use the fact that options are in zero net supply and thus OMM positions must offset proprietary traders' and public customers' positions. Option deltas are from OptionMetrics.

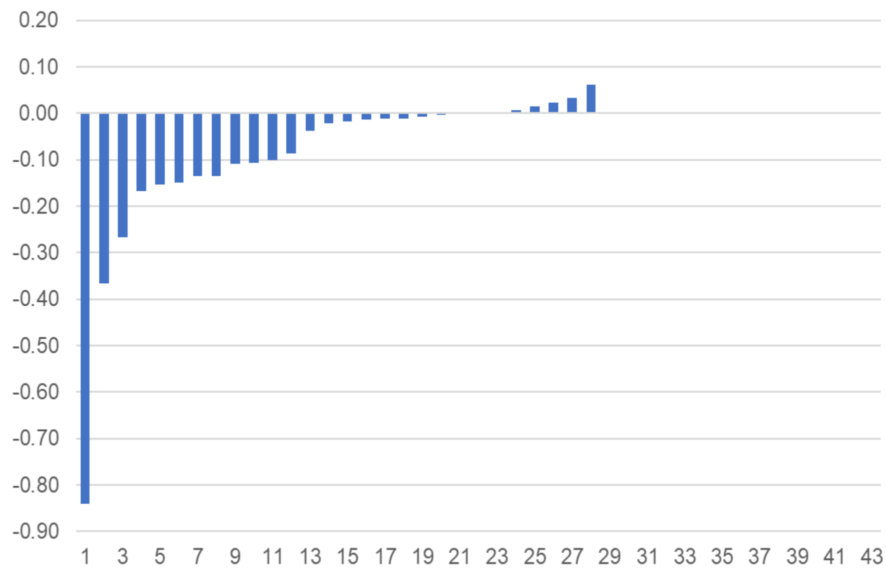
Variable	**mean**	**std**	**min**	**q1**	**median**	**q3**	**max**
OMM Trading Volume	415,840	335,637	139	121,159	370,189	615,871	2,784,562
OMM Absolute Naïve Delta-hedge Volume	110,953	91,068	1	39,509	91,923	154,118	783,238
Absolute Change in call OMM Open Interest	5,999	7,432	0	1,671	3,864	7,982	295,078
Absolute Change in put OMM Open Interest	9,020	10,655	1	2,441	5,644	11,783	192,631
Absolute Delta-adjusted Change in OMM Open Interest	3,466	4,722	0	987	2,260	4,439	219,766

Appendix

Figure A1. Replication of Figure 2 using midday instead of end-of-day delta positions

This figure illustrates the extent of intraday delta hedging by 43 market makers in our sample. Panel A shows the hedge ratios, defined as the slope from the regression of midday futures delta positions on options delta positions, estimated separately for each market maker. A hedge ratio of -1 indicates a perfect delta hedge. Hedge ratios are ordered from more negative values (indicating stronger delta hedging) to less negative values (indicating weaker delta hedging). Market makers ranked 29 to 43 hold no futures positions at midday, resulting in a hedge ratio of zero. Panel B presents the corresponding R-squared values, indicating the consistency of the hedge ratio for each market maker.

Panel A: Hedge ratio



Panel B: R-squared for hedge ratio

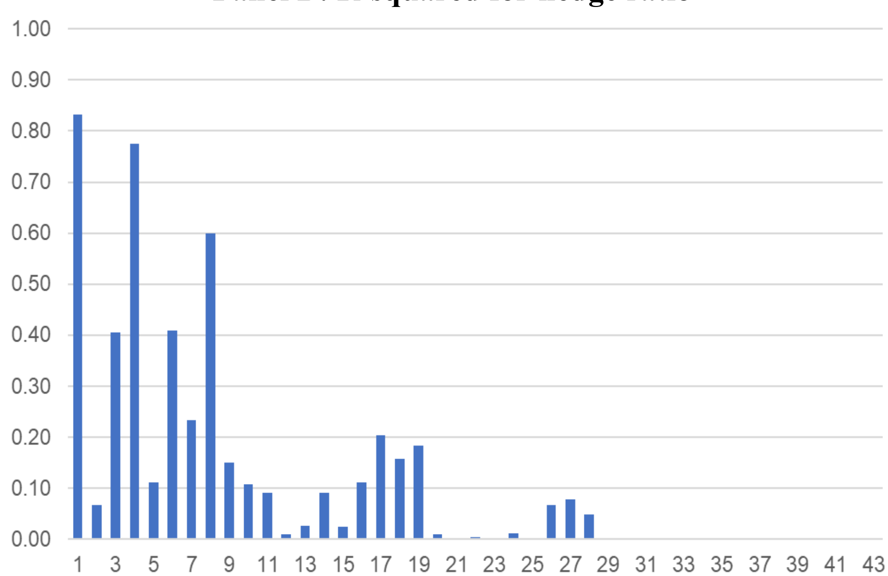


Table A1. Identifying options market makers

This table outlines the criteria used to identify options market makers (OMMs) from a sample of 161,010 option accounts. First, we extract the top 30 accounts based on passive dollar volume each trading day, identifying each account’s most actively traded contract among the top 10 contracts by dollar volume. By reconstructing each account's limit order book, we measure the proportion of time they provide two-sided quotes for this contract. Accounts that quote two-sided prices at least 80% of the time on at least 10 days are retained, resulting in 90 potential OMM candidates. We then examine the full activity of these 90 accounts in all contracts they trade, and we apply three additional criteria to confirm OMM status, as shown in the upper panel below. These criteria focus on monthly trading volume, frequency of two-sided quotes at the Best Bid and Offer (BBO), and scaled end-of-day delta exposure. The bottom panel reports the final sample size after applying these selection criteria, excluding days when accounts are inactive (i.e., when they do not trade or hold positions).

Criteria applied each month:	**Cutoff value**	
Total monthly trading volume in options > 20th percentile	80,083	
Mean portion of the day with two-sided quotes at BBO > 70th percentile	13.75%	
Mean end-of-day absolute delta exposure scaled by mean daily options trading volume < 80th percentile	0.0035	
Sample:	**Starting N obs.**	**Final N obs.**
OMM accounts	90	43
OMM account-months	1858	294
Mean (median) number of OMM accounts active in a month		6 (6)

Table A2. Options and futures trading volumes of delta hedgers

This table presents the average daily contract volumes in options and futures for the four identified delta hedgers. The last two columns show the fraction of total futures volume classified as "initiated" or "aggressive". A trade is considered “initiated” if the account submitted the order after the counterparty’s order, and “aggressive” if the account’s order was executed within 90 milliseconds of order submission.

	Trading volume, daily average			
Account	Options	Futures	total initiated (%)	total aggressive (%)
1	71,066	1,708	93.1%	83.7%
2	376,424	1,216	39.3%	47.4%
3	11,219	393	6.4%	12.5%
4	322,171	1,894	48.9%	47.0%