The Price Isn't Right: Effect of Passive Ownership on Price Informativeness

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Abstract

Passive investing has grown increasingly popular ever since the invention of index funds and ETFs. This paper empirically analyses the effects of passive investing on price informativeness by using volatility as a proxy and earnings announcements to abstract away from structural models. To address endogeneity, inclusion in the S&P 500 index is employed as an instrument for passive ownership. Using U.S. firm level data from 2021 to 2025, this paper finds the results show that higher passive ownership reduces pre-announcement volatility but amplifies post announcement reactions, consistent with slower incorporation of firm-specific information.

JEL Code: G14

Contents

1 Introduction

John Bogle, the founder of Vanguard, introduced the first index fund in 1976, which tracked the S&P 500. Subsequently, in 1993, the first US listed exchange traded fund (ETF) called SPDR, which also tracked the S&P 500, made its debut. These innovations democratised investing, making equity markets accessible to investors who were previously inaccessible.

These instruments have gained popularity since their launch; there are an estimated 12000 ETFs worldwide in 2024 (Investopedia). As assets under management of the ETFs have grown, they have reshaped trading behaviours and market structure. Two of the biggest strategies that grew as a result of the popularity of these instruments are riskless arbitrage of the ETF and Passive investing.

Passive investing has grown significantly over the past decade, surpassing Active investing in equities. It is important to discuss what passive investing is beforehand, as it could be argued that no one is a passive investor, as everyone makes an active decision to invest.

Passive investing has two primary definitions:

a. Passive investors choose a portfolio, buy it, and hold it long-term with no regard for profiting from short term variations or frequent trading. (Moltke & Sløk, 2024)

b. A passive investor holds every security in the market, with each represented in the same manner as in the market. (Sharpe, 1991)

For the purposes of this paper, we will adopt Sharpe's definition.

Recently, Total Assets in Index Funds overtook Total Assets in Non-Index Funds. Figures 1 and 2 illustrate this development, showing the level and share of assets.

Haddad, Huebner and Loualiche (2024) show through their model that an increase in the share of passive investing leads to lower price elasticities of demand, which can lead to higher volatility, lower efficiency and illiquidity. If stocks become less responsive to trading demand, they may also adjust differently to new information. Price informativeness reflects how well prices incorporate firm specific information. A decline in informativeness implies that capital may be misallocated and that prices respond less to fundamentals.

This motivates the research question, "How has passive investing affected the price informativeness of stocks?"

In order to answer this question, we use price volatility around the earnings date as a proxy of price informativeness. The biggest issue of using volatility as a measure of price informativeness is that there are other confounding factors that could lead to changes in volatility. However, this issue is minimized in our case as we focus on a relatively small window around the earning dates.

Volatility can serve as a good measure within this small window, as we'd expect during the pre-earnings periods, investors to revise estimates based on partial information such as management guidance, analyst revisions, or private signals. In the post-earnings period, if there is an unexpected earnings beat or miss, we expect high volatility for a few days, followed by reduced volatility as uncertainty subsides.

My hypothesis is that high passive ownership leads to lower volatility in the pre-earnings period and much higher volatility after the earnings announcement, thus implying lower price informativeness for the stock.

We will focus on a small window around the earnings date, from 30 days prior to 15 days after. This naturally leads me to use an event study model to analyse the effects of passive investing. There are concerns of endogeneity, such as omitted variable bias and simultaneous causality. To mitigate these concerns, we add fixed effects to the model and run a two-stage least squares model with inclusion in the S&P 500 as the instrument.

The S&P 500 is the most popular index, and so inclusion in the index naturally leads to higher passive ownership. This is true in the sample as well; the median stock in the S&P 500 has a 30.29% passive ownership share while the median stock not in the S&P 500 has a 10.75% passive ownership share. This motivates the relevance of the instrument. Inclusion into the index is driven by rules unrelated to volatility. Inclusion in the S&P 500 is not random; however, conditional on firm size and other observables, residual variation in index membership is exogenous to firm level volatility.

This paper contributes to the literature by providing causal evidence on how passive ownership affects price informativeness using a volatility-based event study design.

The paper follows the following structure: Section 2 reviews the literature. Section 3 describes the data and variables. Section 4 outlines the empirical model. Section 5 presents results, and Section 6 concludes.

2 Literature Review

Haddad, Huebner and Loualiche (2024) develop a model that shows the impact of passive investing on stock prices. The authors' primary mechanism operates through the elasticity of demand. They model the individual investor's decision through their demand and their degree of aggressiveness (their elasticity) and then aggregate the investors to reach market equilibrium conditions.

The model shows that as the share of passive investors increases, aggregate elasticity declines if investors are sensitive to market conditions. Their model further shows that a reduction in elasticity leads to more unstable prices.

Kyle (1985) provides a theoretical framework for volatility as a proxy for price informativeness. The author provides a sequential equilibrium model and argues that constant volatility reflects the fact that information is incorporated into prices at a constant rate.

Building on this theoretical foundation, several empirical studies have attempted to measure passive ownership and assess its impact on price informativeness, employing different identification strategies and proxies.

Empirical identification of passive ownership varies across studies. Moltke & Sløk (2024) provide extensive descriptive evidence on passive investing and adopt a measurement of passive investing that differs from mine. Using 13F filings, the authors compute the elasticity of demand of stocks for each fund and if the value is sufficiently close to 0, they flag the fund as a passive investor. This approach has the advantage that it flags funds that are, in practice, passive even if they don't self-identify as passive investors. A key limitation is that 13F filings do not distinguish between funds owned by the same filing manager. This leads to problems where one owner may simultaneously operate one fund that follows the index and another that actively trades, but both are aggregated under a single 13F report.

Samson (2024) investigates the effect of passive ownership on price informativeness. The author's measure of passive investing is the one I employ. However, Samson (2024) uses data from 1990 to 2019, whereas from Figures 1 and 2, it is evident that from 2023 to 2025, the share of passive investing has sharply increased. Samson (2024) in their sample find a negative causal relationship between passive ownership and price informativeness; however, they do not employ volatility as a proxy for price informativeness. They use the price jump measure proposed by Weller (2018).

Overall, the empirical literature around passive ownership and price informativeness has been mixed. Buss & Sundaresan (2020) find that passive ownership positively affects information efficiency. They argue that due to passive investors' inelastic demand, the firm's cost of capital is reduced, allowing it to take on more risk. This would lead to higher cash flow variance, which in turn incentivises active investors to acquire more precise information. Bennett, Stulz & Wang (2020), find that inclusion in the S&P 500 negatively impacts price informativeness. Since the S&P 500 is the largest index, the authors argue that the channel is through passive investing. Coles, Heath & Ringgenberg (2022) find no effect of passive ownership on price informativeness.

This paper contributes to this mixed literature by using a different measure of price informativeness and using earnings announcements to abstract away from any structural model.

3 Data Description

3.1 Data

The share of a company passively owned is the main variable of study, and to construct this variable, we need 3 datasets. To construct the share of passive ownership, we combine three datasets: CRSP's Survivor-Bias-Free US Mutual Fund Database, which identifies index funds; LSEG's S12 filings, which report quarterly mutual fund holdings; and WRDS MFLINKS, which links CRSP fund identifiers to LSEG filings.

The first of the three is CRSP's Survivor Bias Free US Mutual Fund Database. This dataset contains the variable index fund flag, which flags funds that are either index fund based, purely index fund, or index fund enhanced. In this paper, we focus on purely index funds; however, in the robustness analysis, we allow for index fund based funds as well. The second dataset is LSEG's S12 filings, which contain the quarterly holdings for US mutual funds. The third dataset needed is the Wharton Research Data Services' MFLINKS dataset, which provides the codes necessary for merging the LSEG data with the CRSP data.

For each stock-quarter observation, we sum the shares held by funds flagged as index funds to get the total number of shares outstanding owned passively. The drawback of using this method is that we rely on funds flagging themselves as index funds. Funds that don't identify themselves as passive but are in practice index funds are not recorded.

An alternative method to construct the share of passive ownership is to use the 13F filings as employed by Moltke & Sløk (2024). They compute the elasticity of demand of stocks for each fund and if the value is sufficiently close to 0, they flag the fund as a passive investor. A key limitation is that 13F filings do not distinguish between funds owned by the same filing manager. For example, Vanguard may simultaneously operate one fund that follows the index and another that actively trades, but both are aggregated under a single 13F report. Due to this limitation, we adopt the CRSP–LSEG–MFLINKS measurement technique.

In order to construct the dependent variable, we need daily stock data on prices. we use CRSP's daily stock dataset to get daily prices, returns and volume data.

LSEG's IBES dataset provides the earnings dates for each stock. Since exchanges are open from 9:00 am to 4:30 pm, if an earnings announcement takes place after 4:00 pm, we consider the earnings announcement date to be the next day. This is because the markets can only react to announcement after opening the next day.

We use Compustat's quarterly fundamentals for controls and we use Wikipedia to construct data on stocks in the S&P 500 for my instrument.

My sample extends from January 1, 2021 to March 31, 2025 with a total of 17 quarters. The sample starts from 2021 to avoid affects of COVID-19. In total, there are 3502 unique stocks in the dataset.

3.2 Variables

The dependent variable is price volatility, defined as the standard deviation over a window. Since we are looking at a small event window (-30 to +15), we use three different time windows 3, 5 and 7 days. Choosing a large time period, such as 30 days, could lead to other confounding factors affecting the results, which is why we employ to smaller time periods. Figures 3, 4 and 5 provide trends in volatility around earnings dates. These figures clearly suggest that higher passive ownership is correlated with higher volatility and greater spikes in volatility post-earnings.

The main independent variable is the share of stock passively held, defined as:

$$\text{Passive} = \frac{\text{Outstanding Shares Passively Held}}{\text{Total Outstanding Shares}}$$

This variable captures the proportion of a firm's equity passively held by mutual funds, ranging from 0 (no passive ownership) to 1 (fully passive ownership).

Since index-tracking funds must replicate the S&P 500 composition, inclusion in the index mechanically increases passive fund demand for the stock, making it a relevant instrument. The instrument variable is a dummy variable equal to 1 if a stock at time t was in the S&P 500 index and 0 otherwise.

Table 1 provides summary statistics for the variables.

4 Empirical Model

In order to analyse the effect of passive ownership on volatility around earnings dates, we use an event study specification with fixed effects as shown below:

$$\text{Volatility}_{i,t} = \delta \text{Passive}_{i,t} + \sum_{k \neq -1} \beta_k D_{i,k} + \sum_{k \neq -1} \gamma_k D_{i,k} \times \text{Passive}_i + \mathbb{X}_{i,t}\Theta + \alpha_i + \epsilon_{i,t}$$

Where, the unit i is a stock on day t, $\text{Volatility}_{i,t}$ is either 3, 5 or 7 day volatility. $\text{Passive}_{i,t}$ is the share of a stock passively held. $D_{i,t}$ is a dummy variable equal to 1 at time t. $\mathbb{X}$ are controls such as total assets, revenue, volume traded and earnings per share as they are correlated to volatility around earnings dates. α_i are entity fixed effects, which are included to absorb time invariant firm characteristics not included in the controls.

It is important to note that the variable Passive is quarterly, so it does not change day to day. This is also the case for some of the control variables.

β_k captures the average change in volatility on event day k relative to day -1 for all firms, while γ_k captures how this effect differs with passive ownership. A negative γ_k before earnings and a positive γ_k after earnings would indicate that higher passive ownership reduces pre-announcement volatility but amplifies post-announcement reactions.

Since simultaneous causality is a potential endogeneity issue, I use a two stage least squares specification. The key identification assumption is that, conditional on firm characteristics such as size and liquidity, inclusion in the S&P 500 affects volatility only through its effect on passive ownership.

The first stage is:

$$\text{Passive}_{i,t} = \alpha + \beta \text{ S\&P inclusion}_{i,t} + \mathbb{W}_{i,t}\Theta + \nu_{i,t}$$

Using the first stage we compute $\widehat{\text{Passive}}$ and estimate the second stage:

$$\text{Volatility}_{i,t} = \delta \widehat{\text{Passive}}_{i,t} + \sum_{k \neq -1} \beta_k D_{i,k} + \sum_{k \neq -1} \gamma_k D_{i,k} \times \widehat{\text{Passive}}_i + \mathbb{W}_{i,t}\Theta + \alpha_i + \epsilon_{i,t}$$

Similar to the first model, the coefficients β_k and γ_k, $\forall k \in \{-30, \ldots -2, 0, 1 \ldots 15\}$ are the coefficients of interest. However, by substituting the variable Passive with $\widehat{\text{Passive}}$ into the event study specification the coefficients capture the causal response of volatility to exogenous variation in passive ownership.

5 Results & Discussion

5.1 Results

Figures 6-8 show the results for the event study without entity fixed effects. Figure 6 shows that our hypothesis for 3 day volatility holds true; the coefficients of the interaction terms are negative before the announcement date and are positive immediately after the announcement, while the coefficients of the time dummies are 0 in the pre-announcement period and positive, but small, in the post-announcement period. On the announcement day, the coefficient of the interaction term is 3.5733 while that of the time dummy is 0.3168. Figures 7 and 8 follow the same pattern for the post-announcement periods; however, during the pre-announcement periods, the coefficients of the interaction terms are not statistically significant. This could be due to omitted variables bias; to account for this, we also use the fixed effects model.

Figures 9-11 show the results for the event study with entity fixed effects. We drop sector controls as those are absorbed by the fixed effects. Our results for 3 day volatility do not change. However, 5 and 7 day volatility now show the same pre-announcement pattern as 3 day volatility, further validating the results.

Table 2 provides the coefficient for Passive Share and selected time and interaction coefficients in these models. We can interpret the coefficients as follows: a 1% increase in share passively owned is correlated with a $(\delta + \gamma_k) \cdot 0.01$ unit change in volatility on day k relative to day -1, where δ is the coefficient of Share Passive and γ_k is the coefficient of the interaction term on day k. For example, from column 2, a 1% increase in share passively owned is correlated with a 0.041 units increase in 3 day volatility on earnings day relative to a day prior.

We cannot draw any causal implications from the fixed effects event study model, as simultaneous causality could be a source of endogeneity. To combat this, we use inclusion in the S&P 500 as an instrument. Table 3 provides the results of the first stage regression. As we can see, the coefficient for the instrument is statistically significant and so is relevant.

Figures 12-14 show the results for the event study with sector controls with Share Passive replaced by $\widehat{\text{Share Passive}}$ and figures 15-17 show the results with fixed effects. Although our results visually do not change from the results of the fixed effects model, by comparing tables 2 and 4, we can see the levels of the coefficients have changed. Moreover, the coefficients in table 4 have a causal interpretation, under the exclusion restriction that S&P 500 inclusion affects volatility only through passive ownership.

Table 4 provides the coefficient for Passive Share and selected time and interaction coefficients in the second stage. We can now interpret the coefficients as follows: a 1% increase in share passively owned causes a $(\delta + \gamma_k) \cdot 0.01$ unit change in volatility on day k relative to day -1, where δ is the coefficient of Share Passive and γ_k is the coefficient of the interaction term on day k. For example, from column 2, a 1% increase in share passively owned causes a 0.155 unit increase in 3 day volatility on earnings day relative to a day prior.

The consistency of the results across 3, 5, and 7 day volatility measures reinforces the robustness of the finding that passive ownership dampens pre-announcement and amplifies post-announcement volatility.

5.2 Discussion

Table 3 provides the results of the relevance test; as we can see, the F-test result is 134829 and so the instrument is relevant. Since the instrument is just identified, we cannot run a J-test to ensure the instrument is exogenous. Inclusion in the S&P is not random; it is dependent on firm size, so conditional on firm size, the residual variation in index membership is exogenous to volatility.

As discussed earlier, from Table 4 column 2, a 1% increase in share passively owned causes a 0.155 unit increase in 3 day volatility on earnings day relative to a day prior, for 5 day volatility, the effect is 0.142 unit and for 7 day volatility is 0.141 unit. Although the estimated magnitudes appear modest at the percentage point level, they become economically significant given the substantial rise in passive ownership over recent years. Moreover, given that the mean of 3 day volatility is 1.0662, 0.155 represents approximately 14.5% of the mean.

These results contribute to the growing literature suggesting that the expansion of passive investing may impair price discovery. Reduced price informativeness could, in turn, influence capital allocation efficiency and the responsiveness of equity markets to firm specific news.

These results suggest that an increase in the share of passive ownership does lead to lower price informativeness. Although this paper focuses on the magnitude and not the direction, this does provide a potential trading strategy. As passive investing rises and price informativeness drops in the lead up to the earnings, a trader could use soft information in the lead up to earnings to determine the direction of the price after earnings. Since the reaction post earnings will be elevated, they could use options contracts expiring after earnings. An interesting avenue for future research would be to examine this strategy explicitly.

Overall, the findings support the hypothesis that passive ownership affects the temporal pattern of volatility around information events. The results imply that the increasing dominance of passive investing has meaningful consequences for how quickly and efficiently information is reflected in prices.

6 Conclusion

Since the creation of the first index funds and ETFs, passive investing has been growing consistently. As the size of assets under index funds has increased and overtaken assets under non-index funds, price informativeness has decreased.

This paper provides evidence that passive investing does lead to a decrease in price informativeness by using volatility as a proxy. These findings complement recent theoretical work that links the rise of passive investing to declining price elasticity of demand and reduced information efficiency (Haddad et al., 2024). By using an event-study approach focused on earnings announcements, this paper offers empirical evidence of this mechanism at work. Volatility for stocks with higher passive ownership is lower during the pre-announcement period, while volatility for those stocks is elevated during the post-announcement period.

Lower price informativeness leads to capital misallocation, this creates conditions where active investors can benefit from information frictions. In particular a potential trade strategy would involve using soft information in the pre-earnings period and options contracts expiring post-earnings to exploit these frictions.

Although the findings of the paper may seem contradictary to the findings of Buss & Sundaresan (2020), it is important to note that their results are for a longer time scale while the results of this paper focus on day to day volatility in the event window.

The drawback of this paper is that the measure of share passively held relies on funds to self identify as index funds and so misses funds that are in practice index funds but not in name. Future work could provide further robustness by employing an alternative measure using 13F filings to compute the elasticity of demand of stocks for each fund, which could be used alongside the measure employed in this paper.

In summary, this paper provides causal evidence that the growing dominance of passive investing has meaningful effects on how information is incorporated into stock prices. By employing an event study framework with firm fixed effects and two stage least squares estimation, we find that firms with higher passive ownership exhibit lower volatility before earnings announcements and heightened volatility afterwards, consistent with reduced price informativeness. These results underscore the role of passive investing in reshaping market dynamics and contribute to the broader debate on whether the shift toward index-based investing enhances or impairs market efficiency. The findings suggest that as passive ownership continues to expand, the information environment of public equities may become increasingly segmented, with important implications for investors, policy makers, and the efficiency of capital markets.

7 References

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8 Tables & Figures

8.1 Figures

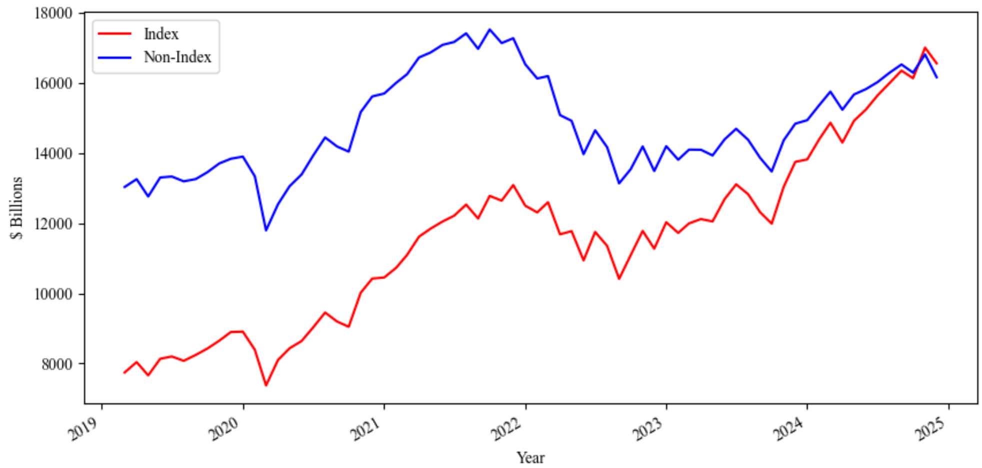

Figure 1: Index vs Non-Index Funds Total Assets

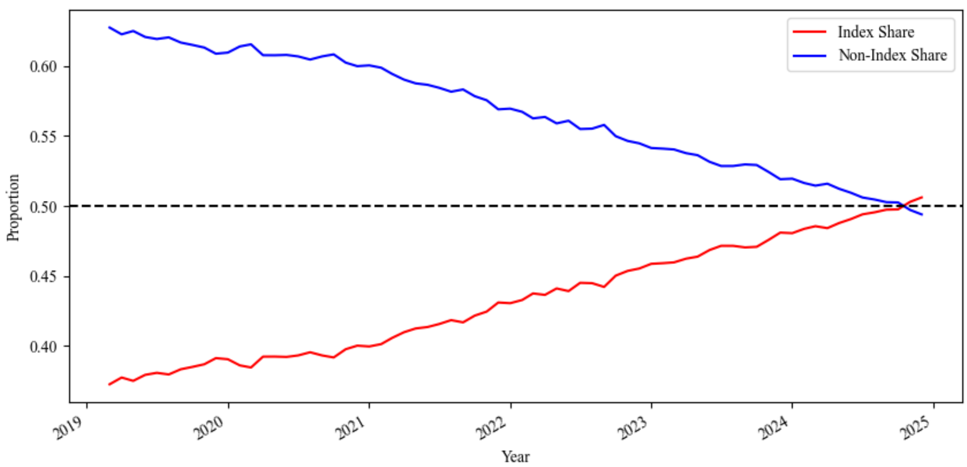

Figure 2: Index vs Non-Index Funds Share of Assets

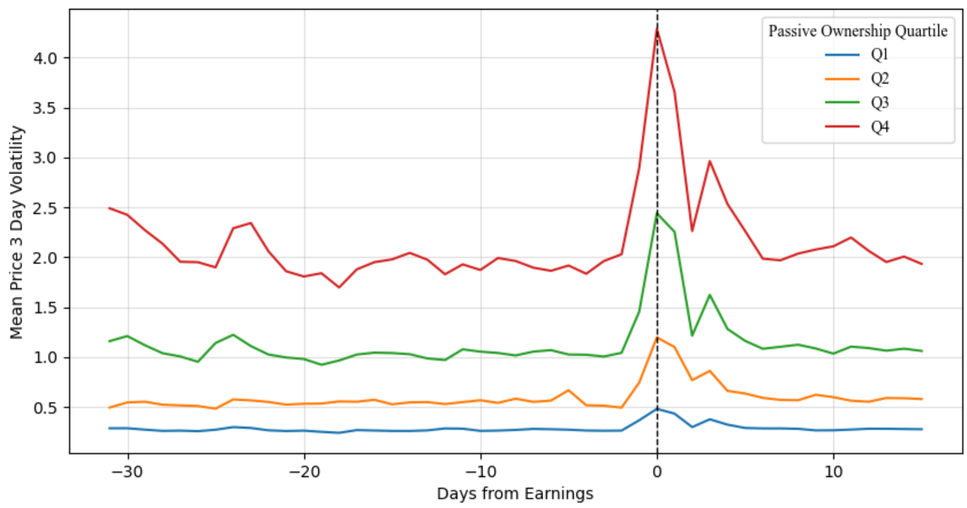

Figure 3: 3 Day Volatility Trends

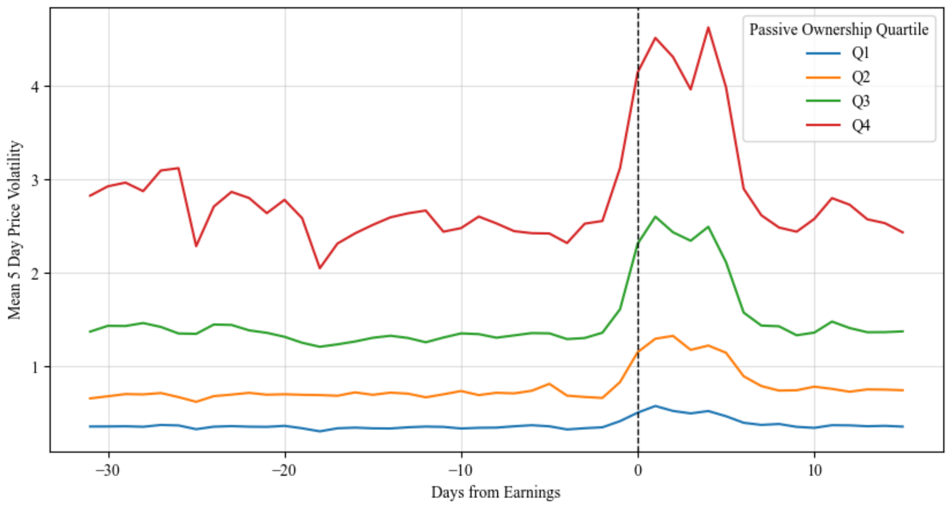

Figure 4: 5 Day Volatility Trends

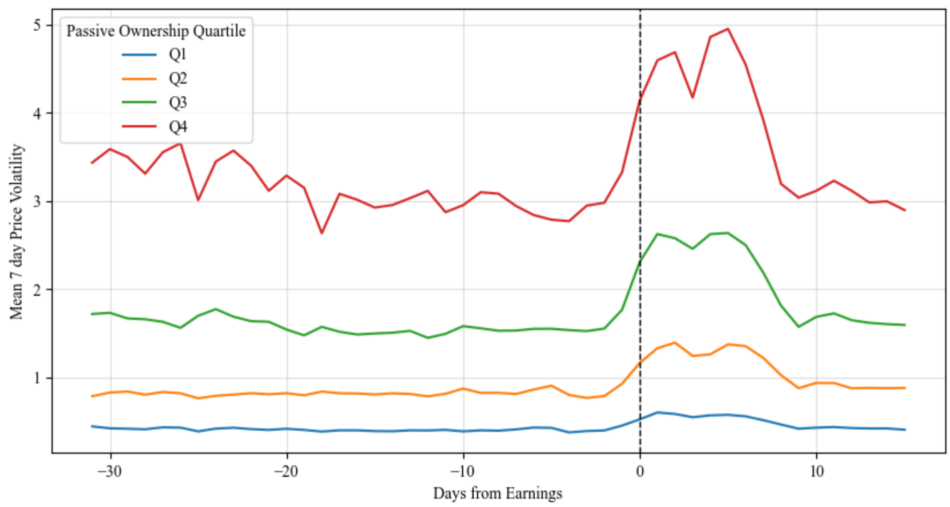

Figure 5: 7 Day Volatility Trends

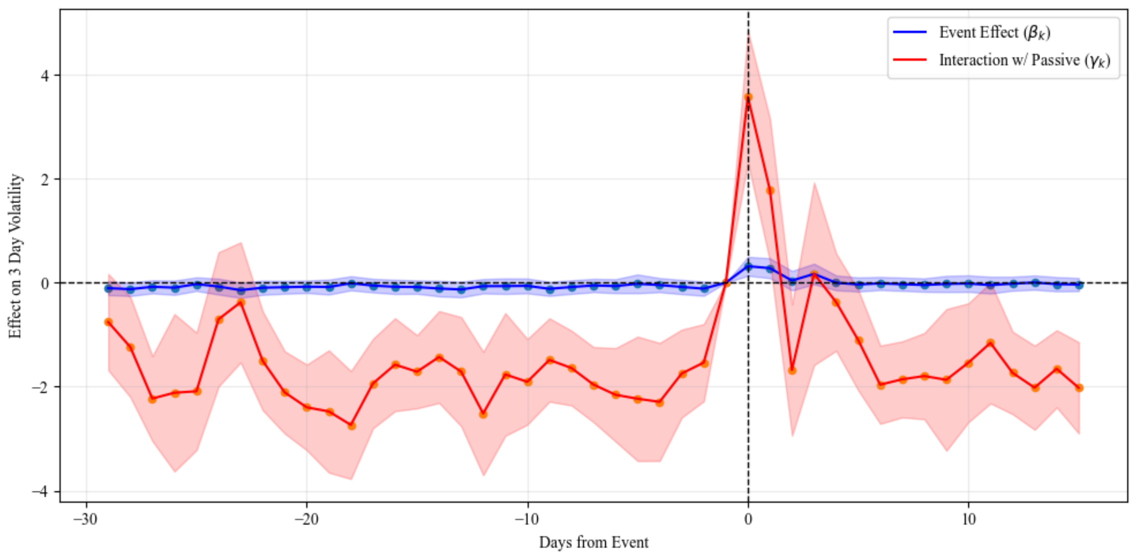

Figure 6: 3 Day Volatility Event Study

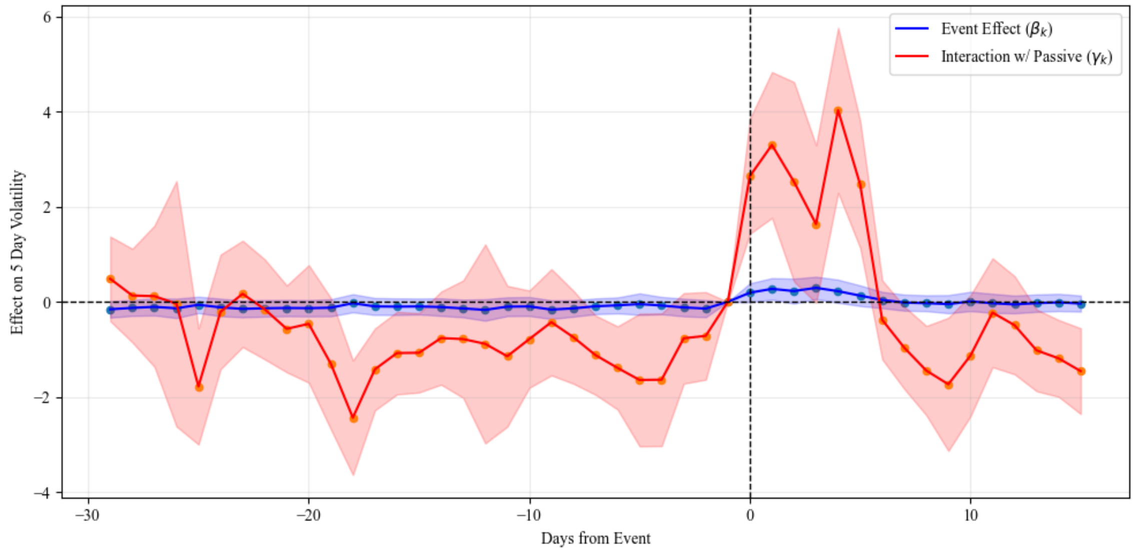

Figure 7: 5 Day Volatility Event Study

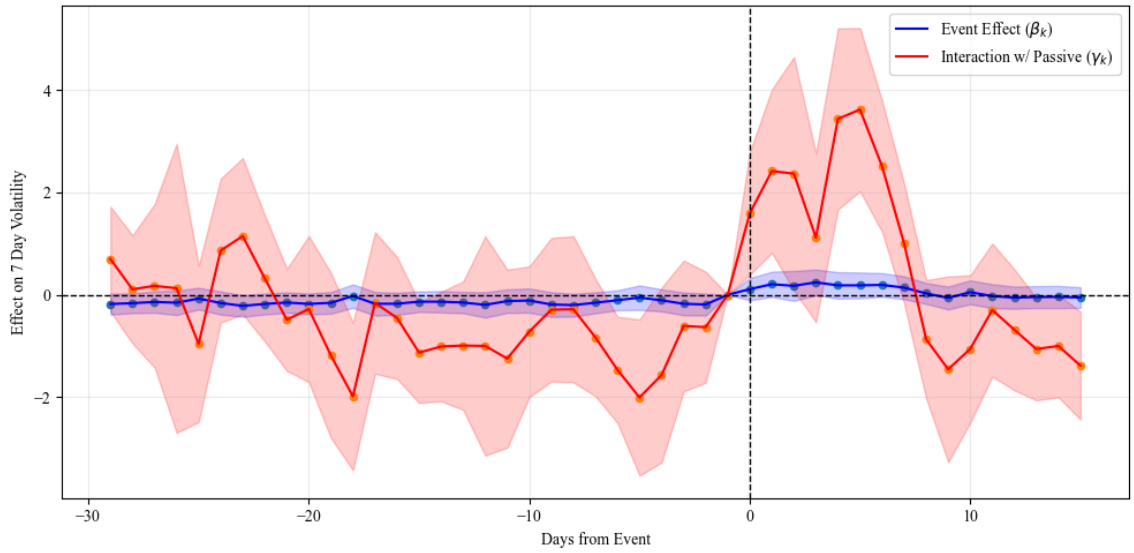

Figure 8: 7 Day Volatility Event Study

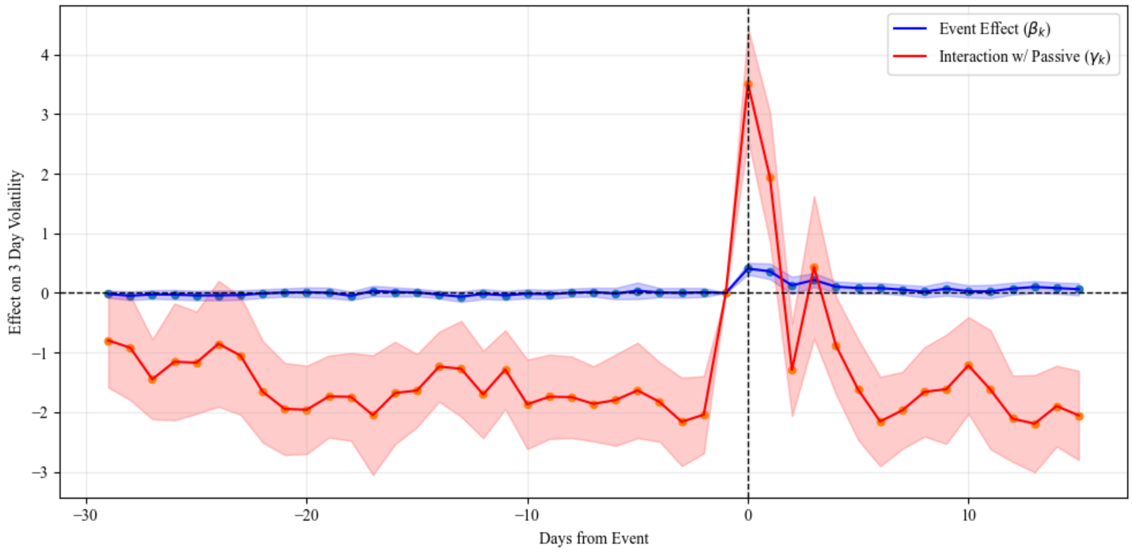

Figure 9: 3 Day Volatility Event Study With Fixed Effects

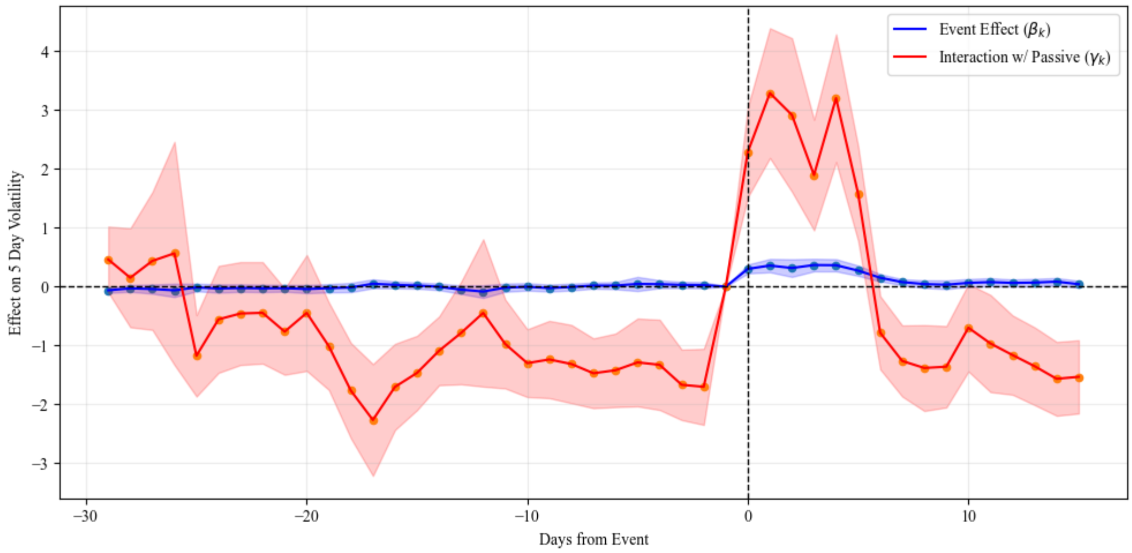

Figure 10: 5 Day Volatility Event Study With Fixed Effects

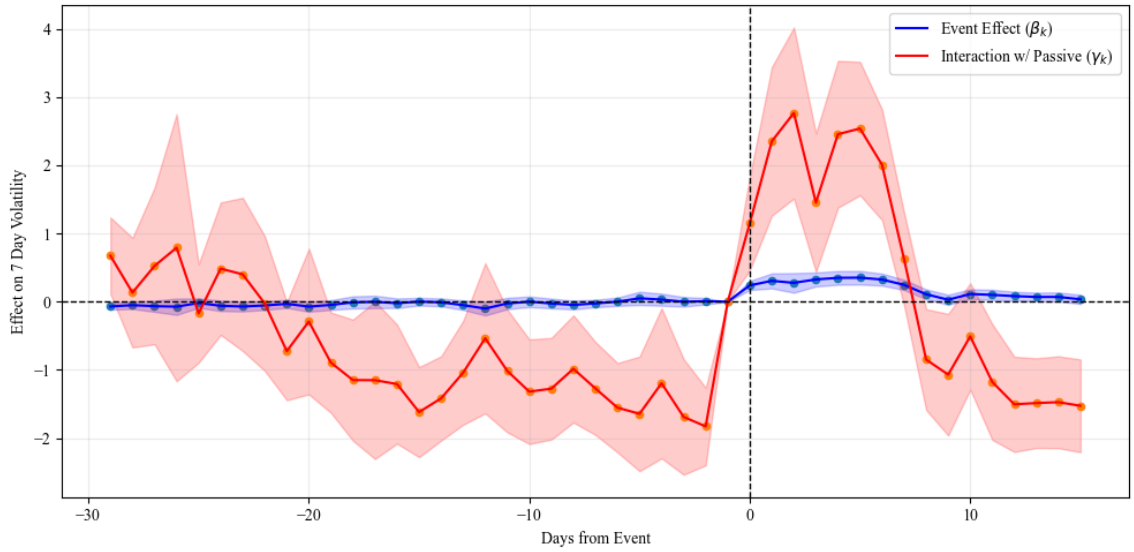

Figure 11: 7 Day Volatility Event Study With Fixed Effects

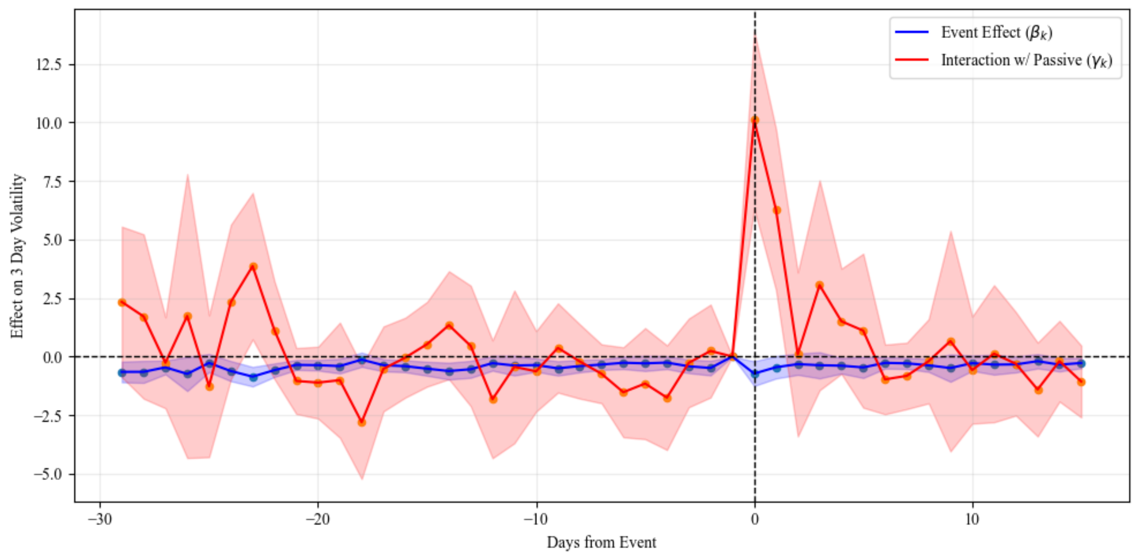

Figure 12: 3 Day Volatility Second Stage Event Study

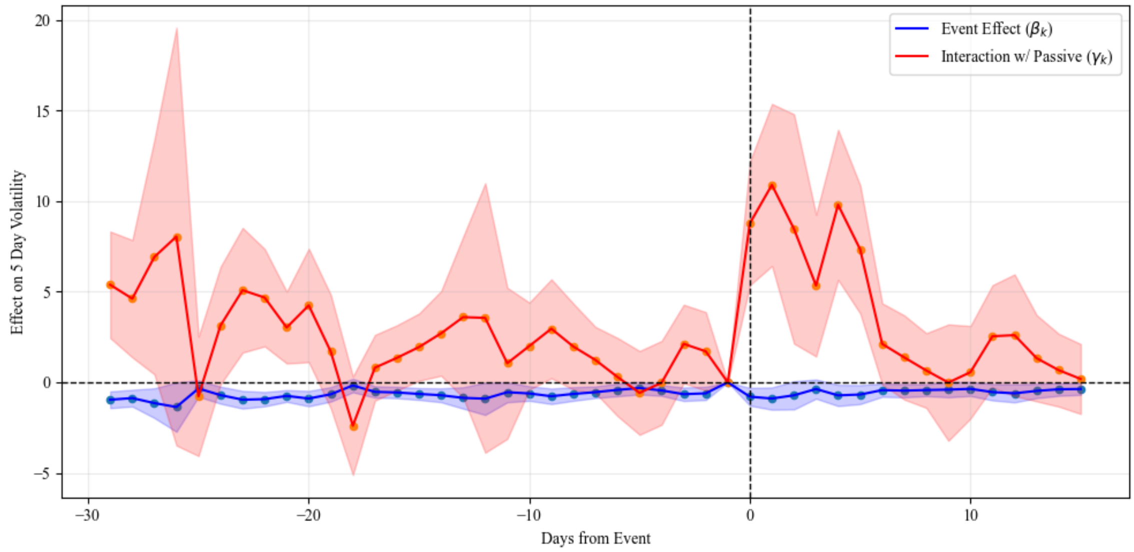

Figure 13: 5 Day Volatility Second Stage Event Study

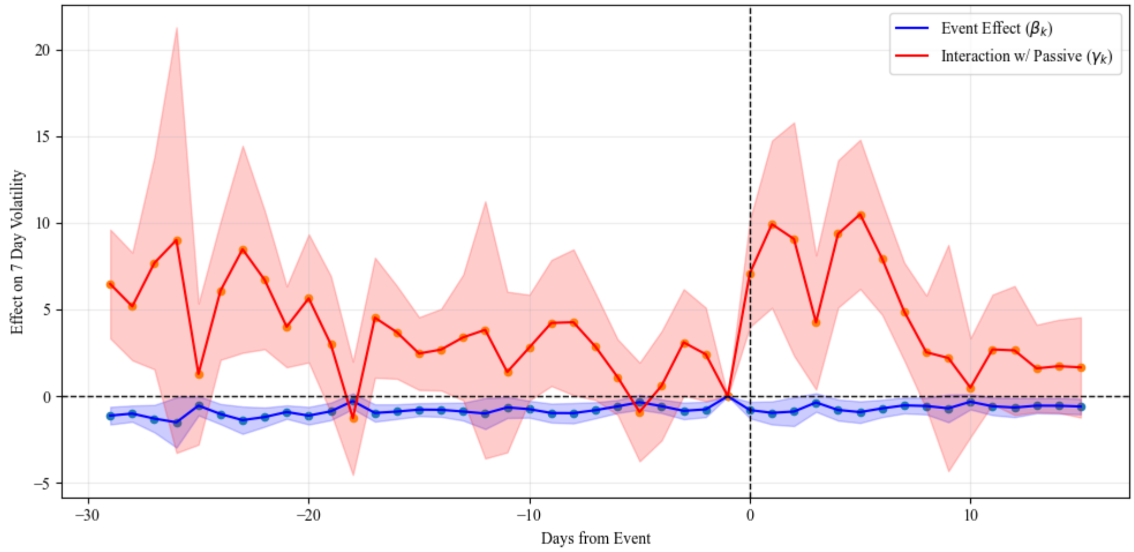

Figure 14: 7 Day Volatility Second Stage Event Study

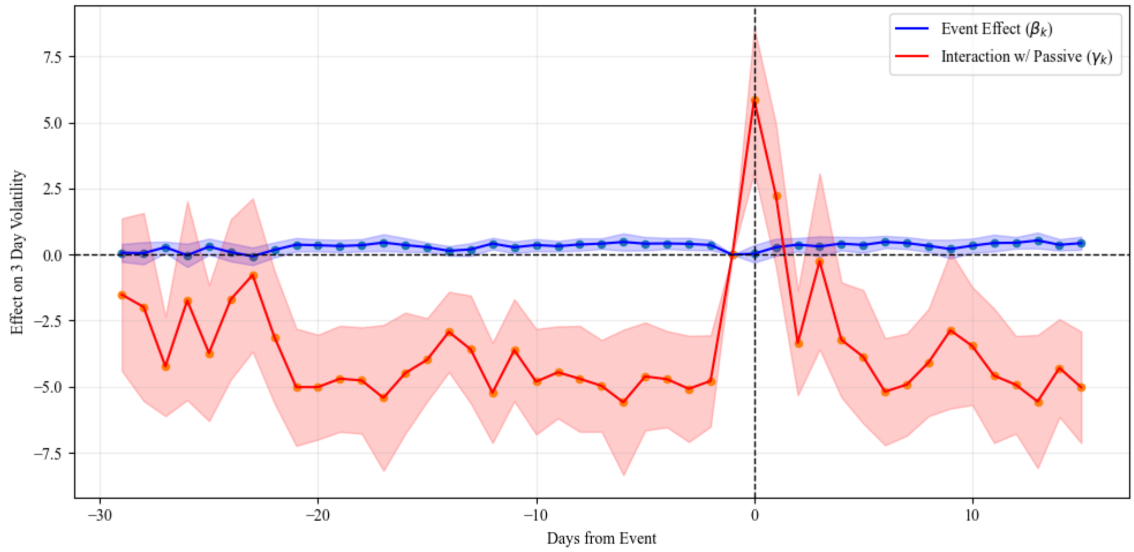

Figure 15: 3 Day Volatility Second Stage Event Study With Fixed Effects

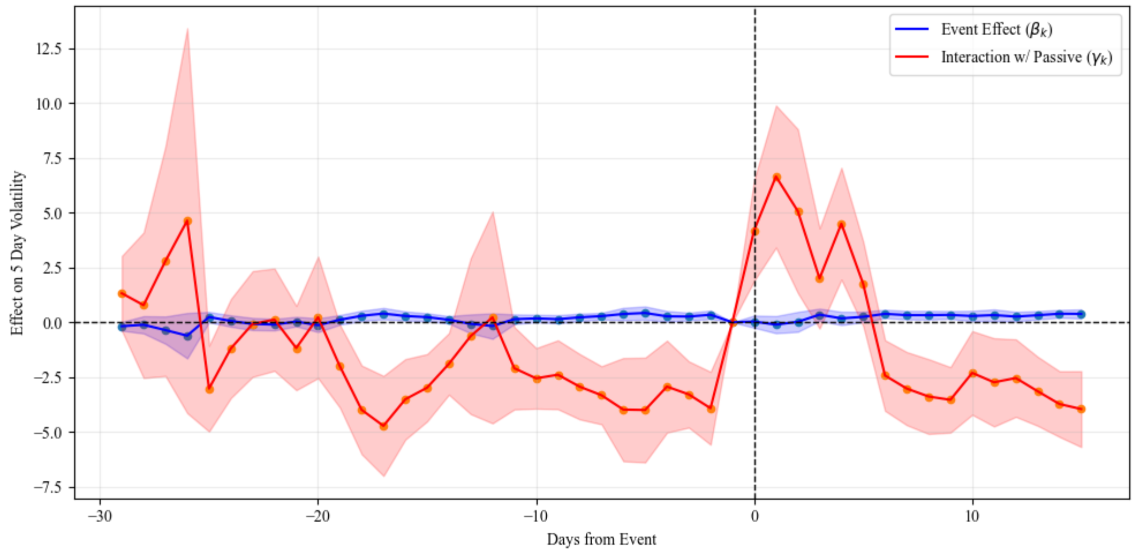

Figure 16: 5 Day Volatility Second Stage Event Study With Fixed Effects

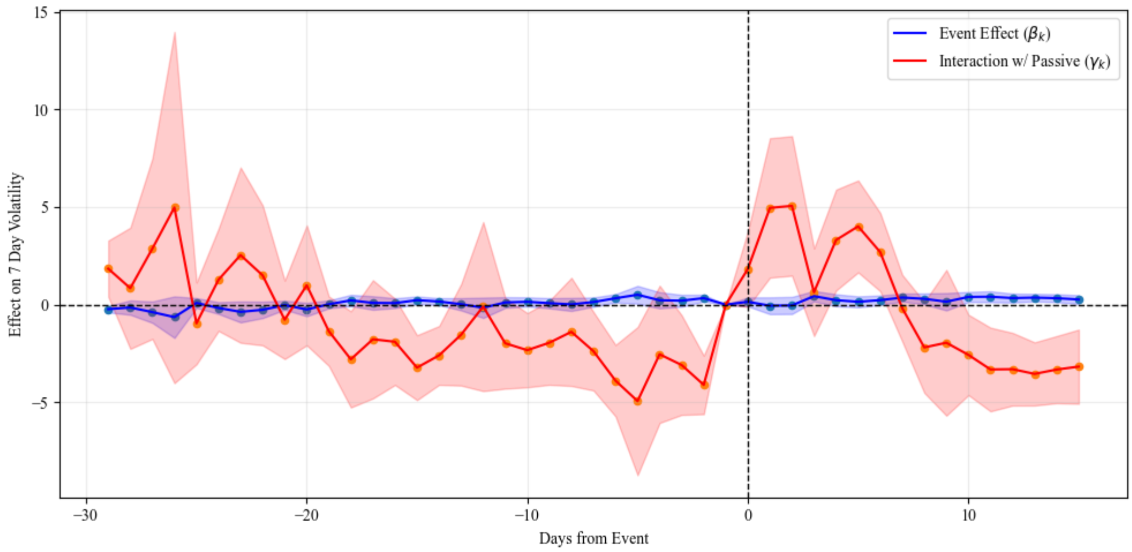

Figure 17: 7 Day Volatility Second Stage Event Study With Fixed Effects

8.2 Tables

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Price	328958	60.1013	175.9282	0.0201	8382.63
Return	328958	-0.0004	0.0468	-0.8041	5.3827
Passive	328958	0.1402	0.1218	0.0	0.9394
3 Day Volatility	328958	1.0662	3.6552	0.0	374.6248
5 Day Volatility	328958	1.3828	4.4345	0.0	355.7887
7 Day Volatility	328958	1.6380	5.1611	0.0005	355.4092

Table 2: Baseline Event Study

	3 Day Volatility		5 Day Volatility		7 Day Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
Passive Share	5.5958***	3.7643***	5.8749***	3.5394***	6.7007***	4.0647***
	(0.666)	(0.569)	(0.808)	(0.678)	(0.942)	(0.958)
Day -2	-0.1147*	0.0057	-0.1418	0.0240	-0.1888*	0.0081
	(0.069)	(0.031)	(0.092)	(0.027)	(0.109)	(0.025)
Day 0	0.3168***	0.3925***	0.1921*	0.2998***	0.1111	0.2393***
	(0.093)	(0.048)	(0.101)	(0.039)	(0.111)	(0.034)
Day 1	0.2791***	0.3379***	0.2724**	0.3567***	0.207	0.3064***
	(0.097)	(0.061)	(0.116)	(0.058)	(0.126)	(0.0561)
Day -2 × Passive	-1.5355***	-2.2602***	-0.7154	-1.7024***	-0.6321	-1.8279***
	(0.378)	(0.371)	(0.469)	(0.329)	(0.553)	(0.291)
Day 0 × Passive	3.5733***	3.3163***	2.6430***	2.2866***	1.5906***	1.1496***
	(0.643)	(0.485)	(0.618)	(0.391)	(0.612)	(0.351)
Day 1 × Passive	1.7811**	1.7712***	3.3009***	3.2858***	2.4176***	2.3515***
	(0.6995)	(0.561)	(0.7829)	(0.562)	(0.815)	(0.556)
Sector Controls	Yes	No	Yes	No	Yes	No
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	328,958	328,958	328,958	328,958	328,958	328,958

Notes: Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3: First Stage Regression

	Share Passive
In S&P 500	0.197***
	(0.001)
Sector Controls	Yes
Observations	328,958
F-test	134829.6395

Table 4: Second Stage Event Study

	3 Day Volatility		5 Day Volatility		7 Day Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Passive Share}}$	8.5789***	9.6878***	9.1813***	10.011***	10.548***	12.234**
	(1.088)	(2.489)	(1.349)	(3.292)	(1.585)	(4.946)
Day -2	-0.4900***	0.3640***	-0.6094***	0.3418***	-0.7599***	0.3358***
	(0.161)	(0.099)	(0.186)	(0.099)	(0.227)	(0.089)
Day 0	-0.7289***	0.0322	-0.7951***	0.0302	-0.7998***	0.1448
	(0.269)	(0.168)	(0.251)	(0.142)	(0.241)	(0.117)
Day 1	-0.4575*	0.2803*	–0.8952**	-0.1078	-0.9609***	-0.0535
	(0.244)	(0.165)	(0.313)	(0.199)	(0.339)	(0.219)
Day -2 × $\widehat{\text{Passive}}$	0.2376	-4.7847***	1.7106	-3.9228***	2.4156*	-4.1086***
	(1.012)	(0.881)	(1.106)	(0.848)	(1.372)	(0.765)
Day 0 × $\widehat{\text{Passive}}$	10.110***	5.8560***	8.7768***	4.1938***	7.0849***	1.8275*
	(1.934)	(1.395)	(1.741)	(1.175)	(1.577)	(0.987)
Day 1 × $\widehat{\text{Passive}}$	6.2813***	2.2324	10.901***	6.6497***	9.9171***	4.9564***
	(1.755)	(1.379)	(2.283)	(1.654)	(2.459)	(1.822)
Sector Controls	Yes	No	Yes	No	Yes	No
Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	328,958	328,958	328,958	328,958	328,958	328,958

Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.