The Impacts of Retail Options Trading and REIT Director Backgrounds

by

Matthew James Flynn

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 3, 2024

Keywords: Options, return predictability, retail traders, asset pricing, governance, REITs

(Pending) Approval by

Jimmy Hilliard, Co-Chair, Harbert Eminent Scholar, and Professor of Finance
Jitka Hilliard, Co-Chair, J.K. Lowder Family Professor of Finance
Justin Benefield, Walker Reynolds Bickerstaff Professor of Finance
Zhongling "Danny" Qin, Assistant Professor of Finance
Denis Nadolnyak, Associate Professor of Agricultural Economics and Rural Sociology

Abstract

Chapter one investigates the pass through of option volume to stock pricing through option intermediary hedging. Increased liquidity in the options market creates price pressure in the underlying stock market through the hedging activity of intermediaries. When public option demand is imbalanced, liquidity providers have inventory imbalance and create predictable price action in the underlying through dynamic hedging. Using a simple proxy for public demand for options, I identify a strong and persistent relationship with synchronous and future stock returns in a manner predicted by net short delta hedgers' trades, distinct from information frictions. This phenomenon is most likely due to retail investors hoarding on specific options.

In chapter two, I document predictability in the cross-section of delta-hedged equity options as a function of Robinhood user holdings. Returns to writing delta-neutral calls to retail traders are highly statistically and economically significant. Returns are robust to several controls, factor risk adjustment, and momentum. Returns originate from retail demand-driven option mispricing and subsequent overpayment for relative exposure to underlying stock volatility. Returns are more substantial in periods of high retail sentiment or concentration.

Chapter three investigates the effect of director characteristics on firm performance. Using REITs as a laboratory to isolate the advisory role of the board of directors, we determine that directors with executive/governance experience in finance and accounting create significant value. Adding “high-value” directors is associated with an increase in monthly returns of between 1.1% and 2%, along with a 50-basis point increase in risk-adjusted return. CARs indicate that high-value directors are added to underperforming REITs, and results hold when controlling for endogeneity. High-value board members increase capital use efficiency, sell

underperforming properties, and focus future investments on outperforming submarkets, while having higher pay-to-performance sensitivity and shorter tenure than average directors.

Acknowledgments

I would like to express my deepest thanks to my committee members, Dr. Jimmy Hilliard, Dr. Jitka Hilliard, Dr. Justin Benefield, and Dr. Zhongling Qin for their invaluable time and contributions to my research, but more importantly, their investment in me. If not for this wonderful group of mentors and scholars, I would not be where I am today. I am also deeply appreciative of the help and guidance offered by *all* members of the finance department at Auburn University, but namely, my fellow Ph.D. students, Dr. Keven Yost, Dr. Jason Chen, Dr. David Cicero, Dr. Marlin Jensen, Dr. Stace Sirmans, Dr. Joseph Stover, Dr. Albert Wong, and Mrs. Karen Cochran, all of whom I am certain I bothered more than the average Ph.D. student. I also extend a special thank you to the late Dr. James Barth, whose positive impact on the lives of his students cannot be understated, and whose deep-rooted curiosity and love for his job will forever serve as a shining example for what it means to be a scholar.

Finally, I owe an unpayable debt and immense gratitude to my family and friends who have supported me throughout my life and academic journey. My mother, my father, Ferron, Aunt C, Jack, and countless others. Their unconditional love and unwavering belief in me have served as an inspiration more than even they know. If life gives me nothing more than my family, I am the richest man who ever lived.

"Waste no more time arguing what a good man should be. *Be one.*" – Marcus Aurelius

Table of Contents

List of Tables

List of Figures

List of Abbreviations

2SLS	Two-Stage Least Squares
API	Application Programming Interface
ATM	At the Money
BD	Broker Dealer
BPS	Basis Points
CAR	Cumulative Abnormal Return
CBOE	Chicago Board Options Exchange
CEO	Chief Executive Officer
CRSP	Center for Research and Security Prices
DEC	Decile
DID	Difference in Differences
DVN	Delta-Vega Neutral
ECOV	Excess Call Option Volume
EOV	Excess Option Volume
EPOV	Excess Put Option Volume
EPS	Earnings Per Share
ESV	Excess Stock Volume
ETF	Exchange Traded Fund
EW	Equal Weighted
FD	First Difference
FF	Fama and French
HML	Fama and French (1993) High minus low book-to-market Factor

ILLIQ	Amihud (2002) Illiquidity Measure
ITM	In the Money
IV	Implied Volatility
IVOL	Idiosyncratic Volatility
KURT	Kurtosis
LDA	Latent Dirichlet Allocation
LTIP	Long Term Incentive Pay
MAX5	Bali, Cakici, and Whitelaw (2011) Lottery Measure
MKT	Market Return
MM	Market Maker
MOM	Carhart (1997) Momentum Factor
MSA	Metropolitan Statistical Area
N	Number of Observations
NAREIT	National Association of Real Estate Investment Trusts
NI	Net Income
NO	Non-Operating
NYSE	New York Stock Exchange
O/S	Option to Stock
OLS	Ordinary Least Squares
OTM	Out of the Money
RE	Real Estate
REIT	Real Estate Investment Trust
REOC	Real Estate Operating Company

RH	Robinhood
S&P500	Standard and Poor’s 500 Index
SD	Standard Deviation
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
SMB	Fama and French (1993) Small minus Big Factor
SPDR	Standard & Poor’s Depositary Receipts
ST	Short Term
STIM	Stimulus Checks
US	United States
UTD	University of Texas at Dallas
VRP	Volatility Risk Premium
VW	Value Weighted

Chapter 1

Charming! Retail Option Volume and Delta Hedging Effects on Stock Pricing.

1.1. Introduction

Options markets are an attractive destination for speculative trades due to the embedded leverage available for a small capital outlay. Influential studies such as Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2015) have shown that option markets can predict stock prices. Although the most popular mechanism for this predictive ability is attributed to informed trading in the option market, new studies such as Ni, Pearson, Poteshman, and White (2021), Barbon and Burashi (2021), and Bryzgalova, Pavlova, and Sikorskaya (2023) have highlighted the mechanical connection between the option and underlying stock market. Specifically, how the option inventories of market makers and broker dealers can impact stock prices through dynamic hedging techniques. In this study, I provide evidence that retail option trade has exacerbated hedgers' inventory imbalances and created considerable predictable price pressure in stocks.

The impetus of this study is the substantial increase in options market liquidity due to the participation of retail investors. Under pressure from retail-focused zero commissions brokerage Robinhood, Charles Schwab, the largest brokerage in the world[1], instituted commission free trading in October 2019. Almost all other brokerages followed this move to remain competitive. As a result, traded equity options have increased by roughly 67% year over year. Further, this increase is concentrated in options with a "gambling" tilt, short term, out of the money call options. These calls reflect positive sentiment and have the largest embedded leverage available due to their low price. These options are consistent with the behavioral motivations of retail

[1] For context, Schwab had AUM of over $3.5 trillion and approximately 33 million active accounts in 2019.

traders, who have been shown to value lottery characteristics such as low prices, high idiosyncratic volatility, and high idiosyncratic skewness[2]. From 2019 – 2022, the average volume traded for 0-2 weeks calls in billions of dollars was roughly $500 billion greater than all other expiry classifications combined. The increase in liquidity and the changing preference of options calls for a reexamination of the interconnectedness of the option and stock markets.

I hypothesize that increased demand for long option positions from retail traders will primarily be serviced by market makers to fulfill their liquidity provision to the market. Market makers are noted delta hedgers [Cox and Rubinstein (1985), Hull (2000), among others]; thus, the hedging trades resulting from their short option positions create price pressure in the underlying stock. As such, delta hedging has two empirically testable implications:

1. Contemporaneous stock returns vary with the net option delta position of market makers. Short delta (short calls) = buying pressure, long delta (short puts) = selling pressure.
2. Future returns on stocks where market makers are net short options will vary with the process of the option's delta.

The derivative of delta with respect to time is an option's charm. Because charm is strictly positive or negative depending on the characteristics of the option, it allows for inference about the future stock trades of delta hedgers. This claim is verified in aggregate data and signed trades with identified accounts of origin, i.e., tagged retail and market maker trades. The effect of charm is in addition to hedgers' net gamma position, which captures the rate of change of delta and, thus, rebalancing of hedges. Due to heightened imbalances, mechanical decay of delta induced by time is an essential consideration in addition to the first-order rebalancing effect

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[2] Bauer, Cosemans, and Eichholtz (2009), Kumar (2009), Green and Hwang (2012), Han and Kumar (2013), Hvidkjaer (2008), Barber, Odean, and Zhu (2009), Kaniel, Liu, Saar, and Titman (2012), and Kumar, Page, Spalt (2013).

captured by gamma imbalance. That is to say, the rebalancing implied by charm can *cause* stock price pressure independent of information or demand driven price shifts in the stock.

To test the stock pricing implications of options volume, I developed two simple measures of abnormal option trading: excess call/put option volume, ECOV, and EPOV. The measures are constructed as daily option volume less a rolling average of the previous five days. In aggregate option volume data, these measures capture abnormal trading and proxy for the short inventory of liquidity providers. The idea is that liquidity providers are more likely to take short positions when volume increases unexpectedly. Although not a perfect proxy, these measures have merit in their simplicity and reproducibility. Thus, strategies using excess option volume (EOV) are reproducible with no private information.

EOV relates to contemporaneous and future price pressures in the direction predicted by net short option delta hedging trades of liquidity providers. By multiplying EOV times option delta and charm, I calculate a proxy for the dollar amount needed to enter and rebalance a delta hedge over time. Portfolios sorted by dollar value required to enter a delta hedge on short option positions explain daily contemporaneous stock price pressure by as much as 50 basis points (bps) in either direction. Further, subsequent day returns can be pressured by roughly 40 bps based on the relative volumes in the options market of the stock. By disaggregating the short inventory of liquidity providers EOV into subgroups, I show options traded by retail investors have the highest impact on stock pricing. If option volumes become more imbalanced in specific charm classifications, liquidity provider inventory becomes more imbalanced, and predictability increases. Predictability also increases in the average gamma of the options traded as higher gammas represent a larger dollar amount needed to rebalance hedges. These price effects are unlikely to be driven by information as they are highly transitory, with predictability rarely lasting past one day.

These results broadly suggest that mechanical price pressure caused by option inventory imbalances of delta hedging liquidity providers can have economically significant impacts on stock pricing. Mechanical effects even outpace private information that may be nested in option volumes. For example, a one standard deviation increase in high embedded leverage call options corresponds with decreased stock returns of roughly 35 bps on the next trading day. While this result is consistent with mechanical rebalancing induced by net charm position, it makes little sense in an informational context, as one would assume informed trading in high leverage call options should relate to good news and increases in stock price.

A zero-investment portfolio created by grouping deciles of stocks based on gamma weighted charms of their options earns excess returns of 7.755 bps per day with a highly significant t-stat of 3.246, or 19.5% per annum unadjusted for transaction costs. This portfolio has relatively low risk as returns rely on mechanical pressure from hedging flow. Returns also survive risk adjustment from the Fama French 3 factor model plus momentum.

Several pieces of information suggest that retail traders are the driving force behind the stock price pressure caused by hedging. Tests using CBOE data bucketed by user account indicate that most predictability occurs when retail traders are long options written by delta hedging liquidity providers. A one standard deviation increase in long holdings by retail accounts is associated with a 40 basis point decrease in the stock's next day return and correlates highly with hedger charm position. Future returns are also much lower for stocks with high excess call option volumes simultaneously highly held by Robinhood investors, despite the generally good timing of Robinhood investors documented in Welch (2022). The differing outcomes of retail interest in stocks and options are puzzling if not for considering the hedging flow of intermediaries servicing retail flow in the options market. Results linking retail option trade to stock pricing are novel and support the conclusions of Bryzgalova, Pavlova, and Sikorskaya (2023), that retail option trade affects stock price through the hedging of intermediaries servicing retail order flow.

The paper proceeds as follows. Section 1.2 outlines the place and contribution of the paper. Section 1.3 documents the abrupt increase in options volume following broad access to commission free trading, section 1.4 models option charm and presents testable hypotheses, section 1.5 documents data and variable construction, section 1.6 shows stock price pressure in the aggregate, section 1.7 connects aggregate predictability to retail trade, and section 1.8 concludes.

1.2. Place and Contribution

The predictive ability of the relative volume of options to stocks is well documented by Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), Ge, Lin, and Pearson (2015), and Pan and Poteshman (2006). Primarily, these studies suggest an informed trading explanation in which negative information for stocks is nested in higher options volume, leading to a negative relation between the O/S ratio and future stock returns. This is because of short-sale constraints in the stock market and the embedded leverage provision of options. However, these explanations leave many existing studies with somewhat puzzling findings. Work by Ge, Lin, and Pearson (2015), among several others, finds the predictability of signed option volume is more robust for out-of-the-money options and trades originating from small accounts. In addition, existing studies find the negative relation between the O/S ratio holds even when considering only call options, which should have a positive relationship with future returns if the option trading is informed.

Others have considered stock clustering or pinning, the phenomena by which stocks stick close to the strike price of options near expiry, such as Ni, Pearson, and Poteshman (2004). Such studies offer a joint explanation, citing hedge rebalancing and informational channels working independently or in conjunction. The delta hedging method of predicting mechanical pressure differs from existing studies because it does not rely on an informational channel. Excess demand for call (put) options should *strictly* predict positive (negative) future returns in an informational channel. Instead, they will depend only on the option's moneyness within the delta hedging channel. In several instances, a delta hedging channel will predict opposite price movement to an informational one. In this way, I can plausibly separate the effects of private information and mechanical pressure when considering the interconnectedness of the option and stock markets and provide insight into which channel dominates and in what situations.

While other authors such as Hu (2012) and Ni, Pearson, Poteshman, and White (2021) have considered the mechanical effects of delta hedging, these studies primarily focus on the volatility of the underlying due to hedging trades. I supplement this work by showing instances where hedging creates directional pressure in addition to volatility changes. Stivers and Sun (2013) show that stock prices are pressured on option expiration weeks in a manner consistent with net long option delta hedgers. I provide evidence that this relation has flipped since their study, as retail traders have forced market liquidity providers into a net short option position. This research is broadly related to the effect of option derivatives on underlying pricing, such as Barbon and Burashi (2021) and Ni, Pearson, Poteshman, and White (2021). This study is the first to sort by option charm, a purely mechanical movement that does not rely on the independent price discovery of the underlying.

This paper also relates to much of the behavioral literature on retail trading. Retail investors have been shown empirically to value lottery-like payoffs in their direct investments. Bauer, Cosemans, and Eichholtz (2009), Kumar (2009), Green and Hwang (2012), and Han and Kumar (2013) document the tendency of retail investors to speculate in equity markets by overpaying for stocks with features exhibiting a higher probability of significant magnitude returns, such as low prices, high idiosyncratic volatility, and high idiosyncratic skewness. The correlated trading decisions of return-seeking retail investors are also shown to move stock prices in a manner inconsistent with market efficiency and stock fundamentals by Hvidkjaer (2008), Barber, Odean, and Zhu (2009), Kaniel, Liu, Saar, and Titman (2012), Han and Kumar (2013), and Kumar, Page, Spalt (2013), among others. In a more recent and pertinent example, Umar, Gubavera, Yousaf, and Ali (2021) use the case of GameStop to provide evidence that this type of sentiment-driven trading by retail investors can cause extensive and economically significant asset mispricing. In the managed fund literature, Agarwal, Jiang, and Wen (2021) provide evidence that mutual fund managers strongly prefer stocks with "lottery-like" characteristics at the behest of their investors. Funds holding more lottery stocks attract higher flows than their conservative counterparts. Retail investors tend to overweight small probability events that have impacts of a large magnitude. This behavioral phenomenon is the same as identified in much of the theoretical risk management and insurance literature, where individuals are willing to pay a premium to avoid the chance of exceptionally bad or damaging outcomes, no matter the actual probability [Mendez and Hanson (1970)]. The options market is an obvious destination for investors seeking lottery-like returns due to the limited downside risk and large amounts of embedded leverage. Choy (2014) shows that a higher retail trading proportion in an option chain is related to significantly lower option returns. This evidence suggests that retail investors speculate on options and pay a "lottery premium" on expected future volatility, resulting in more expensive options with higher implied volatilities. Choy and Wei (2020) show retail investors tend to buy more calls and puts on the daily winner and loser stocks, leading to an overvaluation of those options. I add to this literature by linking the behavioral tendencies of retail traders in the derivatives market to price pressures in the underlying.

1.3. Option Volume after Broad Access to Commission Free Trading

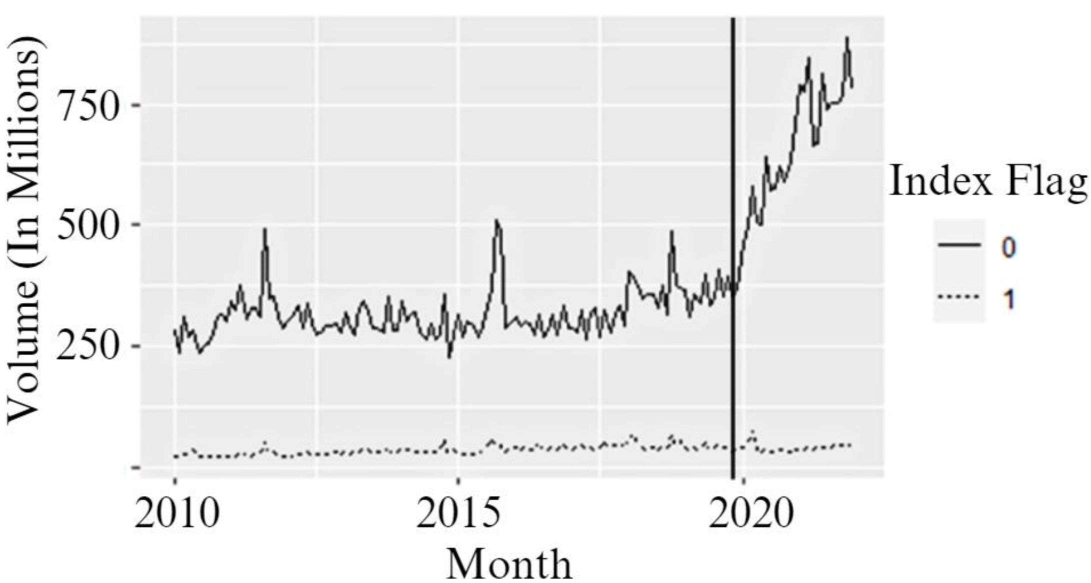
Robinhood was founded on April 18th, 2013, with the mission of *"democratizing finance for all"* – Vlad Tenev, Robinhood CEO. Robinhood targets a user base of inexperienced clientele by offering commission-free trades and simplifying trading with a user-friendly app as its primary interface. As an example of the tailored experience for novice investors, Robinhood offers a learning experience in its host of brokerage services. The learn tabs on the Robinhood website include articles such as *"What is an investment?"* and *"What is the stock market?"*. Robinhood quickly grew in popularity, accruing more than fifteen million active accounts as of 2023. The growth of Robinhood also coincides with a cultural shift in how young retail traders view investing. Investment-related topics receive more public attention than ever in traditional media and social media, such as the online Reddit community behind the GameStop short squeeze: *WallStreetBets*. Increased public interest in finance is also evident in the success of several recent films, such as *Dumb Money* and *The Big Short*, with prevalent themes of risk and the gamification of trading. These cultural headwinds culminated in Charles Schwab's decision to implement commission-free trading in October 2019, reducing options trading costs from $4.95

to $0.65 per contract. Other major brokerages quickly followed with similar reductions in the price of options trading to remain competitive in the global marketplace.

To visualize the resultant effects, Figure 1.1 plots the time series of monthly aggregate option volume from January 2010 to December 2022 with a line indicating the institution of commission free trading by Schwab. As shown in Figure 1.1, options volume remained relatively flat from 2010 – 2019, averaging around 375 million monthly contracts. Since the institution of commission free trading however, the average number of monthly options contracts has increased precipitously, primarily in equity options. The average number of contracts traded after the broad introduction of commission free trading increased by roughly 67% year over year, with an average of 625 million contracts per month in 2021 and over 750 in 2022.

Figure 1.1 – Monthly Option Volume

Aggregate monthly option volume in millions from January 2010 to December 2022. The solid black line denotes equity options, and the dashed line indicates index options. The solid vertical line represents Charles Schwab moving to commission free trade.



Further, the type of options being traded has also shifted. Retail traders have been shown to prefer lottery characteristics in their direct investments[3]. In the options market, these preferences are satisfied with short term single name equity options. Figure 1.2 plots the monthly dollar value of aggregate option volume by expiry classification and call or put.

Figure 1.2 – Grouped Dollar Option Volume

U.S. dollar option volume is computed as the number of contracts traded times the strike price and is represented in billions of dollars monthly from January 2016 – December 2022. Dollar volume is grouped by expiry classification and call/put. The legend matches the color grouping of the figure. The dashed vertical line denotes Schwab commission free trade.

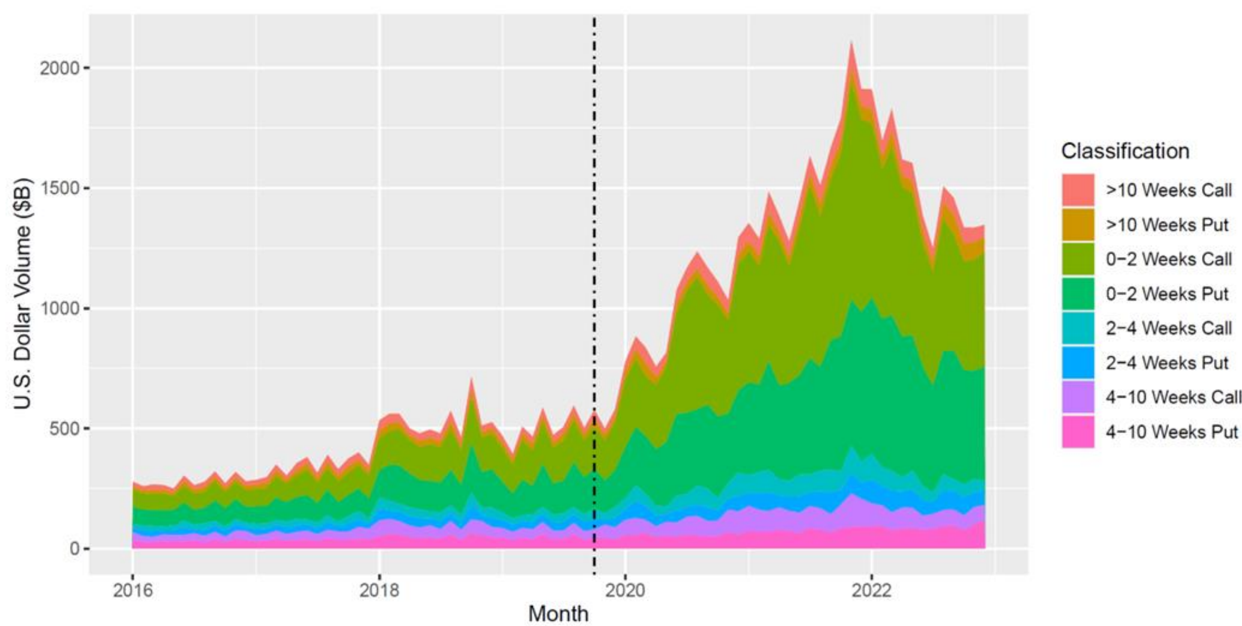


Figure 1.2 indicates that the average volume of options with less than two weeks to expiry is roughly $500 billion greater per month than all other expiry classifications combined after Schwab zero commissions. The aggregate increase is also highly concentrated in calls, with call

[3] Bauer, Cosemans, and Eichholtz (2009), Kumar (2009), Green and Hwang (2012), and Han and Kumar (2013), Umar, Gubavera, Yousaf, and Ali (2021).

options comprising roughly 68% of the total option market after the broad adoption of commission free trading. Untabulated results indicate that highly traded retail "meme" stocks move among the top ten stock option markets by volume from 2019 - 2022.

Because retail traders prefer long option positions to pursue lottery-like returns, liquidity providers such as market makers must take short positions on these options. When the liquidity provider cannot quickly offload the short option position, such as instances of retail hoarding causing limited two-way order flow, they will mitigate their directional risk exposure to the underlying through dynamic hedging. If these inventory imbalances become significant and pervasive, there can be effects on underling asset pricing.

For example, consider the highly media covered case of GameStop. In January 2021, a coordinated effort by retail investors drove GameStop to a market capitalization of over $22 billion, roughly 30 times the valuation at the start of the year. Because approximately 140% of GameStop's public float had been sold short, closing these short positions caused even further price increases (short squeeze). This event resulted in tremendous financial gain for several retail traders. The popular financial streamer, Keith Gill, purchased roughly $53,000 in call options and saw the position rise to $48 million by January 27, 2021. Gill’s story has contributed to a significant rise in derivative investment among retail traders and is the subject of the 2023 film *Dumb Money.* While the gains of this particular trade are stunning, the mechanism that drove the increase is not unique to GameStop. Retail traders *frequently* coordinate online in their option positions, leading to imbalanced markets and imbalanced portfolios for liquidity providers. In addition to the short squeeze, GameStop’s share price was further driven upwards by the hedging flow of short-gamma liquidity providers in the option market.

1.4. Modeling Price Pressure and Hypothesis Development

A market maker's primary function is to service public demand in markets by providing liquidity. This function is crucial in the options market, where unhedged short option positions have damaging implications for retail traders. According to the Chicago Board Options Exchange (CBOE): "for a naked written call or put position, initial margin includes all of the option proceeds and 20% of the value for the underlying securities, whereas, for covered option positions, it includes 50% of the value for the underlying securities." In terms of economic magnitude, a single naked call option contract written on the SPDR S&P 500 ETF (the most popular call option) will require at least $8,000 in cash or cash equivalents in the writer's account based on a $400 strike price. Should the option be called, the writer must produce $40,000. This calculation can be scaled upward by the number of contracts written. Due to the implicit risk, market makers will likely take short option positions of highly demanded options in service of their liquidity provision to the market. Further, the significant increases in options volume shown in section 1.3 implicitly require liquidity provision, especially given the concentration of the option volume.

I formally test the assumption that retail traders primarily take long option positions using the CBOE Open-Close Volume Summary. This data provides aggregated volume bucketed by the account of origin, buy/sell, and open/close. Customer trades under 100 are shown to be a strong proxy for retail trade by Bryzgalova, Pavlova, and Sikorskaya (2023). It should be noted, however, that small lot trades may also capture iceberg orders, which are used to mitigate costs and price impact. The prevalence of iceberg orders should be relatively small, however, given that CBOE identifies nonprofessional public customers and that iceberg techniques are typically used for very large transactions. The data ranges from 2019 to 2021 and covers roughly 30% of all U.S. option volume.

Table 1.1 reports the percentage of volume per account group, per year. Retail traders most frequently buy calls to open and generally buy to open at a much higher rate than any other group, consistent with a gambling preference. While market makers are shown to be balanced at the aggregate, they service a large portion of the retail flow and, thus, frequently have imbalanced inventory at the stock level[4]. In fact, market makers will *pay* to service retail flow due to the larger than average spreads incurred by retail demand. If retail traders begin hoarding on specific options, the market will not clear, and market makers will be forced to hedge directional risk in the underlying stock market.

While market makers do not *typically* pass through all option volume to the underlying stock, hoarding by retail traders creates special market conditions that make delta hedging by intermediaries more likely. The following summarizes the standard risk mitigation practices of market makers and how retail trade complicates these mechanisms:

1. Balanced markets eliminate the need for hedging, i.e., two-way order flow allows market makers to offload option inventory quickly. Because retail traders hoard on options, total demand becomes imbalanced.
2. The net delta impact is muted as net inventory grosses put and call option deltas. Because retail traders overwhelmingly purchase calls, the aggregate portfolio of liquidity providers is more dependent on the delta of these options.
3. Market makers can sometimes use proxy hedges such as ETFs. With such substantial increases in options volume, proxy hedges can become relatively expensive due to fees.

[4] Bryzgalova, Pavlova, and Sikorskaya (2023) indicate that market makers service a large percentage of total retail flow as brokers receive payment for order flow from market makers to preferentially route trades.

Table 1.1 - Signed Trades as a Percentage of Total Group Volume Per Year

Values are reported as a percentage (%) of a signed trade class's total yearly group volume. Groups are firms (firm), broker dealers (BD), customer trades under 100 contracts (Ret), and market makers (MM). Signed trade classifications are buy to open (OB), sell to open (OS), buy to close (CB), and sell to close (CS).

Panel A - 2019	Firm OB	Firm CB	Firm OS	Firm CS	BD OB	BD CB	BD OS	BD CS	Ret OB	Ret CB	Ret OS	Ret CS	MM Buy	MM Sell
C	6.70	16.25	6.80	16.25	6.05	16.30	5.54	16.30	21.21	9.09	14.70	9.09	25.67	26.28
P	8.41	18.68	8.23	18.68	8.60	20.06	7.11	20.06	15.80	8.00	14.10	8.00	23.69	24.36
Panel B - 2020														
C	8.56	13.60	8.58	13.60	4.97	15.54	4.76	15.54	23.73	9.05	14.39	9.05	27.15	26.76
P	10.70	17.23	10.49	17.23	8.89	22.75	4.79	22.75	15.54	7.71	12.83	7.71	23.14	22.95
Panel C - 2021														
C	9.71	12.35	9.62	12.35	3.16	11.42	11.68	11.42	24.51	8.97	14.70	8.97	27.94	27.00
P	13.10	15.47	11.94	15.47	15.71	21.57	3.48	21.57	14.99	7.56	12.74	7.56	22.53	22.53

As a risk-neutral party, market makers will seek to hedge their directional exposure to the underlying stock. Unbalanced option portfolios are becoming more common for liquidity providers as option trade increases in popularity with retail investors, as shown by Barbon and Buraschi (2021). Market makers can manage their risk exposure when inventory is imbalanced through dynamic delta hedging. Option delta represents the change in option value relative to the change in the underlying asset's value. Delta hedging involves trading in the underlying asset to achieve a net-neutral delta position for the complete portfolio. Market makers can offload the directional risk of an unbalanced option portfolio through this practice. As a testament, market makers are noted delta hedgers [Cox and Rubinstein (1985) and Hull (2000)]. Through the hedging channel, option volume can have pricing implications for the underlying stock.

1.4.1. Modeling Market Maker Price Pressure

Suppose one assumes the elasticity of the underlying stock price concerning selling and buying volume is non-zero as in Avellanda and Lipkin (2003). Then, the rebalancing of delta hedges will affect stock prices. To understand how delta hedging creates price pressure, consider the Black-Scholes formula for the price of a call on a non-dividend paying stock:

$$C = SN(d_1) - Ke^{-rt}(d_2),\ \textit{where}\ \ d_1 = \frac{ln\left(\frac{S}{K}\right)+\left(r+\frac{1}{2}\sigma^2\right)t}{\sigma\sqrt{t}},\ \textit{and}\ \ d_2 = d_1 - \sigma\sqrt{t}$$

Within the Black Scholes framework, S = stock price, K = strike price, r = risk-free rate, σ = volatility of the underlying, t = time to expiry, and N (.) = the cumulative normal distribution function. Delta (Δ) is the partial derivative of the call price with respect to the stock price and can be expressed by $\mathrm{N(d_1)}$. Application of the put-call parity allows the delta of a put option to be solved as $\mathrm{N(d_1)} - 1$. This result implies the derivative of delta with respect to time (or charm) is the same for call and puts, as is shown here:

$$\frac{\partial \Delta}{\partial t} = N'(d_1)\frac{ln\left(\frac{S}{K}\right)-\left(r+\frac{\sigma^2}{2}\right)t}{2\sigma t^{3/2}}$$, where $N'(.)$ is the pdf.

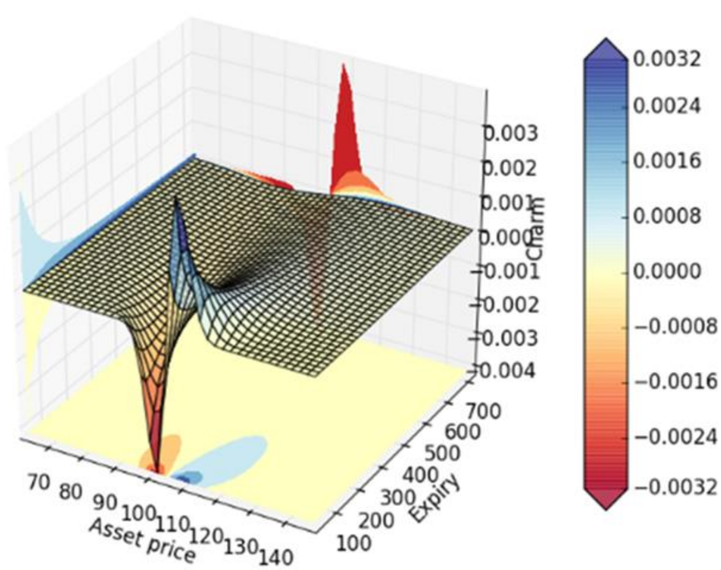
As time to expiry approaches zero, an explicit sign of charm may be inferred by the option's moneyness. As t approaches zero, the term $\left(r + \frac{\sigma^2}{2}\right)t$ becomes insignificantly different from zero, resulting in the following inequalities for charm:

$$\frac{\partial \Delta}{\partial t} = \frac{N'(d_1)\, ln\left(\frac{S}{K}\right)}{2\sigma t^{3/2}} > 0 \; if\, S > K$$

$$\frac{\partial \Delta}{\partial t} = \frac{N'(d_1)\, ln\left(\frac{S}{K}\right)}{2\sigma t^{3/2}} < 0 \; if\, S < K$$

Figure 1.3 models the charm of a call option with a $100 strike price. As the option approaches expiration, the absolute value of charm increases substantially. Charm becomes sharply negative for OTM calls where S < K and vice versa. Charm's effect on option delta can result in large trading volumes in the underlying asset from hedgers.

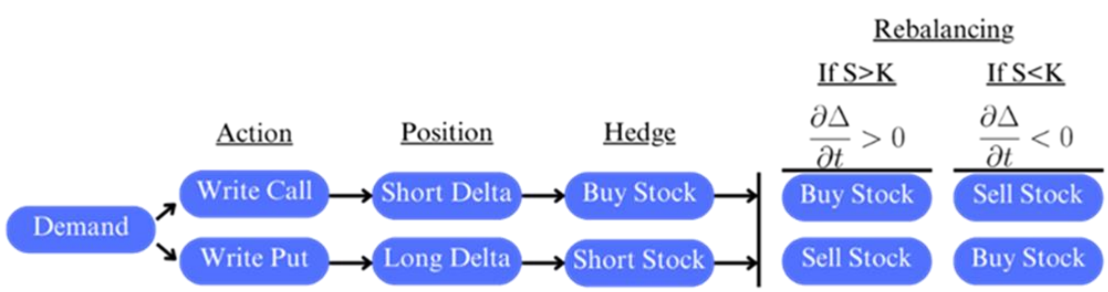
Figure 1.3 – Charm of Call Option



Charm implies that option delta is predictable over time. By this fact, price pressure from delta hedging is also predictable, given the net charm position of hedgers. A long position in stock is a positive delta position. Therefore, a short call is short delta; a short put is long delta, and vice versa. As delta changes, market makers must readjust their stock holdings to retain a delta-neutral position. Depending on the initial delta position of market makers, the charm of the options will imply directional pressure in the underlying stock as market makers trade in the direction of the movement of the delta. This process and resulting price pressure for hedgers' short option positions are described in Figure 1.4.

Figure 1.4 – Price Pressure from Hedging

This figure represents the delta position and corresponding action for parties engaged in delta hedging. These positions and actions assume delta hedgers are short options.



The effect of charm imbalance summarized in Figure 1.4 is necessarily independent of the effect of hedger net gamma position proposed by Ni, Pearson, Poteshman, and White (2021). The effect of charm is purely mechanical and implies price pressure even with static underlying markets. However, this is not to say that the net gamma position does not *influence* the net charm position of liquidity providers. In fact, the directional pressure predicted by the net charm position is increased by the gamma of the traded options. In this way, charm is not a secondary but independent effect.

If public demand is significant enough to create inventory imbalances in the market maker's option portfolio, we should note predictability, as summarized in Figure 1.4. This process implies that large call (put) option volumes will be associated with buying (selling) pressure from market makers contemporaneously. These returns will be large and economically significant as much of the total dollar volume for the life of a delta hedge is the opening of the stock position.

Over time, the delta of the option will evolve in the process described by the option's charm and, thus, will predict the hedging pressure on the underlying stock. Demand for call options with positive (negative) charm implies future buying (selling) pressure as the delta increases (decreases). Conversely, demand in put options with positive (negative) charm means future selling (buying) pressure as the delta increases (decreases).

Notably, many of the predictions of Figure 1.4 are juxtaposed to expectations if options trading were informed. For example, demand for high embedded leverage call options (calls with negative charm) indicates downward price pressure in the delta hedging framework. In contrast, the opposite should be true if trading in the call options is informed, as high leverage calls would be a bullish bet. The differing predictions between the hedging framework presented here and an informed trading hypothesis offer the opportunity to test the relative power of the two channels.

As several previous studies have provided some form of an informed trading explanation[5], heterogeneous results would be interesting.

1.4.2. Hypotheses

I summarize the empirically testable implications of the delta hedging hypothesis as follows:

1. Contemporaneous stock returns will be pressured by option demand through intermediary hedging.
2. Future stock returns will be predictable by proxying for the charm position of option intermediaries.
3. Stock predictability via charm is an increasing function with respect to option gamma.

I validate these hypotheses in the aggregate and in more granular data, allowing for precise trade direction and account of origin identification. While aggregate results speak to the economic magnitude of the price pressure, a study with granular data provides a sharper identification of retail interest and intermediary holdings. Option gamma is the second derivative of the option price with respect to stock price and represents the rate of change of delta. Ceteris paribus, when gamma is larger, rebalancing on delta hedges will be larger. As these price pressures do not necessarily represent information, the impact on prices is transitory and should only have a larger effect when imbalances are of a higher magnitude.

1.5. Data and Important Variable Construction

Aggregate option data is collected daily from Option Metrics and matched with CRSP daily stock files from 2016 – 2022. Account-matched data from the CBOE is collected daily from

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[5] See Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), Ge, Lin, and Pearson (2015), Pan and Poteshman (2006).

2019 to 2021. The relatively short timeframe of this study is due to the limited participation of retail traders pre-2019. Robinhood user holding data is collected from May 5, 2018, to August 13, 2020, from the Robintrack[6] website to document retail equity preferences. Unfortunately, the API used by Robintrack to import user holdings was suspended in August 2020. Factor portfolios are retrieved from Ken French's website for risk-adjusted returns.

1.5.1. Important Variable Construction

To proxy for public demand, I construct the following simple variable that captures abnormal volume in options:

$$E(C/P)OV_{i,t} = \#\ of\ contracts\ traded_{i,t} - \frac{\sum_{t-6}^{t-1} \# conracts\ traded_{i,d}}{5}$$

Excess option volume (EOV) refers to the number of option contracts traded for firm i on day t less a rolling average of the number of contracts traded for firm i on the previous five days[7]. EOV is calculated separately for calls and puts, ECOV, and EPOV at the individual option level. By construction, EOV captures abnormal increases in volume, making it an intuitive measure for capturing option demand and resultant short positions of hedgers. Although simplistic, this measure is advantageous regarding public availability and ease. Further, any private information nested in EOV is very noisy and contains little informational content. Since negative values of EOV have no intuitive meaning, they are set to zero.

Option charm is calculated as:

[6] An excellent description and application of Robintrack data can be found in Welch (2022).
[7] Results using EOV are robust to several choices for number of days used in the rolling average.

$$\frac{\partial \Delta}{\partial t} = \frac{N'(d_1)\, ln\left(\frac{S}{K}\right)}{2\sigma t^{3/2}} \text{ , } where\ d_1 = \frac{log\left(\frac{S}{K}\right)+\left(r+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$$

The sign of charm strictly depends on the characteristics of the traded option. Option deltas and gammas are collected from Option Metrics. EOV is calculated by charm group to proxy for charm position of liquidity providing delta hedgers.

Supposing EOV proxies for written options by liquidity providers, I can then construct net charm and net gamma position by multiplying the short interest of liquidity providers times 100 (as options are written in groups of 100) and option charm and gamma, respectively. Without two-way order flow, we can expect inventory imbalances to be passed through to the underlying stock mechanically, through charm rebalancing, and dynamically, through gamma rebalancing. Because EOV captures abnormal volume by construction, I believe it is reasonable to assume the volume is concentrated on a specific side of the trade, suggesting the ability of liquidity providers to unload inventory quickly is limited.[8]

For comparability to other studies focusing on aggregate option volume, I also include the daily option to stock ratio as a control. I follow Roll, Schwartz, and Subrahmanyam (2010) and construct the option-to-stock ratio as follows:

$$(O/S)_{i,t} = \frac{\#\ of\ option\ trades_{i,t}}{\#\ of\ stock\ trades_{i,t}}$$

Because option volume *causes* stock volume through hedging in the charm model, the O/S ratio will not appropriately capture stock pricing effects and is instead used as a benchmark.

1.5.2. Summary Statistics

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[8] Should a reader find this assertion unconvincing, I validate aggregate results using signed volume in section 1.7.

Summary statistics and correlations are presented in Table 1.2. The differential information captured by the O/S ratio and EOV is underscored by their respective standard deviation in Panel A. The standard deviation of the O/S ratio is low as, by construction, option volumes are normalized by stock volume. In contrast, EOV has a standard deviation of over 13,000 contracts a day. The high variability of EOV is critical as I assume *abnormal demand* is likely to be written by hedging liquidity providers. Hoarding events on an option will cause substantial spikes in EOV that are likely to be written and subsequently hedged by option liquidity providers. Because these spikes are unexpected and large in magnitude, the pass through to the stock market causes transitory price pressure. The heightened variability of EOV after commission free trading can be seen in Figure 1.5. The increase in the volatility of EOV is most likely due to retail participation in the options market, which further suggests EOV captures public long interest in an option and, thus, written short positions by liquidity providers.

Figure 1.5 – Variability of EOV

This figure plots the aggregate EOV in millions of monthly option trades from 2016 to 2022 by calls and puts. The red line plots calls and puts the green line. The black vertical line denotes the institution of commission free trading by Charles Schwab.

The hedging relationship can also be seen in Panel B of Table 1.2. While the O/S ratio has a relatively low correlation with stock volume, EOV and excess stock volume (ESV) correlate at 25.12%. The relative correlations provide evidence that option volume causes stock volume through hedging in a manner not captured by the O/S ratio.

Unablated results suggest the relationship between stock market volume and options market volume has increased by 13% since the institution of broad commission free trading. Further, a Chow test indicates a structural break in the time series of options to stock volume after the Schwab decision in October 2019 with an F-statistic of 44.951. This relation can be understood through intermediary hedging outlined in section 1.4, whereby option inventory imbalances due to the increased long volume are passed through to the underlying stock.

Table 1.2 - Summary Statistics and Correlations

Summary statistics and correlations are calculated from a merged panel of Option Metrics and CRSP daily data from 2016 - 2022. EOV and ESV are computed as daily option/stock volume less a rolling average of the previous five days. The O/S ratio is calculated as daily option volume divided by daily stock volume.

Panel A – Summary Statistics

Variable	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile	N
O/S	0.00092	0.005576	0.00005	0.00022	0.00077	4,263,105
ECOV	4.5	13,766	-157	-16	28	4,263,105
EPOV	0.5	13,608	-124.4	-13.7	22.3	4,263,105
ESV	-2,163	3253739	-208,433	-27,659	96,937	4,263,105

Option Volume	4,381	40,805	18	115	761	4,263,105
Stock Volume	2275000	8143250	247,900	653,300	1,787,000	4,263,105

Panel B - Correlations

Correlation	Stock Volume	EOV	ESV	O/S
Stock Volume	1	0.0469	0.1386	0.0051
EOV	0.0469	1	0.2512	0.0128
ESV	0.1386	0.2512	1	-0.0031
O/S	0.0051	0.0143	-0.0031	1

1.6. Aggregate Stock Predictability

The first two implications of the delta hedging hypothesis summarize empirically testable patterns in stock price as a function of option volume. These patterns should be consistent with hedging pressure by net short option intermediaries.

1.6.1. Contemporaneous Returns

Suppose liquidity providers are net short options and delta hedge. In that case, higher ECOV (EPOV) will predict higher (lower) synchronous returns as hedgers must buy (sell) the underlying stock to enter the hedge. To test for this relation, I sort stocks by:

$$\$Enter_{i,t} = \sum EOV_{o,t} * Stock\ Price_{o,t} * Option\ Delta_{o,t} * 100$$

$Enter approximates the short interest of liquidity providing delta hedgers and estimates the dollar amount needed to enter a delta hedge. For example, consider a market maker short ten call options (proxied by EOV) with an underlying price of $60 and a delta of 0.8. Because options are executed in orders of 100, the market maker must purchase 10*60*(0.8)*100 = $48,000 worth of the underlying stock to hedge directional exposure. Because calls/puts have a positive/negative delta, $Enter will correlate positively to stock return. Table 1.3 sorts stocks into deciles based on their respective values of $Enter.

Table 1.3 – Contemporaneous Stock Return by $Enter

$Enter is calculated by multiplying the EOV of an option times stock price, option delta, and 100. N denotes the number of observations, return is the average daily return, and trades represent the average number of stock trades per day per firm. T-statistics are reported from a one-sample t-test per group where the theoretical mean is the full sample daily return. The sample period is from January 2016 – December 2022.

Decile	N	Return	t-stat	Trades
1 (Lowest)	380,037	-0.00523	-147	10,101
2	380,037	-0.00315	-97.6	4,735
3	380,037	0.00000005	-28.5	2,355
4	380,036	-0.000138	-28.7	2,462
5	380,036	-0.000647	-40.1	3,011
6	380,036	-0.000298	-26.9	3,146
7	380,036	0.00105	-1.68	4,302
8	380,036	0.00192	16.2	5,743
9	380,036	0.00318	41.5	8,039
10 (Highest)	380,036	0.00515	79.5	14,299
High-Low		0.01038	102.6	4,198

Per Table 1.3, equal-weighted returns increase nearly monotonically by $Enter. Firms in the lowest decile of $Enter have average returns of -0.523% per day, and firms in the highest decile have average returns of 0.515% per day. Although impossible to recreate given that returns are contemporaneous, a long-short strategy on $Enter would produce returns of 1.038% per day.

Table 1.4 – Synchronous Returns by ECOV and EPOV Decile

This table presents the daily summary statistics of firms sorted by ECOV (Panel A) and EPOV (Panel B) levels. EC(P)OV is the daily call (put) volume on an underlying stock minus a rolling average of the previous five trading days. N denotes the number of firm day observations within each decile sort, return is the average daily return of the associated decile, and trades indicate the average number of stock trades per day per firm in the associated decile. T-statistics are reported from a one-sample t-test per group where the theoretical mean is the full sample daily return. The sample period is from January 2016 – December 2022.

Panel A – ECOV

Decile	N	Return	t-stat	Trades
1 (Lowest)	428,927	-0.00232	-80.1	14,569
2	428,373	-0.00176	-71.7	11,478
3	427,863	-0.00143	-64.2	10,039
4	427,365	-0.00109	-55.4	9,179
5	426,814	-0.00069	-45.2	8,717
6	425791	-0.000158	-31.2	8,285
7	425,244	0.000955	-3.92	8,853
8	424,732	0.0025	26.7	10,337
9	424,237	0.00476	60.4	12,784

10 (Highest)	423,759	0.012	105	22,104
High-Low		0.01432	152.94	7,535
Panel B – EPOV				
1 (Lowest)	371,328	0.00115	0.318	16,378
2	370,763	0.0011	-0.617	13,249
3	370,240	0.00118	1.07	11,570
4	369,726	0.000987	-3.15	10,670
5	369,144	0.000988	-3.13	10,036
6	368,206	0.000726	-8.81	9,695
7	367,709	0.000633	-9.82	10,340
8	367,182	0.000223	-16.1	12,096
9	366,706	-0.000291	-21.6	14,931
10 (Highest)	366,189	-0.00112	-20.3	24,964
High-Low		-0.00227	-78.3	8,586

The relationship between $Enter and stock return in Table 1.3 is also broadly consistent with informed option trading. Because option and stock markets are complementary, traders will rationally allocate some of their investment to the stock market and some to the option market when new information arises. In this way, higher volumes in the options market for calls (puts) will indicate good (bad) news for the stock and can cause the observed relation in Table 1.3. However, if this is the case, one would rationally assume that demand driven pricing effects should be similar across calls and puts. To compare, Table 1.4 sorts stocks into deciles by their contemporaneous level of excess call and put option volume.

Interestingly, the relationship between option volume and stock return grows stronger when focusing exclusively on call options. By simply sorting stocks into deciles based on call option volume, a contemporaneous long-short strategy produces returns of 1.432% per day from 2016 – 2022, roughly six times greater than the returns generated by recreating the same strategy with puts. In an informational context, this is puzzling, given that puts should have a *higher* correlation with the price discovery of stocks due to short sale constraints in the stock market. The stronger correlation of call option volume with contemporaneous return is therefore likely due to vastly larger volumes in call vs. put options and resultant hedging flow. Further, the call long-short strategy annual returns increase by 21% after the broad adoption of commission free trading in 2019. Back of the envelope calculations suggest that hedging flow proxied by $Enter comprises roughly 25% of total stock volume from 2019 – 2022.

1.6.2. Predictable Future Returns

After liquidity providers make contemporaneous trades to open a delta hedge, future rebalancing trades should be predictable by the charm of short option inventory. To test future predictability and the ability of EOV to proxy for short positions, I generate EOV in four charm subgroups per underlying stock. I summarize the groups, their delta implication, and their price pressure predictions below:

1. Negative Charm Call Options = Decreasing Delta = Selling Pressure
2. Positive Charm Call Options = Increasing Delta = Buying Pressure
3. Negative Charm Put Options = Increasing Delta = Buying Pressure
4. Positive Charm Put Options = Decreasing Delta = Selling Pressure

If EOV captures delta hedging and impacts pricing, more extreme values of charm will indicate more significant changes in delta and, thus, more price pressure. In addition, the predictive ability of charm should be an increasing function of gamma since gamma represents the rate of change of delta. To account for this effect, I also compute the average option gamma of each charm group.

1.6.2.1. Net Pressure

Hedging pressure generated from option inventory imbalance in different charm categories will sometimes compete with one another at the stock level. For example, excess short inventory in *both* calls and puts with negative charm imply opposite directional pressure and thus will net out in the aggregate. Due to this, I proxy for the complete inventory of liquidity providers by constructing a stock-level net hedge. Net hedge sums together EOV for all charm subgroups that indicate future buying pressure less EOV for all subgroups that indicate future selling pressure:

$$\begin{aligned} Net\ Hedge_{i,t} = {} & ECOV\ Positive\ Charm_{i,t} + EPOV\ Negative\ Charm_{i,t} \\ & - ECOV\ Negative\ Charm_{i,t} - EPOV\ Positive\ Charm_{i,t} \end{aligned}$$

By construction, net hedge should positively correlate with future returns as hedgers rebalance their positions according to their net inventory charm. Individual option charm values are weighted by volume, and by gamma times volume. Gamma weighting should increase the magnitude of predictability as higher gamma implies larger absolute rebalancing trades. To test this relation, I regress the following model:

$$Ret_{i,t+1} = Net\ Hedge_{i,t} + Gamma\ Weighted\ Net\ Hedge_{i,t} + Controls + \epsilon_{i,t}$$

This model tests the average change in the next day returns for the net change in EOV over charm subgroups. Table 1.5 presents the results.

Table 1.5 – Aggregate Return Predictability

This table analyzes next day return predictability as a function of option volume in charm subgroups. Columns 1 and 2 estimate separately for net hedge and gamma weighted net hedge:

$$Ret_{i,t+1} = Net\ Hedge_{i,t} + Gamma\ Weighted\ Net\ Hedge_{i,t} + Controls + \epsilon_{i,t}$$

Where Net Hedge is constructed as $\text{ECOV Positive Charm}_{\text{i,t}} + \text{EPOV Negative Charm}_{\text{i,t}} - \text{ECOV Negative Charm}_{\text{i,t}} - \text{EPOV Positive Charm}_{\text{i,t}}$, and gamma weighted net hedge is weighted by the average gamma of the subgroups. Daily observations span from January 1, 2016 – December 31, 2022. Controls include lags of return, market return, stock volume, and stock size. T-stats are reported in parentheses. Coefficients represent a one standard deviation change.

	Dependent Variable:	
	Next-Day Stock Return (bps)	
	(1)	(2)
Net Hedge	2.97	
	(15.587)	
Gamma Weighted Net Hedge		41.1
		(11.874)
Controls	YES	YES
Observations	587,926	587,926
R^2	0.141	0.141

The coefficients on net hedge and gamma weighted net hedge in Table 1.5 are positive and highly significant in both specifications. A one standard deviation increase in volume weighted net hedge is associated with a 2.97 bps increase in the stock's subsequent day returns. Gamma weighting the EOV in charm subgroups dramatically increases the magnitude of the coefficient to 41.1 bps. The large increase in magnitude when gamma weighting is consistent with hedging pressure from option liquidity providers hedging net short exposure in the options market, as higher gammas indicate larger absolute changes in delta. Further, the significance of the hedge coefficients dissipates past a one-day lead of returns. Transitory pressure is consistent with mechanical effects from hedging, but not informed trading.

1.6.2.2. Decomposed Pressure

Differential price impacts from EOV in different charm groups will be informative for two main reasons:

1. Because retail option trading is highly condensed in specific options, liquidity providers likely have higher imbalances on specific equities. This relationship lends itself to higher directional pressure consistent with long option retail traders.
2. Decomposing net pressure to charm subgroups allows for a direct comparison of the informational explanation of price predictability to mechanical hedging.

To test these propositions, I regress the following model:

$$Ret_{i,t+1} = \sum Charm\ Groups_{i,t} + \sum Average\ Group\ Gamma_{i,t} + \left(\sum Charm\ Groups_{i,t}\right) * \left(\sum Average\ Group\ Gamma_{i,t}\right) + Controls + \epsilon_{i,t}$$

If EOV proxies for the short inventory of hedgers, the coefficients on charm subgroups should be significant and sign in the direction predicted by delta hedge rebalancing with increased magnitude when interacted with average group gamma. Table 1.6 reports the results.

Table 1.6 – Decomposed Price Pressure

This table analyzes next day return predictability as a function of option volume in disaggregated charm subgroups. Columns 1 and 2 estimate without and with gamma interaction coefficients:

$$Ret_{i,t+1} = \sum Charm\ Groups_{i,t} + \sum Average\ Group\ Gamma_{i,t} + \left(\sum Charm\ Groups_{i,t}\right) * \left(\sum Average\ Group\ Gamma_{i,t}\right) + Controls + \epsilon_{i,t}$$

Where charm groups refer to the EOV within respective charm subgroups, and average option gamma is calculated for each group. Controls include lags of return, market return, stock volume, and stock size. Daily observations span from January 1, 2016 – December 31, 2022. T-stats are reported in parentheses. Coefficients represent a one standard deviation change.

	Dependent Variable:	
	Next-Day Stock Return (bps)	
	(1)	(2)
ECOV Negative Charm	-13.766	-10.3245
	(-12.045)	(-8.997)
ECOV Positive Charm	-2.0649	-1.3766
	(-1.421)	(-0.0675)

EPOV Negative Charm	0.9788	13.608
	(0.6585)	(0.8525)
EPOV Positive Charm	2.0412	12.247
	(1.9225)	(2.3695)
ECOV Negative*Avg Gamma		-27.532
		(-4.349)
ECOV Positive*Avg Gamma		55.064
		(2.251)
EPOV Negative*Avg Gamma		-34.02
		(-2.112)
EPOV Positive*Avg Gamma		-115.67
		(-5.213)
Controls	YES	YES
Observations	587,926	587,926
R^2	0.142	0.143

All but one of the marginal effects of charm subgroups in Table 1.6 column two enter as significant, with the sign hypothesized by the delta hedging hypothesis. In the standalone specification of model one, only the coefficient on ECOV negative charm is statistically significant (t-stat of -12.045). Negative charm call options are the highest traded options by dollar volume and comprise the vast majority of all option trade in the zero-commissions era.

Results are uniformly higher in magnitude and significance for larger absolute values of charm and gamma, which indicates increased hedging flow to the stock. To illustrate the economic impact of these coefficients, let us consider the marginal effect of EOV in negative charm call options. In line with the predictions of the delta hedging hypothesis, demand in this group of options should indicate future selling pressure. Indeed, the marginal effect on next day bps returns of an increase in EOV for this group is -10.3245 – 27.532 *(Average Gamma). Therefore, a one standard deviation increase in EOV for negative charm call options equates to a 10.3 bps decrease in subsequent day returns for options with zero average gammas or a 37.86 bps decrease as gamma approaches one. Conservatively, such a decrease represents a 21.55 basis point drop from the total sample average, or a 193% decrease.

The coefficients are consistent with retail option demand driving stock predictability. The most significant and largest magnitude coefficients are on the highest retail demanded options, negative charm calls and positive charm puts. Section 1.3 shows these options are traded much more than any other subgroup following broad access to commission free trading. As retail traders hoard on these options, liquidity providers short the options and hedge exposure consistent with the charm and gamma of the options. Further, the coefficients on these are opposite to what would be expected with an informational explanation. It is difficult to understand a negative coefficient on excess demand in call options if trading was informed. This result suggests that hedging pressure from liquidity providers can, at the least, mute price movement from informed option trade. This effect reduces the cleanliness of using aggregate option volumes to infer directional information.

1.6.2.3. Hedging Portfolios

I now construct a trading strategy based on relative option volumes with no private information. Because most of the increase in options volume is concentrated on short term calls and puts, I consider EOV in those option groups. I sort stocks daily into two groups based on median, quartiles, and deciles, weighted strictly by EOV and gamma weighted. I then construct a zero-investment portfolio by going long the highest group and short the lowest group. EOV in short term calls (puts) implies forward selling (buying) pressure per delta hedging. Table 1.7 reports excess returns from this strategy in bps.

Table 1.7 - Zero Investment Portfolio on Charm Signal (Daily Rebalancing)

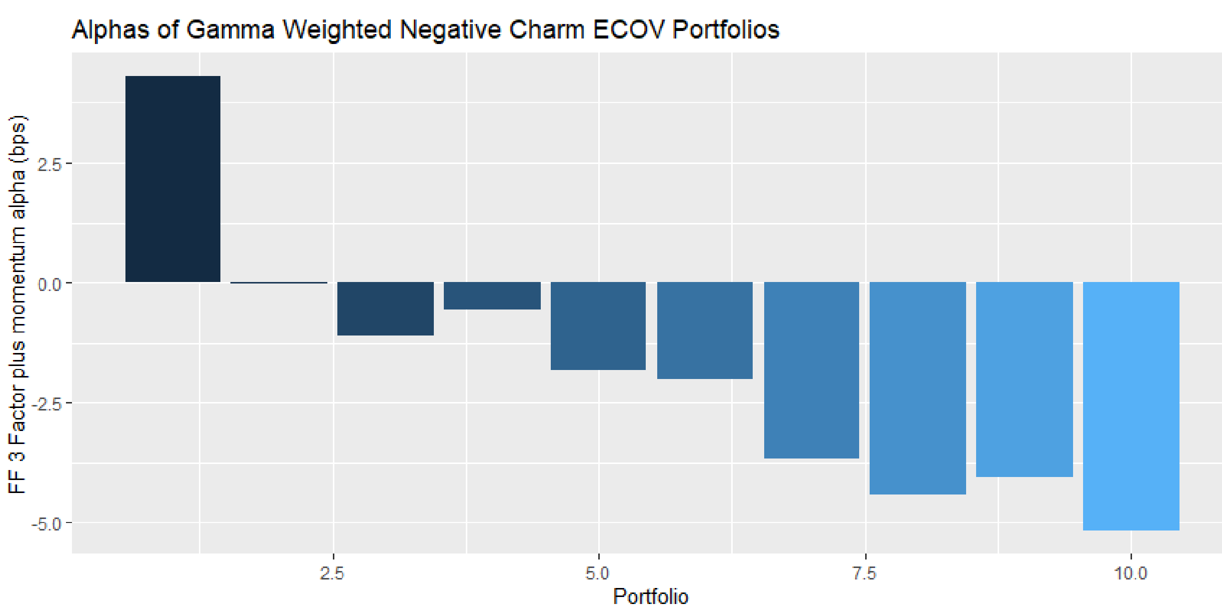
This table presents returns of a zero-investment portfolio for median, quartile, and decile sorts based on 0-2 week EOV in calls and puts. The top panel is equally weighted; the bottom panel is weighted by the gamma of the options. Portfolios are rebalanced daily from January 1, 2016, to December 31, 2022. T-statistics are reported from a one sample t-test per group where the theoretical mean is the total sample daily return. Excess return is defined as portfolio return less the daily risk-free rate.

	Median		Quartiles		Deciles	
	Calls	Puts	Calls	Puts	Calls	Puts
Average Excess Return (bps)	-1.755	0.357	-3.18	0.476	-6.353	1.2
t-stat	(-1.829)	(0.39)	(-2.239)	(0.33)	(-2.808)	(0.443)
	Gamma Weighted Charm Signal					
Average Excess Return (bps)	-3.135	0.947	-5.033	0.325	-7.755	0.617
t-stat	(-3.058)	(0.99)	(-3.298)	(0.209)	(-3.246)	(0.217)

The returns from the portfolios in Table 1.7 are highly significant for call options and increase in magnitude when weighting observations by gamma and choosing more extreme sorts. A strategy that longs stocks in the lowest decile of gamma weighted charm and shorts stocks in the highest decile generates an excess return of 7.755 bps per day or 19.5% per annum, unadjusted for fees or trading costs. Since retail traders overwhelmingly trade call options with negative charms, these results are consistent with downward stock price pressure caused by intermediary hedging.

The returns of the portfolios also survive risk adjustment. Specifically, I regress the daily returns of the gamma weighted ECOV portfolios against the Fama French 3-factor model plus momentum from 2015 - 2022. Figure 1.6 presents the alphas of each portfolio.

Figure 1.6 – Alphas of Gamma Weighted ECOV Portfolios



Alphas are highly significant for 7/10 of the decile portfolios and decrease as ECOV in negative charm options increases. Again, the decrease is consistent with net short liquidity providers selling stock to rebalance their hedge.

1.7. Connection to Retail Option Trade

Several pieces of evidence point to retail trade as the driving force in liquidity provider inventory imbalance. Per Table 1.1, the option trading patterns of institutional and professional investors have not materially changed after the broad adoption of zero commission trading. Further, the concentration of options volume in short term out of the money calls in high attention stocks is broadly consistent with the documented behavioral patterns of retail traders. As further evidence for this proposition, I directly link option volume and price pressure to retail activity.

1.7.1. Robinhood User Holdings

Using the Robintrack database, I collected Robinhood user equity holdings from May 5, 2018, to August 13, 2020. Although Robintrack does *not* contain option data, it is likely that equity holdings correlate highly with option holdings for retail traders. While there is no concrete way of testing the relationship, I believe it is a reasonable assumption. To test the relationship between option volumes and Robinhood user holdings, I construct the following model:

$$Ret_{i,t+1} = Dec(ECOV)_{i,t} + Hold\_FD_{i,t} + Dec(ECOV)_{i,t} * Hold\_FD_{i,t} + Controls + \epsilon_{i,t}$$

Where $\mathrm{Ret}_{\mathrm{i,t+1}}$ refers to a one-day lead of returns for firm i on day $\mathrm{t}+1$. $\mathrm{Dec(ECOV)}_{\mathrm{i,t}}$ measures a stock's decile of excess call option volume per day. I focus on call options in this test as they represent a bullish position and have a more intuitive relationship with equity holdings than put options. $\mathrm{Hold\_FD}_{\mathrm{i,t}}$ is calculated as $\mathrm{Daily\ RH\ Holders}_{\mathrm{i}} - \mathrm{lag(Daily\ RH\ Holders)}_{\mathrm{i}}$ for each stock i on day t, creating a first difference of the holdings of Robinhood users. Hold_FD represents aggregate changes in Robinhood user holdings and proxies for positive retail sentiment on a stock. Because retail investors concentrate their options trades in short term out of the money call options and liquidity providers delta hedge their short call option exposure, I expect a negative coefficient on the interaction term $\mathrm{Dec(ECOV)}_{i,t} * \mathrm{Hold\_FD}_{i,t}$, as these options have negative charm and imply selling pressure from rebalancing. This coefficient is key as it highlights the liquidity provision of hedgers to long demand from retail traders. Table 1.8 presents the results.

Table 1.8 – ECOV and Robinhood Holdings

The full model in column 5 with all controls is:

$$Ret_{i,t+1} = Dec(ECOV)_{i,t} + Hold\_FD_{i,t} + Mkt_t + SMB_t + HML_t + MOM_t + ESV_{i,t} +$$
$$Illiq_{i,t} + Ret_{i,t} + Dec(ECOV)_{i,t} * Hold\_FD_{i,t} + \epsilon_{i,t}.$$

Where $\mathrm{Ret}_{i,t+1}$ is a one-day lead of returns for firm i and $\mathrm{ECOV}_{i,t}$ and $\mathrm{ESV}_{i,t}$ are measures for a stock's excess option /stock volume. Ken French's website gathers Fama French 3 factor portfolio returns plus momentum. The Amihud (2002) measure is constructed as $\mathrm{Illiq}_{i,t} = \frac{|\mathrm{R}_{i,t}|}{\mathrm{Vol}_{i,t}}$. Hold_FD is constructed as $\text{Weekly RH Holders}_{i,t} - \text{lag(Weekly RH Holders)}_{i,t}$. Huber-White robust standard errors are used with four lags. T-statistics are reported in parentheses. Coefficients represent a one standard deviation increase.

	Dependent variable:				
	Next-Day Stock Return (bps)				
	(1)	(2)	(3)	(4)	(5)
Dec (ECOV)	-4.01	-4.01	-4.01	-4.01	-4.01
	(-49.26)	(-48.26)	(-49.06)	(-49.87)	(-48.06)
Hold_FD		0.641	0.641	0.641	0.641
		(45.57)	(45.28)	(45.26)	(45.67)

Dec (ECOV)*Hold_FD		-0.101	-0.101	-0.101	-0.101
		(-32.051)	(-32.16)	(-32.615)	(-32.674)
Controls	YES	YES	YES	YES	YES
Observations	374,970	370,834	370,834	370,834	370,834
R^2	0.017	0.017	0.017	0.018	0.018

The decile of ECOV enters every regression as negative and highly significant. Firms moving one decile higher in ECOV experience a four-basis point decrease in the next week's return. This result implies that firms in the highest decile of ECOV have weekly returns 40 basis points lower than firms in the lowest decile of ECOV, even when including all controls. The interaction term of Hold_FD and ECOV enters as negative and highly significant despite the standalone term of Hold_FD having a significant positive relation with returns.[9] The marginal effect of ECOV on return in bps is -4.1 – 0.101*(Hold_FD). This effect implies returns will decrease 14 bps for a modest increase in Robinhood holdings of 100 shares if a stock's EOV decile increases by one. In an informational context, it is puzzling why Hold_FD and the interaction term of Hold_FD and ECOV have opposite signs. If private information or stock picking ability drives the positive relation between retail holdings and stock performance, option trades should also display this relation, which is not observed empirically. Instead, these results are consistent with option liquidity providers servicing retail demand and subsequently creating downward price pressure in the underlying stock through hedging.

[9] Welch (2022) also notes stock picking ability of retail traders in their direct equity investments.

1.7.2. Sharp Identification of Hedgers and Retail Trades

Although the return relations in the aggregate are consistent with liquidity provider hedging, further rigor is needed to identify the source of return predictability. In this section, I document two stylized facts which support the conclusions drawn from the aggregate relationships.

1. Options spreads are sensitive to market maker inventories and charm imbalance, and retail traders are predominantly insensitive to option price.
2. Market makers' rebalancing trades pressure stock returns, and the direction of these trades is predictable given the net charm position of delta hedgers.

These propositions are tested with the Chicago Board of Options Exchange (CBOE) Open-Close Volume Summary. This data provides aggregated volume bucketed by account of origin (customer, professional, broker-dealer, and market maker), buy/sell, and open/close.

1.7.2.1. Hedger Imbalance and Option Spreads

In addition to the dynamic hedging techniques (delta hedging) summarized in section 1.4, market makers often adjust option spreads when their inventory becomes imbalanced. As imbalanced inventory exposes market makers to higher risk, spreads can be widened to discourage further trading in the direction that exacerbates the inventory imbalance. Higher spreads on options also compensate market makers for carrying more inventory risk as they represent higher premiums on facilitated trades.

A natural question to the documented aggregate price pressures in section 1.6 is why these inventory imbalances are not absorbed at the stock level if they are predictable. The predictability of returns at the stock level relies on two key assumptions. First, retail spikes in trading in the option market are largely unexpected¸ and second, retail option traders are insensitive to transaction costs (option spread). Because retail spikes are not driven by one large trade, aggregate increases in costs are not absorbed by any singular party and are instead broken up among many traders. This insensitivity can further create inventory imbalance. To test these proposed relations empirically, I present the following model:

$$SD\ of\ Option\ Spreads_{i,t} = \alpha + |mm\ net\ charm|_{i,t} + |bd\ net\ charm|_{i,t} + \ retail\ long_{i,t} + pro\ long_{i,t} + \sum Controls + \ \varepsilon_{i,t}$$

MM / BD net charm is constructed as the short inventory of each party in a respective option multiplied by the option charm, underlying stock price, and 100[10]. This measure is then aggregated to the stock level (i) to represent the dollar amount needed to rebalance a delta hedge on day (t). Therefore, a negative value would imply the need to short stock to rebalance a position. Retail/pro bull is the number of open long positions the respective party holds. Controls include several MM / BD charm lags, SD of option spreads, and group and time fixed effects. Table 1.9 reports the results.

Table 1.9 – Hedger Charm Relation to Option Spreads

This table reports the results of the regression: $\mathrm{SD\ of\ Option\ Spreads}_{i,t} = \alpha + |\mathrm{mm\ net\ charm}|_{i,t} + |\mathrm{bd\ net\ charm}|_{i,t} + \ \mathrm{retail\ long}_{i,t} + \ \mathrm{pro\ long}_{i,t} + \sum \mathrm{Controls} + \ \varepsilon_{i,t}$. The dependent variable measures the volatility of option spreads on a given underlying stock throughout a trading day. MM / BD net charm is constructed as the short inventory of each party in a respective option multiplied by the option charm, underlying stock price, and 100. This measure is then aggregated to the stock level (i) to represent the dollar amount needed to rebalance a delta hedge on day (t). Retail/pro long is the number of open long positions the

[10] This measure is multiplied by 100 as option contracts are traded in orders of 100.

respective party holds. Controls include five lags of MM net charm, five lags of SD of options spread, and unit and time fixed effects in certain specifications. Coefficients represent a one standard deviation increase.

	Dependent Variable:			
	SD of Option Spreads			
	(1)	(2)	(3)	(4)
| MM Net Charm |	0.10931	0.10929	0.06300	0.02114
	(126.52780)	(126.529)	(62.5447)	(30.41469)
| BD Net Charm |			-0.05917	0.00328
			(-9.76640)	(2.32625)
Retail Long		-0.00651	-0.00239	0.00247
		(-12.1858)	(-10.9243)	(5.76663)
Pro Long			-0.00029	-0.00068
			(-0.51455)	(-1.4097)
Controls	YES	YES	YES	YES
Unit Fixed Effects	NO	NO	NO	YES
Time Fixed Effects	NO	NO	NO	YES
Observations	708,514	708,514	708,514	708,514
R^2	0.0497	0.0500	0.1331	0.0141

Results from Table 1.9 support the proposition that option spreads are sensitive to market maker charm position and end-user demand. The coefficient on the absolute value of MM net charm position is positive and highly significant in every specification. These coefficients indicate between a two and ten cent increase in the standard deviation of option spreads for a one standard deviation increase in MM net charm. The ability of the MM to adjust spreads can be noted in the significant increase in magnitude and statistical significance compared to the coefficients for broker dealer net charm.

Spreads are also sensitive to the type of option trader. Coefficients on net retail long positions are statistically significant in every specification, while the coefficient on professional trader long positions is never significant. Further, while retail long positions are negatively related to spread in the pooled models, the relation flips to positive with the inclusion of unit and time fixed effects. While one would typically expect end user demand to lead to tighter spreads naturally, this positive coefficient on retail long indicates that after controlling for the type of option, retail traders are insensitive to transaction costs and thus create more volatile spreads.

The coefficients on MM net charm and retail long positions provide evidence for a passthrough effect in risk management from the option to the stock market. The MM cannot fully balance inventories within the options market and must adjust option spreads, allowing for greater flexibility in dynamic hedging in the underlying stock market. When risk-seeking retail traders begin to hoard on specific options, they are largely insensitive to option price and create significant imbalances in MM portfolios that must be hedged via the underlying.

1.7.2.2. Hedger Imbalance and Stock Return Predictability

If inventory imbalances in the options market are passed through to the underlying stock market, returns should be predictable with respect to hedge rebalancing. Following Barbon and Burashi (2020), I consider market makers and broker dealers as likely to be engaged in delta hedging. To test for stock return predictability as a function of delta hedging, I regress the following model:

$$Ret_{i,t} = hedger\ net\ charm_{i,t} + retail/pro\ long_{i,t} + high\ imbalance\ hedger_{i,t} +$$
$$hedger\ net\ charm_{i,t} * retail/pro\ long_{i,t} * high\ imbalance\ hedger_{i,t} + \sum Controls + \ \varepsilon_{i,t}$$

Hedger net charm is constructed as MM net charm plus BD net charm and is aggregated to the stock level (i) to represent the dollar amount needed to rebalance a delta hedge on day (t). For example, if the hedger net charm was -$100, hedgers would need to short $100 worth of the underlying stock to rebalance their delta position. High imbalance hedger is an indicator variable equal to one if the hedger's short option interest on a day is in the top decile for that calendar year. The model is split into two specifications with retail and pro traders to test for heterogeneous results based on the account of origin. The triple interaction term of hedger net charm, retail long, and high imbalance is of particular interest as it indicates the effect of hedge trades when inventories are highly imbalanced in conjunction with high retail demand. The delta hedging hypothesis predicts this coefficient should be positive and significant as hedgers rebalance their trades due to imbalanced inventories driven by retail demand. Table 1.10 presents the results from this model.

Table 1.10 – Hedger Net Charm and Stock Returns

This table reports the results of the regression: $\mathrm{Ret_{i,t}} = \mathrm{hedger\ net\ charm_{i,t}} +$ $\mathrm{retail/pro\ long_{i,t}} + \mathrm{high\ imbalance\ hedger_{i,t}} + \mathrm{hedger\ net\ charm_{i,t}} * \mathrm{retail/pro\ long_{i,t}} *$

high imbalance $\text{hedger}_{i,t} + \sum \text{Controls} + \varepsilon_{i,t}$. Hedger net charm is constructed as MM net charm plus BD net charm and is aggregated to the stock level (i) to represent the dollar amount needed to rebalance a delta hedge on day (t). High imbalance hedger is an indicator variable equal to one if the hedger's short option interest on a day is in the top decile for that calendar year. This model is split into two specifications with retail and pro traders to show heterogeneous results based on the account. Controls are 3-day lags of stock return, Amihud illiquidity, O/S ratio, option volume, stock volume, and market return. Coefficients represent basis point increases for a one standard deviation increase.

	Dependent Variable:	
	Stock Return (bps)	
	(1)	(2)
Hedger Net Charm	-1.11180	-0.99045
	(-1.36632)	(-0.93510)
Retail Long	-37.91351	
	(-49.41058)	
Pro Long		-1.85304
		(-3.26531)
High Imbalance Hedger	-10.39614	-9.65696
	(-4.87163)	(-4.52309)
Hedger Net Charm*Retail Long*High Imbalance	2.87404	
	(15.30288)	

Hedger Net Charm*Pro Long*High Imbalance		0.33895
		(0.62224)
Controls	YES	YES
Observations	1,259,373	1,259,373
R2	0.10780	0.10267

The results from Table 1.10 help to illustrate the differential effects of retail and professional trade in the options market. The magnitude of the effect of retail long options positions on stock returns is roughly twenty times greater than that of professional trade. A one standard deviation increase in retail long option positions is equivalent to a 37.9 basis point decrease in the next day's stock return, consistent with the aggregate level estimates in section 1.6 and highly statistically significant. Unconditional on option trading, retail traders have been shown to make good stock predictions; Welch (2022) shows from mid-2018 to mid-2020, an aggregated crowd consensus portfolio (a proxy for the household-equal-weighted portfolio) had both good timing and good alpha. The differing predictions of retail stock and option trade can be understood through the hedging trades of option intermediaries.

Additional evidence indicates that hedging pressure from parties servicing retail order flow significantly contributes to the negative relation of retail long option positions and stock returns. The coefficient on high imbalance hedger is significant at the 1% level and indicates a roughly 10 basis point decrease in stock return when hedgers are in the top decile of inventory imbalance for a calendar year, consistent with negative charm inventory imbalance. Further, the coefficient on the triple interaction term of hedger net charm, retail long, and high imbalance is positive and highly significant, compared to an insignificant coefficient when retail long is substituted for professional traders. Because retail traders overwhelmingly purchase calls with negative charm, rebalancing delta hedges by parties short this demand creates short lived downward price pressure in the stock, and the observed relations in Table 1.10. In all, these results indicate that mechanical pressure from net short intermediaries servicing retail option demand results in stock return predictability and validate conclusions drawn from using proxies for short market maker inventory in the aggregate.

1.8. Conclusion

I provide evidence of a significant and persistent relationship between the net charm position of option liquidity providers and underlying stock returns. This relation is consistent with the mechanical rebalancing of hedges of intermediaries in the options market servicing long retail demand. The charm effect is distinct from gamma as it is purely mechanical and exists even with static underlying stock price processes.

Since the broad institution of commission free trading in late 2019, retail option trading has exploded in popularity. Total option volume has increased by roughly 67% year over year. Further, the increase in options volume is concentrated primarily in short-term call options, as these options serve as a gambling preference for retail traders. The total dollar volume of 0 – 2 weeks to expiration options is roughly $500 million greater per month than all other expiry classifications combined.

Due to these large increases in long demand, liquidity providers in the options market have been forced into net short option positions. In the absence of two-way order flow, intermediaries have been forced to hedge inventory imbalance risk exposure in the underlying stock market. The price pressure caused by hedging flow is observable using both aggregate proxies and signed volume data that identifies the account of origin.

In the aggregate, the contemporaneous stock price can be pressured by as much as 50 bps based on a proxy for net short option liquidity providers entering a delta hedge. This pressure is much more significant when focusing exclusively on call options due to vastly higher call option volume relative to put option volume post commission free trading. Estimates suggest that hedging flow comprises roughly 25% of total stock volume from 2019 – 2022. Future stock returns are also pressured by the rebalancing of hedges. Subsequent day returns are pressured by 40 bps based on the net charm position of option liquidity providers. Again, this predictive power is highly concentrated in short term call options.

Evidence suggests that long retail demand in the options market ultimately drives aggregate stock pressure. Robinhood user holdings in stock are strongly predictive of lower future returns when considering abnormal call option volume in the stock, despite Robinhood users' generally good stock picking ability. Retail option trade is also shown to be directly related to lower future stock returns by using signed account data from the CBOE. A one standard deviation increase in long option holdings by retail investors correlates with a 40 bps decrease in subsequent day returns, consistent with aggregate proxies for the net charm position of liquidity providers. This evidence is consistent with net short option liquidity providers hedging exposure in the underlying stock market and creating predictable price action.

Chapter 2

Selling Call Options to Robinhood Investors

2.1. Introduction

The depth and liquidity of the single-name equity options market have increased substantially in recent years due to the heightened participation of retail investors. The public face of this movement is the popular retail brokerage Robinhood (RH), which primarily caters to young, technologically advanced, but beginner investors. According to the NYSE[11], retail option trading has comprised around forty-five percent of total market volume since late 2019. Furthermore, retail volume is highly concentrated in short-maturity, out-of-the-money calls with high embedded leverage and low sticker prices. Ni, Pearson, Poteshman, and White (2021), Barbon and Burashi (2021), Flynn (2024), and Bryzgalova, Pavlova, and Sikorskaya (2023) show how increased inventory risk of liquidity providers from servicing demand in the option market can affect underlying stock prices through dynamic hedging. From a new perspective, we ask how retail demand affects the price and profitability of selling delta-neutral call options.

To answer this question, we focus on the returns of selling call options to RH investors. By construction, selling delta-neutral calls nets out short-term directional risk exposure in the underlying stock market, and allows us to focus solely on RH price impact on the options[12]. From May 2018 to June 2020, we can directly measure the equity preferences of RH investors using the website Robintrack.net, which used an API from RH to track the number of user accounts holding a particular stock. As evidence for the correlated preferences of RH direct

[11] https://www.nyse.com/data-insights/trends-in-options-trading
[12] Broadie, Chernov, and Johannes (2009) show that delta-hedged options are more informative regarding potential option mispricing than unadjusted option returns.

equity investment and call option holdings, we find that RH portfolio holdings are highly correlated with daily Reddit mention counts and that Reddit users mention an option term at least 25 percent of the time the stock itself is mentioned. Further, implied option volume from the RH portfolio is correlated with the Chicago Board of Options Exchange measure *"customer trades less than 100 contracts"* at 76 percent, and the Bogousslavsky and Muravyev (2024) top stocks with retail volume from account-matched brokerage data at 80 percent. This is the first study to use retail (RH) equity preferences to predict the cross-section of delta-hedged equity call option returns, supporting evidence that options are a non-redundant market (Zhan, Han, Cao, and Tong (2022)).

We elect to monetize retail option demand by writing delta-neutral calls. This strategy involves writing a call option on a stock and then purchasing delta shares of the underlying stock to achieve a net neutral delta position. At the beginning of each period, we sort all stocks in the RH portfolio into deciles based on the number of RH users holding. We then sell equally weighted delta-neutral calls on the stocks in each decile. These portfolios are rebalanced continuously for the sample period. We then compute the expectation of future returns as a function of RH holdings by creating a (10 – 1) spread portfolio, which sells dela-neutral calls in the top decile and buys delta-neutral calls in the bottom decile.

The returns of the RH spread portfolios are highly statistically and economically significant. Returns to the monthly rebalanced RH spread portfolio computed from at-the-money call options is 1.99 percent per month with a t-stat of 2.12 and is virtually unaffected by even the most restrictive assumptions on transactions and margin costs. The RH spread portfolios have larger Sharpe ratios and mean returns than several popular option and equity factors, such as Zhan et al. (2022), Karakaya (2013), and Fama and French (2015). In addition, the RH portfolio outperformed unconditional delta-neutral call sales and the market index several-fold during the sample period.

The effect of RH on the future cross-section of delta-neutral call returns remains significant in Fama MacBeth (1973) regressions including controls for demand pressure (Garleanu, Pedersen, and Poteshman (2009)), investor gambling preference (Byun and Kim (2016)), volatility risk premium, implied volatility (Black and Scholes (1973)), uncertainty of volatility (Baltussen, Van Bekkum, and Van Der Grient (2018)), and jump risk (Broadie, Chernov, and Johannes (2009)). In monthly observations, the coefficient on RH is unaffected even when all controls are included. Further, RH portfolio returns retains significant alpha against various option factor models and option momentum identified by Heston, Jones, Khorram, Li, and Mo (2023).

The returns of the RH portfolios are *most* consistent with demand pressure, leading to overpriced options relative to their exposure to underlying volatility. Without two-way order flows, such as periods of concentrated demand, options market liquidity providers face increased inventory risk and charge a higher premium on options. However, increased inventory risk by market makers in the option market can also affect underlying volatility through risk mitigation techniques such as dynamic hedging. Barbon and Burashi (2021), Ni, Pearson, Poteshman, and White (2021), and Flynn (2024) also show that imbalanced option inventory by market makers can cause elevated stock volatility through hedging trades. Building on this research, the returns to selling delta-neutral calls on stocks with high option demand will depend on the relative effects of option premium (implied volatility or IV) and the pass-through of option demand to the underlying stock market through intermediary hedging (realized volatility). The difference between implied volatility and realized volatility is the volatility risk premium (VRP), which will capture the returns to selling delta-hedged calls. Due to this relationship, the effect of retail demand on call option price and volatility surface is an empirical question of significant interest.

In line with demand pressure driving option mispricing, the effect of RH demand on option IV is several-fold higher than the effect of RH on ex-ante realized volatility. Returns to short call strategies significantly decrease when netting out strategy exposure to IV (Vega) by constructing Delta-Vega neutral portfolios. Therefore, the increased premium charged on the options is not justified by the exposure to underlying volatility, i.e., the options are overpriced. We verify this claim by showing the effects of retail demand on option pricing are substantially greater than those of matched institutional demand. In addition, we find that returns to the RH portfolio significantly increase in magnitude during periods of increased retail demand, such as when commission-free trading becomes broadly available, during months when COVID stimulus checks were delivered, and on days when the overall market has positive returns.

This is the first study to document returns to selling options to retail investors, specifically the Robinhood crowd. This paper contributes to the nascent literature on retail option trading, Bryzgalova, Pavlova, and Sikorskaya (2023), Lipson, Tomio, and Zhang (2023), Bogousslavsky and Muravyev (2024), Silva and So (2023). It also broadly contributes to the literature on retail and Robinhood trading in several asset classes, Welch (2022), Ozik, Sadka, and Chen (2020), Moss, Naughton, and Wang (2020) and Umar, Gubavera, Yousaf, and Ali (2021). Further, we provide evidence for retail demand as a powerful predictor in the cross-section of option returns. Other studies considering predictability in the option market include Zhan et al. (2022), Karakaya (2013), Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009), Muravyev (2016), Heston et al. (2023), Weinbaum, Fodor, Muravyev, and Cremers (2023), and Bali, Beckmeyer, Moerke, and Wiegert (2023).

2.2. Data, Trading Strategy, and Summary Statistics

Call option data on U.S. equity options is collected from the Option Metrics price file and merged with the CRSP daily stock file from May 2018 to July 2020, the period of available Robinhood user holdings. We impose a daily filter requiring calls with non-zero volume and open interest to ensure that calls are actively traded. This process results in roughly five and a half million observations of active call options.

2.2.1. Robinhood User Holdings

We collect Robinhood (RH) user holdings from Robintrack to proxy for retail trading in call options. Robintrack.net is a free-to-use data depository that measures the number of anonymous Robinhood user accounts holding a particular stock daily. Robintrack was active from May 2018 to July 2020, when RH unfortunately suspended the API used to collect data. Following Welch (2022), we construct an aggregate RH portfolio each day that holds $w_i = N_i / \sum_i N_i$ of each stock, where weights are assigned based on the number of accounts holding a stock daily, scaled by the total number of accounts. This portfolio serves as a "consensus" for RH user preferences during this time.

2.2.1.1. Robinhood Equity Holdings as a Proxy for Call Interest

Although the RH portfolio directly measures equity holdings, we contend it will also highly correlate with retail trading in call options. Because these are both bullish positions, there will rationally be a substitution between the two based on individual preference and utility. Further, there is substantial evidence that retail investors trade options at an extremely high rate. Following the broad adoption of commission-free trading by brokerages in late 2019, the average number of option contracts has increased roughly 60 percent year over year, with call options comprising 68 percent of the aggregate increase. Using a trader-level dataset that accurately identifies retail accounts, Bogousslavsky and Muravyev (2024) estimate that options trades account for nearly half of all retail transactions in 2022, with many accounts exclusively trading options. The dramatic increase in options volume has also garnered public and regulatory attention, with the SEC proposing amended rules to protect retail investors (SEC Release No. 34-96495; File No. S7-31-22).

Despite the popularity of retail option trading, specifically identifying this trade has been a challenging issue in the literature. Short of using brokerage data that *explicitly* tags retail accounts, e.g., Silva and So (2023) and Bogousslavsky et al. (2024), studies must make assumptions about the aggregate data. We present several stylized facts as evidence for the correlation between RH equity holdings and options trading.

1. Using a sample of posts from the Reddit site *WallStreetBets,* we found that RH portfolio holdings are highly correlated with Reddit mention counts, with a p-value of less than one percent. Further, Reddit users mention an option term *at least* 25 percent of the time the stock itself is mentioned.
2. Using data from the Chicago Board of Options Exchange (CBOE) that buckets option data into user accounts, we construct an aggregate daily call option portfolio of retail traders via the CBOE classification "customer, quantity of trades <100"[13]. The underlying stock holdings CBOE retail portfolio correlate with the RH portfolio at roughly 76 percent.

[13] There is some concern that this classification captures "iceberg trades", in which institutions or professional traders break up large transactions into smaller pieces for execution quality.

3. The RH portfolio exhibits similar stock holdings to the retail options trade identified in Bogousslavsky et al. (2024). The top twenty holdings of both portfolios correlate at roughly 80 percent.
4. In line with studies documenting the behavioral motivations of retail traders, Bauer, Cosemans, and Eichholtz (2009), Kumar (2009), Green and Hwang (2012), and Han and Kumar (2013), RH implied call purchases exhibit short-term speculation. For stocks in the top quartile of RH holdings, calls with 0 – 2 weeks to expiration comprise 77 percent of the total dollar value of call options traded on the stock.

These facts provide strong evidence of the correlation between RH equity holdings and RH call option holdings. From this point forward, we assume the RH portfolio adequately captures retail option trading.

2.2.1.2. Robinhood Implied Option Trading Summary

Table 2.1 presents summary statistics of call options traded on stocks grouped by their decile of RH equity holdings. Table 2.1 shows that stocks held at higher levels by RH uniformly have more call option activity than stocks with low RH holdings despite all RH deciles having roughly the same aggregate stock size. For calls with 0 – 2 weeks to expiration, decile ten stocks average $374,549 more dollar volume than decile one stocks per day. Further, the bulk of *all* option volume in this timeframe was concentrated in stocks in the top three deciles of RH holdings, comprising 83 percent of all dollar option volume from 2018 to 2020.

Table 2.1 – RH Option Summary Statistics

This table reports summary statistics by decile of Robinhood user holdings and option classification. Option classifications are 0-2, 2-4, 4-12, and >12 weeks to expiration and at the money, in the money, and out of the money. ATM is options with 0.45 – 0.55 delta, ITM is options with > 0.55 delta, and OTM is options with <0.45 delta. Panel A reports the average daily dollar option volume per group, calculated as daily option volume times the daily average stock price, and rounded to the nearest dollar. Panel B reports the average option spread calculated as: (ask price – bid price) / midpoint. Panel C reports the average implied volatility of the options in each group from Option Metrics.

RH Decile	1	2	3	4	5	6	7	8	9	10	(10 - 1)
Panel A: Option Volume ($)											
0-2 ATM	4,235	8,582	8,308	13,906	21,083	20,038	41,101	86,440	397,449	697,556	693,321
0-2 ITM	2,717	5,268	4,775	6,826	8,534	8,379	14,094	24,317	90,014	138,297	135,581
0-2 OTM	4,100	9,101	8,088	13,637	16,829	14,411	26,214	52,459	214,727	298,846	294,746
2-4 ATM	3,195	5,120	5,071	6,909	8,766	7,187	12,725	21,002	65,503	88,968	85,773
2-4 ITM	1,894	2,738	3,359	3,623	3,932	3,673	5,870	8,119	21,111	24,599	22,706
2-4 OTM	3,394	5,854	5,414	8,050	9,223	6,714	10,562	17,143	55,882	50,727	47,333
4-12 ATM	2,660	4,623	5,087	6,667	9,322	8,104	12,852	20,194	56,265	67,474	64,814
4-12 ITM	1,514	2,215	2,582	3,310	3,831	3,848	5,656	8,176	20,627	23,565	22,050
4-12 OTM	2,835	4,941	5,586	7,226	10,149	8,156	11,870	17,709	53,957	40,510	37,676
>12 ATM	1,692	2,339	2,307	3,256	3,698	4,045	5,823	7,926	18,652	23,819	22,126
>12 ITM	1,022	1,182	1,234	1,541	1,637	1,906	2,615	3,178	7,014	10,375	9,353
>12 OTM	1,790	2,487	2,412	3,162	3,639	3,852	5,804	7,214	19,852	17,822	16,031
Panel B: Average Spread (%)											
0-2 ATM	39.93	27.06	24.72	21.47	19.09	16.41	13.89	12.28	6.80	4.32	-36
0-2 ITM	28.78	19.19	17.23	15.03	13.28	11.54	9.79	8.55	5.53	3.97	-25

0-2 OTM	108.81	93.21	90.15	87.27	83.55	81.21	78.88	75.68	67.96	67.68	-41
2-4 ATM	29.72	20.24	18.31	16.44	15.17	14.22	12.77	11.62	8.02	5.82	-24
2-4 ITM	22.02	15.28	13.52	11.97	10.96	9.98	8.68	8.15	5.88	4.92	-17
2-4 OTM	79.35	66.52	61.88	58.34	53.89	51.99	49.33	46.61	39.29	38.92	-40
4-12 ATM	24.63	18.66	16.89	15.61	14.57	14.18	12.41	12.51	10.06	7.53	-17
4-12 ITM	18.25	13.56	12.26	11.00	10.18	9.46	8.13	7.99	6.36	5.28	-13
4-12 OTM	61.96	54.04	52.17	49.13	46.44	45.17	40.90	40.13	33.58	29.59	-32
>12 ATM	23.72	18.89	17.90	16.36	15.13	13.59	11.79	10.92	7.58	6.14	-18
>12 ITM	17.73	14.51	13.69	12.75	11.49	9.96	8.85	8.06	6.27	4.65	-13
>12 OTM	52.59	45.10	44.05	41.88	39.89	35.94	32.50	31.30	24.57	18.61	-34
Panel C: Average IV (%)											
0-2 ATM	49.82	51.16	51.05	49.45	54.15	53.77	53.64	53.33	52.96	58.00	8
0-2 ITM	61.38	60.30	58.30	57.42	61.19	61.10	60.55	60.62	60.14	73.47	12
0-2 OTM	56.01	56.30	57.66	55.05	58.60	58.69	58.87	58.91	61.14	71.35	15
2-4 ATM	44.34	45.19	45.07	43.69	46.93	46.66	46.92	47.68	47.83	53.16	9
2-4 ITM	48.98	50.62	49.72	48.67	50.96	49.59	48.26	49.07	48.49	57.33	8
2-4 OTM	44.46	46.36	47.07	45.09	47.08	46.55	45.84	45.91	47.77	55.21	11
4-12 ATM	41.52	44.90	45.95	45.47	46.72	46.11	44.83	45.66	46.20	51.12	10
4-12 ITM	44.65	48.40	49.37	49.40	50.82	49.87	47.40	48.58	47.28	54.66	10
4-12 OTM	40.29	43.51	45.35	44.44	45.43	45.33	42.85	42.91	43.78	49.69	9
>12 ATM	40.00	43.20	45.03	45.32	46.67	46.07	42.80	42.92	39.15	45.04	5
>12 ITM	44.82	49.56	50.90	51.87	52.78	50.92	48.02	48.84	45.05	49.22	4
>12 OTM	37.48	40.35	42.55	42.43	43.63	42.06	39.50	38.95	37.31	43.83	6

RH options also differ in their specific characteristics. Contrary to previous studies that show retail investors pay wide bid-ask spreads[14], decile ten options display uniformly tighter spreads than decile one options. This disparity can be seen clearly in short-term out-of-the-money (OTM) calls, which are traded at disproportionately higher rates by retail investors (roughly ten percent of total dollar option volume for the top three deciles). Although the spread of decile ten 0 – 2 OTM calls is large relative to other groups, it is forty-one percent *less* than the spread for short-term OTM calls in decile one. Therefore, although retail investors are willing to pay large spreads for the leverage provision of low liquidity short-term OTM options, retail demand in net leads to tighter spreads for all investors. Focusing purely on the aggregate spreads paid by retail investors can be misleading relative to the unconditional spreads paid on the classification of the traded options.

However, RH's beneficial effect on transaction price is partially offset by RH's impact on option price measured by implied volatility (IV). Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009), and Muravyev (2016) show that demand pressure impacts option prices. This relation is because market makers charge a higher premium due to increased inventory risk without two-way order flow. Mechanically, demand pressure can be measured through option IV as Option Metrics iteratively backs out IV from the option midpoint (price). Per Table 2.1, IV is positively correlated to the level of RH holding.

The impact on option IV may also be a function of retail preference for high volatility in their option investments, which would more closely resemble a gamble or "lottery" investment, which is preferred by retail traders, Choy (2015), Choy and Wei (2020). Although plausible, the

[14] Silva and So (2023) and Bogousslavsky and Muravyev (2024).

lottery characteristics of stocks in decile one and ten of the RH portfolio are not noticeably different. The Max 5 measure of Bali, Cakici, and Whitelaw (2011), which is the average of the five highest daily stock returns over the previous month, is only 3 percent larger for decile ten than decile one at the aggregate (8.57% vs. 5.98%) and is not statistically significant. Further, Max 5 is highly variable among the deciles and does follow a consistent pattern. For example, decile nine Max 5 (6.68%) is lower than decile two Max 5 (7.07%). Although this does not rule out retail gambling preference as a factor for the RH and IV relationship, it is more robust evidence for the relationship between demand pressure and IV.

2.2.2. Strategy for Monetizing Retail Option Demand

The trading strategy we use to monetize retail option demand is delta-neutral call writing. This strategy involves writing a call option on a stock and then purchasing delta shares of the underlying stock. Because delta represents the change in call price for a change in the stock price, the negative delta position of selling a call option (exposed to underlying price changes) is offset by the positive delta position of holding stock. This process hedges out the implicit directional risk of being naked short call options. As in Zhan, Han, Cao, and Tong (2022), the returns to buy and hold delta-neutral call writing can be expressed by:

$$Ret = \frac{\Delta_t * S_{t+1} - C_{t+1}}{\Delta_t * S_t - C_t} - 1$$

To open a delta-neutral position, the writer of a call option must purchase delta shares of the underlying stock, leading to an initial cost of $\Delta_t * S_t - C_t$. The payoff of this investment is subsequently realized at the end of the holding period by selling the underlying stock position and buying to close the open short option position, $\Delta_t * S_{t+1} - C_{t+1}$. Call prices are computed at the spread midpoint unless otherwise stated. Returns are expressed as a percentage. Holding periods and the call options involved in the strategy vary depending on the specific use case. All strategies are rebalanced either weekly or monthly, with weekly strategies selling calls with 7 – 30 days to expiration and monthly strategies selling calls with 30 – 90 days to expiration. Call options traded are classified as at-the-money (ATM), in-the-money (ITM), or out-of-the-money (OTM). ATM call options have a Black-Scholes computed delta of 0.45 – 0.55, ITM > 0.55, and OTM <0.45. Table 2.2 presents summary statistics of *unconditional* delta-neutral call writing and option characteristics per group.

Table 2.2 – Unconditional Delta-Neutral Short Call Returns and Group Summary

This table reports returns and standard deviations from selling delta-neutral calls by option classification and period of rebalancing. Panel A returns and standard deviations are calculated by selling call options and purchasing an amount of the underlying stock equivalent to $\Delta_t S_t$. Holding period returns are then calculated by $\frac{\Delta_t S_{t+1} - C_{t+1}}{\Delta_t S_t - C_{t1}} - 1$. Where (S) refers to stock price, (Δ) refers to option delta, and (C) refers to call price. Week denotes selling calls with 7 – 30 days to expiration and weekly rebalancing. Month denotes selling calls with 30 – 90 days to expiration and monthly rebalancing. ATM is options with 0.45 – 0.55 delta, ITM is options with > 0.55 delta, and OTM is options with <0.45 delta. Each group represents returns for selling delta-neutral calls for options only in that group. Returns and standard deviations are reported as percents. Panel B reports the average option spread and dollar volume per group, where option spread is computed as (ask price – bid price) / midpoint, and average daily dollar option volume is computed as daily option volume times the daily average stock price.

Panel A: Returns	Mean Return (%)	Std Dev (%)
Weekly OTM	-0.06	11.02
Weekly ATM	0.55	7.65
Weekly ITM	0.77	11.76
Monthly OTM	-1.27	26.23
Monthly ATM	0.83	21.15
Monthly ITM	0.76	27.00
Panel B: Group Summary	**Average Spread (%)**	**Average Option Volume ($)**
7 - 30 OTM	59.32	24,760.84
7 - 30 ATM	16.38	28,231.70
7 - 30 ITM	11.11	11,864.38
30 - 90 OTM	45.69	15,204.87
30 - 90 ATM	15.38	16,179.87
30 - 90 ITM	10.26	7,394.097

Table 2.2 shows that the average delta-neutral strategy selling ITM and ATM call options is slightly positive when rebalanced weekly or monthly. On the contrary, the returns to selling OTM call options are negative with both rebalancing structures. Despite this, OTM calls are highly traded, with an average daily dollar option volume of more than double ITM calls and only 16 percent less dollar volume than highly liquid ATM calls. Average strategy returns should not be interpreted as an endorsement or condemnation of a particular strategy, as the sample window is relatively small and contains periods of significant market volatility, but rather as a benchmark against which to compare conditional delta-neutral short call strategies.

2.3. Returns to Selling Delta-Neutral Calls to Retail Traders

We begin analysis by comparing the returns of selling delta-neutral calls across groups of RH interest. As in Table 2.2, the strategies are sorted by week/month, OTM, ATM, and ITM. At the beginning of each holding period, stocks are sorted according to their level of RH holdings, and a portfolio is formed for each decile that equally weights stocks per group and sells delta-neutral calls. This portfolio is held for the specified period and continuously rebalanced for the study timeframe. Therefore, the returns to the delta-neutral portfolio per decile are computed as the average return of all delta-neutral short call positions per stock within the decile. As in Bali, Beckmeyer, Moerke, and Weigert (2023), this process can generally be modeled as:

$$Ret_{i,t} = E\left[Ret_{i,t-1}\right] + \varepsilon_{i,t-1}$$

Where the purpose of the study is to connect expected future returns to retail interest in the prior period via the RH equity portfolio.

$$E\left[Ret_{i,t}\right] = function(RH_{i,t-1})$$

We express the expectation of future returns as a function of previous period RH holdings by computing a (10 – 1) portfolio, which sells delta-neutral calls in the top decile and buys delta-neutral calls in the bottom decile. Practically, this would involve "flipping" the short call option delta-neutral strategy and buying calls while shorting delta shares of the underlying stock.

Table 2.3 reports average returns to selling delta-neutral calls for stocks in each decile of RH holdings by option characteristics and rebalancing period. Returns are uniformly positive for the top RH deciles and the (10 – 1) portfolios. The returns to the (10 – 1) portfolio are also highly significant for three of the option classifications with a p-value of less than five percent computed from t-tests with a hypothetical mean of zero.

In addition to their statistical significance, the returns of the (10 – 1) portfolios are highly economically significant. The return of the weekly rebalanced (10 – 1) portfolio on OTM calls is 1.54 percent (t-stat of 4.43) higher than the unconditional OTM delta-neutral call return *per week.* The (10 – 1) monthly rebalanced strategy of OTM options returns 6.98 percent (t-stat of 2.12) higher than the unconditional return. Although challenging to realize due to high average spreads and transaction costs, these differences represent an annualized increase of over 70 percent. Further, RH holdings have a pervasive impact on strategy returns, even for the most liquid ATM options. The monthly rebalanced (10 – 1) portfolio on ATM calls returns 1.99 percent per month (t-stat of 2.12), an increase of 1.16 percent per month over the unconditional average. Due to the tight spreads of the traded options and the limited trades of monthly rebalancing, the decile ten ATM monthly rebalanced RH portfolio is statistically and economically profitable even when assuming that traders pay 100 percent of the quoted spread, which is highly unlikely, as DeFontnouvelle, Fishe, and Harris (2003) and Mayhew (2002) show that the ratio of paid spread to quoted spread is less than 0.5. The returns of the RH portfolios in Table 2.3 provide strong evidence that RH demand has significant predictive power of the future cross-sectional returns of selling delta-neutral call options.

Table 2.3 – Returns to Selling Delta-Neutral Calls to RH Users

This table reports returns and t-statistics from selling delta-neutral calls by decile of Robinhood user holdings, option classification, and period of rebalancing. Returns and t-stats are calculated by selling call options and purchasing an amount of the underlying stock equivalent to $\Delta_t S_t$. Holding period returns are then calculated by $\frac{\Delta_t S_{t+1} - C_{t+1}}{\Delta_t S_t - C_{t1}} - 1$. Where (S) refers to stock price, (Δ) refers to option delta, and (C) refers to call price. Week denotes selling calls with 7 – 30 days to expiration and weekly rebalancing. Month denotes selling calls with 30 – 90 days to expiration and monthly rebalancing. ATM is options with 0.45 – 0.55 delta, ITM is options with > 0.55 delta, and OTM is options with <0.45 delta. Each group represents returns for selling delta-neutral calls for options only in that group. T-stats are reported in parentheses. The (10 – 1) column represents returns and statistics from a long-short strategy. T-stats from this column are generated by comparing the mean returns of the two groups. Returns are reported as percents.

Group	1	2	3	4	5	6	7	8	9	10	(10 – 1)
Week	-0.38	-0.16	0.01	0.08	0.44	0.42	0.37	0.87	0.58	1.10	1.48
OTM	(-13.00)	(-3.20)	(0.13)	(1.18)	(5.18)	(4.83)	(4.18)	(3.76)	(4.34)	(3.30)	(4.43)
Week	0.41	0.57	0.59	0.62	0.75	0.55	0.38	1.04	0.74	0.54	0.13
ATM	(21.48)	(14.34)	(12.39)	(11.97)	(11.93)	(7.86)	(5.22)	(3.43)	(5.57)	(3.89)	(0.91)
Week	0.58	0.77	0.81	0.90	1.07	1.11	0.70	0.96	1.24	1.51	0.93
ITM	(19.05)	(13.63)	(11.32)	(11.12)	(10.15)	(10.03)	(6.23)	(6.73)	(6.64)	(2.83)	(1.74)
Month	-2.21	-1.94	-1.42	-0.04	0.41	1.22	0.21	0.71	1.07	3.50	5.71
OTM	(-23.41)	(-10.39)	(-5.13)	(-0.11)	(0.87)	(2.28)	(0.34)	(1.38)	(1.58)	(1.30)	(2.12)
Month	0.23	0.15	0.92	1.54	2.05	2.22	1.97	2.14	2.03	2.22	1.99
ATM	(2.82)	(0.90)	(3.71)	(4.12)	(4.80)	(4.53)	(3.07)	(3.41)	(2.82)	(3.14)	(2.8)
Month	0.20	-0.07	0.73	1.22	2.03	2.32	2.00	2.16	2.23	6.45	6.25
ITM	(1.90)	(-0.36)	(2.50)	(3.18)	(4.70)	(4.75)	(3.15)	(3.13)	(2.57)	(1.84)	(1.78)

2.3.1. Time Series of Strategy Returns Compared with Other Option Predictors

Next, we compare the returns of the (10 – 1) spread RH strategies to other popular option price predictors in the current literature. In the following subsections, we summarize the other predictors and their construction. Because the RH call portfolios are formed based on sorted equity holdings, we also include the Fama and French (2015) five-factor model. Due to the widespread use of the paper, we omit the construction of the FF factors from this summary. FF factor returns are gathered from Ken French's website and aggregated to the holding period as needed.

2.3.1.1. Idiosyncratic Volatility and Amihud Illiquidity

Research by Cao and Han (2013) and Christoffersen, Fournier, and Jacobs (2018) shows that stock level idiosyncratic volatility (IVOL) and liquidity of the underlying stock have a pervasive effect on option return. Following Zhan et al. (2022), we construct the IVOL and option illiquidity factor as the (10 – 1) spread of returns by sorting stocks into deciles each month by idiosyncratic volatility and Amihud (2002) illiquidity factor, then selling equally weighted delta-neutral calls in decile ten and buying equally weighted delta-neutral calls in decile one.

2.3.1.2. Karakaya Three Factors

Karakaya (2013) constructs three option factor portfolios that explain variation in the cross-section of option returns. These portfolios are not delta-neutral and capture the return from naked selling options of different characteristics.

1. The *level* factor is the average return from selling ATM option portfolios.
2. The *slope* factor is the average return from selling options with 0 – 60 days to expiration minus the average return of selling options with 120 – 180 days to expiration.

3. The *value* factor is the average return of selling the lowest three "value" decile portfolios minus the highest three "value" portfolios. Value is defined as the options' volatility risk premium (VRP) and is equal to implied volatility minus the previous month's historical volatility.

2.3.1.3. Time Series of Returns

Table 2.4 reports the time series summary statistics of the returns of the various investment strategies. For both weekly and monthly rebalancing, the RH spread portfolios have the largest mean return (1.39%, 4.76%, and 1.54% for the weekly rebalanced OTM and monthly rebalanced OTM and ATM, respectively) apart from the Karakaya slope factor. However, the Karakaya slope factor has a significantly (roughly three times) larger standard deviation and lower Sharpe ratio. Annualized returns to the RH portfolios are 66.72%, 57.12%, and 18.54% for weekly rebalanced OTM and monthly rebalanced OTM and ATM, respectively. While returns for the OTM portfolios are affected by transaction costs due to the relatively large spreads of OTM options, the ATM returns are largely unaffected, even assuming the paid spread is 100 percent of the quoted. Monthly ATM also has a significantly larger Sharpe ratio than any of the other strategies. Further, the maximum period drawdown is only -7.67%, -6.06%, and -8.95% for the RH week OTM, month OTM, and month ATM, respectively. The OTM RH spread portfolios are positively skewed and have relatively sizeable excess kurtosis. This relation is unsurprising given that returns to selling these options were overwhelmingly positive during the sample period. Figure 2.1 shows the cumulative returns of investing one dollar in the continuously rebalanced weekly OTM RH spread portfolio against the returns of continuously rebalanced unconditional delta-neutral call selling and the S&P500 index.

Figure 2.1 – Cumulative Returns of RH Spread Portfolio

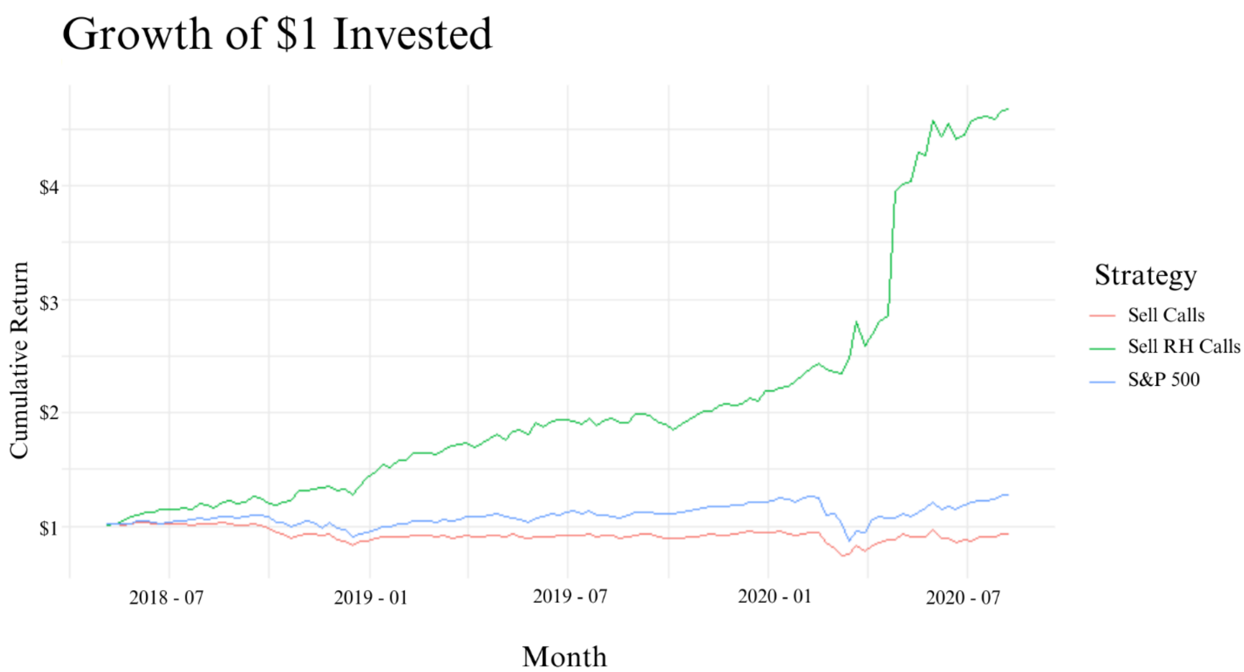


Table 2.4 – Summary Statistics of the Time Series of Strategy Returns

This table reports summary statistics for portfolio returns. Panel A rebalances portfolios weekly, panel B monthly. Robinhood (RH) portfolio returns are constructed by forming long-short portfolio based on the decile of Robinhood user holdings and holding for the proceeding week/month. Market, SMB, HML, RMW, and CMA compute returns for the Fama French five-factor model portfolios. Amihud and IV factor portfolio returns are constructed as in Zhan, Han, Cao, and Tong (2021) by selling delta-hedged calls in decile sorts by Amihud illiquidity measure and idiosyncratic volatility. Reported measures are from the (10 – 1) portfolios. The Karakaya (2013) three-factor model includes level, slope, and value factors, constructed as the return from selling ATM options, short minus long-term options, and high volatility risk premium minus low volatility risk premium options. All return measures are presented in percentage points.

Panel A: Weeks

Portfolio	Mean	Median	Q1	Q3	Min	Max	SD	Skewness	Excess Kurtosis
RH Week OTM	1.39	0.70	-0.48	2.53	-7.67	38.28	4.36	5.24	41.72
Market	0.26	0.49	-1.02	1.72	-14.53	11.94	3.19	-0.96	6.59
SMB	-0.15	-0.20	-0.97	0.73	-7.90	4.58	1.66	-0.41	3.67
HML	-0.38	-0.38	-1.29	0.58	-8.30	9.31	2.36	0.22	3.64
RMW	0.06	0.03	-0.56	0.61	-2.27	2.72	0.92	0.37	0.22
CMA	-0.05	-0.10	-0.57	0.46	-1.76	2.12	0.74	0.18	-1.78
Amihud	-3.26	-2.84	-4.28	-1.96	-11.76	1.30	2.25	-1.25	2.01
IVOL	-3.17	-2.13	-4.42	-0.93	-19.46	2.66	3.47	-1.82	4.75

K Level	-0.53	-0.09	-4.19	2.81	-23.01	17.50	6.88	0.12	1.00
K Slope	1.73	1.11	-6.48	11.74	-38.11	60.41	15.40	0.18	1.35
K Value	-15.04	-12.14	-46.58	24.75	-297.86	160.96	66.20	-1.04	3.35
Panel B: Months									
RH Month OTM	4.76	2.24	-1.45	5.95	-6.06	59.30	12.22	3.33	12.39
RH Month ATM	1.54	1.02	-3.63	5.45	-8.95	20.56	7.11	0.80	0.39
Market	1.28	2.39	0.07	3.84	-10.67	13.44	5.63	-0.52	0.12
SMB	-0.78	-0.41	-2.61	0.88	-9.41	4.57	2.90	-0.75	1.11
HML	-1.87	-1.94	-3.19	-0.28	-15.36	6.78	3.80	-1.14	4.53
RMW	0.25	0.34	-0.68	0.88	-2.68	4.07	1.40	0.35	0.69
CMA	-0.34	-0.61	-1.37	0.33	-2.82	3.71	1.62	0.65	0.10
Amihud	-2.89	-2.45	-3.25	-2.17	-8.96	1.25	2.03	-0.93	1.82
IVOL	-2.99	-2.83	-4.72	-0.90	-14.35	2.20	3.31	-1.26	3.03
K Level	-1.88	-1.04	-7.69	3.33	-22.72	19.99	9.56	-0.06	-1.86
K Slope	7.26	3.09	-4.37	24.84	-49.52	53.70	22.38	-0.17	0.47
K Value	-11.52	-16.55	-62.10	25.40	-103.26	120.45	60.07	0.50	-1.51

2.4. RH Return Robustness

In this section, we test the robustness of the returns to writing delta-neutral calls sorted by RH holdings. We use Fama and MacBeth (1973) regressions, option factor models, and option momentum portfolios to accomplish this task. While some tests using monthly returns lack power due to constrained timeframe and small sample size, weekly RH returns remain significant in every specification. Further, we provide evidence that RH returns are driven by consistent retail demand pressure for high-leverage value options despite consistently *losing* money on these investments. In this way, wealth-destructive behaviors by long call option retail investors are monetized by short call option sellers.

2.4.1. Fama MacBeth Controls

Following Zhan et al. (2022), we use Fama MacBeth regressions to estimate the effect of RH holdings on the return to writing delta-neutral calls. Specifically, we model forward period returns to selling delta-hedged calls as:

$$Ret_{i,t+1} = \alpha_i + \beta_i Decile\ RH_{i,t} + \sum \delta_i Controls_{i,t} + \varepsilon_i$$

The basic idea is to compare the statistical significance and magnitude of the RH decile before and after the addition of controls to identify how much of the coefficient (β) can be explained. In the following, we summarize the controls and their significance to the model. Results of the model, including only RH decile, including each control individually, and finally, including all controls, are presented in Table 2.5.

1. *Demand Pressure.* Demand pressure is aggregated option volume divided by stock volume, as proposed by Garleanu, Pedersen, and Poteshman (2009). Without balanced

two-way order flow, option market makers will charge a higher premium for options with significant demand.

2. *Max 5.* Max 5 is the average of the highest five returns for a stock over the previous month. Bali, Cakici, and Whitelaw (2011), Byun and Kim (2016) provide evidence that this “lottery preference” for options leads to higher returns to selling delta-neutral calls.
3. *Volatility Risk Premium (VRP).* VRP is the implied volatility of stock computed via Black-Scholes minus the realized volatility of the stock over the previous month. This measures the expensiveness of the traded options relative to historical volatility.
4. *Implied Volatility (IV).* IV is the Black-Scholes computed implied volatility of the underlying stock given the option price. This measures the market’s expectation of future volatility on the underlying stock.
5. *Uncertainty on Stock Volatility (Vol of Vol).* Vol of Vol is the second order of stock volatility as measured by Baltussen, Van Bekkum, and Van Der Grient (2018). This measure proxies for the market’s uncertainty of stock volatility, under which option sellers will rationally charge a higher premium due to elevated risk.
6. *Jump Risk.* Jump risk is measured by the skewness and kurtosis of the traded options, Bakshi and Kapadia (2003) and Bakshi, Kapadia, and Madan (2003). Although delta hedging nets out exposure to short-term variation in stock price, delta-neutral strategies are still exposed to large price swings. Broadie, Chernov, and Johannes (2009) show that jump risk significantly affects option return.

Table 2.5 – Determinants of the Returns to Selling Delta-Hedged Calls

This table presents Fama MacBeth regressions with next period returns as the dependent variable. Panel A presents weeks, panel B months. Each regression includes a stock's decile of Robinhood user holdings and an explanatory variable. Model eight includes all controls. Demand is aggregated option volume divided by stock volume, Garleanu, Pedersen, and Poteshman (2009). Max 5 is the average of the highest five returns for a stock over the previous month, Bali, Cakici, and Whitelaw (2011). VRP measures the volatility risk premium as option implied volatility minus realized volatility over the previous period. IV measures implied volatility computed from stock options. Vol of vol measures the volatility of stock volatility and proxies for uncertainty of stock volatility, Baltussen, Van Bekkum, and Van Der Grient (2018). Skew and kurt measure the skewness and kurtosis of stock options and capture jump risk, Bakshi, Kapadia, and Madan (2003). Newey-West (1987) t -statistics with four lags are reported in parentheses. P values are denoted as *p<0.1, **p<0.05, ***p<0.01.

	Dependent Variable:							
	Next Period Delta-Hedged Call Return							
	1	2	3	4	5	6	7	8
Panel A: Weeks								
Decile RH	0.0015***	0.0013***	0.0012***	0.0014***	0.0014***	0.0017***	0.0008*	0.0008*
	(4.25)	(3.51)	(3.56)	(4.23)	(4.24)	(5.89)	(2.05)	(2.37)
Demand		1.11*						0.37
		(2.22)						(0.79)
Max 5			0.26***					0.55***
			(4.51)					(6.15)
VRP				0.003				0.20**
				(0.92)				(2.90)
IV					0.003			-0.21**
					(0.91)			(-3.07)
Vol of Vol						-0.03***		-0.02***
						(-5.77)		(-4.61)
Skew							-0.004	-0.004
							(-1.20)	(-0.99)
Kurt							0.006**	0.006**
							(2.97)	(2.92)

Obs	50,056	50,056	50,056	50,056	50,056	29,059	28,799	28,799
R^2	0.06	0.06	0.10	0.07	0.07	0.13	0.13	0.22
Panel B: Months								
Decile RH	0.004*	0.005***	0.004*	0.004*	0.004*	0.005***	0.005*	0.004**
	(2.19)	(3.38)	(2.53)	(2.24)	(2.26)	(4.17)	(2.55)	(3.25)
Demand		2.71						3.00
		(1.60)						(1.67)
Max 5			-0.19					-0.11
			(-1.02)					(-0.55)
VRP				0.01				0.54
				(0.01)				(1.86)
IV					0.005			0.50
					(0.33)			(-1.77)
Vol of Vol						-0.08**		-0.08*
						(-3.11)		(-2.48)
Skew							-0.05**	-0.03*
							(-2.75)	(-2.07)
Kurt							0.02*	0.02*
							(2.14)	(2.00)
Obs	16,158	11,242	16,158	16,158	16,158	11,320	11,242	11,242
R^2	0.13	0.20	0.15	0.15	0.15	0.19	0.20	0.24

The standalone specification (1) in Table 2.5 Panel A indicates that increasing a stock's RH decile by one will increase the following week's return to selling delta-neutral calls by 0.15 percent (t-stat of 4.25). This coefficient indicates that selling delta-neutral calls on stocks in the highest decile of RH will have returns 1.5 percent larger per week than selling calls on stocks in the lowest decile of RH, which is similar to the difference indicated by portfolio sorts in Table 2.3. Decile RH remains significant at a p-value of less than 0.05 in all specifications, including (8), which includes all controls. While the coefficients on demand, max 5, and vol of vol are significant, the magnitude of the coefficient on RH is essentially unaffected by all controls aside from the measures of jump risk (skew and kurtosis) in specification (7), which reduces the magnitude of the coefficient by roughly 50%. While jump risk explains significant variation in RH, 50% of the effect is still unattributable to any of the included controls.

In contrast, the coefficients on RH in Table 2.5 Panel B for monthly rebalanced delta-neutral call return do not drop in magnitude in any specification. The only significant coefficient for controls is volatility uncertainty and jump risk, and the inclusion of these variables *increases* the magnitude of the coefficient on RH, from 0.4 percent per month in the standalone specification (1) to 0.5 percent per month in specifications (6) and (7). In every specification in both panels, returns to selling delta-neutral calls are statistically and economically significantly greater in higher deciles of RH holdings.

2.4.2. Option Factor Models

Next, we test the returns of the (10 – 1) RH spread portfolios against option factor models in the existing literature. Due to the short-lived run of Robintrack and the size of the sample timeframe, we can only test the returns of the weekly OTM (10 – 1) spread portfolios. Monthly rebalanced

(10 – 1) spread portfolios include only 28 observations and therefore lack statistical power. Hereafter, in this section, we refer to the week OTM spread portfolio as the RH portfolio.

The returns of the RH spread portfolio are regressed against the factor models as follows. Alpha measures the portion of RH return unattributable to variation in the factor portfolios. Results from the factor models are presented in Table 2.6.

$$RH\ Ret_{i,t} = \alpha_i + \sum Factor\ Return_{i,t} + \varepsilon_i$$

The included factors are:

1. Karakaya (2013) three-factor option model of level, slope, and value. These measures capture variation in returns attributable to option moneyness, maturity, and volatility surface. The construction of these factors is summarized in section 2.3.1.2.
2. Zhan, Han, Cao, and Tong (2021) two-factor option model of stock Amihud illiquidity level and idiosyncratic volatility. In their paper, these two factors reduce the profits of selling delta-neutral call options sorted by equity characteristics by 80% on average and remove the statistical significance of nine out of ten spread portfolios. The construction of these factors is summarized in section 2.3.1.1.
3. Fama and French (2015) five-factor stock model. These factors are well known to capture cross-sectional variation in equity returns. Because RH measures stock holdings, we include these factors for completeness.

The alphas in Table 2.6 remain significant in every specification. In specification (1), the Karakaya (2013) factors do not have significant coefficients, and the constant implies weekly alpha of the RH portfolio of 1.3 percent (p-value < 0.01). In specification (2), neither the Amihud nor IVOL factor have significant coefficients, and the constant implies weekly alpha of the RH portfolio of 1.4 percent (p-value < 0.01). In specification (3), the RH portfolio loads positively on SMB with a coefficient of 0.568 (p-value < 0.05) and negatively on CMA with a coefficient of -0.986 (p-value < 0.1). Despite the significance of these coefficients, the constant implies weekly alpha of the RH portfolio of 1.5 percent (p-value < 0.01). Based on these alphas, conservatively, the RH portfolio has annualized risk-adjusted returns of 62.4 percent[15]. Interestingly, only the equity factors in the Fama French five-factor model exhibit joint significance. In contrast, the documented option factors have no explanatory power (F-stats of 0.386 and 0.005 for the Karakaya and Zhan et al. factors, respectively). These results indicate that retail option preference influences return in a way not identified in prior literature. We further explore the source of the RH return in the following sections.

Table 2.6 – RH (10 – 1) Spread Portfolio Factor Regressions

This table reports the results of regressions in which the returns of the weekly rebalanced OTM long-short Robinhood portfolio are risk-adjusted using the Karakaya (2013) three-factor model, Zhan, Han, Cao, and Tong (2021) two-factor model, and the Fama French five-factor model. Standard errors are reported in parentheses. P values are denoted as *p<0.1, **p<0.05, ***p<0.01.

	Dependent variable:		
	RH Week OTM		
	(1)	(2)	(3)
K Level	-0.034		
	(0.059)		
K Slope	-0.006		
	(0.027)		
K Value	-0.006		

[15] This does *not* imply that these returns are investable. Call prices are computed at the midpoint and OTM options frequently have large spreads and thus incur large transaction costs.

	(0.006)		
Amihud		0.006	
		(0.246)	
IVOL		0.009	
		(0.159)	
Market			0.192
			(0.133)
SMB			0.568**
			(0.270)
HML			0.250
			(0.241)
RMW			0.278
			(0.500)
CMA			-0.986*
			(0.581)
Alpha	0.013***	0.014**	0.015***
	(0.004)	(0.007)	(0.004)
Observations	119	119	119
R^2	0.010	0.0001	0.187
F Statistic	0.386	0.005	5.205***

2.4.3. Option Momentum

Momentum is the tendency for assets to continue periods of outperformance. Although primarily thought of as a feature of equities (Jegadeesh and Titman (1993)), momentum has been shown to hold in several asset classes, including options by Heston, Jones, Khorram, Li, and Mo (2023). To test if RH returns are affected by momentum, we regress the following model:

$$RH\ Ret_{i,t} = \alpha_{n,t} + \beta_{n,t} RH\ Ret_{i,t-n} + \varepsilon_{i,t}$$

RH ret captures the return of the (10 – 1) spread portfolio in month t. As in Fama (1976), beta captures the return of RH lagged by n periods. We include twelve lags in each model. Results from the regression are presented in Table 2.7 and include weekly rebalanced and monthly rebalancing strategies, although the monthly rebalanced strategies have low statistical power.

From Table 2.7, monthly rebalanced RH strategies exhibit no momentum. Models (2) and (3) have no significant coefficients and no explanatory power, with F-stats of 0.609 and 0.448 for Month OTM and Month ATM, respectively. The weekly OTM strategy exhibits reversal at lagged weeks four and eight (p-values < 0.05) and momentum at lagged week five (p-value < 0.01). However, model (1) in totality exhibits little joint significance of the explanatory variables, with an F-stat of just 1.645 (p-value < 0.1). When these results are taken together, momentum and reversal are unlikely to explain the returns of the RH portfolios.

Table 2.7 – RH Momentum

This table reports the results of the following regression: $Ret_{i,t} = \alpha_i + \beta_i \sum_{n=t-12}^{n=t-1} Ret_{i,n} + \varepsilon_i$. Strategy return represents selling delta-neutral calls by decile of Robinhood user holdings and constructing a long-short strategy that is long the highest decile and short the lowest decile. Holding period returns are calculated by $\frac{\Delta_t S_{t+1} - C_{t+1}}{\Delta_t S_t - C_{t1}} - 1$. Where (S) refers to stock price, (Δ) refers to option delta, and (C) refers to call price. Week denotes selling calls with 7 – 30 days to expiration and weekly rebalancing. Month denotes selling calls with 30 – 90 days to expiration and monthly rebalancing. ATM is options with 0.45 – 0.55 delta and OTM is options with <0.45 delta. Standard errors are reported in parentheses. P values are denoted as *p<0.1, **p<0.05, ***p<0.01.

	Dependent variable:		
	RH Week OTM	RH Month OTM	RH Month ATM
Lag 1	-0.025	0.083	-0.260
	(0.103)	(0.445)	(0.530)
Lag 2	0.057	-0.410	-0.144
	(0.104)	(0.448)	(0.489)
Lag 3	0.117	-0.651	-0.555
	(0.104)	(1.169)	(0.588)
Lag 4	-0.244**	0.697	-0.372
	(0.105)	(3.302)	(0.674)
Lag 5	0.276***	-1.065	-0.646
	(0.104)	(3.110)	(1.042)
Lag 6	0.042	-0.757	-0.184
	(0.108)	(1.891)	(0.775)
Lag 7	-0.003	-0.268	-0.494
	(0.108)	(1.158)	(0.593)
Lag 8	-0.249**	-1.436	-0.990
	(0.106)	(3.281)	(0.811)
Lag 9	0.026	-1.618	-0.597
	(0.105)	(1.386)	(0.711)
Lag 10	0.034	-0.174	0.078
	(0.105)	(1.347)	(0.570)
Lag 11	0.013	-0.441	-0.584
	(0.105)	(1.517)	(0.657)
Lag 12	-0.084	-2.069	-0.771

	(0.106)	(2.674)	(0.851)
Observations	107	16	16
R^2	0.187	0.798	0.744
F Statistic	1.645*	0.609	0.448

2.5. Option Mispricing / Subperiod Evidence

The aggregate increase in options volume following broad access to commission-free trading in late 2019 is unprecedented at any other time in history. Silva and So (2023) estimate that in 2020 alone, retail investors accounted for more than $250 billion of total single-name option volume. Furthermore, they estimate that the extent of retail trading in options has increased tenfold over the past decade. We contend that the increased demand for call options from retail traders primarily drives the observed returns of the RH spread portfolios. Without two-way order flows, options market liquidity providers face increased inventory risk and, therefore, charge a higher premium on options. However, Barbon and Burashi (2021), Ni, Pearson, Poteshman, and White (2021), and Flynn (2024) also show that imbalanced option inventory by market makers (MM) can cause elevated stock volatility through hedging trades. Should the option inventory risk of MMs pass through to the underlying stock, there would be a muted effect on the VRP of options and, thus, no impact on the returns of selling delta-neutral calls. Thus far, how retail demand affects option price and VRP remains an open empirical question.

2.5.1. RH Effect on Option Volatility Surface

Demand pressure should only lead to increased profitability of selling delta-neutral calls if implied volatility increases faster than realized volatility. If the two increase at the same rate, the VRP will remain unchanged, as will the premium for selling the call. To test if RH demand has a pass-through effect on the underlying stock through intermediary hedging, we regress the following Fama MacBeth models. The observations for each model are filtered to include only OTM calls, then only ITM and ATM calls. Because OTM calls are traded at a relatively higher rate by retail investors, differential coefficients on the OTM volatility surface can be interpreted as the effect of increased retail demand.

$$IV/VRP/Spread_{i,t} = \alpha_i + Decile\ RH_{i,t-1} + \varepsilon_i$$

Where IV, VRP, and percentage spread are averaged for option classifications over a week, and RH is the decile of RH user holdings for the previous week. Table 2.8 presents the results.

As predicted by demand pressure, the effect of RH holdings on IV and VRP is more substantial in significance and magnitude for OTM calls than ITM/ATM calls. The coefficient on IV is 59 percent larger (1.78% vs. 1.12%), and the coefficient on VRP is 61 percent larger (1.72% vs. 1.07%). In addition, the effect of RH on subsequent IV is much higher than realized volatility. The coefficient on RH for OTM calls implies that increasing the RH decile of a stock by one will increase the forward IV of OTM call options traded on the stock by 1.78 percent (t-stat of 12.77). Backing out the effect of RH on realized volatility from VRP, increasing the RH decile by one will only increase forward stock volatility by 0.06 percent (t-stat of 12.92). Taken together, Table 2.8 suggests that retail demand leads to a significant overvaluation of call options. Although option liquidity providers will undoubtedly pass through *some* of their inventory risk to the underlying stock, options preferred by retail investors are frequently on mega-cap stocks, with stock markets plenty liquid to absorb the shock of the pass-through. Therefore, increased underlying volatility does not justify the increased premium on the options. In options of all moneyness, RH significantly decreases forward spread (-2.71% with a t-stat of -15.29 and -2.65% with a t-stat of -27.13 for OTM and ITM/ATM calls, respectively). This relation indicates that market makers reap profits from servicing retail flow and, therefore, do not widen the spread to increase costs and discourage trade.

Table 2.8 – RH Effect on Option Volatility Surface

This table presents Fama MacBeth regressions with weekly average IV, VRP, and option spread (%) as the dependent variables. Lag RH is the previous week decile of Robinhood user holdings per stock. All calls have 0 – 30 days to expiration, OTM refers to deltas of less than 0.45, ITM/ ATM is delta greater than 0.45. Newey-West (1987) t -statistics with four lags are reported in parentheses. P values are denoted as $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

	OTM Calls			ITM / ATM Calls		
	IV	VRP	Spread	IV	VRP	Spread
Lag RH	0.0178^{***}	0.0172^{***}	-0.0271^{***}	0.0112^{***}	0.0107^{***}	-0.0265^{***}
	(12.77)	(12.92)	(-15.29)	(8.74)	(8.63)	(-27.13)
Obs	50,056	50,056	50,056	47,392	47,392	47,392
R^2	0.18	0.16	0.10	0.17	0.15	0.09

2.5.2. Subsample Analysis

Further evidence for the concentrated demand pressure of retail traders leading to call option overvaluation can be found by examining subperiods of outperformance within the Robintrack sample timeframe. The subperiods we examine, and their rationale are summarized as follows:

1. *Pre and Post Commission Free Trading.* We identify the start of broad-based commission-free trading as October 2019 when Charles Schwab, followed by nearly all the large brokerages, moved to a payment for order flow commission-free model.

Differential results can be attributed to increased aggregate option demand after commission-free trading was instituted.

2. *Stimulus Months and Summer 2020.* Stimulus months refer to April and May of 2020 when stimulus checks were delivered to American citizens by the U.S. government as part of a COVID relief package. All Americans who filed a tax return in previous years received a base of $1,000 plus additional payments for dependents, etc. The stimulus check became a popular meme on the subreddit *r/WallStreetBets*, where investors referred to using the funds as "investing the stimmy". Differential results can be attributed to increased aggregate volume from stimulus check investments relative to the immediately proceeding months of June and July 2020. Because most retail option trades are wealth-destructive, there should be little reinvestment after the initial capital is deployed.
3. *Market up and Market down.* These subperiods capture days when the overall stock market rose and days when the market fell. The investments of retail investors are primarily bullish, (Bauer, Cosemans, and Eichholtz (2009), Kumar (2009), Green and Hwang (2012), Han and Kumar (2013)), and they are therefore more likely to demand call options when the overall market is doing well.

The average return of the three RH (10 – 1) spread portfolios within the subperiod and associated t-statistics are presented in Table 2.9.

Table 2.9 shows that RH strategy returns are uniformly higher in the post commission free period, during stimulus check distribution months, and when the market is up. Averaging among all three RH strategies, returns increased tree-fold after the broad adoption of commission-free trading (t-stat of 3.2), fourteen-fold during stimulus months compared to the subsequent summer months (t-stat of 5.3), and two-fold during positive market return days compared to negative market return days (t-stat of 3.02). Although these results represent huge returns, they also capture outlier events that will be difficult to replicate. In all, the results of Table 2.9 strongly support the notion that aggregate retail demand contributes to option mispricing and, thus, the returns of selling delta-neutral options on the RH portfolios.

Table 2.9 – RH Returns in Subperiods

This table reports average return of the three profitable Robinhood strategies in different subsamples. Returns are averaged before and after major brokerages move to the commission free trading model in October 2019, during the months when stimulus checks were received (April and May 2020) and the proceeding summer month (June and July 2020), and in weeks when the market index is positive and weeks when the market index is negative. Returns are reported in percentage points. T-statistics are in parentheses.

Strategy	Pre-Commission Free	Post-Commission Free	Stim	Summer 2020	Mkt Up	Mkt Down
Week OTM	0.90	2.19	7.03	0.09	2.36	-0.21
	(3.20)	(2.32)	(1.76)	(0.11)	(4.09)	(-0.58)
Month OTM	2.03	8.98	38.89	5.18	6.93	-1.75
	(1.44)	(1.67)	(1.90)	(0.90)	(2.39)	(-1.08)
Month ATM	0.37	3.34	16.62	2.56	3.93	-5.63
	(0.23)	(1.43)	(4.24)	(0.58)	(2.80)	(-4.67)

2.6. Aggregate Retail Option Demand and Vega Risk

To provide further support for our contention that aggregate retail demand leads to option mispricing, we document two stylized facts in this section.

1. RH equity holdings proxies for aggregate retail option demand.
2. Returns to selling delta-neutral call options to RH investors are *primarily* driven by RH's overestimation of ex-post stock volatility and, thus, option overvaluation.

These propositions are tested with the Chicago Board of Options Exchange (CBOE) Open-Close Volume Summary. This data provides aggregated option volume of calls and puts, bucketed by the account of origin (customer, professional, broker-dealer, and market maker), buy/sell, and open/close. Following previous studies[16], we consider customer open buy orders of *less* than 199 contracts as a proxy for retail option demand. Correspondingly, professional open buy orders *greater* than 199 contracts proxies for institutional demand. We impose several filters for the accuracy and completeness of the data, including removing options with negative bid-ask spread, maturities shorter than seven days, and midpoint prices approaching zero. This data ranges from 2019 – 2021 and covers roughly 30% of the total US option market volume during this timeframe.

2.6.1. Delta-Vega Neutral Portfolio Construction

The heterogeneity of portfolio return in Table 2.3 and subsequent analysis suggests that RH demand contributes to option mispricing via an increase in implied volatility. Therefore, the outperformance of delta-neutral strategies that sell call options to high retail demand stocks is

[16] Customer trades under 100 are shown to be a strong proxy for retail trade by Bryzgalova, Pavlova, and Sikorskaya (2023).

due to inflated volatility risk premium (VRP) *relative* to the actual amount of volatility risk exposure.

In this section, we further consider the effect of retail demand on option mispricing through option Vega. Vega is the measurement of an option's price sensitivity to changes in the implied volatility (IV) of the underlying asset and is shown to strongly affect the performance of delta-neutral strategies by Bakshi and Kapadia (2003). To provide additional evidence that increased IV drives the RH portfolios' abnormal returns, we now construct delta-vega neutral (DVN) positions. Returns to DVN positions are unaffected by IV by construction allowing us to study the portion of RH portfolio return attributable to inflated IV. DVN positions are formed by selling a call option and buying a put option and the underlying stock. Returns to buy and hold DVN call writing are computed as:

$$Ret = \frac{\left(\Delta_{c,t-1} - \left(\frac{\nu_{c,t-1}}{\nu_{p,t-1}} * \Delta_{p,t-1}\right)\right) * S_t - C_t + \left(\frac{\nu_{c,t-1}}{\nu_{p,t-1}} * P_t\right)}{\left(\Delta_{c,t-1} - \left(\frac{\nu_{c,t-1}}{\nu_{p,t-1}} * \Delta_{p,t-1}\right)\right) * S_{t-1} - C_{t-1} + \left(\frac{\nu_{c,t-1}}{\nu_{p,t-1}} * P_{t-1}\right)} - 1$$

In week t-1, we construct a DVN position by selling one call option (C_{t-1}), purchasing $\frac{\nu_{c,t-1}}{\nu_{p,t-1}}$ contracts of put options (P_{t-1}), and purchasing $\left(\Delta_{c,t-1} - \left(\frac{\nu_{c,t-1}}{\nu_{p,t-1}} * \Delta_{p,t-1}\right)\right)$ shares of stock (S_{t-1}). The purchased put option has the highest liquidity available on the same underlying stock as the call. At week t, we close all open positions and compute returns.

The average Vega of options grouped by maturity, moneyness, and level of retail demand proxied by CBOE open buy orders are presented in Table 2.10. As a baseline, Table 2.10 illustrates that retail traders typically prefer options with higher absolute levels of Vega. If the volatility risk premium is overstated on high Vega / retail demand options, we will note profitability to strategies that are short these options, as in previous sections.

2.6.2. Returns to Selling DVN Calls to Retail Traders

In this section, we compare the returns to selling DVN calls to the returns to selling delta-neutral calls. In contrast to earlier sections, which grouped sold options by maturity and moneyness, here we sell call options to all stocks, only imposing that options do *not* expire over the holding period of one week. Strategy returns are computed on all optionable stocks within our timeframe and then sorted into equally weighted decile portfolios based on the aggregate level of CBOE retail call option demand over the previous week. Portfolios are rebalanced weekly. As before, we express the expectation of future returns as a function of prior period retail demand by computing a (10 – 1) spread portfolio, which sells delta-neutral (DVN) calls in the top decile and buys delta-neutral (DVN) calls in the bottom decile. Equally weighted returns for the decile portfolios are presented in Table 2.11.

As predicted by retail demand pressure, the returns of the (10 – 1) spread portfolios in Table 2.11 are significant and positive. Further, the return of the DVN spread portfolio (36.8 bps) is significantly *less* than that of the delta-neutral spread portfolio (62.8 bps) per week. Through the lens of option mispricing, once the exposure to Vega is netted out of the delta-neutral portfolios, returns decrease dramatically, with an annualized return difference of 12.48 percent. Such a difference indicates that a large portion of the heterogeneous return across deciles of retail demand can be attributed to differential (inflated) VRP due to retail demand pressure. In other words, selling volatility is profitable once IV returns to normal levels.

2.6.3. Modeling Portfolio Return

We model the relationship between delta-neutral and DVN position returns as follows:

$$Weekly\ Return_{i,s,t} = \alpha_{i,s,t} + \beta_1 Retail\ Vol_{i,s,t-1} + \beta_2 Institution\ Vol_{i,s,t-1} + \varepsilon_{i,s,t}$$

Where $\text{Weekly Return}_{\text{i,s,t}}$ is the $\text{Delta neutral return}_{\text{i,s,t}}$ or $\text{Delta Vega neutral return}_{\text{i,s,t}}$ of call option i in week t on underlying stock s. $\text{Retail Vol}_{\text{i,s,t}-1}$ is call option i's aggregated retail open call volume in week t-1 and $\text{Institution Vol}_{\text{i,s,t}-1}$ is call option i's weekly aggregated institutional open call volume in week t-1. Institutional volume is included as a benchmark for the retail volume results. Although we expect both β_1 and β_2 to be significantly positive, β_1 should have a larger magnitude if retail investors cause more mispricing than institutions. Ex-ante, we also expect the coefficient on retail volume to be significantly larger for the returns of delta-neutral positions compared to DVN positions, as the premium for inflated IV is netted out of the DVN return. Table 2.12 presents the results of this model.

The coefficient on retail volume in the delta-neutral return model is consistent with return differences sorted by RH holdings. An increase of 10,000 open buy orders by retail accounts is associated with a 9.11 percent increase (t-stat of 35.73) in the next week's delta-neutral position return on that option. The coefficient on retail volume is benchmarked by the relatively meager effect of institutional volume on delta-neutral return, only a 0.445 percent increase (t-stat of 3.29) for the same magnitude increase of open buy orders. The differential impact of retail volume persists in the model with DVN return as the dependent variable, whereby the coefficient on retail volume is roughly fifteen times larger than the coefficient on institutional volume.

Further, the effect of retail volume is significantly muted in the DVN model compared to the delta-neutral model. For the same increase of 10,000 open buy call orders, the returns to a delta-neutral short call position increase by 9.11 percent (t-stat of 35.73), and the returns to a DVN position only increase by 3.97 percent (t-stat of 19.08). These results suggest that heterogenous cross-sectional VRP can explain up to 56.42 percent of the total return attributable to retail demand. These results strongly support the notion that retail investors overpay for exposure to volatility and that most of the delta-neutral portfolio return is from overstated IV. When focusing on delta-vega neutral portfolios, the movement in implied volatility no longer impacts portfolio returns. Thus, the predictive power in of retail investors' open call volume in the cross section of delta-hedged short call return becomes significantly weaker in magnitude and significance.

Table 2.10 - Average Vega Per Group

This table presents the average Vega of options by retail demand, moneyness, and maturity. Retail demand is proxied by CBOE open buy orders with a total volume of less than 100 contracts and sorted into deciles daily. Option moneyness and maturity are computed via Option Metrics. Data is daily and covers January 1st, 2019 – December 31st, 2021.

	Average Vega										
Decile	1	2	3	4	5	6	7	8	9	10	(10-1)
0-2 ATM	1.70	3.29	4.85	6.24	7.72	9.14	12.53	17.17	19.90	38.33	36.63
0-2 ITM	0.88	1.81	2.89	4.12	5.49	6.53	7.85	11.25	16.43	28.29	27.41
0-2 OTM	2.89	4.82	6.42	8.10	9.92	12.05	15.13	18.09	22.28	36.82	33.93
2-4 ATM	1.70	3.58	5.77	8.24	10.36	12.70	15.57	24.56	37.25	57.30	55.61
2-4 ITM	0.86	1.97	3.33	5.05	7.24	8.92	10.64	14.03	24.07	39.80	38.94
2-4 OTM	3.39	5.86	8.05	10.13	12.57	15.67	20.71	27.87	33.86	50.72	47.33
>4 ATM	1.58	3.62	6.15	9.14	12.64	15.42	18.88	26.65	48.34	74.30	72.71
>4 ITM	0.83	2.04	3.43	5.24	7.66	10.28	12.78	15.87	25.54	47.12	46.28
>4 OTM	3.88	6.72	9.42	12.23	15.05	18.55	23.87	32.72	42.82	61.40	57.52

Table 2.11 - Delta-Neutral and DVN Portfolio Returns by Retail Volume

This table presents weekly portfolio decile returns sorted by one-week lagged retail open call option volume. Delta-neutral portfolios are constructed by selling a call option and buying delta stocks in the market to achieve zero delta. Delta-Vega-neutral portfolios are formed by selling a call option, buying put options, and buying stocks to achieve zero delta and Vega. Option price, volume, delta, and Vega are from the CBOE and Option Metrics from January 2019 to December 2021. Corresponding stock prices are gathered from CRSP. Decile ten has the largest retail investors' open call volume, and decile one the least.

	Weekly Return (%)	
Decile	Delta-Neutral Portfolio	Delta-Vega-Neutral Portfolio
1	-0.01529	-0.01226
2	-0.01537	-0.01289
3	-0.01250	-0.01060
4	-0.01260	-0.00992
5	-0.01268	-0.01024
6	-0.01230	-0.00985
7	-0.01178	-0.00989
8	-0.01136	-0.00971
9	-0.01059	-0.00922
10	-0.00903	-0.00858
10-1	0.00626	0.00368

Table 2.12 – Weekly Return Pooled OLS

This table presents the pooled OLS regression results of delta-neutral portfolio weekly return and Delta-Vega-neutral portfolio weekly return on retail investors' open call option volume and institutional investors' open call option volume. Options trading volumes and option prices data are from the CBOE spanning from January 2019 to December 2021. Stock price data is from the Center for Research in Security Prices (CRSP), covering the same window. T statistics are reported in parentheses. Volume is measured in millions of contracts traded. P-values are denoted as $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

	Dependent Variable: Weekly Return (%)	
	Delta Neutral	Delta-Vega Neutral
Retail Volume	9.11^{***}	3.97^{***}
	(35.73)	(19.08)
Institutional Volume	0.45^{***}	0.27^{**}
	(3.29)	(2.42)
Observations	3,786,543	3,786,543
R^2	0.01	0.01

2.7. Conclusion

This study documents predictability in the cross-section of short delta-neutral call option returns as a function of Robinhood user equity holdings. These returns are statistically and economically significant, robust, and pervasive for the study period.

Using the Robintrack database, which documents aggregate Robinhood (RH) user holdings from May 2018 – July 2020, we sort individual stocks into deciles according to their respective level of RH holdings and sell delta-neutral call options within each decile. Short call positions are adjusted to be delta-neutral by purchasing delta shares of the underlying stock when opening the position. RH (10 – 1) spread portfolios are then constructed by subtracting the returns of the lowest RH decile from the highest. The returns of the RH spread portfolios are statistically and economically significant even when imposing restrictive assumptions on effective spread and margin costs. The monthly rebalanced RH spread portfolio returns for ATM call options exceed 15 percent annually, have a maximum drawdown of less than 10 percent in a month, have significantly positive skewness, and have a higher Sharpe ratio than many other common option return predictors in the literature.

The returns of the RH portfolios are robust after the inclusion of several controls that have been shown to predict the cross-section of delta-hedged option return, with minimal decrease in magnitude and virtually no decrease in significance. The returns of the RH portfolios survive the Karakaya (2013) three-factor option model, the Zhan et al. (2022) two-factor option model, and the Fama French (2015) five-factor equity model with no decrease in magnitude or significance. In addition, the returns of the RH portfolios are not subject to momentum or reversal, as documented in the options market by Heston et al. (2023).

We attribute the returns of the RH portfolios primarily to retail demand-driven mispricing of the traded options. As a consequence of servicing concentrated retail demand, option liquidity providers will charge a higher premium as compensation for increased inventory risk. We show empirically that the effect of RH demand on option price (measured by implied volatility/vega risk) is significantly larger than any resulting pass-through of inventory risk to the underlying stock market (ex-ante realized volatility). The result is overpriced options relative to the exposure to underlying volatility and, thus, high returns for selling these options. This effect is specific for retail call option demand as compared to institutional demand. This assertion is also verified in subsample tests where RH portfolio return significantly increases in periods of higher retail demand.

These results have implications for academics, practitioners, and policymakers alike. With their growing presence and influence, retail investors significantly affect the price and volatility surface of single-name equity options. This influence becomes particularly evident during periods of heightened market volatility or when certain stocks attract retail attention, ala GameStop January 2021. The pricing effects of the online generation of retail investors will continue to increase as they become a more substantial portion of the options market over time, and future research is needed to frame how speculative trading in options affects pricing models.

Chapter 3

Director Characteristics and the Advisory Role of Board's Effect on Performance: Evidence from REITs

With Justin D. Benefield, Ph.D. and Sean P. Salter, Ph.D.

3.1. Introduction

Fama and Jensen (1983) describe boards of directors as "the apex of decision control systems." With their great power, a firm's board of directors is expected to serve as a watchdog for the shareholders. In practice, however, there is substantial variation in the quality of directors and the degree to which they value shareholder interests. This prompts the question: What characteristics are predictive of director quality? Many studies have attempted to answer this question, often with differing conclusions about the impacts of specific attributes.[17] Adams, Akyol, and Verwijmeren (2018) account for some discrepancies by studying director characteristics as a multidimensional web rather than individual features. However, all studies focusing on director characteristics face a particularly challenging identification issue in the dual role of boards as advisors and monitors (Adams and Ferreria (2007) and Adams, Hermalin, and Weisbach (2010)). If a trait positively correlates with better monitoring, does it also positively correlate with better advice? Are there tradeoffs between the two? And, as boards serve both functions simultaneously, is it possible to disentangle the channels through which characteristics affect performance?[18] As a testament to these issues, Faleye et al. (2011) show that the improvement in board monitoring

[17] For example, while Drobetz et al. (2018), Dass et al. (2014), and Faleye et al. (2018) find that directors' industry experience adds value, Kang et al. (2017) find that the effect of industry experience is insignificant in some circumstances. Similarly, Fich (2005) finds that shareholders seem to value Chief Executive Officer (CEO) experience of directors, while Fahlenbrach et al. (2010) find that CEOs do not add value.
[18] Brickley and Zimmerman (2010) and Dass et al. (2014) speak to the difficulty of disentangling the effects of characteristics on the monitoring and advising roles.

quality comes at the cost of directors' weaker strategic advising, and Masulis et al. (2012) find that foreign independent directors' advisory services come at the expense of worse monitoring. Given this empirical challenge, we propose a new laboratory to study boards' advisory roles.

3.1.1. Using REITs to Study the Advisory Role of Boards

The impetus of the monitoring function of boards is the agency problem described by Jensen and Meckling (1976). As an agent of the shareholder, management will often make decisions in their interest instead of that of the shareholder. This misalignment manifests as the allocation of company funds to projects benefiting management instead of the distribution of wealth back to the shareholders. Therefore, boards must monitor management, and as shown in Schwartz-Ziv and Weisbach (2013), spend nearly all their time doing so.

The unique structure of REITs eliminates the agency problem. To qualify as a REIT, a company must have most of its assets and income in real estate investment and distribute at least 90 percent of its annual taxable income to shareholders as dividends. According to the SEC, "A company that qualifies as a REIT can deduct from its corporate taxable income all the dividends that it pays out to its shareholders. Because of this special tax treatment, most REITs pay out 100 percent of their taxable income to their shareholders and, therefore, owe no corporate tax." This incentive structure directly aligns management with shareholders as strong and pervasive incentives exist for no income to be retained by the firm, thus relaxing the agency problem.[19] As evidence for this claim, we perform tests indicating that more entrenched CEOs are likelier to add influential directors to REITs. Within this setting, the monitoring function of boards is significantly lessened if not eliminated, and we may focus our study solely on the advisory function. To our

[19] REITs alleviate the structural problem described in Chen, Goldstein, Jiang (2008) where they describe mutual funds as "prone to principal-agent problems".

knowledge, this is the first study to disentangle boards' dual role explicitly. By utilizing the unique features of REITs, we provide evidence of the advisory relationship between director characteristics and firm performance.

Additionally, real estate investing and, consequently, REITs are an excellent venue for talented managers or trustees to exploit their superior skill or informational advantages due to the relative illiquidity of the real estate market compared to equity. In this extreme case, understanding the relationship between governance characteristics and firm performance can help companies design effective governance mechanisms to improve performance and provide valuable insights for policymakers and investors.

3.1.2. Overview

We hand collect the biographies of all members on the boards of directors from January 2000 to December 2022 for all REITs in the NAREIT index, a vast majority of the publicly traded U.S. REITs. Information contained within the biographies varies significantly from firm to firm. Generally, it includes employment history, education history, relevant certifications, positions within the REIT, and approximate start dates. Using innovative machine learning techniques, we classify these biographies as belonging to one of ten background groups based on the content of the biography.

Directors with backgrounds consisting of executive or governance experience in finance or accounting roles are identified as having positive correlations with firm performance. Firms with a greater proportion of directors with executive or governance expertise in accounting and finance roles have between 1.8 and 2% greater monthly returns than the average REIT within the sample period. This return increase represents a 64% increase over the total sample average monthly REIT return of 1.1%. These results are robust to various specifications with little change in magnitude and significance. Results hold in two-stage least squares where director's attended university finance and accounting rankings are used as an instrument for director background, and in a generalized difference in difference model where the returns of firms with high value directors are compared to control firms. Both tests indicate that a one standard deviation increase in the proportion of high value directors within the firm increases monthly returns by roughly 2%.

The relationship between board background and firm returns appears linear in the case of directors with executive experience in finance or accounting roles. There is a large and statistically significant return spread between the highest and lowest quartiles based on the number of directors with executive experience in finance and accounting positions. The spread of returns between firms in the lowest and highest quartiles is 48.2 basis points per month. This difference in means is highly significant. In addition, the level of monthly return is monotonically increasing as more directors with executive experience in finance or accounting are added to the board.

Returns vary in the cross-section of REITs dependent on the board's composition and over time. Adding a director with a background in executive or governance roles in accounting and finance will increase firm risk-adjusted returns by 50 basis points per month based on the Fama French 3-factor model plus momentum. The univariate differences in the before and after director starts groups are striking. Returns for firms before adding high-value directors average around 98.58 monthly basis points. These returns increase to 150 basis points a month after adding a high-value director, a 52% return increase. This jump in returns provides evidence that REITs that add high-value members to the board were underperforming. Returns before the addition are 12% lower than the REIT average and 36% greater after adding the high-value director.

Through an event study framework, we show that REITs typically add high-value directors when underperforming relative to a broad real estate benchmark. Cumulative abnormal returns are reliably negative at a 95% confidence interval in the two years before a high-value director joins the board. After the fact, the high-value director seems to stabilize the firm, and the CARs become indistinguishable from zero at a 95% confidence interval. This relationship is mutually beneficial for REIT management and the director, as the director receives reputational benefits leading to enhanced career opportunities and more prestigious directorships after service to the REIT.

The way a high-value director creates value for their firm changes over time. For the two quarters immediately after the addition of the high-value director, the most considerable changes come in non-operating income, net income, and the sale of real estate, increasing by 37%, 25%, and 31%, respectively. These increases suggest that high-value directors influence the sale of property, leading to significant increases in non-operating income and, subsequently, net income for the firm. These sales result in a short-term net income and earnings boost while allowing the REIT to focus on its best properties instead of having a non-focused or poorly managed portfolio. When considering their entire tenure, high-value directors can influence how REITs are operated and REIT investment strategy, focusing their portfolio on higher quality properties. Cash, funds from core real estate, and gain on real estate sales are all negative and significant, at least at the 5% level, related to EPS before adding a high-value director but become positive and significant at the 1% level after the addition. This flip in the sign of the coefficients on these variables after the start of a high-value director is informative as the operation of the REIT. Whereas the negative coefficients once indicated that REITs mismanaged cash, poorly managed properties, and sold the wrong properties, the positive coefficients after the addition indicate the opposite. REITs with high-value directors now efficiently manage cash, efficiently manage properties, and sell the best properties for their strategy. These results suggest that high-value directors are pivoting the REITs they govern to more profitable property submarkets.

This study provides evidence that governance can have strong and persistent effects on returns, specifically within less liquid asset classes such as real estate. Talented directors with strong backgrounds in accounting and finance can exploit their relative advantages in skill and information to create significant benefits for the firm they govern.

3.2. Place and Contribution

We contribute to governance literature by providing evidence that director characteristics matter for their advisory function. This is unique in that REITs allow us to study the advisory role separately from monitoring. We also provide a new method of characterizing director traits and experience using Latent Dirichlet Allocation. This study suggests that director skill is heterogeneous, and directors may exploit relative differences to create benefits for the firm they govern.

3.2.1. Director Characteristics and Governance

The primary contribution of this study is uncovering the relation between director characteristics and firm performance through the advisory function of boards. Adams and Ferreira (2007) provide a model analyzing the consequences of the board's dual role as an advisor as well as a monitor of management.[20] This model suggests that shareholders are at least weakly better off when boards have an advisory role. Given the importance, some studies have considered how director characteristics affect director performance within their advisory function. Chen et al.

[20] Several European countries have a dual board structure to account for the fundamental difference in the advisory and monitoring functions.

(2020) utilize an exogenous shock to the operation of manufacturing firms to provide evidence that experienced directors positively affect firm value after an appointment and through future investment. Cai, Nguyen, and Walkling (2022) show that boards are more likely to appoint connected directors with similar experience and industry backgrounds to themselves. Greater uniformity can help to alleviate deadlock, as discussed by Donaldson et al. (2020), albeit at the expense of board diversity (a topic of several studies).[21] The primary challenge when interpreting this research thus far has been the entanglement between the dual roles of the board. We directly address this entanglement using REITs and provide evidence supporting Adams and Ferreira (2007) and Adams, Hermalin, and Weisbach (2010) that the advisory function of boards is strongly related to firm performance.

We contribute to the extensive literature on the connection between individual director characteristics and firm decisions. Individual director characteristic studies span a wide range, including but not limited to the effect of financial expertise on corporate decisions (Güner, Malmendier, and Tate (2008)), industry expertise and monitoring effectiveness (Wang, Xie, and Zhu (2015)), the importance of board expertise from related industries (Dass et al. (2014)), foreign experience in international firms (Giannetti, Liao, Yu (2015)), board composition (Adams, Mansi, Nishikawa (2010)), political connections on firm value (Goldman, Rochell, and So (2009)), executive experience in related industries (Kang, Kim, Lu (2018)), director bankruptcy experience and risk tolerance (Gopley, Gorman, Kalda (2021)), and demographic factors such as Adams and Ferreira (2009). However, there is much disagreement within the literature about the direction and magnitude specific experiences and characteristics have on firm decisions and performance. Adams, Akyol, and Verwijmeren (2018) suggest that much of this disagreement is due to the multi-

[21] Bernile, Bhagwat, and Yonker (2018) provide a recent addition to the topic of board diversity.

dimensional nature of director skill sets. In this way, considering only select experiences is likely to be problematic regarding endogeneity. We also address this issue by using Latent Dirichlet Allocation to fully encapsulate a director's background. Our results support those of Adams, Akyol, and Verwijmeren (2018) that uniformity in experiences benefits boards with a specific focus on their advisory role. In addition, our results offer more direct economic benefits (at least within REITs) than a multi-dimensional skill set, as our identified backgrounds are much easier to quantify than a multi-dimensional skillset.

In addition, using a text-based machine learning algorithm is an important contribution to future research into director characteristics. Using Latent Dirichlet Allocation allows for reliable and reproducible classification of biographies without the danger of cherry-picking specific attributes. LDA also safeguards against spurious correlation by enabling the researcher to classify the assigned topics. This evidence supports a recent study by Erel, Stern, Tan, and Weisbach (2021), who show that machine learning algorithms can predict successful directors. These results suggest that director characteristics correlate with measures of success in a way observable through machine learning algorithms. Using an illiquid asset class emphasizes directors' impact on firm performance and allows for further study of director characteristics.

3.2.2. REITs

Due to its comparative illiquidity, the real estate industry is a prime target for a skilled manager director to reap the benefits of superior ability or knowledge. Outperformance in equity markets is difficult because of high liquidity. Mispricing in equity markets is quickly and efficiently corrected, narrowing the window for investors to extract alpha. On the other hand, the real estate industry is illiquid, with large chunks of time between appraisals. As Gyourko and Keim (1992) show, there is a strong relationship between the appraisal series and real estate portfolios.

Also, as Zhu (2018) notes, most variation in REITs comes from changes in the underlying property value and deviation in the amount of rent paid, both costly to observe by the public. The nature of this market should allow real estate experts to reap the benefits of their superior knowledge. Indeed, extant research by Morningstar and other REIT providers shows that actively managed REITs perform better than their passively managed counterparts, even net of fees. A skilled manager or director with information about future trends can capture returns by strategically positioning the investments of their REIT. Hochberg and Mühlhofer (2017) show relative outperformance of REITs based on the ability of the REIT manager to select profitable property submarkets. We bolster this research by showing the heterogeneous skill levels of directors and associated REIT performance.

A significant strand of literature focuses on information asymmetries in the real estate market. Ling, Naranjo, and Scheick (2021) provide robust evidence that local information plays a significant role in the linkage between local asset concentration and portfolio returns. Specifically, REITs that invest more heavily in local real estate (near headquarters) enjoy higher returns than more geographically diversified REITs. This return divergence is more significant when information asymmetries in the REIT's home MSA are more significant. In a concrete example of the superior information of real estate professionals relative to the public, Shen, Hui, and Fan (2021) provide evidence that REIT insiders significantly reduced their holdings before the financial crisis of 2008. Difference in difference analysis indicates that REIT insiders liquidated their real estate positions even more quickly than insiders in real estate and construction firms, providing evidence that REIT insiders possess more significant information advantages regarding real estate markets. A broad study of REIT-holding mutual funds (Kallberg, Liu, and Trzcinka, 2000) found that the average and median alphas of actively managed funds are positive. In mainstream finance, Ravina and Sapienza (2010) provide evidence that directors have private information in their firms and earn large abnormal returns on their trades. We support these ideas by offering evidence that directors have private information on the markets in which they specialize and may exploit this information to benefit their firm.

Specifically, we uncover how the REIT board's background or "expertise" affects their returns. A similar study to this paper (Howe & Shilling, 1990) examined whether the performance of REITs is correlated with advisor type. The definition of advisor is ambiguous in the paper; still, assuming this is closely related to the modern board of directors, the authors identify significant differences between the types of advisors and the performance measures of the REIT they advise. Indeed, relative performance differences of REITs documented by Hochberg and Mühlhofer (2017) could be correlated with differences in the background of managers. Our study provides novel results on how the board of directors' experience affects REIT returns.

Directly relating to the REIT board of advisors, Ghosh and Sirmans (2003) find that independent directors enhance REIT performance at lower levels than conventional firms, providing additional evidence that agency problems are mitigated within REITs. Sirmans, Friday, and Price (2006) study management changes in REITs and find a strong relation between poor performance management turnover. Although they do not uncover predictive capabilities of negative performance on manager changes, Sirmans, Friday, and Price's results could indicate that REIT boards are sensitive to performance and, therefore, demand skilled managers. This level of oversight from boards indicates that boards have a good deal of control over the performance of the REIT, bolstering the assumptions made by the present study.

3.3. Biography Collection and Topic Modeling

A list of REITs for data collection was obtained from the National Association of Real Estate Investment Trusts (NAREIT). The NAREIT sample is comprehensive regarding publicly-traded REITs in the United States. Director and top-listed executive biographies are hand-collected from firm websites or proxy statement filings.[22] This process is completed for 147 REITs and creates a sample of 1,722 individuals with matched biographies. There is no standard for the publication of biographies by firms. Therefore, the length and informativeness of the biographies vary significantly from firm to firm. The most common information discussed in biographies is the person's role, start dates, previous work experience within the firm or elsewhere, education experience, and any relevant certifications. When the information the firm reports via its website is sparse, data is supplemented with LinkedIn profiles and other publicly available sources using an internet search. An example of a standard biography from Mr. John Doe is as follows:

> "Mr. Doe currently serves as a Chief Executive Officer of GSI Capital Advisors, an investment manager focused on investment opportunities in publicly traded real estate securities, primarily REITs. Previously, he was with Green Street Advisors, Inc., a commercial real estate, news, data, analytics, and advisory services firm, for over 26 years, serving as its President and Chief Executive Officer for 13 years. Before Green Street Advisors, Mr. Doe worked as a real estate consultant at Kenneth Leventhal and Company and as a commercial real estate lender at Union Bank of California. He received a bachelor's degree in management science from

[22] Defined as the listed executives on the REIT website.

the University of California, San Diego, and an MBA in finance and real estate from Columbia Business School."

To classify the background of the directors reliably and reproducibly, we use a topic modeling procedure known as Latent Dirichlet Allocation (LDA). LDA is a commonly used algorithm in topic modeling literature. An in-depth description of the foundation and uses of LDA can be found in Blei, Ng, and Jordan (2003). For this study, LDA can be understood as being guided by two principles[23]:

1. Each biography is a mixture of topics: Each will contain words that will be identified with a particular topic in specific proportions. For example, in a two-topic model, John Doe's biography may be classified as 20% "Topic 1" and 80% "Topic 2".

2. Each topic is a mixture of words: In a two-topic model, we could imagine topics we define broadly as "finance" and "real estate". These topics describe the primary background of the individual based on the firm-reported biography. The most common words for finance may be "investment", "equity", or "interest". The most common words for real estate may be terms such as "property", "development", or "building". There may also be some common words between the two topics, such as "asset".

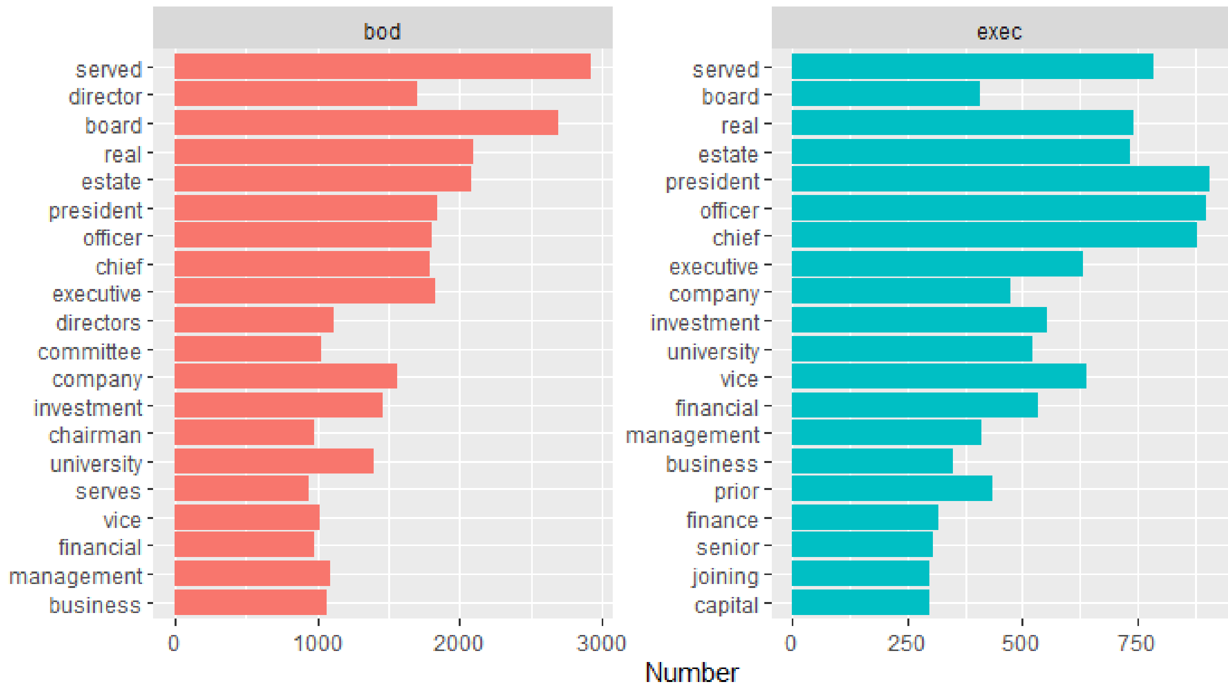
[23] See Silge, Julia, and Robinson, David. Text Mining with R. O'Reilly Media, 2017.

Table 3.1 – LDA Topics, Classifications, and Top Terms

Topic 1: Governance Experience	Topic 2: Executive Experience Accounting and Finance	Topic 3: Legal Experience, Highly Educated	Topic 4: Highly Awarded, Many Philanthropic Activities	Topic 5: Investing or Banking Experience	Topic 6: Real Estate Development Experience	Topic 7: Board Experience Accounting and Finance	Topic 8: Technology Experience	Topic 9: Real Estate Investment Experience	Topic 10: Hotels, Hospitality, Resorts Experience
Served	President	University	University	Investment	Real	Board	Served	Real	President
Officer	Officer	Law	Business	Real	Estate	Served	University	Estate	Executive
Chief	Served	Served	Board	Estate	Board	Committee	Board	Investment	Chief
Executive	Chief	Board	Real	Capital	Company	Directors	Director	Director	Officer
Board	Executive	School	Estate	Director	Executive	Company	President	Committee	Hotels
Real	Vice	Counsel	School	Managing	Experience	Audit	Technology	University	Resort
Estate	Company	Serves	Executive	Served	Investment	Executive	Business	Board	University
President	Financial	Health	Award	Equity	University	Serves	Developed	Served	Hospitality
Director	Accounting	Business	Served	Management	Management	Director	Serves	Manage	Vice
Chairman	Board	Committee	Companies	Banking	President	Governance	Prior	Serves	Business

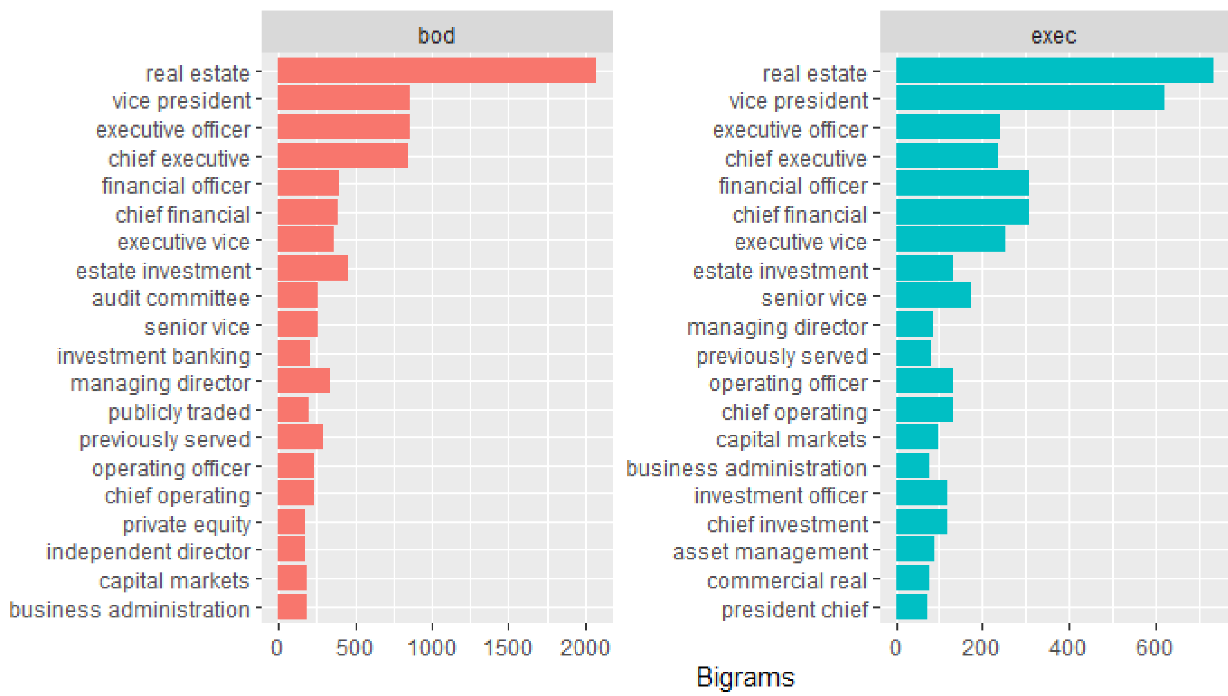
Topics are generated based on the Latent Dirichlet allocation algorithm running on the board of director biographies for REITs. The number of output topics is ten. The top ten terms based on beta, the probability that a certain word belongs in each topic, for each topic are displayed. Classification of the topics into a background group is done after the fact and is based on the terms in the topic along with a sanity check by randomly sampling biographies which match a type and hand classifying to check matches.

Figure 3.1 – Top Terms



Top terms are computed by tokenizing the text content of biographies and computing the number of times a word appears in the full sample after removing names and stop words.

Figure 3.2 – Top Bigrams



Top bigrams are computed by tokenizing bigrams within the text content of biographies and computing the number of times a given bigram appears in the full sample after removing names and stop words.

LDA is a machine learning algorithm that estimates both principles, finding the mixture of words associated with each topic and determining the mix of topics that make up a biography. It will assign each term with a beta representing the per-topic-per-word probabilities. It will then assign each document with a gamma representing the per-document-per-topic probability. In Mr. Doe's case, LDA may decide his biography is 60% "real estate" with a 0.6 gamma and 40% "finance" with a 0.4 gamma. LDA computes this by examining the mixture of words in the biography.

Figures 3.1 and 3.2 display the top twenty words and bigrams, respectively, in the biographies of executives and directors after cleaning out names and stop words with low informational content, such as "the" and "a."[24] One can quickly see how several of these words and bigrams contain informative content regarding the background of the individual in whose bio it appears. For example, a strong case is to be made that the word "finance" or the bigram "investment banking" appearing in the biography will indicate an individual with finance experience. When conducting topic modeling, we subset the biographies to just those of directors. This decision is because there is very little uniformity in the executives reported on firm websites. Some may report only the CEO, others the executive team and vice presidents. Focusing on the complete directors helps the cleanliness of the study and the interpretation of results.

We chose ten topics for LDA, as we believe this number will capture sufficient variation in backgrounds without becoming overly specific for any one topic (i.e., an investment banker with an accounting degree from a university in the South), thus increasing the applicability of our

[24] Defined in text modeling literature as words with little to no informational content.

results and mitigating the risk of overfitting.[25] The LDA topic numbers, their classifications, and the top terms by beta within each topic are reported in Table 3.1.[26] It should be stressed that characterization of the topics, and thus of the backgrounds, is done by hand. LDA reports a list of words for each topic based on their patterns within the bios. It is then left to the researcher to apply meaning to the grouped terms and find the pattern. We believe our characterization of the topics to be highly correlated with the actual background of the individuals described. We also conduct robustness checks for which biographies matching each topic are randomly sampled and read thoroughly to confirm that the characterizations of the topics are accurate. It may also be noted that several terms overlap between the topics. This overlap is due to the similarity of the roles all held *currently* as each of the biographies describes the background of a current REIT director, e.g., “serves”, which is likely to be describing their current service to the REIT. Heterogeneity can be found in less common terms, such as “accounting”, which is unlikely to represent anything other than an accounting degree or position. It should also be noted that although some groups are similar, all groups describe distinct types of biographies. For example, topics two and seven correlate highly with backgrounds in accounting and finance roles; however, topic two aggregates directors with executive experience in these roles, and topic seven aggregates directors with governance experience.

3.4. Background Connection with REIT Performance

After characterization of the topics created by LDA, we may assign each individual a gamma for each topic, which is the probability they belong to that topic. This process results in

[25] Results are robust for alternative numbers of topics. Since LDA just groups biographies by their content, more (less) topics will result in more specific (more general) groupings but will ultimately identify the same directors.
[26] Probability a given term belongs to a given topic.

each individual having an associated gamma for all ten topics, where all gammas for each sum to 100%. We then assign each director to a background group based on their highest gamma, indicating their most likely background topic. Matched gammas and background groups are then linked with monthly firm returns downloaded from the Center for Research and Security Prices (CRSP). The CRSP file encompasses all real estate firms screening on standard industrial code from January 2000 to December 2022, resulting in 135 matched REITs. Panel A in Table 3.2 provides summary statistics. Returns over this timeframe were 1.1% for REITs and .55% per month for a broad market index. "Topic Class" refers to the matched topic background for each individual in the sample. A mean of roughly 5 for topic class indicates the distribution of topics is relatively normal, and no large group of individuals is assigned to any particular topic. This normality suggests the LDA-assigned backgrounds capture significant variation in the biographies.

Panel B in Table 3.2 reports summary statistics of various accounting measures of interest from Compustat in millions of dollars from January 2000 to December 2022. Compustat data is retrieved for all REITs in the NAREIT database, resulting in matched accounting information for 135 REITs. The average REIT in our sample owns roughly $4.5 billion worth of real estate and generates a net income of around $44 million per quarter. These variables are used primarily in section 3.6 to investigate how a director can affect firm value represented by earnings per share.

Table 3.3 provides summary statistics for gamma at the director and firm level. Although some directors are classified as belonging to only one topic group, most directors have a multi-dimensional background.[27] Results from this study help to identify the specific characteristics that are most beneficial in generating outperformance.

[27] This is consistent with evidence presented by Adams, Akyol, and Verwijmeren (2018).

Table 3.2 – Summary Statistics

Variable	N	Mean	SD	Min	Pct. 25	Pct. 75	Max
			Panel A: Months				
Returns	2,080,810	0.011	0.098	-0.77	-0.031	0.053	2.9
Volume	2,080,810	191,577	305,804	60	34,563	237,109	11,272,466
Topic Class	2,080,810	5.3	2.9	1	2	8	10
Market Return	2,080,810	0.0055	0.045	-0.17	-0.018	0.032	0.13
			Panel B: Quarters				
Total Assets	5,957	6,429	10,093	60	1,425	7,137	125,172
Current Assets	5,957	175	340	0	15	177	6,835
Cash	4,676	169	342	0	12	172	6,719
Income	4,243	55	152	-1,787	4.3	61	3,758
Long Term Debt	5,957	2,871	4,248	0	589	3,193	46,727
Depreciation of RE	5,310	49	70	-142	9.1	55	835
Core RE Funds	4,061	99	164	-1,148	20	108	1,649
Long Term Investment	5,521	4,714	6,283	0	997	5,542	83,142
Short Term Investment	4,412	37	85	0	0	40	2,002
Non-Operating Income	5,945	12	83	-1,699	0	6	3,747
Net Income	5,953	44	124	-1,616	4.7	49	3,588
Total Real Estate	5,380	4,493	5,763	0	1,032	5,475	73,323
Sale of Real Estate	5,236	10	68	-115	0	1.3	3,735
EPS	5,956	0.33	0.76	-12	0.08	0.49	15

Panel A represents monthly summary statistics for all REITs. Panel B represents quarterly summary statics for all REITs matched with Compustat data. Returns and Market Return represent monthly returns for REITs and a broad market index, respectively. Volume represents the number of trades per month for REITs. Topic Class Represents the characterization of each REIT to a topic by board of director biographical information. All values in panel B are reported in millions of dollars aside from EPS, which measures the earnings per share with magnitude matching the reported value. Time is from January 2000 – December 2022.

Table 3.3 – Gamma Summary Statistics

Topics	N	Mean	SD	Min	Pct. 25	Pct. 75	Max
			Panel A: Director Level				
1	1419	0.15	0.26	0.000076	0.00035	0.23	1
2	1419	0.06	0.17	0.000071	0.00029	0.0007	1
3	1419	0.11	0.23	0.000073	0.00031	0.041	1
4	1419	0.13	0.25	0.000073	0.00033	0.14	1
5	1419	0.13	0.24	0.000071	0.00033	0.14	1
6	1419	0.083	0.22	0.000071	0.00029	0.00074	1
7	1419	0.066	0.19	0.000071	0.00029	0.00074	1
8	1419	0.07	0.19	0.000071	0.00028	0.00071	1
9	1419	0.094	0.23	0.000071	0.00029	0.00097	1
10	1419	0.11	0.23	0.000071	0.00031	0.087	1
			Panel B: Firm Level				
1	148	0.16	0.14	0.00032	0.06	0.2	0.65
2	148	0.059	0.072	0.00019	0.00054	0.089	0.52
3	148	0.11	0.11	0.000094	0.032	0.16	0.54
4	148	0.13	0.11	0.000094	0.049	0.2	0.46
5	148	0.12	0.12	0.00025	0.026	0.19	0.52
6	148	0.084	0.12	0.000094	0.00043	0.11	0.55
7	148	0.068	0.11	0.000094	0.00083	0.077	0.75
8	148	0.071	0.1	0.000094	0.00063	0.1	0.67
9	148	0.09	0.11	0.00021	0.0051	0.13	0.78
10	148	0.11	0.12	0.000094	0.021	0.16	0.58

Panel A presents summary statistics for gamma on the director level. Gamma is calculated as the probability that a particular biography belongs to a topic as classified by the LDA algorithm. Panel B presents summary statistics for gamma on the firm level. Firm level gammas are computed as the average gamma amongst all directors within a firm.

3.4.1. Effect of Firm-Level Gamma on Returns

The effect of gamma on firm returns is the relation between the increasing probability of a director being from a particular background group and that firm's returns. As firms have several directors, we create an aggregate gamma score for each firm by averaging the gamma of all the firm's directors for each topic. Therefore, the average gamma per topic for any firm is $agam_i =$

$\frac{\sum BoardMemberGammas}{\#ofBoardMembersinfirm}$. This process results in ten average gammas per firm, measuring the likelihood that a board comprises directors from a specific topic (background). Average gamma is time-invariant because director biographies are constant over time, and thus, any differences in returns based on average gamma will be across REITs and not over time[28].

To test the relationship between board backgrounds and monthly firm returns, we begin with the following simple model from January 2000 – December 2022:

$$Ret_{i,t} = agam_i + \sum_{n=1}^{10} topic_n + \sum_{n=1}^{10} topic_n * agam_i + e_{i,t} \tag{1}$$

Model 1 regresses monthly returns on the average gamma of each firm per topic, where topic is a dummy variable indicating which average gamma background match is being used. The coefficient of interest is the interaction of topic and average gamma, representing the average change in monthly firm returns for a one standard deviation increase in the likelihood that a firm's directors belong to a given topic. In other words, as it becomes more likely that a firm's directors belong to a topic group based on their biographies, what happens to return? Table 3.4 presents the results of Model 1.

Table 3.4 shows a strong relationship in terms of magnitude and statistical significance between topics 2 and 7 average gamma and firm returns. From Table 3.1, these topics describe individuals with experience in executive roles or other boards with a focus on accounting and finance. The coefficients from Table 3.4 indicate that firms that add directors with executive or governance experience in accounting and finance roles will have between 1.8 and 2% greater monthly returns than the average REIT within the sample period. These coefficients are significant

[28] This does not imply that ***actual*** director backgrounds are constant over time, only that their reported biographies are rarely updated on REIT websites, therefore making gamma largely time invariant in our sample.

at the 5% level, and the associated increases are economically large. However, one must be careful not to interpret these results as an endorsement of adding any specific number of directors but rather as the effect of increasing the likelihood that the board is composed of directors from topics 2 and 7. Return effects to the firm for adding a single director with experience in executive roles or other boards focusing on accounting and finance are addressed later, along with potential endogeneity concerns.[29] This return increase represents a 64% increase over the total sample average monthly REIT return of 1.1% and a 227% increase over the total sample monthly market return, providing strong evidence that directors with specific backgrounds are relatively more valuable to their firms than other individuals. Directors from topics 2 and 7 who LDA characterizes as having executive or governance experience focusing on accounting and finance roles are hereafter referred to as "high-value directors." Interestingly, high-value directors are also the least common classification as seen from their associated gammas in Table 3.3.

We also test several specifications with additional controls. The following two models represent an OLS regression with controls and a fixed effects model with group effects based on the type of REIT:

$$Ret_{i,t} = \sum topic_n + agam_i + volume_{i,t} + vw_i + sp_i + \sum topic_n * agam_i + e_{i,t} \qquad (2)$$

$$Ret_{i,t} = \sum topic_n + agam_i + volume_{i,t} + \sum topic_n * agam_i + \lambda_i + e_{i,t} \qquad (3)$$

[29] As noted in many studies, the construction of the board of directors is likely endogenous when considering performance outcomes. We attempt to mitigate this concern through an instrumental variables approach.

Table 3.4 – Topic Gamma Effect on Returns

	Dependent variable:
	Returns
Topic 1*Average Gamma	0.004
	(0.008)
Topic 2*Average Gamma	0.020**
	(0.008)
Topic 3*Average Gamma	-0.004
	(0.010)
Topic 4*Average Gamma	0.012
	(0.010)
Topic 5*Average Gamma	-0.005
	(0.009)
Topic 6*Average Gamma	0.007
	(0.008)
Topic 7*Average Gamma	0.018**
	(0.009)
Topic 8*Average Gamma	0.004
	(0.011)
Topic 9*Average Gamma	-0.009
	(0.009)
Constant	0.011***
	(0.001)
Controls	YES
Observations	40,296
R^2	0.0001
Adjusted R^2	0.00002
Residual Std. Error	0.099
F Statistic	1.195

Note: Significance is denoted as *p<0.01**p<0.05***p<0.01. Results are from the following model: $Ret_{i,t} = agam_i + \sum_{n=1}^{10} topic_n + \sum_{n=1}^{10} topic_n * agam_i + e_{i,t}$. Where ret is the monthly returns for firm i, and topic is a dummy variable for a topic and gamma match. Average gamma is computed as $agam_i = \frac{\sum Board\ Member\ Gammas}{\#\ of\ Board\ Members\ in\ firm}$. A characterization of the topics for board background can be found in table 3.1. Monthly observations are used from January 2000 – December 2022.

Table 3.5 – Effect of Gamma on Returns (With Controls)

	Dependent variable:	
	Returns	
	OLS	FE
	(2)	(3)
Topic 2	-0.002**	-0.002
	(0.001)	(0.001)
Average Gamma	-0.004**	-0.003
	(0.002)	(0.002)
Topic 7	-0.002**	-0.001
	(0.001)	(0.001)
Volume	-0.000	-0.000
	(0.000)	(0.000)
VW Return	1.775***	
	(0.026)	
S&P500 Return	-0.824***	
	(0.027)	
Topic 2*Avg. Gamma	0.019***	0.013**
	(0.005)	(0.006)
Topic 7*Avg. Gamma	0.017***	0.011*
	(0.006)	(0.006)
Constant	0.004***	
	(0.0003)	
Group Effects	NO	YES
Observations	40,296	40,296
R^2	0.210	0.00003
Adjusted R^2	0.209	-0.0001
Residual Std. Error	0.088	
F Statistic	7,747.762***	1.227

Note: Significance is denoted as *p**p***p<0.01. Results are from the following models, from left to right: $Ret_{i,t} = \sum topic_n + agam_i + volume_{i,t} + vw_i + s\&p_i + \sum topic_n * agam_i + e_{i,t}$ and $Ret_{i,t} = \sum topic_n + agam_i + volume_{i,t} + \sum topic_n * agam_i + \lambda_i + e_{i,t}$. Where ret is the monthly returns for firm i, topic is a dummy variable for topic and gamma match, volume is the monthly trading volume of firm i, vw is the monthly return on a value weighted index, s&p is the monthly return on an S&P500 index, and average gamma is computed as $agam_i = \frac{\sum Board\ Member\ Gammas}{\#\ of\ Board\ Members\ in\ firm}$. λ_i represents group fixed effects by type of REIT. A characterization of the topics for board background can be found in table 3.1. Monthly observations are used from January 2000 – December 2022.

Model 2 regresses monthly returns on the topic dummies, average gamma of the firm, firm trading volume, and monthly price series of the value-weighted market index and S&P500 index. The coefficient of interest is the interaction of topic and firm average gamma, showing the increase in monthly firm returns for a one standard deviation increase in the associated topic gamma.

Model 3 regresses monthly returns on the topic dummies and average gamma of the firm and adds a group fixed effect for the type of REIT traded, i.e., timberlands, apartments, resorts, etc. Again, the coefficient of interest will be the interaction term of the topic and average gamma, which will now represent the within-group differential monthly return for a standard deviation change in gamma. Only the significant background topics 2 and 7 describing high-value directors are used in these regressions to compare the coefficients to a larger baseline group. Table 3.5 presents the results of models 2 and 3.

High-value directors in all specifications retain an economically and statistically significant positive relationship with monthly firm returns. The coefficients on topic*average gamma from the OLS results in the left column of Table 3.4 increase in significance by adding controls to the 1% level, with minimal reduction in magnitude. These coefficients indicate that increasing the likelihood of high-value director board composition by one standard deviation is associated with an increase in firm returns of between 1.7 and 1.9% per month, a 55% and 73% increase over the baseline average return of 1.1%.

High-value directors retain a significant effect on returns within REIT subgroups. The coefficients on topic*average gamma retain statistical significance in the right column of Table 3.5, which considers group fixed effects. These coefficients indicate that REITs that increase the likelihood of high-value board composition by one standard deviation enjoy 1.1 to 1.3% greater monthly returns than other REITs within their specific subgroup. For example, these coefficients compare the returns of two REITs that own apartment buildings, one with high-value directors and one without. All evidence supports the relationship between high-value directors and excess returns.

3.4.2. Firm Returns Across Gamma Quartile

The previous section documents the effect of adding high-value directors on returns. Also of interest is the relationship between returns and firm average gamma within each topic group. As the average gamma of any topic increases for a firm, we may say it is much more likely most of their directors belong to that background classification. Extant literature disagrees about the benefits of firm diversity. While studies like Carter, Simkins, and Simpson (2003)[30] and Bernile, Bhagwat, and Yonker (2018) suggest there are performance benefits to diversity, others argue that disagreement caused by diverse directors can destroy value through instances like board deadlock (Donaldson, Malenko, Piacentino (2020)). Within the purview of our study, we wish to understand if returns are monotonically increasing as boards become more homogenous in terms of their background. If one believes homogenous boards generate value, ex-ante, one expects returns to increase for firms concerning the gamma level of high-value topic classifications. On the other hand, if one believes diverse backgrounds generate value, then returns should not have a distinguishable pattern concerning the gamma level of high-value topic classifications.

Table 3.6 – Return Difference Across Gamma Quartile

Topic	Gamma Quartile	Average Returns	Q4 - Q1
1	1	0.0137	
1	2	0.00977	
1	3	0.0108	
1	4	0.0103	-0.0034
2	1	0.00778	

[30] It should be stressed, the term "diversity" in the context of this study refers purely to diversity in background and work experience. It is unlikely demographic diversity will be captured within LDA topics.

2	2	0.00883	
2	3	0.0108	
2	4	0.0126	0.00482
3	1	0.0111	
3	2	0.0108	
3	3	0.00973	
3	4	0.00999	-0.00111
4	1	0.0103	
4	2	0.0108	
4	3	0.0105	
4	4	0.0111	0.0008
5	1	0.0124	
5	2	0.0103	
5	3	0.0115	
5	4	0.00975	-0.00265
6	1	0.00911	
6	2	0.0117	
6	3	0.01	
6	4	0.0108	0.00169
7	1	0.0101	
7	2	0.00823	
7	3	0.0102	
7	4	0.0128	0.0027
8	1	0.0106	
8	2	0.0108	
8	3	0.0105	
8	4	0.0101	-0.0005
9	1	0.0119	
9	2	0.0118	
9	3	0.0101	
9	4	0.00823	-0.00367
10	1	0.0111	
10	2	0.0101	
10	3	0.0114	
10	4	0.0093	-0.0018

Average returns are the mean of returns for all firms per month per topic per gamma quartile. Gamma is computed within the LDA algorithm as the per-topic-per-firm probability. Q4 – Q1 refers to the 4th gamma quartile (highest gamma) average returns minus the 1st gamma quartile (lowest gamma) returns within each topic. Monthly returns are used from January 2000 to December 2022.

Average monthly firm returns for the January 2000 – December 2022 sample, sorted by topic and gamma quartile, are reported in Table 3.6. Supporting the value of homogenous boards, there is a large and statistically significant spread between the highest and lowest quartiles of gamma for the high-value backgrounds represented by topics 2 and 7. The spread of returns between firms in the lowest and highest quartiles of gamma is 48.2 and 27 basis points per month for topics 2 and 7, respectively. Welch two-sample t-tests indicate the difference in returns between the lowest and highest quartiles of gamma is significant at the 5% level for topic 2 and the 10% level for topic 7. Specifically, the level of monthly return is monotonically increasing with respect to gamma in topic 2, which describes directors with executive experience in finance and accounting roles. This monotonic increase indicates a positive linear relationship between the board composition with high-value directors and firm returns. The return spreads across quartiles are strong evidence of the positive relationship between high-value directors and returns. As more high-value directors are added, firm returns increase. These results favor homogenous boards in terms of their background within REITs.

3.4.3. Firm Returns Before and After Addition of High-Value Directors

Previous sections have examined returns across firms concerning the average gamma of directors. Cross-sectional study allows us to understand how high-value directors affect returns across firms but does not provide information on how the high-value director affects returns within firms over time. To understand the impact adding a high-value director has on the firm, we subset the data to only include firms with a high-value director on the board during the sample window from January 2000 to December 2022. We then created two groups, one before the high-value director was added (before-start) and one after (after-start).

The univariate differences in the before and after-start groups are apparent. Returns for firms before adding high-value directors average 98.58 basis points per month. These returns increase to 150 basis points a month after adding a high-value director, a 52% increase. Results are quantitatively similar if high-value directors are broken down to their respective backgrounds of executive or governance experience in accounting or finance roles (topics 2 and 7). The jump in returns also provides evidence that REITs that add high-value directors to the board were underperforming before the addition. Returns before the addition are 12% lower than the total sample REIT monthly return but become 36% after adding the high-value director. This evidence indicates that high-value directors substantially impact firm performance and that their services may be in greater demand when REITs are underperforming. Given that REIT investors are particularly performance-sensitive, such large increases in return are highly economically significant.

For risk-adjusted returns, we regress the returns of REITs with a high-value director in the sample period against the Fama French 3-factor model plus momentum. The model specifications are as follows:

$$Ret_{i,t} = \alpha + mom_t + mkt_t + SMB_t + HML_t + RF_i + e_{i,t} \qquad (4)$$

Model 4 regresses the monthly returns of each REIT against the Fama French three-factor model containing market return (mkt), returns on a portfolio of small minus big stocks (SMB), and returns on a portfolio containing high book-to-market stocks minus low book-to-market stocks (HML), the risk-free rate, plus the Carhart (1997) momentum factor. The alpha in model 4 will represent the REIT's risk-adjusted returns after accounting for the four factors. A significant alpha represents returns unexplained by the factor model. We check the risk-adjusted returns before and after the

REITs add the high-value director. If risk-adjusted returns increase after adding the high-value director, we may say this director will correlate with increased returns in a way unexplained by the factors. Table 3.7 reports the results of Model 4, with the timeframe before adding the high-value director in the left column and after the addition in the right column.

Table 3.7 – Risk Adjusted Returns

	Dependent variable:	
	Returns	
	Before	After
Momentum	-0.002***	-0.002***
	(0.0001)	(0.00004)
Market	0.009***	0.007***
	(0.00005)	(0.00005)
SMB	0.003***	0.004***
	(0.0001)	(0.0001)
HML	0.002***	0.004***
	(0.0001)	(0.0001)
RF	0.013***	0.022***
	(0.002)	(0.001)
Constant	0.002***	0.007***
	(0.0002)	(0.0002)
Observations	40,296	40,296
R^2	0.243	0.163
Adjusted R^2	0.243	0.163
Residual Std. Error	0.088	0.095
F Statistic	13,492.270***	10,728.070***

Note: Significance is denoted as *p**p***p<0.01. Both columns represent the results of the following model: $Ret_{i,t} = \alpha + mom_t + mkt_t + SMB_t + HML_t + RF_i + e_{i,t}$. The left column represents results before the addition of a high value board member, the right column after. This model represents a factor regression of each REIT against the Fama French three factor model containing market return (mkt), returns on a portfolio of small minus big stocks (SMB), and returns on a portfolio containing high book-to-market stocks minus low book-to-market stocks (HML), the risk-free rate, plus the Carhart (1997) momentum factor. Monthly observations are used from January 2000 – December 2022.

Indeed, we observe a large and significant increase in the risk-adjusted returns for firms after adding a high-value director. A comparison of the constants in the two columns of Table 3.7 indicates that adding a high-value director will increase firm risk-adjusted returns by 50 basis points per month. This increase is in line with the univariate results. An increase of this magnitude indicates that the high-value directors are, in some way, imparting significant value to the firms and increasing the risk-adjusted returns. The channel of the value is studied in section 3.6.

3.4.4. Two-Stage Least Squares

Endogeneity issues generally confound empirical evidence on the relationship between board composition and firm performance. Following Knyazeva, Knyazeva, and Masulis (2013), we account for the endogeneity problem by implementing an instrumental variables approach. Specifically, we argue the propensity of directors to have strong accounting and finance backgrounds is likely impacted by the accounting and finance ranking of their attended universities. Directors are more likely to have degrees or stronger connections in the accounting and finance field if their university was particularly strong in these majors. It is also unlikely that the accounting and finance ranking of the universities attended by directors will have any effect on firm performance other than through the expertise of the directors. Therefore, this instrument fulfils the relevance and excludability conditions. F-statistics from the first-stage regression of university ranking on background classification indicate this instrument is sufficiently strong at a <0.01 p-value.

University ranking is retrieved from the University of Texas at Dallas (UTD) publication scores from 2000 – 2022.[31] As returns are a firm-level variable, we create a board-level ranking

[31] UTD ranking scores are a function of the number of elite publications of the university's finance and accounting departments.

measure by summing together the UTD rankings for each university attended by the respective board members. We also create a variable entitled high-value proportion (HV prop), which we construct as the proportion of a board composed of high-value members over time. The first stage is conducted by regressing board university ranking on HV prop plus controls, then the fitted values for HV prop are used in the second stage regression given in model 5.

$$Ret_{i,t} = \alpha + HV\_prop_{i,t} + \delta_{i,t} + e_{i,t} \tag{5}$$

where the fitted value of HV prop from the first stage regression and a vector of controls are regressed on yearly REIT returns. The coefficient on HV prop represents the average change in monthly returns from a one standard deviation increase in the fitted value of HV prop. Results for model 5 are presented in Table 3.8.

Table 3.8 – Two Stage Least Squares High Value Director Effect on Returns

	Dependent variable:
	Monthly Returns
HV Proportion	0.026 **
	(0.012)
Constant	0.00286 ***
	(0.007)
Controls	YES
Observations	23,380
R^2	0.2373
Adjusted R^2	0.2371
Residual Std. Error	0.08664

Note: Significance is denoted as *p<0.1 **p<0.05 ***p<0.01. HV proportion is defined as $\frac{num\ of\ high\ value\ directors_{i,t}}{num\ of\ total\ directors_{i,t}}$ so that hv proportion defines the fraction of a board i that it composed of high value directors at any given year t. Results are reported from a second stage regression. The first stage results are achieved by regressing hv proportion on the summed ranking of the finance and accounting departments of the board’s university degrees.

Results from Table 3.8 indicate that after accounting for endogeneity, firms that increase the proportion of high-value directors on their board by one standard deviation increase monthly returns by 2.6%, significant at the 5% level. Although this increase is highly economically significant, it is important not to interpret this as the result of adding any particular number of high value directors, as the size of the board will directly affect the HV prop variable. Though the dual use of REITs to eliminate the monitoring function of boards and 2 stage least squares to account for endogeneity, we provide compelling evidence that the relationship between director characteristics and a value-adding advisory role is causal.

3.4.5. Generalized Difference in Differences

To further provide a case for a causal relationship, we also implement a generalized difference in differences (DiD) framework. This model compares returns across firms which add a high value director before and after the appointment and allows for time variance of the "treatment", in this case, the addition of a high value director. The framework is as follows:

$$Ret_{i,t} = \beta_0 + \alpha_i + \delta_t + \sum \rho_t (start_t * treat_i) + \epsilon_{i,t} \quad (6)$$

Model 6 includes individual and time fixed effects. Start and treat are dummy variables that equal 1 when a high value director is appointed and for firms employ high value directors some time in our sample. The DiD estimator on the interaction of start and treat captures dynamic treatment effects and measures the difference in returns between firms that add a high value director after they start to matched firms that do not add a high value director. Table 3.9 presents the results of model 6.

Even within the restrictive framework of model 6 the significant effects of adding a high value director persist. Table 3.9 indicates that the addition of a high value director increases returns by 30 basis points per month compared to the control group. This represents an annualized increase of 3.6% over their closest match peers.

Table 3.9 – Generalized Difference in Differences

	Dependent variable:
	Yearly Returns
Treatment*Post	0.003***
	(0.001)
Time Effects	YES
Unit Effects	YES
Observations	40,296
R^2	0.00004
Adjusted R^2	0.001
F Statistic	8.419

Note: Significance is denoted as $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$. Results are reported from a generalized difference in difference framework where firms are considered treated if the firm adds a high value board member and treated on the date the board member joins the firm. Unit and time fixed effects are included in the model.

3.5. When Do Firms Add a High-Value Director?

Univariate evidence from section 3.4.3 indicates that REITs might have some awareness of the value of director background and add in new directors in times of underperformance. To understand the timing of additions to the board, we use an event study framework with the "event date" being the addition of a high-value background director to the firm. We focus our study on two years before and after the appointment of the high-value director to the firm. This window is long enough to observe the effects of the high-value director but not too long for interpretation to be muddied from potentially confounding events.

We follow Marais (1984) and Hein and Westfall (2004) and use bootstrapping for the confidence intervals of our event study models as this addresses concerns of sample size and time-series correlation of returns. We begin with a "naïve" model, which compares returns after adding a high-value director to those before with no model. These results are presented in Figure 3.3.

We also seek to understand the performance of the REITs regarding a real estate index benchmark. This specification is a market model where the market returns are substituted for the value-weighted average monthly returns of all real estate firms in CRSP identified by the SIC code. The parameters of the market model are as follows:

$$r_{i,t} = \alpha + \beta rre_t + e_{i,t}$$

where r is the return of firm i in month t, and rre is the return of the value-weighted real estate index at time t. The estimated parameters of this model are used to obtain "normal" returns. Abnormal returns are obtained by computing:

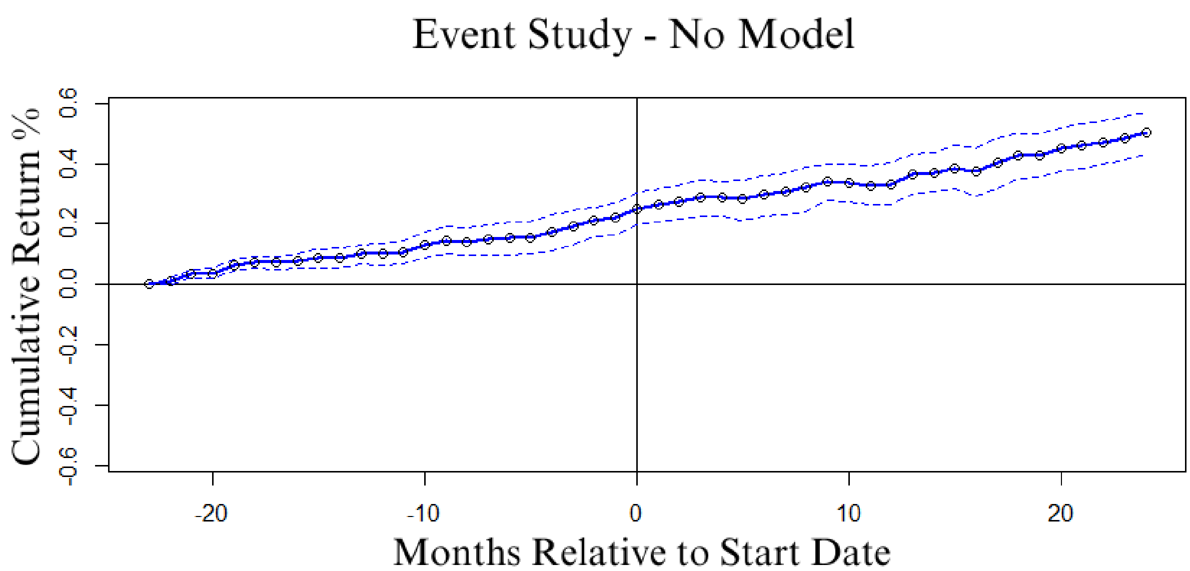
$$AR_{i,t} = r_{i,t} - E[r_{i,t}|rre_t] + e_{i,t}$$

where $E[r_{i,t}|rre_t]$ is the fitted value of REIT return given the returns of the value-weighted real estate index. We then compute cumulative abnormal returns (CAR) for the sample period by summing all abnormal returns. The sample period for both models is January 2000 to December 2022. Results of the event study using the real estate market model are presented in Figure 3.4.

Results of the naïve event study presented in Figure 3.3 indicate that REITs that add high-value directors experience positive cumulative returns before and after the addition. This uniformity would suggest that successful REITs select high-value directors, high-value directors select themselves into high-value REITs, or potentially both. The naïve study is subject to criticism, however. Although the bootstrapping procedure mitigates the influence of serial correlation within the data, there is still a generally positive trend in the returns of REITs during the period of this study, so it is possible the linear trend documented in Figure 3.3 may not best describe the relationship between the REIT and director. These issues highlight the importance of benchmarking the returns against some index.

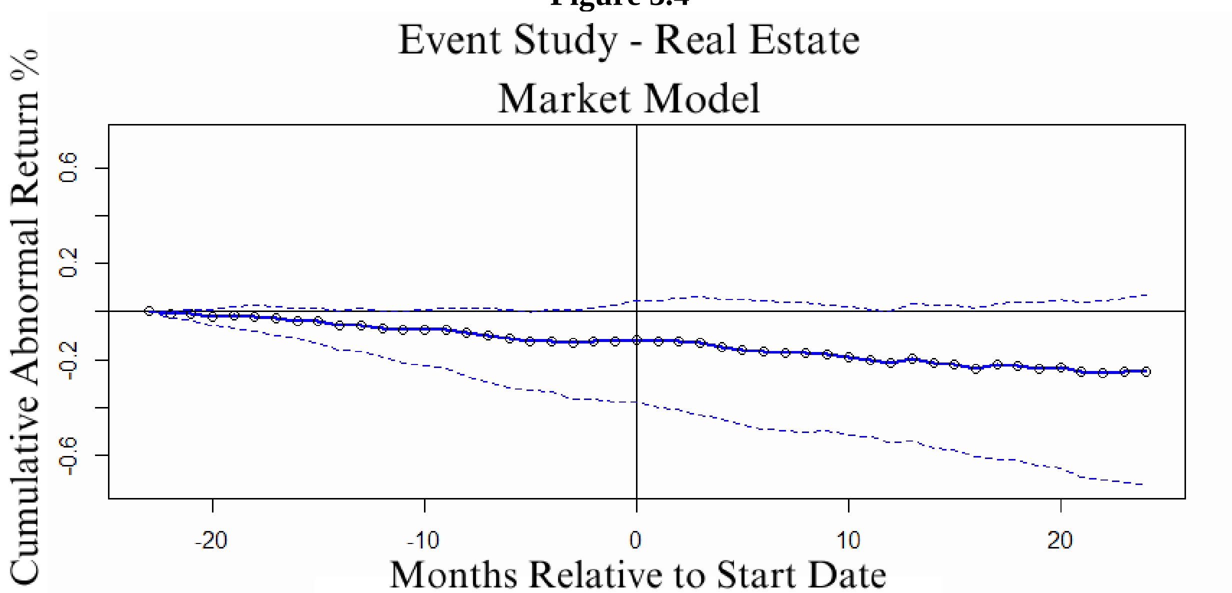
The more robust real estate market model specification is presented in Figure 3.4. Figure 3.4 indicates that REITs that appoint high-value directors underperform relative to the broad real estate index in the time before the appointment, with the CARs being reliably negative at a 95% confidence interval in the two years before the appointment. After an appointment, the high-value director seems to stabilize the firm, and the CARs become indistinguishable from zero at a 95% confidence interval. The slight increase in returns in the months immediately preceding the appointment of the high-value directors is due to the public announcement of the appointment before the director's start date. This evidence is consistent with the univariate evidence in section 3.4.3, which suggests that REITs that appoint high-value directors are underperforming firms that receive a boost in performance from the new high-value directors. In addition to 2SLS and generalized DiD in sections 3.4.4 and 3.4.5, the appointment of high-value directors by underperforming firms also mitigates endogeneity concerns in board construction. If high-performing firms attracted directors with executive or governance experience in finance and accounting roles, it would stand to reason that they would be high performing before the addition. The relative underperformance of REITs before adding high-value directors suggests a causal relationship between director characteristics and firm performance.

Figure 3.3



Cumulative return is computed as the summation of monthly return in the sample period window 24 months before and after the appointment of a high value individual to the board. 95% Confidence intervals are constructed using bootstrapping.

Figure 3.4



Cumulative abnormal return is computed as the summation of abnormal returns: $AR_{i,t} = r_{i,t} - E[r_{i,t}|rre_t] + e_{i,t}$. Where $E[r_{i,t}|rre_t]$ is the fitted value of REIT return given the returns of the value weighted real estate index from $r_{i,t} = \alpha + \beta rre_t + e_{i,t}$. CARs are computed for 24 months before and after the addition of a high value individual to the board. 95% Confidence intervals are constructed using bootstrapping.

However, these results prompt a concerning question. Why, if these directors are recognized as high value by the markets, would they join underperforming firms? In a recent study, Dou and Zhang (2022) provide evidence that upon entering poorly performing firms, directors are more likely to fill leadership positions without necessarily receiving higher pay and that the benefits are primarily reputational. In line with this study, we propose that high-value directors are added to underperforming REITs to serve as advisors to management and receive a reputational benefit for doing so. In this way, directors gain prestige and experience from their tenure, and management avoids the reputational loss of "admitting defeat" by hiring consultants (Bergh and Gibbons (2011)).

Table 3.10 presents compensation and tenure for high-value vs. other REIT directors tabulated from BoardEx. A comparison of the means in Table 3.9 indicates that although high-value directors are paid less in base salary, a significantly larger portion of their total compensation is tied to performance metrics, 68.63% vs. 62.51%. High-value directors also have tenures roughly two and a half years shorter than other directors. Performance-based pay and shorter tenures are consistent with high-value directors primarily serving an advisory role to management. High-value directors are brought in to perform a strategic function and then matriculate to other opportunities. Untabulated results also indicate that high-value directors receive more directorships after service to REITs, which is considered a reward for director quality (Chin, Tran, Wu, Zhivotova (2022)). In line with Dou and Zhang (2022), high-value REIT directors seem to be providing their services for reputational benefit, and firms improve after adding these directors. These results suggest the relationship between high-value directors and REITs is mutually beneficial, and both parties recognize the value of the director.

Table 3.10 – Director Compensation and Tenure

High Value	Salary	Bonus	Total Comp	Equity	LTIP	Options	Total Direct Comp	Perf Comp (%)	Wealth Delta	Tenure (Days)
0	478.8	1056	756.2	90208	15712	22691	848.2	62.51	591.9	2928
1	173.8	933.7	260.4	9859	4762	10807	294.3	68.63	164.1	2147

All dollar values are reported in hundreds of thousands (000) and represent averages over the individual director's tenure. High value denotes directors with executive or governance experience in finance or accounting roles. Wealth delta is the change in wealth in the company (Total Equity Linked Wealth) for each 1% change in the stock price at the Annual Report Date selected for the individual. LTIP represents long term incentive pay for performance metrics. Performance compensation % refers to Performance to total - Ratio of Value of LTIPs Held to Total Compensation for the period. Monthly observations are used from the period Jan 2000 – December 2022.

3.6. How do Directors Affect Returns?

Due to the unique tax incentive structure of REITs, we propose the primary channel through which directors affect returns is their advisory function. A wealth of literature describes the differences between traditional and REIT governance. As support for our claims, we posit that more powerful management will be more likely to add high-value directors. This claim stands opposed to traditional wisdom and the consensus of empirical findings in governance literature: that powerful CEOs avoid strong independent directors (Fracassi and Tate (2012), Jiraporn et al. (2016), Morse et al. (2012)). In REITs, because the monitoring function of boards is significantly lessened, CEOs will logically seek better directors as advisors. This prediction aligns with the theoretical framework by Adams and Ferreira (2007).

To test this prediction, we regress the following model:

$$HV\_prop_{i,t} = \alpha + CEO\_chair_{i,t} + \delta_{i,t} + e_{i,t} \quad (7)$$

where HV prop is the proportion of high-value directors on the board, CEO chair is a dummy variable equal to one when the CEO is concurrently the chair of the board, and $\delta_{i,t}$ is a vector of controls. If directors in REITs primarily serve an advisory role, one should observe a positive coefficient on the CEO chair, indicating that more powerful CEOs will add more high-value directors. Table 3.11 tabulates the results of model 7.

Indeed, we observe a positive and strongly significant coefficient on CEO chair in Table 3.10. This coefficient indicates that REITs where the CEO concurrently serves as the board chair have an average proportion of high-value directors 2.9% greater than REITs with less powerful CEOs. The increased propensity of powerful CEOs to add high-value directors is strong evidence that REIT directors primarily serve in an advisory capacity, as powerful CEOs would not rationally add strong monitors.

3.6.1. Univariate Evidence

In their advisory capacity, directors may affect returns through two avenues in REITs.

1. Investment influences, e.g., the relative outperformance of REITs based on the ability to select profitable property submarkets (Hochberg and Mühlhofer ,2017).
2. Managerial influences, e.g., cost savings, increased oversight, etc.

A high-value director may exert one or both influences over the REIT, leading to outperformance, but will most likely be constrained by time. Regulations on REITs and the relative illiquidity of real estate compared to other managed asset classes make it harder for REITs to pivot investment strategies quickly. Furthermore, the return increase after appointing a high-value director is likely too fast to be strictly due to adding new properties. One may reason that although the high-value directors may eventually affect investment strategy, short-term changes may also be made, which result in increased returns.

Due to these restrictions in the short term, it is our opinion that increased returns in the short term are due to cost-cutting measures and the immediate sale of low-performing assets. Then, in the long run, directors will be able to implement more significant changes and focus the portfolios of their respective REITs on more profitable classes of real estate, leading to sustained outperformance via the selection of higher-quality and more profitable property submarkets.

We created two groups to parse the high-value director's effect on the firm relative to time. The first group compares firm performance measures before and after adding the high-value director for the entire sample period. Differential outcomes in this group are more likely to result from significant changes in the firm's investment strategy since the high-value director will have longer timeframes to accomplish these changes. For comparison, we also created a second group which only includes observations occurring in a two-quarter window around the appointment of the high-value director to the firm's board. Any difference in firm performance within this group is much more likely due to faster changes such as cost cutting, liquidation of assets, etc., and much less likely to be due to large-scale changes in investment strategy. By comparing the two groups, we can understand the governance relationship between the high-value director and REIT and how the director imparts value over time. Table 3.12 reports the change in accounting values after a high-value director joins a REIT.

Table 3.11 – Determinants of Board Structure

	Dependent variable:
	Proportion of High Value Directors
CEO Chair	0.029***
	(0.003)
EPS	-0.002**
	(0.001)
Assets	0.0001***
	(0.00003)
Cash	-0.00004***
	(0.00000)
ST Investment	-0.0001***
	(0.00002)
Non-Operating Income	-0.0001
	(0.00004)
Net Income	0.00002
	(0.00003)
Sale of Real Estate	0.00003
	(0.00004)
Constant	0.122***
	(0.002)
Observations	4,935
R^2	0.041
Adjusted R^2	0.039
Residual Std. Error	0.110
F Statistic	23.202***

Note: Significance is denoted as *p<0.1**p<0.05***p<0.01. Results are reported from the following model: $HV\_prop_{i,t} = CEO\_chair_{i,t} + Assets_{i,t} + Cash_{i,t} + Short\ Term\ Invest_{i,t} + Non - Operating\ Income_{i,t} + Net\ Income_{i,t} + Gain\ on\ Real\ Estate\ Sales_{i,t} + e_{i,t}$. Subscripts i and t denote REIT and quarter, respectively. HV_prop is the proportion of high value board members (directors with a finance or accounting background in director or executive roles), EPS is the earnings per share of common stock, assets is the total reported assets, cash is cash in U.S. dollars, short term invest is the amount of short-term investment, non-operating income is funds not from core real estate rents, net income is the net income in U.S. dollars, and gain on real estate sales is the amount gained on the sale of property. CEO chair is a dummy = 1 if the CEO is also the chair of the board. Observations are quarterly from Q1 2000 – Q4 2022.

Table 3.12 – Change in Accounting Values after High Value Appointment

Variable:													
Start	Total Asset	Cash and Short-Term Invest	Cash	Inc.	Total Long-Term Debt	Dep of RE	Funds from Core RE	Long Term Invest	Short Term Invest	Non-Oper. Inc.	NI	Tot RE	Sale of RE
Panel A: 2 Quarters Around Appointment													
0	6235.2	170.86	164.04	53.67	2929.7	50.38	113.64	4748.6	33.48	9.43	39.79	4573.7	10.09
1	6717.1	176.53	169.19	59.63	3187.0	57.57	124.32	5441.6	32.42	12.91	49.84	5148.8	13.19
% Δ	8%	3%	3%	11%	9%	14%	9%	15%	-3%	37%	25%	13%	31%
Panel B: Full Sample													
0	7694.7	206.91	182.82	57.55	3317.4	52.17	101.57	4864.8	39.46	14.95	50.83	4649.7	12.61
1	5083.0	142.10	146.79	49.10	2395.8	44.85	95.78	4539.9	33.99	8.53	37.67	4305.7	7.38
% Δ	-34%	-31%	-20%	-15%	-28%	-14%	-6%	-7%	-14%	-43%	-26%	-7%	-41%

All values are sample means for their respective variables reported in millions of dollars. Panel A only includes observations within a two-quarter window around a high value board member appointment. Panel B includes all observations. “0” represents observations before high value appointment, “1” after. “% Δ” represents percentage change in the variable mean after the board of director addition. Observations are quarterly and the sample period is from Q1 2000 – Q4 2022.

As predicted, Table 3.12 illustrates that high-value directors have differential impacts on their firm concerning time. In panel A, for the two quarters immediately after the addition of the high-value director, the most considerable changes come in non-operating income, net income, and the sale of real estate, increasing by 37%, 25%, and 31%, respectively. These increases suggest that high-value directors influence the sale of property, leading to significant increases in non-operating income and, subsequently, net income for the firm. The increase in the sale of property is not only large relative to the firm's average before the addition of the new director but also for the total sample average. The post-director addition average of $13.19 million in real estate sold per quarter is 30% higher than the mean for all REITs per quarter. These changes in the short term are consistent with the notion that underperforming REITs add high-value directors, as shown by the univariate and event study evidence in sections 3.4.3 and 3.5. Once added to the underperforming firm, high-value directors cut non-performing assets by selling off properties. One may think of these sales as "trimming the fat" on the underperforming REITs. These sales result in a short-term net income and earnings boost while allowing the REIT to focus on its best properties instead of having a non-focused or poorly managed portfolio.

The short-term increases documented in the accounting variables for panel A are juxtaposed to the long-term decreases in panel B. Whereas non-operating income, net income, and sale of real estate all significantly increased in the quarters immediately following the start of a high-value director, we now observe a significant reversal in these trends for the whole sample period. The changes in panel B characterize a smaller but much more focused REIT. As time passes, the high-value director oversees the sale of much of the REITs previous property and focuses purchases and operations on only high-quality properties. In practice, this can be understood by comparing the changes in total assets and total real estate in panel B. While total assets decreased by 34%, total real estate owned decreased by a comparably meager 7%. The difference in the respective changes of these two variables is representative of a REIT which has efficiently deployed its capital on high-quality real estate. The full sample change in real estate sales is -41%, as the REIT has now focused its portfolio on desirable properties and is less likely to sell. These changes in portfolio composition are consistent with earlier studies documenting the ability of skilled managers to select outperforming asset classes. When considering their full tenure, high-value directors can influence how REITs are operated and REIT investment strategy, focusing their portfolio on higher quality properties.

3.6.2. Multivariate Evidence

For additional statistical rigor and to supplement the story told in section 3.6.1, we also study the effect of high-value directors on firm performance by comparing the relation of accounting variables and firm earnings per share before and after the high-value director starts at the firm. We frame this relationship according to the following models:

$$EPS_{i,t} = Assets_{i,t} + Cash_{i,t} + ShortTermInvest_{i,t} + Non - OperatingIncome_{i,t} + NetIncome_{i,t} + CoreRealEstateFunds_{i,t} + GainonRealEstateSales_{i,t} + \sum(AllVariables) * start_{i,t} + e_{i,t} \quad (8)$$

$$EPS_{i,t} = Assets_{i,t} + Cash_{i,t} + ShortTermInvest_{i,t} + Non - OperatingIncome_{i,t} + NetIncome_{i,t} + CoreRealEstateFunds_{i,t} + GainonRealEstateSales_{i,t} + \sum(AllVariables) * start_{i,t} + \gamma_i + \delta_t + e_{i,t} \quad (9)$$

Subscripts i and t denote REIT and quarter, respectively. EPS is the earnings per share of common stock, assets is the total reported assets, cash is cash in U.S. dollars, short-term invest is the amount of short-term investment, non-operating income is funds not from core real estate rents, net income is the net income in U.S. dollars, core real estate funds are the total rents drawn, and gain on real estate sales is the amount earned on the sale of property. Start is a dummy variable that indicates the start of a high-value director at a firm. The coefficients of interest are those on the interaction of start and the accounting variables. After the directors have begun, they will show how firm activities affect firm EPS. If the sign of a coefficient on any variable flips after the start of a high-value director, we may infer that the director has generated value from that activity. For example, if assets typically have a negative coefficient on EPS, we may assume the firm is adding assets that lower EPS. Suppose this coefficient becomes positive after adding the high-value director. In that case, the addition of new assets now correlates with an increase in EPS, suggesting the director is imparting value to acquiring assets that did not previously exist. Model 9 also incorporates quarter and group fixed effects. Both models are run for the entire sample period and for a two-quarter window around the start date of the director to test for heterogeneity in the governance relationship between the director and the firm over time. Table 3.13 presents the results of models 8 and 9 for the full sample and the two quarters around the appointment.

Table 3.13 – High Value Channel of Effect on EPS

	Dependent variable:			
	EPS			
	Full Sample		2 Quarters Around Appointment	
	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)
Assets	-0.001***	-0.001***	-0.003***	-0.002*
	(0.0002)	(0.0002)	(0.001)	(0.001)
Start	0.002	0.017	0.107	0.033
	(0.025)	(0.037)	(0.077)	(0.067)
Cash	-0.0001**	-0.0001**	-0.0001	0.0002
	(0.00005)	(0.0001)	(0.0002)	(0.0001)
ST Invest	-0.00003	0.0003**	0.0001	0.0005
	(0.0002)	(0.0002)	(0.001)	(0.001)

Non-Operating Income	-0.0001	-0.001***	-0.005**	0.001
	(0.0003)	(0.0002)	(0.002)	(0.002)
Net Income	0.006***	0.006***	0.008***	0.007***
	(0.0002)	(0.0002)	(0.001)	(0.001)
RE	-0.00002***	-0.00001**	0.00003**	-0.00001
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
Gain on RE Sale	-0.002***	-0.002***	0.0004	-0.001
	(0.0002)	(0.0002)	(0.002)	(0.001)
Assets*Start	-0.002***	-0.002***	0.0001	0.0002
	(0.0003)	(0.0003)	(0.001)	(0.001)
Cash*Start	0.0002***	0.0002**	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0003)	(0.0002)
ST Inv*Start	0.0003	-0.0001	0.001	0.001*
	(0.0003)	(0.0003)	(0.001)	(0.001)
NO Inc*Start	-0.001**	-0.0003	0.009	-0.002
	(0.001)	(0.0005)	(0.006)	(0.003)
Net Inc*Start	0.002***	0.001***	0.001	0.001
	(0.0004)	(0.0004)	(0.002)	(0.001)
RE*Start	0.00002***	0.00002***	-0.00002	-0.00002
	(0.00001)	(0.00001)	(0.00002)	(0.00001)
RE Gain*Start	0.002***	0.002***	-0.005	0.003
	(0.001)	(0.0005)	(0.005)	(0.003)
Constant	0.195***		0.105**	
	(0.015)		(0.050)	
Time FE	NO	YES	NO	YES
Group FE	NO	YES	NO	YES
Observations	3,689	3,689	211	211
R^2	0.569	0.577	0.572	0.858
Adjusted R^2	0.567	0.550	0.539	0.617
Residual Std. Error	0.540		0.374	
F Statistic	323.291***	315.721***	17.371***	31.336***

Note: Significance is denoted as *p<0.1**p<0.05***p<0.01. Columns 1 and 3 represent results from the following model: $EPS_{i,t} = Assets_{i,t} + Cash_{i,t} + Short\ Term\ Invest_{i,t} + Non-Operating\ Income_{i,t} + Net\ Income_{i,t} + Core\ Real\ Estate\ Funds_{i,t} + Gain\ on\ Real\ Estate\ Sales_{i,t} + \sum(All\ Variables) * start_{i,t} + e_{i,t}$. Columns 2 and 4 results from $EPS_{i,t} = Assets_{i,t} + Cash_{i,t} + Short\ Term\ Invest_{i,t} + Non-Operating\ Income_{i,t} + Net\ Income_{i,t} + Core\ Real\ Estate\ Funds_{i,t} + Gain\ on\ Real\ Estate\ Sales_{i,t} + \sum(All\ Variables) * start_{i,t} + \gamma_i + \delta_t + e_{i,t}$. Subscripts i and t denote REIT and quarter, respectively. EPS is the earnings per share of common stock, assets is the total reported assets, cash is cash in U.S. dollars, short term invest is the amount of short-term investment, non-operating income is funds not from core real estate rents, net income is the net income in U.S. dollars, core real estate funds are the total rents drawn, and gain on real estate sales is the amount gained on the sale of property. Start is a dummy variable which indicates the start of a high value board member at a firm. $\gamma_i + \delta_t$ represent group and quarter fixed effects. Observations are quarterly from Q1 2000 – Q4 2022.

There are several variables whose coefficients flip in sign once the director is added for the entire sample period. Cash, funds from core real estate, and gain on real estate sales are all negative and significant, at least at the 5% level, related to EPS before adding a high-value director but become positive and significant at the 1% level after the addition. In column one of Table 3.13, the start interaction coefficients on cash, core real estate funds, and real estate sale indicate that for a $1 million increase in each, EPS will increase by 0.0002, 0.00002, and 0.002, respectively. The magnitude and significance of these coefficients are unaffected by the inclusion of fixed effects in column two, aside from a slight decrease in the significance of cash*start to the 5% level. Flipping the relation between these variables and EPS to positive after adding a high-value director is quite meaningful. Whereas the negative coefficients once indicated that REITs mismanaged cash, poorly managed properties, and sold the wrong properties, the positive coefficients after the addition indicate the opposite. REITs with high-value directors now efficiently manage cash and properties and sell the best properties for their strategy.

The evidence from the flipping in the sign of coefficients in the first two columns provides strong support for the channel of high-value directors' effects on returns in section 3.6.1. Once added to a firm, the high-value director makes a series of decisions resulting in significantly improved capital management and a focused real estate portfolio on high-quality and well-managed properties. Thus, after adding the high-value director, the positive relationship between cash, core real estate funds, and property sales with EPS. The previous negative relationship between these variables and EPS provides additional evidence that high-value directors join underperforming firms which do not allocate capital efficiently.

There is little evidence of change in columns three and four of Table 3.13 when considering only the two quarters around the appointment of a high-value director, aside from marginal positive significance on the short-term investments after the start of a high-value director in the fixed effects specification. This insignificance is unsurprising due to the low sample size and resultant lack of power of these tests. Given a larger sample size, we are confident that similar relationships will appear as in the univariate tests.

3.7. Conclusion

Because of the relative infrequency of appraisals and opaque informational environment of real estate vs. more liquid assets, real estate investing invites talented money managers. These money managers can more easily extract alpha from their relative skills or informational advantages. REITs are a perfect laboratory to examine the relationship between director characteristics and their advisory function, as the special tax incentives of REITs lower the need for monitoring. This assumption is bolstered by our findings that powerful CEOs are more likely to add high-value directors. We find large and significant differences in firm performance based on the backgrounds of their directors.

Using hand-collected biographies from REIT websites and 10k proxy filings, we place directors into ten background groups using a machine-learning algorithm that finds text patterns. Director backgrounds are then tabulated within the firm to find the average background of the entire board of directors. Increasing the probability that a board contains directors with executive or governance experience in accounting and finance roles increases monthly returns by 1.8% to 2%. These results are robust to various econometric specifications adding in additional controls with minimal loss in magnitude. Returns increase monotonically with the likelihood that a firm's board comprises directors with executive experience in accounting or finance roles based on their reported biographies. Risk-adjusted returns increase by 50 basis points per month after adding a director with a background of executive or governance experience in accounting or finance roles.

Significant return differences persist when accounting for the endogenous selection of directors in a two-stage least squares specification and generalized difference in differences.

High-value directors that correlate with increased returns go to REITs that underperform relative to the broad real estate market. Returns before the addition are 12% lower than the total sample benchmark monthly return but become 36% greater than the benchmark after adding a high-value director. High-value directors affect returns by improving the capital use efficiency of the firms they govern, cutting low-quality properties, and pivoting REIT investments to more profitable property submarkets. Such changes within the REIT stabilize the REIT returns and lead to sustained outperformance of the new, better, governed REIT relative to other firms. High-value directors have a significantly higher proportion of performance-based pay and shorter tenures than other directors.

This study provides evidence that the advisory function of governance can have strong and persistent effects on returns, specifically within less liquid asset classes such as real estate. Talented directors with strong backgrounds in accounting and finance can exploit their relative advantages in skill and information to create significant benefits for the firm they govern. Furthermore, our study demonstrates the value of utilizing machine learning algorithms to classify and analyze large amounts of unstructured data. By using this innovative approach, we were able to classify director backgrounds and quantify their impact on firm performance reliably and consistently.

Our findings have implications for investors, managers, and policymakers, as they suggest that careful selection and recruitment of directors with specific expertise can significantly improve firm performance. These results may also inform future research on the advisory function of governance, particularly in the real estate sector, and help guide the development of policies to improve corporate governance practices.

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