Growth of income funds and death of volatility

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Abstract

Over the past decade, income funds employing the call overwriting strategy have emerged as one of the fastest-growing segments in the mutual fund industry. By using N-PORT disclosure, this study explores the consequential impact of these income funds on the volatility of underlying assets, uncovering a noteworthy connection between their call overwriting activities and future volatility. Notably, the aggregate selling of call options by these income funds on the underlying assets demonstrates a robust predictive capability for subsequent monthly option implied volatility and realized volatility. Its predictive power stems from income funds, which repetitively overwrite calls rather than engaging in informed selling for volatility timing, indicating that the inelastic supply from repetitively selling in option markets from these funds influences volatility, and their impact does not stem from volatility timing but from their sizable selling pressure. This is an important implication because such an inelastic supply can detrimentally impact potential profits, as lower implied volatility diminishes the option premium, consequently reducing the cash flow stream for income funds. The findings of this study make a substantial contribution to the expanding literature that studies the influence of institutional investors on financial markets and the timing of volatility.

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1 Introduction

According to the Wall Street Journal on February 10, 2023, despite the S&P 500 seeing a substantial decrease of 18.1%, JPMorgan Equity Premium Income ETF (JEPI) demonstrated exceptional outperformance by limiting its losses to just 3.5%. In addition, the Global X Nasdaq 100 Covered Call ETF (QYLD) only suffered a relatively moderate loss of 19% despite a significant 32% decline in the Nasdaq index. These funds that significantly outperformed the benchmark have one thing in common: they are all income funds that employ the call overwriting (also called covered call) strategy[1]. The attractiveness of income funds utilizing the call overwriting approach is seen not only in their remarkable performance to withstand market fluctuations but also in their significant growth in assets under management (AUM). During the past 10 years, the persistent superior performance of these funds has gained growing attention from investors, resulting in a continuous increase in their AUM. One exceptional example of this pattern is JEPI, which, as stated in the aforementioned Wall Street Journal article, experienced an amazing influx of $12.9 billion in funds during the past year. This represents the highest yearly increase ever recorded for an actively managed ETF. In addition, the article emphasizes that three funds employing covered call tactics, specifically Global X's funds tied to the Nasdaq 100, S&P 500, and Russell 2000, attracted a total of $5.2 billion in fund inflow during 2022.

This is where our research question arises. Given this fast-growing AUM of this fund category, we question how their options trading could impact the option and underlying stock markets. To our best knowledge, this is the first academic study in recent decades to examine income funds employing the covered-call strategy. Although the strategy itself was

[1]The covered-call (call overwriting) strategy is one of the simplest option strategies in the derivatives field and is widely discussed in textbooks covering derivative instruments. This strategy combines both purchasing a stock and selling a call option on the underlying of the same stock, allowing the investor to receive an option premium. The rationale for this method is the potential to enhance profits by selling the call option at a higher strike price, thereby generating supplementary yield alongside an increase in stock value, although it limits the upside by the strike price plus the option premium. In addition, it receives dividends from holding stocks, while it does not have to pay dividends for selling its call option.

popular in research nearly half a century ago[2], its popularity in fund formats is a more recent development. Also, one is likely to think that, in comparison to the entire fund market, a specific kind of fund has a lower AUM and may have no influence. However, given its growing scale and its concentration on a smaller number of underlyings in overwriting compared to typical equity mutual funds, its influence might be greater than previously thought. This motivates us to study income funds and their influence in the financial market.There are two major obstacles to overcome in order to do this analysis efficiently. First, there is an absence of data. 13-F disclosures have traditionally been used in financial studies to track fund positions, but they do not include specific information about option transactions, such as expiry, strike price, and so on for individual options. This limitation makes it impossible to undertake a thorough position analysis. The second challenge is to determine their strategy. Some income funds repeatedly overwrite calls depending on their regulations, while others overwrite them at their discretion. The former scenario could overwrite calls at any price, indicating inelastic overwriting demand (inelastic supply in option). On the other hand, the latter instance is more difficult to track and has numerous variations in terms of strategy.

To overcome the first challenge, we leverage relatively recent disclosure, N-PORT. Starting in 2019, the Securities and Exchange Commission (SEC) has required all mutual funds to disclose N-PORT which discloses all individual holdings in their portfolios, encompassing stocks, bonds, options, futures, forwards, swaps, and all other financial instruments. The implementation of N-PORT has allowed for greater transparency, providing researchers with extensive information on the composition of mutual funds. This enables a more comprehensive analysis of the covered-call overwriting approach conducted by income funds. With the data access through N-PORT disclosure, we examine the market impact of those income funds that employ the covered-call overwriting strategy. The main results of this study demonstrate the significant power of call overwriting of income funds to predict both real-

[2]See Pounds (1978), Mueller (1981), and Grube, Panton, and Terrell (1979). Additionally, research on portfolio insurance was once popular, as highlighted in Brennan and Solanki (1981)

ized and implied volatility in the future. It is noteworthy that when income funds have a larger aggregate position in overwriting calls on underlying assets, it has a strong connection with lower levels of implied and realized volatility in the subsequent month.

Additionally, as outlined in the second challenge, the observed outcomes may stem from the entangled effect of option supply or the fund manager's informed actions on volatility timing. To disentangle the effects of option supply and informed selling, we applied the Jaccard similarity measure to differentiate between two types of income funds. The first type systematically sells call options on the same underlying assets at regular intervals, representing an inelastic supply in the option market, because their supply is mandated by rules. This activity does not correlate with skills in timing market volatility. The second type sells call options at irregular intervals based on discretionary decisions, potentially aligning with volatility forecasting skill. This group adjusts their option overwriting strategies over time and across different assets, indicating a possible focus on volatility timing. By aggregating the option positions sold by each type of two funds, the analysis tests the main hypothesis again. The results show that only call overwriting activities of income funds that sell call options repetitively, regardless of the information or volatility timing, exhibit a robust correlation with future implied and realized volatility. It implies that only the repeated selling by income funds had a significant impact on implied volatility, and any source of information or discretion is not directly related to the predictive power for future volatility. This aligns with the expectation that call option overwriting with discretion is influenced more by the underlying asset's price path than a bet on volatility. The importance of this observation lies in recognizing the potential negative implications: the inelastic supply can adversely affect the potential profits of those income funds. Specifically, lower implied volatility resulting from such inelastic supply reduces the option premium, thereby diminishing the cash flow stream for income funds selling those call options.

After we shed light on how income fund flows predict future volatility via the supply channel, we provide a more comprehensive analysis of the destinations of these supplies.

We explore the specific areas and instruments where income fund flows are predominantly directed, enhancing our understanding of the market dynamics at play. The findings indicate that income funds are more likely to engage in call overwriting for stocks that pay high dividends, and their impact on those stocks is more significant. Furthermore, this effect is notably more pronounced in Financial industries experiencing mature growth. These conditions create optimal scenarios for employing a call-overwriting strategy, as there is a relatively lower likelihood of the stocks surpassing the call option strike price plus the option premium. Additionally, their impact is more noticeable when they overwrite stock underlyings rather than indexes and ETF underlyings. It reinforces previous findings regarding the supply impact of call overwriting. Although the relationship between call overwriting and stock volatility may stem from both supply effects and the realization of information, the correlation in underlying indices could primarily be attributed to informational factors, especially given their high liquidity. Overall, our analysis sheds light on the significant role of call overwriting by income funds in affecting the implied and realized volatility of underlying stocks. It contributes to a deeper understanding of the complex interactions between option supply, informed actions, and market dynamics.

This study significantly contributes to multiple strands of financial literature. Firstly, it addresses the impact of institutional flows on asset pricing. Although there has been a significant amount of research conducted on the impact of the fund on asset pricing, the majority of the existing literature focuses on the impact of aggregate fund flows, as done by Warther (1995), Edelen and Warner (2001), Ben-Rephael, Kandel, and Wohl (2011), Lou (2012), Vayanos and Woolley (2013) and Dam, Davies, and Moon (2023). In recent years, there have been studies examining the effects of specific categories of funds. Despite having a smaller AUM compared to aggregate mutual funds, recent findings indicate that they can still significantly impact the market, and their potential for further growth could be even more influential. For example, Parker, Schoar, and Sun (2023) noted that the rebalancing flow initiated by Target Date Funds (TDFs) results in a contrarian effect as it reverses their position to stabilize their funding, subsequently reducing stock returns for stocks held by the funds after a period of strong performance. Similarly, we examine the income fund category, which has experienced substantial growth over the past decade. In the end, we find that the growth of this fund category significantly stabilizes the market's volatility, encompassing both option implied volatility and realized volatility. Furthermore, literature of institutional flows on asset pricing in the context of volatility has studied through two mechanisms: informed trading and nonfundamental trading. (Aragon & Spencer Martin, 2012) identified a correlation between hedge funds' option positions and stock volatility, while (Aragon, Chen, & Shi, 2023) demonstrated that hedge funds' ETF option positions serve as an informational conduit predicting future volatility across ETFs. Conversely, (Ben-David, Franzoni, & Moussawi, 2018) and (Ben-David, Franzoni, Moussawi, & Sedunov, 2021) have shown that ETFs enhance the nonfundamental volatility of securities in their portfolios and that significant institutional ownership forecasts increased stock volatility and noise, particularly during crises. Our study further distinguishes between the effects of informational influences and supply impact. By categorizing the option positioning of income funds into non-discretionary versus discretionary flows, we ascertain a significant supply impact on both implied and realized volatility from non-discretionary flows. Our findings reveal that the inelastic option supply (inelastic overwriting demand) from the income fund category impacts asset pricing regardless of the fundamentals of the underlying assets. This finding is also important because the investigation of inelastic institutional demand and supply in relation to stock price and volatility has become increasingly prevalent in the recent literature, as studied in Koijen and Yogo (2019), and Gabaix and Koijen (2022).

Secondly, our study enhances the growing body of research on the imbalance of option market makers and its influence on the underlying markets. Earlier studies, notably those by Ni, Pearson, Poteshman, and White (2020) and Barbon, Beckmeyer, Buraschi, and Moerke (2021), have empirically demonstrated that non-informational mechanisms, such as the hedge rebalancing by option market makers, can influence the intraday momentum of underlying assets. Specifically, a greater long gamma imbalance among market makers tends to diminish realized volatility by counteracting intraday momentum. The long gamma position of delta-neutral traders, like market makers, is mechanically increased through substantial overwriting activities by income funds. Furthermore, lower implied volatility, holding other factors constant, heightens gamma sensitivity and thus increases the long gamma exposure for market makers, which typically leads to reduced realized volatility. Additionally, the impact of changes in implied volatility is critical in understanding how option market makers adjust their strategies. As demonstrated by Kyle (1985), market makers alter their pricing strategies in response to shifts in demand; in scenarios where there is an influx of call options, they tend to lower their bids, which subsequently decreases the implied volatility.

Moreover, this study makes a notable contribution to the field of volatility forecasting. As underscored by Bollerslev, Hood, Huss, and Pedersen (2018) and Campbell, Lo, and MacKinlay (1997), the examination of volatility stands at the core of financial economic theory and practice, having been subjected to extensive study in terms of methodology and its testing over the decades. Notable contributions from Figlewski (1997), Andersen, Bollerslev, Diebold, and Labys (2003), Andersen, Bollerslev, Christoffersen, and Diebold (2005), and Ghysels, Santa-Clara, and Valkanov (2006) further substantiate the significance of volatility research. Also, the study of US stock volatility, as demonstrated by Buncic and Gisler (2016) and Liang, Li, Ma, and Wei (2021) holds considerable sway over the investigation of other asset classes within the broader market. Nevertheless, the previous literature does not encompass the influence of income funds on volatility. Our study enhances predictive capabilities regarding volatility by examining the exogenous impacts of inelastic demand for overwriting from a growing category of institutions.

Lastly, it contributes to the recent expansion of research using publicly available data such as N-PORT. Since Koski and Pontiff (1999) studied the usage of derivatives by mutual funds, recently, thanks to N-PORT disclosure, the literature on the derivative usage of mutual funds has been expanded. Since Kaniel and Wang (2022) conducted research on the use of derivatives of mutual funds, N-PORT research has been increasing from various angles. Choi (2022) showed an increase in return volatility for fixed-income funds, reflecting a reduction in return smoothing through N-PORT disclosure. Our study extends the application of the recent N-PORT disclosure to research on asset pricing and demonstrates its usefulness.

The remainder of the paper is as follows: Section 2 provides an overview of the background of the income funds. Section 3 provides a detailed description of how the N-PORT data was extracted and processed to construct the position data for income funds and aggregate position data for each stock with summary statistics. Section 4 presents the results of our analysis. Section 5 concludes.

2 Review of Income Funds using call overwriting strategy

The call overwriting (or covered call) strategy is an options trading strategy when an investor has a long position in an underlying asset, such as stocks, and simultaneously sells (writes) an out-of-money (OTM) call option on the same asset. The objective of the covered call strategy is to produce enhanced income by selling the call option and collecting the premiums while still benefiting from any potential upward price movements of the underlying asset until the call option strikes plus the option premium earned by overwriting.

[Insert Figure 1 here]

Figure 1 (a) displays a textbook example of a typical expiry payoff graph of the covered call strategy. In this scenario, an investor buys a stock at the price of \$100 and simultaneously writes a call option with a strike of \$104, receiving a call option premium of \$2. The green line illustrates the net payoff. It outperforms the blue dotted line, representing the sole long stock payoff for any downward stock movement and upward movement by the strike price plus the premium level. Above this level (\$106 = \$104 + \$2), the call overwriting strategy underperforms the long-only stock position. While this payoff structure may seem attractive for downward and staggered stock movements, it loses its appeal in a strong upside scenario because it sacrifices upside potential. This is one reason why this strategy has not seized the interest of many investors. However, considering that the average annual return of the S&P 500 has been 10.13% since its inception in 1957 through the end of 2022, the simple expectation of quarterly upside would be less than 3% on average. This is especially true if the strategy employs underlying stocks with relatively slow but solid growth, attributed to their mature, stable business conditions and a sustainable dividend.

Figure 1 (b) provides an example of employing the strategy on this type of underlying stock and clearly shows its pros and cons. The blue line represents the payoff from buying one share of ExxonMobil (XOM) at the beginning of 2013 and holding it for ten years. The orange line depicts the payoff from buying one share of XOM and selling one call option every quarter.[3] Unsurprisingly, the covered call strategy exhibits superior performance during ordinary periods but falls short during significant upward movements. Particularly during the COVID-19 pandemic, it excels in the first downward movements but falls short in the next rebounding movement. The fact that investors usually do not believe in any catastrophic event, such as COVID-19, is one of the reasons why they are drawn to this characteristic. Additionally, some discretionary income funds manage their overwriting timing by avoiding selling their holdings during periods of strong recovery. Thanks to this feature, this category of mutual fund has expanded its position in the financial market.

[Insert Figure 2 here]

Figure 2 shows the growth of mutual funds' total AUM along with the total AUM of income funds since 2008. The total AUM of mutual funds has increased steadily, and by the end of the third quarter of 2023, it reached $ 32.9 trillion. Although smaller when compared

[3]The example involves selling a call option at the beginning of the quarter. The selection criteria are as follows: First, filter call options by delta between 0.30 and 0.40, and among them, select those with maturity ranging from 61 to 91 days. Then, find and sell the option with the highest strike price and the longest maturity.

to the AUM of all mutual funds, the total AUM of income funds ($826.8 billion) has shown more aggressive growth and has increased their share among mutual funds. We have fitted two trend lines in Figure 2 to demonstrate the difference in the growth rates of mutual funds and income funds. The AUM of income funds has been growing 30% faster than the AUM of mutual funds on average between January 2008 and September 2023.

The following section introduces our method of webscraping N-PORT and explores the summary statistics of our interests in the upcoming empirical analysis.

3 Data and Methodology

3.1 Web scraping and cleaning N-PORT disclosures

The SEC's Form 13-F has extensively been used in the literature on institutional holdings. However, it lacks sufficient derivatives position details for a complete study of institutional positions because it limits instrument details such as expiry, strike, contracts, and so on. This constraint hinders in-depth investigation of the institutional impact on other variables. However, in accordance with the Investment Company Reporting Modernization Reforms, implemented in October 2016 and revised in January 2019, mutual funds (excluding money market funds and small business investment companies) are obligated to submit the SEC's Form N-PORT every month. This regulatory framework necessitates the comprehensive disclosure of a fund's investment instruments, extending beyond traditional stocks to encompass a diverse array of financial instruments, including options, futures, forwards, swaps, and others. The position information is publicly provided on a quarterly basis.

To systematically capture and analyze this rich dataset, we use Python for web scraping, leveraging the regex and BeautifulSoup packages. This approach allows for the extraction of N-PORT disclosures for all available mutual funds on a quarterly basis. The disclosed documents adopt a hierarchical structure presented in XML format, with a specific example provided in the Appendix. The hierarchy of investment instruments commences with the `<invstOrSec>` tag, housing various instruments that furnish detailed information such as stock position, size, mark-to-market value, balance, and more. For funds holding derivatives positions, an additional hierarchy within the `<invstOrSec>` entity is nested. The instances involving derivatives are labeled `<derivativeInfo>` beneath the `<invstOrSec>` tag. This section offers specific details related to derivatives. The details of derivatives also vary by the derivative category, `<derivCat>`, whose values are "FUT" for futures, "FWD" for forwards, "OPT" for options, "WAR" for warrants, "SWAP" for swaps, etc. Our focus is on the option instruments with a tag, "OPT" and "WAR," with option structure. Within `<derivativeInfo>` with "OPT" or "WAR" of the `<derivCat>`, elements of option-related information are nested, such as `<exercisePrice>` for the strike price, `<expDt>` for the expiry date for options, `<putOrCall>` for call or put options, `<writtenOrPur>` for writing or purchasing, and so on.

Following the extraction of hierarchical data, we proceed to clean option (or warrant) position information and transform it into a flattened data table. This flattening transformation ensures that each row in the resulting table corresponds to a single option position held by a fund series during a specific quarter.

Next, income funds are filtered based on the classification by Morningstar. We use the "Derivative Income" category on 'https://investor.morningstar.com'. Furthermore, any fund bearing the terms "income" or "covered call" in its name is considered, excluding those incorporating terms such as "Bond," "Rate," "Fixed," or "High Yield." Manual verification solidifies their classification as income funds for the purposes of this study, and a total 316 income funds from 216 fund families are filtered. Subsequently, we filter each row of holding positions by call option and written positions. The next step is to produce the monthly holding data according to their expiration, with the assumption that the income fund will carry the option overwriting position by the expiration based on its strategy profile. Suppose that, in a report released at the end of June, a fund has an option position that expires on

August 15th. This procedure considers that the fund still has the same position at the end of July. This assumption aligns with the principles of an overwriting strategy, which typically involves holding positions until expiration. Unwinding the positions may happen in rare cases, such as when the options are very close to expiration or significantly far OTM due to the downward movement of the underlying asset. One might raise concerns about the possibility of early exercise. Early exercise could occur within the sample period, potentially leading to differences in estimated positions. However, early exercise typically only arises when the stock price significantly exceeds the strike price as shown in Jensen and Pedersen (2016). In these instances, including the deep OTM case, the optionality almost disappears, and the effect of call overwriting is negligible regardless of estimating errors.

3.2 Merging with the OptionMetrics

To comprehensively evaluate the impact of income fund activity in call option overwriting, we need to identify and analyze the various sensitivities of each option held by income funds. Leveraging the 'opprcd' data table within OptionMetrics, which publishes option prices and Greeks (Delta, Gamma, Vega, Theta, etc.) at fixed strike and expiry levels, we merge these essential metrics into each option position held by income funds. The integration of option Greeks into each position is a crucial step, as it provides an understanding of the risk exposures associated with the income funds' options portfolio. Given that our primary focus is the call overwriting activity of income funds in the context of the underlying market impact, we specifically utilize the Gamma Greek among these sensitivities. Since income funds typically overwrite relatively short-dated options with less than three month tenors, Gamma sensitivity is the most noticeable. Gamma plays a significant role in the impact of options on the underlying market, as Ni et al. (2020), Barbon et al. (2021), and Baltussen, Da, Lammers, and Martens (2021) demonstrate. One might opt to utilize Vega Greek for testing purposes. However, another rationale for employing Gamma arises from its inverse relationship with implied volatility. By definition, Gamma sensitivity decreases with higher implied volatility[4], while Vega sensitivity increases with higher volatility. This inverse relationship between Gamma and volatility provides a more conservative test setup and mitigates concerns regarding reverse causality. Therefore, we employ Gamma in our testing rather than overwritten contracts or notional. Finally, to measure the activity of income funds in the option market, we utilize the dollar Gamma position normalized by the market capitalization of each stock as below.

$$NormGamma_{i,t} = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{j,i,k,t} \cdot S_{i,t} \cdot Contracts_{j,i,k,t} \cdot Multiplier_{j,i,k,t}}{MarketCap_{i,t}} \tag{1}$$

where i denotes the underlying asset, j represents the fund, k represents each option structure, $\gamma_{j,i,k,t}$ represents Gamma Greek for each option k on the underlying i held by a fund j, and $S_{i,t}$ denotes the underlying asset price. The subsequent calculation involves multiplying the unit Greeks obtained from OptionMetrics by the corresponding balance and multiplier of each position held by each income fund every month. This computation results in the derivation of dollar-based Greeks, offering a more tangible and comprehensive measure of the funds' risk exposures in monetary terms. To finalize this analytical process, we aggregate the option holding data across all income funds, grouping them by each underlying stock at the monthly level. This aggregation results in a monthly dataset that encapsulates crucial information, specifically detailing the dollar value of Greek positions initiated during each month for each underlying stock. Each row within this panel data effectively encapsulates the outstanding dollar-based Greek positions on a specific stock at the month-end,

[4]From Hull (2012),

$$e^{-q\tau} \frac{\varphi(d_1)}{S\sigma\sqrt{\tau}} = Ke^{-r\tau} \frac{\varphi(d_2)}{S^2\sigma\sqrt{\tau}}$$

where stock price S, strike price K, risk-free rate r, dividend yield q, time to maturity $\tau = T - t$, and volatility σ.

representing the collective exposure of the entire income fund to each stock. By synthesizing and consolidating this dataset, the study aims to provide a comprehensive and granular understanding of the dynamics of income funds' option positions.

3.3 Summary statistics

Within this section, we examine the summary statistics before advancing to the empirical analysis. Panel A of Table 1 displays the descriptive statistics that represent the overall distribution of income fund reports for each quarter. The number of 'Investor Securities' is the quantity of the investment instruments, which is categorized by the tag `<invstOrSec>` in N-PORT. When comparing the quantity of 'Investor Securities' to the quantity of derivatives, it is evident that derivatives make up roughly ten percent of the total instruments employed by funds on average. Significantly, despite the fact that the income fund has a median size above five hundred million dollars, the average net asset value of the fund is nearly three billion dollars. Furthermore, it is important to mention that the upper decile of income funds possess a substantial number of call option selling positions in terms of contracts. This motivates a deeper investigation into the impact of the income funds because the large AUM does not always stand for being more active in the option markets, and also because their positions are concentrated.

[Insert Table 1]

Panel B displays the distribution of the main variables and control variables in the empirical analysis. In the universe of income funds, the average market capitalization of the stocks is $17.48 billion with a relatively low standard deviation. The variable of our interest, $NormGamma_{i,t}$, which measures the activity of income funds, shows a short position of -181.5 ($\times 10^6$). In contrast, the control variable $NormGammaOthrs_{i,t}$, which measures the activity of the rest of mutual funds in option markets on average, shows a long position of 1,984 ($\times 10^6$). These statistics prompt the question of whether the comparatively small position held by income funds significantly impacts the volatility of the underlying stocks. This is especially intriguing considering the contrast in investment positions between income funds and other mutual funds, raising a discussion about the true influence of smaller fund positions on market dynamics. We will discuss $NormGammaRpt_{i,t}$ later in Section 4.2.

Table 2 shows the rankings of income funds, stocks, and industries based on various metrics. The top 20 funds are presented in Panel A of Table 2, based on their size in terms of AUM and the extent of call overwriting actions they executed. The top four income funds do not highlight the call overwriting technique as a core part of their strategy because they primarily focus on fixed income funds. Other income funds rated in the top twenty are widely regarded as reputable funds within the industry, such as JEPI discussed previously in this document. Interestingly, in terms of call overwriting activities, based on the number of contracts, different income funds are ranked among the top twenty participants. These contradictory details again highlight the necessity of conducting tests to see whether their overwriting truly has an influence on the market because the increase in AUM size may not relate to the active call overwriting activity or its market impact.

[Insert Table 2 here]

Panel B displays the ranking of the popular underlying assets for income funds by different metrics, such as aggregated dollar delta, gamma, vega, and notional. Due to the ease of accessing liquidity, the index underlyings consistently placed high in several metrics, and large-cap companies in the mature stage of their business cycle are also ranked highly. The subsequent panel displays the identical hierarchy of metrics organized by industry. The dataset is divided into separate industry groupings by stratifying it based on Standard Industrial Classification (SIC) codes at the two-digit level. In general, sectors such as Retail, Manufacturing, Financial, Services, and Mining are typically ranked highly. However, within our sample, we observe a prevalence of energy-related stocks. For instance, ExxonMobil (XOM) is categorized under Manufacturing, while Chevron (CVX), initially classified under Mining, transitions to Retail during the sample period according to the SIC method. In summary, the statistical research demonstrates noticeable differences in the preferences of income funds based on various underlying assets and industries. The popularity of particular underlyings to overwrite call options may result in concentration and imbalance on those underlying assets. As a result, income funds are probably going to directly affect their price movement. This interesting hypothesis inspires a more thorough examination to evaluate and analyze the possible influence of income funds on these underlyings. The following sections examine the hypothesis that the call overwriting strategies employed by income funds are associated with future market volatility, as measured by both option-implied volatility and realized volatility.

4 Empirical analysis

This section presents the regression results that scrutinize the relationship between call overwriting activity of income funds and volatilities. Each column within the table represents the dependent variables for the subsequent month, denoted as $t + 1$, with independent variables for the current month, t. For instance, $IV30d_{i,t+1}$ represents the 30-day at-the-money (ATM) volatility of stock i measured at the next month, $t+1$, while $RV30d_{i,t+1}$ indicates the 30-day realized volatility of stock i measured at the next month, $t+1$. The explanatory variable of interest is $NormGamma_{i,t}$, which represents the total dollar gamma position that all income funds held on the underlying asset i at time t. This variable is normalized by the market capitalization of the underlying asset. Control variables include $NormGammaOthrs_{i,t}$, $Log(MktCap)_{i,t}$, $Log(Volm)_{i,t}$, and $VRP_{i,t}$. $NormGammaOthrs_{i,t}$ stands for the total dollar gamma position held by all mutual funds except for income funds on the underlying asset i at time t. This variable strengthens the argument that the regression result is not associated with the impact of other mutual funds but rather with those of the income fund. $Log(MktCap)_{i,t}$ is the logarithm of the market capitalization for the underlying asset i at the month t. $Log(Volm)i, t$ is the logarithm of the volume on the underlying asset i at the month t. Additionally, $VRP_{i,t}$ denotes the variance risk premium (VRP) estimated by the logarithm of the ratio of option impled variance to realized volatility. Following Carr and Wu (2008), the VRP is approximated by the difference between the value of options and realized volatility. The model-free implied volatility of Martin and Wagner (2019) is used to find the variance from option data with the help of Python codes from Vilkov (2018). $IV30d_{i,t}$ and $RV30d_{i,t}$ represent the 30 days of ATM volatility and realized volatility for the current month, respectively. This addition helps exclude any serially correlated movements in volatility. All regressions in this section employed clustered standard errors at each underlying asset level and incorporated fixed effects for each stock and each year. The appendix also features a similar regression following the approach by Newey and West (1987).

4.1 Overwriting impact by income funds to implied and realized volatility

The primary objective of this part is to examine the presence of a predictive relationship between future volatility and the call overwriting activity of income funds. The investigation seeks to determine if the call overwriting activities can serve as reliable indicators for forecasting future volatility patterns. The analysis encompasses two main aspects: implied volatility and realized volatility. By conducting tests on these variables, we aim to assess the extent to which the call overwriting practices of income funds can be correlated with future fluctuations in the volatility of underlying assets first before we test more detailed analysis in later sections. The regression models are represented as:

$$IV30d_{i,t+1}, IV91d_{i,t+1}, RV30d_{i,t+1} \text{ or } RV91d_{i,t+1} = \beta NormGamma_{i,t} + \gamma X_{i,t} + FEs + \epsilon_{i,t+1}$$

Table 3 shows the testing results and are divided into two parts: the upper section focuses on the impact of income funds on implied volatility, while the lower section represents the one on realized volatility.

[Insert Table 3 here]

Panel A shows that the active call overwriting position in month t (stronger sell) measured by $NormGamma_{i,t}$ has a high correlation with lower implied volatility in month $t+1$. The p-values of several cases show robust statistical significance for the observed relationships. The coefficients of 0.283 in column (2) and 0.204 in column (6) suggest that one percent of dollar gamma size overwriting to the market capitalization is associated with a 0.283 and 0.204 decrease in the implied volatility points (%) next month.[5] This empirical finding enhances our understanding of the significance of call overwriting within income funds in relation to volatility. The results suggest considering two potential mechanisms at play: the first is the impact of option supply, which persists into the following month; the second is the activity associated with informed selling. The first reason for these outcomes likely stems from the supply-side impact on implied volatility, whereby income funds' selling pressure influences option prices and subsequently reduces implied volatility. While their selling pressure is focused on specific strikes and tenors, its impact may extend beyond a single point to a relatively broader local area. The presence of an arbitrage condition on the volatility surface leads to selling pressure in one area, which in turn triggers selling in other areas and purchasing in the local area. Numerous studies have addressed the concept of an arbitrage-free volatility surface (Fengler (2009)), and they are widely utilized by practitioners in the field (Gatheral (2006)). The alternative explanation could be that an income fund is informed about future implied volatility and responds to it to maximize its returns, because the lower implied volatility potentially gives an extra choice for the fund manager to monetize the reduced call option premium sold by buying back the overwriten options and selling other structures.

The results in Panel B also show that there is a clear connection between income fund

[5] In other words, one unit of overwriting size in $NormGamma_{i,t}$ which is overwriting dollar gamma size of the market capitalization, is related to 28.3% points and 20.4% points of implied volatility.

overwriting and subsequent realized volatility in the next month. The coefficients of 0.44 in columns (2) and (6) suggest that one percent of dollar gamma size overwriting to the market capitalization is associated with a 0.44 decrease in the realized volatility points (%) next month. As in the case of Panel A testing the implied volatility, this result can also be attributed to two cases. The first case is the channel through lower implied volatility demonstrated in Panel A. Specifically, larger call overwriting activities by income funds tend to increase the long gamma positions of delta-neutral traders, such as market makers, in a systematic manner. This relationship is primarily due to the mechanics of option pricing and hedging strategies: as implied volatility decreases, all else being equal, the gamma sensitivity of an option increases, leading to a heightened long gamma exposure for market makers. A larger long gamma imbalance among market makers reduces realized volatility by their contrarian delta rebalancing, which counters intraday momentum trends. This phenomenon occurs as market makers adjust their positions throughout the trading day, thereby exerting a stabilizing influence on the market. Such findings have been supported by empirical evidence, as highlighted in the research conducted by Ni et al. (2020) and Barbon et al. (2021). They have shown that the non-informational mechanisms associated with the hedging and rebalancing actions of option market makers can significantly affect the intraday price of underlying assets. The alternative explanation could be that an income fund is informed about future realized volatility and responds to it to maximize its returns because lower realized volatility implies a higher chance that the underlying asset price does not go over the strike level of call options sold.

Both Panel A and Panel B demonstrate that the aggregate activity of income funds in call overwriting has a significant predictive power for the implied volatility and realized volatility of the following month. Both results likely stem from entangled channels such as supply impact, informed action, or both. This question is further examined in Section 4.2 by separating their selling flows into two parts: repetitive selling (measuring supply) and non-repetitive selling (measuring discretion with information).

4.2 Information vs Demand/Supply?

This section delves deeper into the analysis to find whether the influence of this income fund on volatility can be traced back to information related to the underlying asset or the supply of options. To disentangle the specific cause contributing to this impact, we adopt an approach by categorizing income funds into two distinct styles: repetitive overwriting executed periodically and discretion-based overwriting. The former case involves the consistent sale of call options for the same underlying asset in their universe on a regular basis, irrespective of the option price, thereby establishing an inelastic supply within the option markets. In this case, the call overwriting from this fund is non-informative and works primarily as liquidity supply in the option market. The latter case overwrites call options in different ways across time and the universe, at their discretion, based on their evaluation of the underlying assets. This approach is not rule-based but rather reflects the fund managers' insights and information. This categorization of income funds allows us to systematically investigate and compare the impact of each style on volatility, facilitating a more granular understanding of the dynamics at play within income funds. By isolating the different approaches to overwriting, we aim to shed light on whether they are more linked to the selling pressure in options within the fund or whether the observed effects on volatility are primarily driven by strategic decisions based on information about the underlying assets. This analytical framework not only enhances our comprehension of the mechanisms influencing volatility but also contributes to a more comprehensive evaluation of income fund performance in financial markets.

In order to distinguish between funds that employ systematic or repetitive trades vs. funds that actually act on their information, we employed a Jaccard similarity to define a "similarity score" based on how repetitive the trades of a fund are in subsequent N-PORT disclosures. Jaccard similarity is a statistical measure utilized to evaluate the similarity and diversity between sample sets. It quantifies how similar two sets are by dividing the size of their intersection by the size of their union. This metric was originally introduced in

1912 by Swiss botanist Paul Jaccard [6], primarily for use in the field of ecology to assess the biodiversity between different habitats through the comparison of plant species. As time progressed, the utility of Jaccard similarity broadened, transcending its ecological roots to find applications in numerous other disciplines, including machine learning, computer vision, and social network analysis. In recent years, its relevance has notably expanded within the business literature, particularly in the textual analysis of financial documents, demonstrating its versatility and widespread applicability. This trend is well exemplified in works such as that cited in Brown, Ma, and Tucker (2023) and Bochkay, Brown, Leone, and Tucker (2022), underscoring the growing significance of the Jaccard similarity in contemporary research and application fields.

The methodology is straightforward. Note that in Section 3.1, after filtering for the income funds, we have panel data of each call written position of all income funds for each quarterly disclosure. Using its quarterly call overwriting position data, we first construct two sets of underlying assets from two subsequent N-PORT disclosures of each fund, j, (say, set $Und_{j,t-1}$ is the set of underlying assets in the N-PORT disclosure related to period $t-1$ and set $Und_{j,t}$ is the set of underlying assets in the N-PORT disclosure related to period t). We then calculate the intersection ($Und_{j,t-1} \cap Und_{j,t}$) and union ($Und_{j,t-1} \cup Und_{j,t}$) of these two sets. The ratio of the number of elements in the intersection set to the number of elements in the union set yields a similarity score between 0 and 1. If all of the tickers of the sets $Und_{j,t-1}$ and $Und_{j,t}$ are the same, then the intersection equals the union, making the ratio 1, indicating the fund merely repeats the overwriting call option with the same underlying. Conversely, if none of the elements of sets $Und_{j,t-1}$ and $Und_{j,t}$ are the same, then the intersection, hence the ratio, becomes zero. Equation 2 shows our similarity score specification.

$$SimilarityScore_{j,t} = \frac{|Und_{j,t-1} \cap Und_{j,t}|}{|Und_{j,t-1} \cup Und_{j,t}|} \tag{2}$$

[6] See Jaccard (1912)

Now, we have the similarity score of each fund at each quarter, t. We then calculate the average similarity score for each fund and find the median of average similarity score (0.73) Funds with above-median average similarity scores are classified as repetitive funds, which sell call options repetitively without discretion, and those with below-median average similarity scores are considered discretion-based overwriting funds. One might argue that the classification of fund characteristics is based on their past positions, but Koijen and Yogo (2019) emphasizes that the majority of institutions do not publicly disclose their investment mandates. Consequently, they define the investment universe as stocks that are currently held or have been held in the previous 11 quarters. Similarly, not all income funds transparently disclose their overwriting scheme regarding whether they sell call options systematically based on their rule or sell based on their information and view. However, relying on their past holdings remains the most viable approach to discerning these strategies.

The subsequent steps in the procedure mirror the original method detailed in Section 3.2. However, a key departure lies in the aggregation process. In contrast to the previous approach, where all call overwriting positions of income funds were aggregated, we now aggregate only the positions created by income funds employing the repetitive overwriting style. This distinction in aggregation is pivotal for elucidating the nature of the impact. Selling flows of call options from income funds employing repetitive overwriting have a more straightforward impact rooted in option supply. These funds engage in periodic selling to enhance their return profiles, contributing to a more consistent and predictable supply of options. In contrast, discretionary selling from income funds employing discretion-based overwriting encapsulates the fund manager's subjective views, influenced by proprietary information. By segregating the analysis based on overwriting styles, specifically focusing on the repetitive overwriting subset, we aim to discern whether the observed impact stems primarily from the option supply dynamics within the income fund or if it is more intricately linked to proprietary information held by fund managers.

[Insert Table 4 here]

Table 4 presents the results of the analysis. $NormGammaRpt_{i,t}$ indicate the dollar gamma position, normalized by market capitalization, aggregated from income funds that repetitively sell call options. Conversely, $NormGammaDisc_{i,t}$ represents the dollar gamma position, also normalized by market capitalization, but aggregated from income funds that sell call options based on discretion. The analysis shows that $NormGammaRpt_{i,t}$ significantly predicts future implied and realized volatility, whereas $NormGammaDisc_{i,t}$ exhibits no significant relationship with either implied or realized volatility. This implies that the predictive power of future implied and realized volatility from income fund activity is not due to information flow. Instead, income fund flows involved in repetitively supplying call options without discretion have a pronounced impact on both implied and realized volatility. In other words, the call overwriting of income funds predicts the future implied and realized volatility through the channel of option supply impact that persists into the next month. As mentioned in the previous section, the selling activity of income funds affects option prices, leading to a decrease in implied volatility and mechanically increasing market makers' long gamma imbalance. They typically maintain delta neutrality, which leads them to perform contrarian delta rebalancing when they carry long gamma exposure. It thereby lowers realized volatility. This finding aligns with the literature validated in studies by Ni et al. (2020) and Barbon et al. (2021) introduced in the previous section. On the other hand, no significance of discretion-based selling aligns with the principal of call option overwriting strategies because those executed with discretion are primarily influenced by the underlying asset price rather than the view on volatility fluctuations. The significance of this finding extends beyond mere statistical observation and revealing the channel. It prompts a critical acknowledgment of the potential negative implications stemming from the inelastic supply in the options market. Specifically, the persistent selling pressure of income funds engaging in call overwriting strategies through repetitive selling can adversely impact the profitability of the income funds and the income of the investors because the decrease in implied volatility resulting from this inelastic supply dynamic leads to diminished option premiums.

Consequently, this phenomenon curtails the cash flow stream available to income funds.

Now, we have established how income fund flows can predict future volatility via the supply channel. To provide a more comprehensive analysis, the following sections will delve deeper into the destinations of this supply. We explore the specific areas and instruments where income fund flows are predominantly directed, enhancing our understanding of the market dynamics at play.

4.3 Stock vs Non-stock

This section expands an empirical examination of the base regression model across distinct subsets of underlying assets, specifically categorizing them as either *Stock* or *Non-Stock*, the latter including indices and ETFs. This segmentation is pivotal and useful in not only delineating where income funds exert a noteworthy influence on the underlying volatility but also bolstering whether the sources of prediction stem from the inelastic supply or information. A crucial element in this analysis is the consideration of the liquidity gap between *Stock* and *Non-Stock* categories. In essence, this investigation aims to discern the dynamics by which income funds' call overwriting strategies impact different types of underlying assets. For *Stock*, the impact is likely multifaceted, involving both the supply of options and the information content embedded in these transactions. In contrast, the influence on *Non-Stock* assets, represented by indices and ETFs, is primarily attributable to information transmission because, due to the high liquidity of *Non-Stock*, compared to the call overwriting activities of income funds, it's less likely that any pronounced influence in *Non-Stock* group is attributed to the supply impact. In other words, the rationale behind this setup lies in the understanding that the call overwriting strategy of income funds can exert a considerable effect on individual *Stock* assets due to a combination of influencing the supply of options and disseminating valuable information, but the impact on *Non-Stock* assets is primarily driven by the information content, as the liquidity of indices and ETFs far surpasses that of income funds' call overwriting activities.

[Insert Table 5 here]

Columns (1)-(4) of Table 5 show the outcomes of the base regression model for stock underlyings, *Stock*, while columns (5)-(8) detail the corresponding results for indices and ETF underlyings, *Non-Stock*. Notably, the significance of the observed impact is discerned within the *Stock* groups for the implied volatility, with weak or no statistical significance evident in the context of ETFs and indices. This outcome suggests an absence of information-related overwriting effects in ETFs and indices and confirms again that the income fund impact on volatility is primarily driven by the call option supply rather than the information channel.

Additionally, it is worth noting that the coefficients from the *Non-Stock* category are significantly higher, exceeding those of the *Stock* category by over 100 times. This substantial difference in magnitude arises due to a notional gap. Compared to the underlyings in the *Stock* category, those in the *Non-Stock* category, such as indices and ETFs, have an incomparably higher market capitalization. Consequently, when normalized by market capitalization, the $NormGamma_{i,t}$ significantly decreases, yet the impact remains substantial. This discrepancy in slope units emerges from these conditions. It also suggests that, in terms of impact on underlying market volatility, even a smaller trade size in the *Non-Stock* category can make a considerable impact.

Subsequent sections of the paper delve into a more comprehensive discussion of the call option supply driven by the income funds. By unraveling the specific preference of income funds in terms of choosing the universe of their underlying, we aim to enhance our understanding of the role of institutional investors in shaping volatility patterns in the underlying markets.

4.4 Industry-specific impact

In this section, we extend our examination of the regressions presented in the previous section by various industry groups. The focus is on regressing the 91 days of at-the-money (ATM) implied volatility and realized volatilities in the next month, $t + 1$ on the normalized dollar gamma position ($NormGamma_{i,t}$) and other pertinent control variables. The dataset is stratified based on Standard Industrial Classification (SIC) codes at the two-digit level, facilitating categorization into distinct industry groups. The identified industries encompass Mining, Utility, Manufacturing, Financial, Retail, Wholesale, Services, and Transportation, each delineated by its own unique SIC code. It's noteworthy that income funds typically do not overwrite call options within the Construction, Agriculture, and Wholesale, indicating a scarcity of positions within these sectors and therefore being excluded from this test. By conducting these subgroup analysis, we aim to discern potential variations in the impact of income funds' call overwritings across different industry groups. This approach acknowledges the diverse nature of businesses within each sector and allows for a more granular understanding of how income funds' strategies may impact different economic domains.

[Insert Table 6 here]

The results presented in Table 6 from our analysis reveal distinct variations in implied and realized volatility attributable to income fund activities across various industries. Significantly, we observe that both implied and realized volatilities are substantially affected by income fund operations within the Financial and Retail sectors. This observation is likely a consequence of the shared characteristics inherent to companies within these sectors. Drawing on the insights from Fama and French (1997), it is noted that the Financial and Retail sectors typically demonstrate lower market betas, indicating a lower correlation with overall market movements. Furthermore, businesses within these sectors are generally less likely to experience extreme upward price movements due to the nature of their business models. These sector-specific attributes create a conducive environment for executing call overwriting strategies effectively. The tendency for companies in these sectors to exhibit more stable and predictable price movements makes them attractive targets for income funds employing call overwriting strategies to generate consistent returns.

Now, we shift our focus towards another critical component of income fund profitability: the dividend payoff. In the following section, we aim to examine any existing heterogeneity among stocks that distribute high dividends, particularly in the context of the effects of income funds' call overwriting practices. This exploration is essential as it strengthens the argument about the supply impact of call overwriting by income funds by showing their preference in choosing the underlying assets for their universe.

4.5 High dividend-paying stock

The table in Appendix A2 compares call overwriting activity among dividend groups across industries. We estimated the average yearly dividend rate using the CSRP dataset from the N-PORT sample period of 2019–2022. Subsequently, we classified the data based on the average yearly dividend rate; the high dividend group contains values above the median, while the low dividend group includes values below it. The data clearly show that income funds' activities vary depending on the dividend rate. Specifically, the supply of options by income funds is significantly greater in the high dividend group. This finding prompts us to investigate whether the concentrated supply in the high dividend group also has a significant effect on future implied and realized volatility.

[Insert Table 7 here]

Table 7 presents the same regression models as before, but with the main independent variable, $NormGamma_{i,t}$, interacted with $HighDiv_i$. It demonstrates that generally, the interaction between $NormGamma_{i,t}$ and $HighDiv_i$ exhibits a significant relationship with future volatility in both implied and realized volatility setups. This suggests that the call overwriting activity of the income fund is not only prominent within high dividend stock groups but also exerts a stronger impact on stocks within those groups. This result arises not only from the potential for enhanced returns through higher dividends but also due to the intrinsic characteristics of these high-dividend sectors. Typically, such sectors represent mature stages of a firm's lifecycle with relatively slow growth prospects. This characteristic is in line with the observation that these industries tend to exhibit lower volatility, as demonstrated in the work of Lin, Liu, Zhang, and Lung (2019). The lower volatility is attributed to the inherent stability and mature nature of companies in this high dividend paying group, making them less susceptible to abrupt and substantial price fluctuations. Consequently, these mature industries are less likely to experience sustainable growth that surpasses the strike prices of written call options, reinforcing the effectiveness of the call overwriting strategy for income funds.

5 Conclusion

Income funds employing a covered call strategy have experienced a notable surge in popularity and have enjoyed the influx of billions of dollars over the past decade because their payoff structures attract investors who prefer to have stable growth with resilience to market volatility. This growth has led to a concentration within the market, resulting in unexpected impacts that raise closer examination.

This study has elucidated the significant role that income funds employing a covered call strategy play in the financial markets, particularly in terms of their impact on volatility. Leveraging the recently available data from N-PORT disclosures, our findings underscore the robust predictive power of call overwriting strategies used by income funds, both in terms of implied and realized volatility. In addition, our research highlights the nuanced behaviors of income funds - distinguishing between those that employ a systematic approach to call overwriting and those that exercise discretion based on market conditions. It provides a comprehensive examination of how the repetitive, non-discretionary sale of call options by these funds reduces volatility, reflecting an inelastic supply of options. Our finding demonstrates the inelastic supply of repetitively selling call options significantly influences underlying stock volatility, while discretion-based sales of call options are not related to the reduction of volatility. In other words, the volatility impact of income funds does not come from volatility timing but from purely inelastic supply. This finding contributes significantly to the literature, particularly on the impacts of institutional flows on asset pricing in the context of demand-based asset pricing. Our study also opens new avenues for future research. As the AUM of the income funds grows fast, it is imperative to further explore the long-term implications of the call overwriting strategy on market returns and to assess whether the performance of these funds aligns with investor expectations.

In conclusion, as income funds continue to evolve and their strategies become increasingly influential, it is essential to monitor their market impact. This study has laid a foundation for ongoing research into the complex interactions between institutional strategies and market dynamics, providing valuable insights that can inform investors, fund managers, and policymakers alike.

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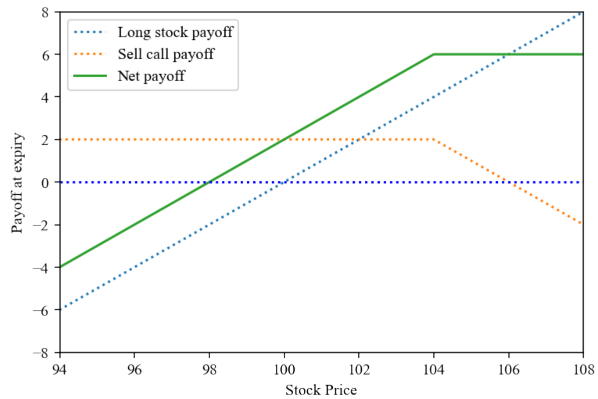
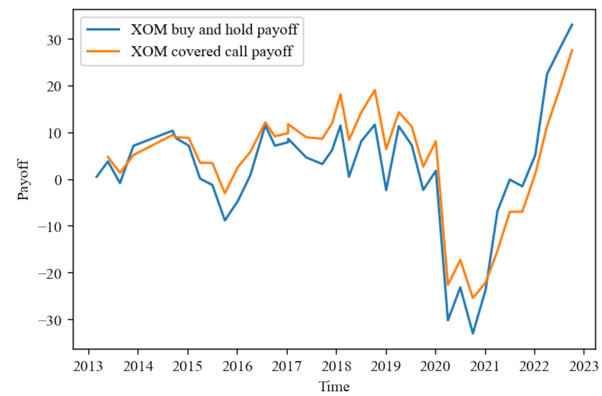


(a) Covered call payoff



(b) Cumulative covered call performance

Figure 1: Covered call payoff and an example of ExxonMobil (XOM)

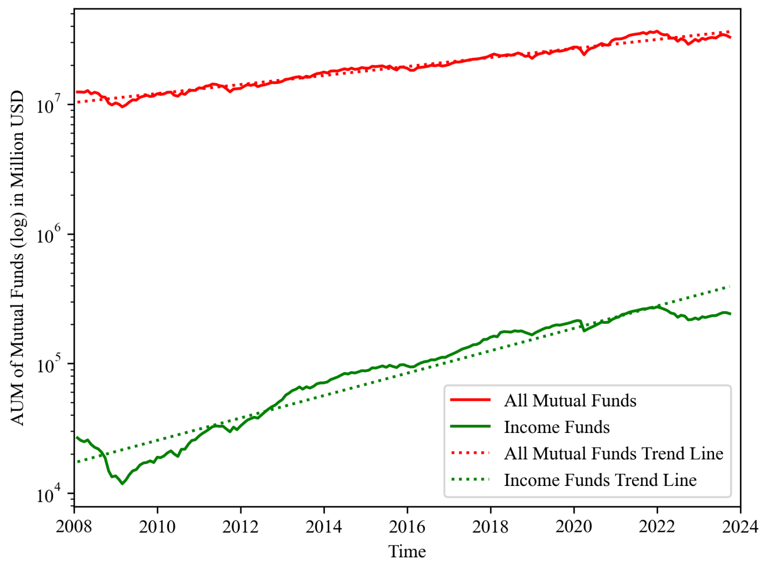


Figure 2: AUM of Mutual Funds vs. Income Funds

Table 1: Summary statistics

This table shows the summary statistics of main income fund characteristics and the variables used in the analysis. Panel A displays the descriptive statistics that represent the overall distribution of income fund reports for each quarter. Panel B shows the summary statistics of the variables used in the analysis. $Log(MktCap_{i,t})$ is the logarithm of market capitalization, $Log(Volume_{i,t})$ is the logarithm of trading volume in the underlying asset, and $VRP_{i,t}$ is the logarithm of the variance risk premium ($\equiv log(E_t(RV_{i,t\to t+1}/IV_{i,t\to t+1}))$. $IV30d_{i,t+1}$ ($IV91d_{i,t+1}$) represents the ATM implied volatility of a 30-day (91-day) option in the next month, while $RV_{i,t+1}$ stands for the realized volatility of the underlying asset in the same period. $NormGamma_{i,t}$ is the market-cap normalized dollar gamma position of the underlying asset aggregated from all income fund supplies, while $NormGammaOthrs_{i,t}$ is the market-cap normalized dollar gamma position of the underlying asset aggregated from all other mutual fund supplies. $NormGammaRpt_{i,t}$ is the one from income funds, which sell call options at rule-base repeatedly. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

Panel A: Summary statistics of income funds

	Mean	Std. Dev.	P10	P25	Median	P75	P90
Total Assets $\times 10^9$	2.968	14.02	0.0265	0.0969	0.484	1.300	4.172
Total Liabilities $\times 10^9$	0.342	4.934	0.000360	0.00163	0.0131	0.0824	0.363
No of Investor Securities	452.2	739.2	48	103	224	505	1036
No of Derivatives	39.65	70.19	2	4	14	41	103
Call Count	31.21	75.47	1	3	8	23	65
Call Gross Balance $\times 10^3$	740.6	6103.5	0.265	1.062	6.249	47.08	520.9
Put Count	7.837	22.45	0	0	0	6	18
Put Gross Balance $\times 10^3$	39.53	234.9	0.0540	0.258	1.355	8.330	54.50
No of Underlyings	11.67	21.83	1	1	2	11.50	38

Panel B: Summary statistics of variables used in the analysis

	Mean	Std. Dev.	P10	P25	Median	P75	P90
Log(MktCap$_{i,t}$)	17.48	1.387	15.71	16.67	17.53	18.43	19.16
Log(Volm$_{i,t}$)	-8.827	2.128	-11.59	-10.21	-8.726	-7.409	-6.404
NormGamma$_{i,t}$ $\times 10^6$	-181.5	3296.8	-118.6	-37.02	-5.065	0	0
NormGammaRpt$_{i,t}$ $\times 10^6$	-123.2	3127.7	-61.94	-13.23	0	0	0
NormGammaOthrs$_{i,t}$ $\times 10^6$	1980.4	70032.9	-242.8	-62.60	-8.866	0	156.4
VRP$_{i,t}$	-0.772	0.502	-1.404	-1.099	-0.778	-0.458	-0.149
IV30d$_{i,t+1}$	0.378	0.181	0.204	0.258	0.335	0.456	0.607
IV91d$_{i,t+1}$	0.370	0.154	0.217	0.264	0.334	0.444	0.573
RV30d$_{i,t+1}$	0.370	0.237	0.161	0.222	0.311	0.445	0.640
RV91d$_{i,t+1}$	0.387	0.221	0.184	0.242	0.327	0.472	0.666

Table 2: Rankings of income fund, stock and industry

This table shows the rankings of funds, stocks, and industries by various metrics measuring income fund activity. Panel A demonstrates the top income funds by average size (in billions of USD) and average number of call overwriting contracts. Panel B lists the top stocks by income fund activity (by Delta, Gamma, Vega, and Notional). Similarly, Panel C shows the top industries by income fund activity (by Delta, Gamma, Vega, and Notional). The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

Panel A: Top Income Funds

By Average Size

	By average size		By average call overwriting	
Rank	Series Name	Avg Size ($ bln)	Series Name	Overwriting (contracts)
1	Pimco I.F.	126	Blackrock Enhanced Equity Dividend Trust	9,088,506
2	I.F. Of America	116	Blackrock Enhanced International Dividend Trust	6,635,435
3	Franklin I.F.	70	Blackrock Enhanced Global Dividend Trust	4,568,868
4	American High Inc.Tr.	18	Voya Balanced Income Portfolio	4,013,625
5	Blackrock Multi-Asset Income Portfolio	16	Thornburg Income Builder Opportunities Trust	1,543,716
6	Blackrock Equity Dividend Fund	16	Voya Natural Resources Equity I.F.	954,855
7	Jpmorgan U.S. Equity Fund	15	Cohen & Steers Real Estate Opportunities & I.F.	733,208
8	Calamos Market Neutral I.F.	14	Blackrock Enhanced Capital & I.F., Inc.	721,637
9	Jpmorgan Hedged Equity Fund	14	Blackrock Enhanced Capital And I.F., Inc.	721,637
10	Jpmorgan Income Builder Fund	13	Gamco Global Gold, Natural Resources & Inc.Tr.	470,666
11	Invesco S&P 500 Equal Weight Etf	12	Franklin I.F.	412,628
12	Cohen & Steers Preferred Securities & I.F., Inc.	12	Voya Asia Pacific High Dividend Equity I.F.	382,089
13	Equity I.F.	11	Shelton Equity I.F.	269,836
14	Jpmorgan I.F.	9	Voya International High Dividend Equity I.F.	150,177
15	Blue Chip Income And Growth Fund	8	Franklin Managed I.F.	93,362
16	Fidelity Growth And Income Portfolio	7	Gamco Natural Resources, Gold & Inc.Tr.	80,963
17	Virtus Income & Growth Fund	6	Calamos Market Neutral I.F.	74,505
18	Allianzgi Income & Growth Fund	6	Cohen & Steers Alternative I.F., Inc.	65,556
19	Tiaa-Cref Growth & I.F.	6	First Trust Mlp And Energy I.F.	57,836
20	Virtus Allianzgi Income & Growth Fund	6	First Investors Premium I.F.	53,325

Panel B: Top stocks by income fund activity

Rank	TICKER	Delta	TICKER	Gamma	TICKER	Vega	TICKER	Notional
1	SPX	38,826,632	SPX	4,371,886	SPX	9,223,628	SPX	173,529,440
2	NDX	2,670,998	NDX	352,498	NDX	346,314	NDX	5,481,039
3	CVX	459,748	JNJ	61,377	CVX	149,139	CVX	1,740,752
4	MRK	448,488	PEP	57,208	XOM	97,815	ABBV	1,446,902
5	XOM	386,773	ABBV	50,569	ABBV	94,557	MSFT	1,259,994
6	ABBV	371,192	CVX	48,846	JNJ	93,003	MRK	1,216,002
7	JPM	352,884	JPM	48,147	SE	83,998	JPM	1,215,369
8	JNJ	339,082	MRK	46,566	JPM	82,978	SE	1,208,247
9	MSFT	302,367	MSFT	44,986	MRK	82,402	LMT	1,173,128
10	GOOG	244,678	LQD	37,139	MSFT	70,513	JNJ	1,058,999

Panel C: Top industries by income fund activity

Rank	Industry	Delta	Industry	Gamma	Industry	Vega	Industry	Notional
1	Retail	68,820	Manufacturing	7,525	Retail	17,591	Manufacturing	218,439
2	Manufacturing	57,821	Retail	7,034	Manufacturing	15,096	Retail	203,211
3	Financial	42,915	Financial	5,031	Financial	11,243	Services	141,738
4	Services	37,122	Services	4,420	Mining	9,985	Financial	138,267
5	Mining	36,830	Utility	3,021	Services	8,745	Mining	100,436
6	Utility	25,233	Transportation	2,830	Utility	6,370	Transportation	92,589
7	Transportation	20,749	Mining	1,846	Transportation	5,654	Utility	80,368
8	Others	18,016	Wholesales	1,834	Others	5,557	Others	71,489
9	Wholesales	15,717	Others	1,494	Wholesales	3,851	Wholesales	54,911
10	Construction	7,936	Construction	689	Construction	1,722	Construction	18,865
11	Agriculture	475	Agriculture	14	Agriculture	650	Agriculture	3,261

Table 3: Call overwriting impact to volatility by income funds

This table shows that the option supply from the income fund predicts the implied volatility of options and the realized volatility of the underlying asset in the following month. $IV30d_{i,t+1}$ represents the 30-day at-the-money (ATM) volatility of stock i measured at the next month, $t+1$, while $RV30d_{i,t+1}$ indicates the 30-day realized volatility of stock i measured at the next month, $t+1$. $NormGamma_{i,t}$ is the market-cap normalized dollar gamma position of the underlying asset aggregated from all income fund supplies. $Log(Marketcap_{i,t})$ is the logarithm of market capitalization, $Log(Volume_{i,t})$ is the logarithm of trading volume in the underlying asset, and $VRP_{i,t}$ is the logarithm of the variance risk premium ($\equiv log(E_t(RV_{i,t\to t+1}/IV_{i,t\to t+1}))$. Standard errors are clustered by stock, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

	(1)	(2)	(3)	(4)	(5)	(6)
	IV30d$_{i,t+1}$	IV91d$_{i,t+1}$	IV30d$_{i,t+1}$	IV91d$_{i,t+1}$	IV30d$_{i,t+1}$	IV91d$_{i,t+1}$
NormGamma$_{i,t}$	0.154***	0.283***	0.122**	0.185***	0.179***	0.204***
	(4.57)	(6.04)	(2.23)	(3.03)	(4.02)	(3.52)
NormGammaOthers$_{i,t}$	0.00103	-0.00267	0.00466	0.0132	0.00334	0.0118**
	(0.35)	(-1.05)	(0.70)	(1.44)	(0.63)	(2.05)
Log(MktCap$_{i,t}$)			-0.0996***	-0.0877***	-0.0728***	-0.0467***
			(-10.97)	(-10.14)	(-8.87)	(-7.97)
Log(Volm$_{i,t}$)			-0.0112***	-0.00921**	-0.00957***	-0.00717*
			(-3.99)	(-2.15)	(-5.77)	(-1.73)
VRP30$_{i,t}$			0.0150***		0.0261***	
			(3.08)		(5.10)	
VRP91$_{i,t}$				0.0355***		0.0594***
				(5.92)		(9.28)
IV30d$_{i,t}$					0.183***	
					(8.08)	
IV91d$_{i,t}$						0.374***
						(15.20)

	(1)	(2)	(3)	(4)	(5)	(6)
	RV30d$_{i,t+1}$	RV91d$_{i,t+1}$	RV30d$_{i,t+1}$	RV91d$_{i,t+1}$	RV30d$_{i,t+1}$	RV91d$_{i,t+1}$
NormGamma$_{i,t}$	0.90***	0.44***	0.30***	0.45***	0.47***	0.44***
	(12.66)	(7.20)	(3.27)	(7.39)	(5.27)	(7.42)
NormGammaOthers$_{i,t}$	-0.01***	-0.01	-0.02*	0.00	-0.02**	-0.00
	(-3.30)	(-1.24)	(-1.96)	(0.04)	(-2.35)	(-0.48)
Log(MktCap$_{i,t}$)			-0.16***	-0.17***	-0.12***	-0.09***
			(-9.91)	(-10.46)	(-8.01)	(-9.70)
Log(Volm$_{i,t}$)			-0.00	0.00	0.00	0.01*
			(-0.63)	(1.34)	(0.25)	(1.79)
VRP30$_{i,t}$			-0.17***		-0.15***	
			(-24.57)		(-21.62)	
VRP91$_{i,t}$				-0.21***		-0.13***
				(-29.70)		(-17.60)
RV30d$_{i,t}$					0.21***	
					(9.61)	
RV91d$_{i,t}$						0.44***
						(21.95)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9563	9563	5254	5254	5254	5254

Table 4: Informed or Supply impact?: Call overwriting impact to volatility by income funds

The following tables show where the option supply comes among two types of income funds: repetitive overwriting and discretion-based selling. All variable descriptions correspond to Table 3. $NormGammaRpt_{i,t}$ and $NormGammaDisc_{i,t}$ stand for the dollar gamma, normalized by the market capitalization, aggregated by the income funds repetitively selling call options and selling call option with their discretion, respectively. Standard errors are clustered by stock, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

Supply	(1) $\mathrm{IV30d}_{i,t+1}$	(2) $\mathrm{IV91d}_{i,t+1}$	(3) $\mathrm{RV30d}_{i,t+1}$	(4) $\mathrm{RV91d}_{i,t+1}$
$\mathrm{NormGammaRpt}_{i,t}$	0.208***	0.203**	0.436***	0.348***
	(2.97)	(2.53)	(3.78)	(5.91)
$\mathrm{NormGammaDisc}_{i,t}$	0.805	0.181	-0.175	-1.499***
	(1.41)	(0.32)	(-0.20)	(-3.26)
$\mathrm{NormGammaOthers}_{i,t}$	0.00369	0.0118**	-0.0184**	-0.00590
	(0.68)	(2.05)	(-2.46)	(-0.65)
$\mathrm{Log}(\mathrm{MktCap}_{i,t})$	-0.0728***	-0.0467***	-0.123***	-0.0900***
	(-8.87)	(-7.97)	(-8.01)	(-9.71)
$\mathrm{Log}(\mathrm{Volm}_{i,t})$	-0.00843***	-0.00721	0.000275	0.00405
	(-2.90)	(-1.49)	(0.04)	(1.26)
$\mathrm{VRP30}_{i,t}$	0.0261***		-0.148***	
	(5.10)		(-21.62)	
$\mathrm{IV30d}_{i,t}$	0.183***			
	(8.08)			
$\mathrm{VRP91}_{i,t}$		0.0594***		-0.128***
		(9.28)		(-17.60)
$\mathrm{IV91d}_{i,t}$		0.374***		
		(15.19)		
$\mathrm{RV30d}_{i,t}$			0.208***	
			(9.61)	
$\mathrm{RV91d}_{i,t}$				0.440***
				(21.95)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	5254	5254	5254	5254

Table 5: Call overwriting impact to volatility by income funds for underlying asset class

This table shows that the option supply from the income fund predicts the implied volatility of options and the realized volatility of the underlying asset in the following month by the category of underlying asset class, stocks vs non stocks including indices and ETFs. All variable descriptions correspond to Table 3. Standard errors are clustered by stock, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

	Stock				Non-Stock			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$IV30d_{i,t+1}$	$IV91d_{i,t+1}$	$RV30d_{i,t+1}$	$RV91d_{i,t+1}$	$IV30d_{i,t+1}$	$IV91d_{i,t+1}$	$RV30d_{i,t+1}$	$RV91d_{i,t+1}$
$NormGamma_{i,t}$	0.141**	0.160***	0.404***	0.364***	70.86*	23.04	278.1***	38.42*
	(2.04)	(4.43)	(3.37)	(3.69)	(2.89)	(1.53)	(23.66)	(2.78)
$NormGammaOthers_{i,t}$	0.500	0.598**	0.762	0.997*	-0.0198	-0.00365***	-0.0449	-0.0300
	(1.35)	(2.07)	(1.48)	(1.95)	(-2.25)	(-6.08)	(-1.19)	(-1.95)
$Log(MktCap_{i,t})$	-0.0725***	-0.0472***	-0.121***	-0.0895***	-0.157**	-0.0709***	-0.374***	-0.136**
	(-8.66)	(-7.91)	(-7.80)	(-9.46)	(-5.53)	(-80.87)	(-6.34)	(-3.79)
$Log(Volm_{i,t})$	-0.00712***	-0.00426	0.00536	0.0126**	-3.356***	-1.174*	-19.77*	-9.876
	(-2.99)	(-1.12)	(0.75)	(2.05)	(-7.66)	(-2.36)	(-2.40)	(-2.04)
$VRP30_{i,t}$	0.0264***		-0.148***		-0.0131		-0.141	
	(5.13)		(-21.57)		(-0.62)		(-1.35)	
$IV30d_{i,t}$	0.185***				-0.143			
	(8.09)				(-1.92)			
$VRP91_{i,t}$		0.0594***		-0.127***		0.0405		-0.212**
		(9.18)		(-17.62)		(1.92)		(-3.21)
$IV91d_{i,t}$		0.371***				0.315***		
		(15.21)				(17.11)		
$RV30d_{i,t}$			0.211***				-0.0600	
			(9.72)				(-0.75)	
$RV91d_{i,t}$				0.441***				0.252*
				(22.02)				(3.01)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5190	5190	5190	5190	64	64	64	64

Table 6: Call overwriting impact on volatility by income funds for the industry

This table shows that the option supply from the income fund predicts the implied volatility of options and the realized volatility of the underlying asset in the following month for each industry. The industry classification follows 'Standard Industrial Classification'. All variable descriptions correspond to Table 3. Standard errors are clustered by stock, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

$\text{IV91d}_{i,t+1}$	(1) Mining	(2) Utility	(3) Manufacturing	(4) Financial	(5) Retail	(6) Wholesales	(7) Services	(8) Transportations
$\text{NormGamma}_{i,t}$	-69.01	50.10***	7.029	0.0495**	24.39**	43.03	3.563	132.7
	(-0.66)	(4.78)	(0.90)	(2.03)	(2.54)	(0.74)	(0.13)	(1.13)
$\text{NormGammaOthers}_{i,t}$	2.623***	-1.213	0.980***	0.0122***	-0.258	0.756	0.958	2.681*
	(3.50)	(-0.90)	(5.13)	(5.33)	(-0.62)	(0.61)	(1.62)	(3.99)
$\text{Log}(\text{MktCap}_{i,t})$	-0.0278**	-0.141***	-0.0378***	-0.0975***	-0.0615***	-0.129**	-0.0494***	-0.164*
	(-2.36)	(-2.89)	(-5.68)	(-5.91)	(-2.96)	(-2.27)	(-3.92)	(-2.94)
$\text{Log}(\text{Volm}_{i,t})$	-3.855***	-2.622	-0.000646	-0.0182***	1.171	-4.042	-1.696***	12.63
	(-2.92)	(-1.13)	(-0.35)	(-6.95)	(1.45)	(-0.60)	(-3.26)	(0.79)
$\text{VRP}_{i,t}$	0.181***	0.0626***	0.0603***	0.0952***	0.0555***	0.104***	0.0510***	0.0801
	(5.46)	(3.74)	(8.10)	(5.04)	(3.55)	(3.95)	(6.96)	(2.73)
$\text{IV91d}_{i,t}$	0.438***	0.458***	0.571***	0.401***	0.399***	0.338***	0.590***	0.207
	(6.55)	(7.17)	(24.25)	(6.87)	(6.38)	(10.24)	(11.05)	(1.79)

$\text{RV91d}_{i,t+1}$	(1) Mining	(2) Utility	(3) Manufacturing	(4) Financial	(5) Retail	(6) Wholesales	(7) Services	(8) Transportations
$\text{NormGamma}_{i,t}$	131.0	19.68	8.812	0.349***	30.05**	80.40	17.31	666.7**
	(1.10)	(0.97)	(0.68)	(14.27)	(2.26)	(0.98)	(0.45)	(6.51)
$\text{NormGammaOthers}_{i,t}$	3.643**	-3.164	2.336***	-0.00690**	-0.991	8.056**	0.578	11.60
	(2.59)	(-0.54)	(4.83)	(-2.10)	(-1.17)	(2.53)	(0.63)	(2.31)
$\text{Log}(\text{MktCap}_{i,t})$	-0.0621***	-0.173***	-0.0787***	-0.153***	-0.0705**	-0.183*	-0.0837***	-0.360*
	(-3.79)	(-3.84)	(-4.83)	(-5.27)	(-2.40)	(-1.84)	(-3.47)	(-4.09)
$\text{Log}(\text{Volm}_{i,t})$	-3.956**	-9.357**	-0.00391	0.00266	1.644	-3.059	-0.806	97.13**
	(-2.19)	(-2.50)	(-1.33)	(1.23)	(1.21)	(-0.44)	(-1.13)	(7.21)
$\text{VRP}_{i,t}$	-0.0172	-0.0512***	-0.0803***	-0.0826***	-0.111***	-0.0505*	-0.103***	-0.155
	(-0.40)	(-3.10)	(-8.02)	(-5.55)	(-6.68)	(-1.83)	(-7.81)	(-2.80)
$\text{RV91d}_{i,t}$	0.579***	0.573***	0.609***	0.553***	0.541***	0.583***	0.555***	0.212
	(16.39)	(17.16)	(25.29)	(15.51)	(11.40)	(17.29)	(15.24)	(0.91)
Observations	381	551	2004	852	384	113	704	58

Table 7: Call overwriting impact on volatility by income funds for high and low dividend groups

This table shows that the option supply from the income fund predicts the implied volatility of options and the realized volatility of the underlying asset in the following month for high and low dividend groups. All variable descriptions correspond to Table 3. $HighDiv_i = 1$ if the stock belongs to the high dividend group in A2 and zero otherwise. To enhance readability, the coefficients of the interaction terms have been multiplied by 10^6. Standard errors are clustered by stock, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\text{IV30d}_{i,t+1}$	$\text{IV91d}_{i,t+1}$	$\text{IV30d}_{i,t+1}$	$\text{IV91d}_{i,t+1}$	$\text{IV30d}_{i,t+1}$	$\text{IV91d}_{i,t+1}$
$\text{NormGamma}_{i,t}$	0.140**	0.237***	0.132*	0.149***	0.132*	0.149***
	(2.28)	(5.82)	(1.77)	(5.03)	(1.77)	(5.03)
$\text{NormGammaOthers}_{i,t}$	-0.0327	0.207	0.500	0.599**	0.500	0.599**
	(-0.11)	(0.76)	(1.35)	(2.06)	(1.35)	(2.06)
$\text{NormGamma}_{i,t} \cdot HighDiv_i$	0.144***	0.142***	0.0500	0.0673***	0.0500	0.0673***
	(2.88)	(3.72)	(1.13)	(2.85)	(1.13)	(2.85)
$\text{IV30d}_{i,t}$			0.185***		0.185***	
			(8.09)		(8.09)	
$\text{Log}(\text{MktCap}_{i,t})$			-0.0721***	-0.0467***	-0.0721***	-0.0467***
			(-8.59)	(-7.79)	(-8.59)	(-7.79)
$\text{Log}(\text{Volm}_{i,t})$			-0.00717***	-0.00433	-0.00717***	-0.00433
			(-3.04)	(-1.14)	(-3.04)	(-1.14)
$\text{VRP30}_{i,t}$			0.0264***		0.0264***	
			(5.12)		(5.12)	
$\text{IV91d}_{i,t}$				0.372***		0.372***
				(15.22)		(15.22)
$\text{VRP91}_{i,t}$				0.0594***		0.0594***
				(9.17)		(9.17)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\text{RV30d}_{i,t+1}$	$\text{RV91d}_{i,t+1}$	$\text{RV30d}_{i,t+1}$	$\text{RV91d}_{i,t+1}$	$\text{RV30d}_{i,t+1}$	$\text{RV91d}_{i,t+1}$
$\text{NormGamma}_{i,t}$	0.862***	0.517***	0.204	0.333***	0.375***	0.358***
	(14.34)	(5.37)	(1.43)	(2.75)	(2.78)	(3.51)
$\text{NormGammaOthers}_{i,t}$	-0.144	-0.689	0.869	1.565*	0.764	0.998*
	(-0.36)	(-0.99)	(1.42)	(1.95)	(1.48)	(1.95)
$\text{NormGamma}_{i,t} \cdot HighDiv_i$	0.313***	0.149**	0.152**	-0.00710	0.169**	0.0351
	(3.63)	(2.00)	(2.07)	(-0.10)	(2.42)	(0.75)
$\text{Log}(\text{MktCap}_{i,t})$			-0.163***	-0.167***	-0.120***	-0.0892***
			(-9.50)	(-10.31)	(-7.64)	(-9.36)
$\text{Log}(\text{Volm}_{i,t})$			-0.0000397	0.0126*	0.00518	0.0126**
			(-0.00)	(1.91)	(0.73)	(2.05)
$\text{VRP30}_{i,t}$			-0.166***		-0.148***	
			(-24.59)		(-21.59)	
$\text{VRP91}_{i,t}$				-0.211***		-0.127***
				(-29.47)		(-17.61)
$\text{RV30d}_{i,t}$					0.211***	
					(9.72)	
$\text{RV91d}_{i,t}$						0.441***
						(22.02)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8982	8982	5190	5190	5190	5190

Appendix

A1: N-PORT XML example

Below is an example of XML code in N-PORT for the series, 1308335 on May 26, 2023.


```
<invstOrSec>
   <name>Options Clearing Corp.</name>
   <lei>549300CII6SLYGKNHA04</lei>
   <title>MICRON TECHNOLOGY INC</title>
   <cusip>000000000</cusip>
   <identifiers>
     <other otherDesc="Bloomberg␣Identifier" value="BBG01G0SC1W0"/>
   </identifiers>
   <balance>-745.00000000</balance>
   <units>NC</units>
   <curCd>USD</curCd>
   <valUSD>-41720.00000000</valUSD>
   <pctVal>-0.00465957492</pctVal>
   <payoffProfile>N/A</payoffProfile>
   <assetCat>DE</assetCat>
   <issuerConditional desc="derivative" issuerCat="OTHER"/>
   <invCountry>US</invCountry>
   <isRestrictedSec>N</isRestrictedSec>
   <fairValLevel>1</fairValLevel>
   <derivativeInfo>
     <optionSwaptionWarrantDeriv derivCat="OPT">
       <counterparties>
         <counterpartyName>Options Clearing Corp.</counterpartyName>
         <counterpartyLei>549300CII6SLYGKNHA04</counterpartyLei>
       </counterparties>
       <putOrCall>Call</putOrCall>
       <writtenOrPur>Written</writtenOrPur>
       <descRefInstrmnt>
         <otherRefInst>
           <issuerName>Micron Technology, Inc.</issuerName>
           <issueTitle>Micron Technology, Inc.</issueTitle>
           <identifiers>
             <cusip value="595112103"/>
             <isin value="US5951121038"/>
           </identifiers>
         </otherRefInst>
       </descRefInstrmnt>
```

```
        <shareNo>100.00000000</shareNo>
        <exercisePrice>68.00000000</exercisePrice>
        <exercisePriceCurCd>USD</exercisePriceCurCd>
        <expDt>2023-05-05</expDt>
        <delta>XXXX</delta>
        <unrealizedAppr>79744.53000000</unrealizedAppr>
      </optionSwaptionWarrantDeriv>
    </derivativeInfo>
```

A2: Newey-West regression for the result in Section 4.1

This appendix table provides the results of the regression presented in Section 4.1, utilizing the Newey-West standard error. The findings echo those of the base regression, reinforcing the consistent implication that, across all cases, income funds maintaining an higher normalized dollar gamma position ($NormGamma_{i,t}$) are associated with increased levels of both implied and realized volatilities across 30-day and 91-day maturities. The utilization of the Newey-West standard error in this analysis is particularly advantageous given the nature of the study, which inherently involves the examination of potential serial correlation in the data. The Newey-West standard error method is robust in the presence of serial correlation, providing more reliable estimates of standard errors when analyzing time-series data. By accounting for potential autocorrelation in the residuals, this method helps produce valid standard errors, ensuring the accuracy of statistical inferences drawn from the regression result.

Table A1: Call overwriting impact to volatility by income funds

This table shows that the option supply from the income fund predicts the implied volatility of options and the realized volatility of the underlying asset in the following month. All variable descriptions correspond to Table 3. Newey-West standard errors are applied, and statistics are reported in brackets, where *, **, and *** denote significance at levels of 10%, 5%, and 1%. The sample period ranges from September 2019 to December 2022, during which N-PORT is available.

	(1)	(2)	(3)	(4)
	$\text{IV30d}_{i,t+1}$	$\text{IV91d}_{i,t+1}$	$\text{IV30d}_{i,t+1}$	$\text{IV91d}_{i,t+1}$
$\text{NormGamma}_{i,t}$	2.23***	2.10***	2.25**	1.44**
	(3.43)	(3.55)	(2.43)	(2.24)
$\text{NormGammaOthers}_{i,t}$	-0.09***	-0.09***	-0.05	-0.03
	(-4.29)	(-3.53)	(-1.36)	(-0.90)
$\text{Log}(\text{MktCap}_{i,t})$			-0.03***	-0.02***
			(-9.37)	(-8.97)
$\text{Log}(\text{Volm}_{i,t})$			-0.08***	-0.07***
			(-4.42)	(-4.28)
$\text{VRP30}_{i,t}$			0.07***	
			(10.29)	
$\text{VRP91}_{i,t}$				0.15***
				(19.79)
N	9610	9610	5282	5282

	(1)	(2)	(3)	(4)
	$\text{RV30d}_{i,t+1}$	$\text{RV91d}_{i,t+1}$	$\text{RV30d}_{i,t+1}$	$\text{RV91d}_{i,t+1}$
$\text{NormGamma}_{i,t}$	2.33***	2.17***	3.37**	2.71**
	(4.15)	(3.43)	(2.32)	(2.20)
$\text{NormGammaOthers}_{i,t}$	-0.09***	-0.10***	-0.12**	-0.08
	(-3.55)	(-3.66)	(-2.01)	(-1.50)
$\text{Log}(\text{MktCap}_{i,t})$			-0.05***	-0.05***
			(-9.94)	(-9.34)
$\text{Log}(\text{Volm}_{i,t})$			-0.12***	-0.12***
			(-4.15)	(-4.52)
$\text{VRP30}_{i,t}$			-0.08***	
			(-9.45)	
$\text{VRP91}_{i,t}$				-0.01
				(-1.02)
N	9610	9610	5282	5282

Table A2: Call overwriting activity by different group of dividends

The following table compares call overwriting activity measured by $NormGamma_{i,t}$ among different dividend groups. Using the CSRP dataset during the N-PORT sample period from 2019 to 2022, we computed the average yearly dividend rate. The data was then sorted by the yearly dividend rate, and the high dividend group consists of values above the median, while the low dividend group consists of values below the median.

Industry	HighDiv	LowDiv	diff	t-stat	p-value
Manufacturing	-367,393	-83,538	-283,855	9.98	0.0
Financial	-155,335	-108,984	-46,351	1.92	0.0549
Services	-72,753	-215,193	142,440	-2.59	0.0099
Wholesales	-33,753	-71,393	37,640	-2.15	0.0329
Utility	-100,258	-60,410	-39,848	2.86	0.0043
Mining	-132,656	-77,041	-55,615	3.5	0.0005
Retails	-341,370	-96,646	-244,724	2.91	0.0038
Transportation	-195,118	-54,175	-140,943	1.98	0.0512