(Why) Have Financial Markets Become More Volatile? The Role of Market Index Trading

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Abstract

We document a persistent doubling of U.S. stock market volatility since the mid-20th century, which cannot be attributed to macroeconomic fundamentals or idiosyncratic firm shocks. Instead, we show that the increased volume and dominance of index trading—via futures, ETFs, and extended trading hours—has structurally raised aggregate stock market volatility. We exploit the introduction of E-mini S&P 500 futures and historical NYSE trading-hour adjustments as natural experiments to provide causal evidence that index-level trading amplifies market variance through trading volume. Our model of index demand shocks rationalizes these findings, predicting higher market-level volatility, reduced return autocorrelation, and an increased share of systematic risk. Fluctuations in asset prices and volatility are increasingly determined by technology and trading structure rather than fundamentals.

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1. Introduction

Over the past seventy years, stock market volatility has roughly doubled from 10% to 20%. Figure 1 plots the volatility of the US stock market from the 1950's to today using 5-year rolling windows from daily data on the value-weighted market return. The increase in volatility is not explained by changes in the volatility of economic fundamentals, which has remained stable or declined, and it holds when we strip out recessions or extreme events. Further, we show that volatility has risen most at high frequencies (daily volatility is up 130%, weekly 75%, monthly 40%), consistent with changes in the market itself rather than changes in fundamentals. The increase is concentrated at the market level so that idiosyncratic volatility now accounts for a smaller share of stock-level volatility.

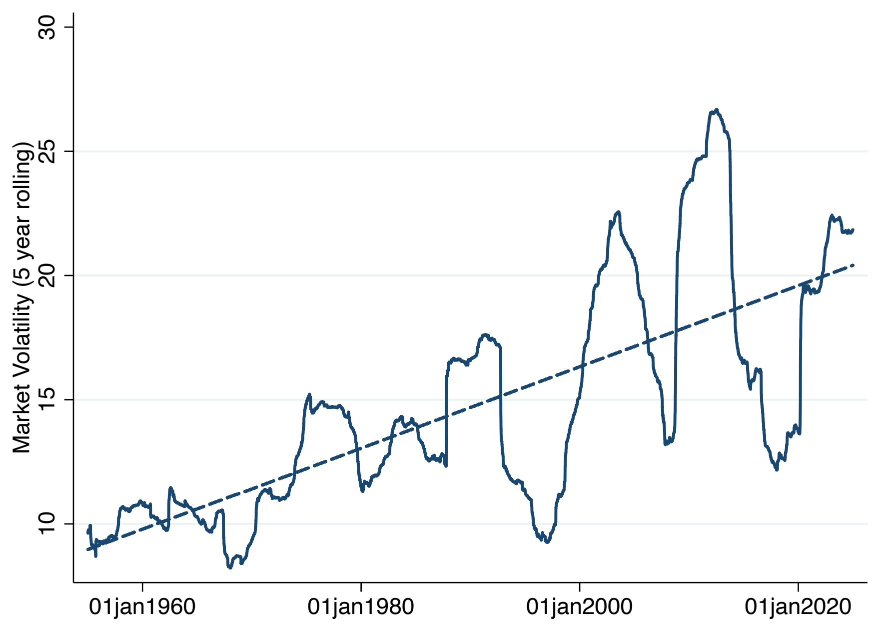

Figure 1: Stock Market Volatility. 5-year rolling standard deviation of market return.

What, then, has changed? We propose that the market is more volatile because investors *trade* the overall market a lot more than they used to. This has come from the prevalence of market index products and advances in technology that allow ease of trading market indices nearly anytime and anywhere.

Specifically, we argue that the rise in market volatility reflects a transformation from trading individual stocks to trading the market itself, along with an overall explosion in trading activity in market indices. Since the 1980s, index investing and index derivatives—S&P 500 futures, index ETFs, index mutual funds, and other vehicles—have grown into a dominant form of market participation. Today, investors can, and do, buy and sell exposure to the entire equity market instantly, around the clock, and in massive size. Volume in index products and volume in the overall stock market have risen dramatically as a result. For example, the *daily* dollar trading volume in S&P500 futures products is in the hundreds of billions and the daily volume in the SPDR ETF (a popular S&P500 ETF) is around $50 billion. We argue that this increased trading activity in market index products has created substantially more volatility in the stock market, particularly at shorter horizons.

The increase in volatility in Figure 1 indeed lines up in time with the growth of index trading and volume rather than macroeconomic fundamentals. We show that overall stock market volume has increased dramatically and that more of this volume looks like "market index" trades in that stock-level volume on a given day is much more proportional to market capitalization than it used to be. We derive a market volume beta – the tendency of the volume of all stocks in given day to be proportional to their market capitalizations – and show that this measure has doubled over the past 70 years. While suggestive, these correlations alone do not mean that trading volume in market index products cause volatility – volatility could instead attract trading volume, or other factors could affect both volume and volatility.

To overcome this issue, we provide causal evidence that index trading increases market volatility. To establish this result, we exploit two complementary natural experiments. First, the introduction of E-mini S&P 500 futures in 1997 created a sharp expansion in after-hours trading of the market index, while trading in individual stocks remained unchanged. Comparing intraday and overnight variance before and after the introduction of the E-mini futures, we find a marked increase in market volatility that is absent for the idiosyncratic variance of the constituent stocks. More generally, the variance of overnight market returns has trended up substantially in the last 30 years. Second, we examine eight historical changes in NYSE trading hours between 1950 and 1985, including the well-known 1968 Wednesday market closures due to paperwork backlogs (French and Roll, 1986). Using changes in trading hours as an instrument for market-level trading activity around these events, we estimate that a 10% increase in aggregate trading volume leads to a 7–14% increase in market volatility. Both experiments point to the same conclusion: trading activity in the stock market causes higher volatility, especially for higher frequency returns.

In both of these experiments, expanding the ability to trade results in both increased trading activity (volume) and in increased volatility. In contrast, in canonical asset pricing models, volatility is based on calendar time and not trade time. That is, if the stock market was only open one hour per week, the volatility of weekly compounded returns should be the same as in the case when the market is open 24 hours a day. In the former case, traders would collect all relevant information through the week and then move prices in large amounts during the short time when the market was open, rather than continuously as information arrived. But price moves over a calendar week would be the same. In reality, increased ability to trade leads to more trade and larger price fluctuations. We find that volatility and volume are more closely aligned with trade time than calendar time. Because of this, much of the rise in volatility we document in the later part of our sample (from 1995 onwards) comes from a rise in volatility of overnight returns as investors are now easily able to trade market indices nearly around the clock.

To interpret these patterns, we develop a simple demand-based model of index trading, along the lines of Campbell et al. (1993). In a market without index trading, investors hold concentrated portfolios (following Merton (1987)), while risk-averse arbitrageurs that trade in all stocks absorb investors' idiosyncratic demand shocks and lean against the systematic component of investors' demand shocks. When index trading is introduced, investors instead trade the market portfolio, which allows a more aggressive allocation to stocks, due to its higher Sharpe ratio relative to undiversified portfolios. Arbitrageurs are thus required to absorb larger systematic demand shocks than before, which they only partially accommodate. This shift in trading structure raises market volatility, reduces return autocorrelation, and increases the share of variance explained by market-wide factors. The predictions of the model are borne out in the data, which show both a decline in return autocorrelations and a rise in the systematic component of stock returns over time. Further, the model matches increased volume in market index trades and the large increase in market volatility.

Our work has important implications for the rise of passive investing. While index investing may be cross-sectionally passive (e.g., not picking individual stocks), the amount of trade in index products themselves is far from passive. To quote David Booth: "*There's been an incredible movement to indexing [...], and yet there's been an incredible increase in trading volume. [...] What's happened, unfortunately, is it turns out, like a lot of things that can be used for good, they can also be used for bad. And you know, index funds are the ideal market timing vehicle. [...] I think that really comes to what happened to the marketplace is it's kind of instead of individual stock selection, it's kind of like a big gambling casino*."[1] Much of the passive literature has focused on market efficiency in the cross-section (Sammon, 2025; Haddad et al., 2021; Brightman and Harvey, 2025) while our focus is on the volume in index products affecting price variation of the market as a whole through large increases in trading activity.

Our findings imply that volatility is no longer solely a reflection of economic uncertainty, but also of how trading is organized. This has several important implications. First, for portfolio choice and diversification, the rise of volatility and of systematic (non-diversifiable) risk is of first order importance. For portfolio allocation, the

[1]Odd Lots Podcast, Eugene Fama and David Booth on the Birth of Modern Finance, minute 27.

mean-variance optimal share in stocks is inversely proportional to variance, so a doubling of volatility implies a reduction in allocation to equities of 75%, all else equal. However, we also demonstrate significant *horizon* effects, that suggest very different implications for long-horizon investors because much of the increase in volatility is concentrated in short-term (daily or weekly) returns. The rise in systematic risk we document implies a much larger number of stocks are needed to achieve diversification and suggests increased co-movement among stocks. The rise in volatility is strongest at high frequencies—particularly in daily returns—consistent with the notion that market structure and trading activity, rather than fundamental news, drive these changes.[2] These results have implications for asset pricing, as standard macro finance models often assume that volatility is linked closely to fundamentals. Discount rate volatility in these models is often quite persistent whereas we document an increase in volatility that is more transitory for returns. Our findings also raise important policy questions, as the rapid growth of passive investing and index derivatives may be affecting aggregate risk as large flows in and out of market indices amplify price changes.

This paper contributes to a growing literature that studies the effects of trading behavior, technology, and market design on asset prices.[3] Our work is closely related to French and Roll (1986), who suggest that trading itself can induce excess volatility, but we show that the effect has grown larger in the era of index trading. Koudijs (2016) documents significant price volatility in stock prices even in the absence of the arrival of news. Our work also connects closely to studies on ETFs and futures, such as Ben-David et al. (2018), who document that ETF ownership increases stock-level volatility. We complement these papers by focusing on the market index, by providing clean causal evidence using natural experiments, and by introducing a model that

[2]Harvey et al. (2025) documents short-term reversal that induces price volatility due to substantial flows from rebalancing. This reversal comes from flows in and out of the overall market and thus contributes to volatility of the overall stock market.

[3]See Haddad and Muir (2025) for a broader view of how market macrostructure affects financial markets.

links demand shocks to volatility at the market level. Basak and Pavlova (2013) consider the effect of benchmarking of institutional investors and how this can lead to increased stock market volatility, volume, and correlation among stocks in the index, as managers over allocate to stocks within the benchmark index. This channel is indeed likely to play a part in the effects we are documenting, though we emphasize the role of direct index investment using index funds, futures, and ETFs.

Our findings suggest that proposals that increase trading volume or activity – for example the NYSE's proposal for 24 hour trading by the end of 2026 – have the potential to increase volatility further.

The themes in the paper also connect to the literature on how trading on private information and/or differences in beliefs relate volume to return volatility. For instance, Admati and Pfleiderer (1988) explains the positive correlation between volume and return volatility as an outcome of the interaction between strategic liquidity traders and informed traders. Our empirical tests, focusing on market level trading and volume, as well as the effect of increases in trading hours in relatively short windows around these changes, make trading on private information an unlikely driver of our results. Moreover, we document a decrease in the autocorrelation of returns, which is more likely driven by transitory price moves induced by noise trading. Hong and Stein (2007) review models on differences in beliefs, which relate trading to return volatility and expected return. Our model falls within this category of models as the demand shocks are driven by belief shocks that result in trading due to differences in beliefs.

The rest of the paper is organized as follows. Section 2 carefully documents the historical rise in market volatility. Section 3 presents causal evidence from the introduction of E-mini futures and changes in trading hours. Section 4 develops the theoretical model of index trading and derives testable predictions. Section 5 concludes.

2. Market Volatility: Broad Facts

We collect data from Ken French on the CRSP value-weighted excess market return at the daily and weekly frequency over the risk-free rate. We compute the sum of squared returns on a rolling 5-year basis and normalize to produce an annualized measure of variance. We compute the square-root of this number as a measure of volatility over the same horizon, where we express volatility in percent per year.[4]

Table 1 runs regressions with a linear time trend using data post 1960. That is, we run

$$\sigma_t = a + b\tilde{t} + \varepsilon_t \tag{1}$$

where the trend $\tilde{t} = (t-1)/(T-1)$ and T is the total number of observations. This means $\tilde{t}$ ranges from 0 at the start of the sample to 1 at the end of the sample. The coefficient a then represents the estimated level of volatility at the beginning of the sample, while b represents the percentage point increase in volatility so that the value is $a+b$ is the level of volatility at the end of the sample. The percentage increase in volatility is then b/a. While we use a simple linear time trend as a way to gauge the increase in volatility, we do not necessarily mean to imply that volatility will continue to increase in the future at this linear rate, or that the increase is necessarily linear from 1960-2025.

For daily data, the coefficient on the trend is 11.5% and the constant is 9%. This highlights that volatility has more than doubled over the sample period. Econometrics with trends can present challenges – here we report standard errors using Newey-West with 10 years as the lag length. We devote a section in the appendix to dealing with econometric issues surrounding trends including the fixed-b standard errors from Vogelsang (1998). Our results are unchanged. We show robustness of the results

[4]Computing volatility at shorter horizons, e.g., monthly, and then averaging these values over a 5-year period produces qualitatively similar results.

to outliers, time-periods, stale prices or other microstructure liquidity issues, alternative ways of measuring volatility, and so on in Section 2.2.

Column 2 uses weekly returns and finds an increase of 8 percentage points, resulting in a total increase in volatility of over 75% over the sample. Column 3 constructs monthly data using compounded overlapping 4-week returns and finds an increase of 5 percentage points, resulting in a total increase of 40%. Thus, while volatility increases substantially across all return horizons, we can see that it is more heavily concentrated in short-horizon returns. Because compounded (log) returns over longer-horizons are equal to the sum of log returns at a daily horizon, the difference in the trend in volatility across horizons necessarily reflects changes in the autocorrelation of returns in the sample. For example, if return autocorrelation at all horizons is zero, then the expectation of squared weekly returns is equal to the expectation of the sum of squared daily returns within a week.

Immediately, the pattern across horizons suggests differences in financial markets and trading behavior itself to explain the increase in volatility. For example, a story of time-varying volatility of fundamentals will not explain the change in volatility patterns across return horizons. One needs an increase in "discount rate" volatility – the volatility of a mean-reverting component of returns – to explain these differential patterns. Because these patterns are at relatively short horizons, this naturally suggests candidates based on trading behavior.[5] We will return to explanations based on fundamentals shortly.

2.1 Volatility, Volume, and Fundamentals

Figure 2 Panel A plots market volatility against total stock market volume as a share of total market capitalization. There is a strong correlation between trading volume and volatility since the 1960's, both in terms of low frequency trend and in the cyclical

[5] Typical discount rate volatility in traditional macro finance models (say, with time-varying risk-aversion) focuses on long-run mean-reversion at the horizon of years rather than weeks.

Table 1: Regressions of Market Volatility on Time Trends

Notes. Sample period is 1960-2024. Trend is linear time trend, normalized to equal 0 in 1960 and 1 in 2010, so that the coefficient represents the increase in volatility over a 65 year period. This choice also means the constant gives the level of volatility around 1960, and the trend coefficient tells how much it increased 65 years later. Thus, a similar magnitude on the trend coefficient indicates that volatility doubled, for example. All volatility numbers are annualized.

	(1) Daily Returns	(2) Weekly	(3) Monthly (4-week)
Trend	11.48***	8.19***	4.88***
	(1.90)	(2.02)	(1.85)
Constant	8.32***	10.76***	12.33***
	(1.18)	(1.16)	(1.06)
N	17,620	3,652	3,652
R^2	0.52	0.37	0.19

movements. A natural story is that higher trading activity leads to higher volatility, especially for shorter horizon returns. This fits well with the return-horizon pattern we've shown so far. Of course, there could be other factors affecting both volatility and volume, and in addition high volatility could lead to more demand for trading activity, a reverse causality story. In Section 3.1 we document a causal relation between volume and volatility by using changes in trading hours as an instrument for volume as well as the introduction of the e-mini futures.

Figure 2 Panel B shows that the increased volatility since 1960 is not driven by more volatile macroeconomic fundamentals. Specifically, we follow the same approach as with returns but using the monthly growth rate in industrial production. We choose this series because it has data going back to 1920. We compute the rolling 5-year volatility of the series and plot it against stock market volatility. Volatility of fundamentals is a good explanation for stock return volatility in the Great Depression and WWII. However, since that period, the volatility of macroeconomic fundamentals has declined substantially (through the "Great Moderation" period of the 1980's to mid 2000's). The macroeconomy has, if anything, looked *less* volatile over time – and hence is a poor candidate to explain the rise in volatility we've seen in the past 65

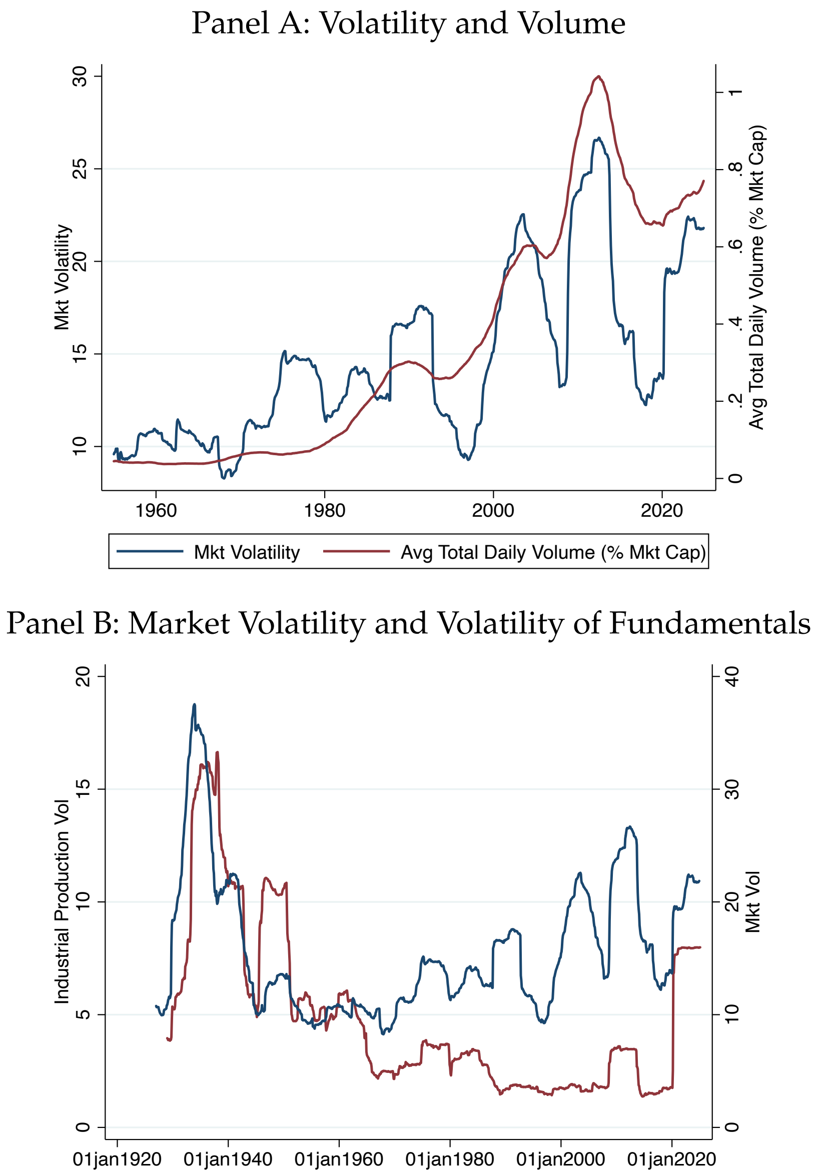

Figure 2: Volatility and Volume.

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years. This echoes a long literature starting with Schwert (1989) which has difficultly tying variation in stock market volatility to fundamentals. Appendix XXX finds similar conclusions for many different measures of fundamentals including GDP growth

Table 2: Robustness on Stale Prices: Volume-weighted returns

Notes. Sample period is 1960-2024. Trend is linear time trend, normalized to equal 0 in 1960 and 1 in 2010, so that the coefficient represents the increase in volatility over a 65 year period. The first column weights stock returns by daily volume, rather than market capitalization. This ensures using returns of stocks that trade heavily and avoids stale-price issues.

	(1) Volume Weights	(2) Mkt Cap Weights (Baseline)
Trend	13.03***	11.48***
	(3.31)	(1.90)
Constant	11.35***	8.32***
	(2.06)	(2.20)
Observations	17,620	17,620
R-squared	0.36	0.52

and corporate profits. Corporate profits are useful because they deal with changes in corporate leverage (they are a levered cash flow). Between these findings and the effects of return horizon, volatility of fundamentals is a poor explanation for return volatility, while trading activity appears a promising explanation.

2.2 Robustness of the rise in volatility

2.2.1 Concerns about stale prices

Table 2 deals with the concern of stale-prices in the earlier part of the sample. Specifically, volatility can appear low if there is no trade in a significant fraction of stocks on a given day. To address this, we weight stocks by total dollar volume on a given day, rather than weight by market capitalization. This insures stocks that don't trade get zero weight and more liquid, heavily traded stocks get higher weight. We find nearly identical results in the trend on volatility whether we use lagged volume or current volume for the weights. Column 1 of Table 2 shows that volume weighting strengthens our results slightly. This implies that stale-pricing is not driving the results on the market portfolio.

2.2.2 Outliers

Is it well known that volatility is right skewed with some extreme events, such as the crash of 1987. Thus, our finding of increased volatility could potentially be driven by several extreme events. To address this, we compute volatility within a month using daily returns in that month, then compute the rolling 5-year *median* of monthly observations. We plot this in Figure 3. The median level of volatility is lower than the average because of right skewness. But the percentage increase in volatility is similar to our earlier findings – volatility roughly doubles from 7% in 1960 to 15% in 2025. Notably, events such as the 1987 crash play no role because they have no effect on the rolling 5-year median.

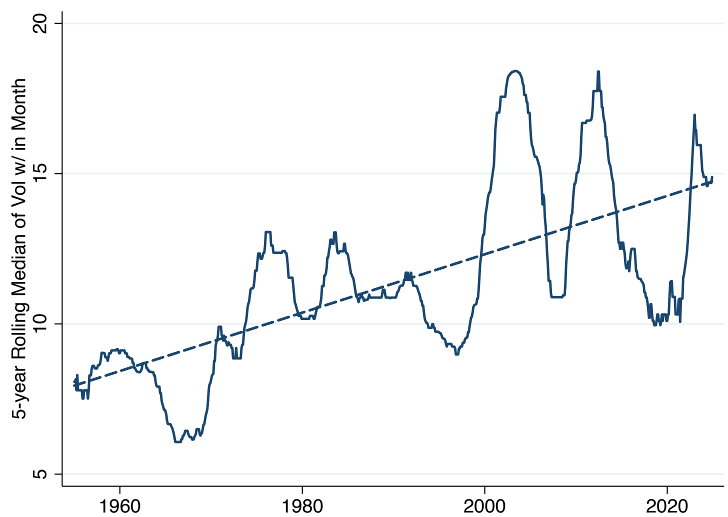

Figure 3: Median Volatility and Outliers.

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2.2.3 Systematic vs. Idiosyncratic Volatility

The rise in stock market volatility is primarily at the market level rather than the individual stock level. That is, the majority of the rise we have documented is market risk and not idiosyncratic risk.

To show this, we run CAPM regressions for the universe of stocks in CRSP on the value-weighted excess market return using rolling 5-year windows. We compute the share of idiosyncratic risk as the ratio of the variance of the residual in this regression to the total variance of the individual stock return. The systematic share is one minus this ratio (or the R-squared of the regression). We aggregate this up to a single measure by value-weighting these shares for all stocks.

Figure 4 plots the results. The systematic share rises from 19% in 1960 to around 35% today, while the idiosyncratic share falls by the same amount. This roughly equates to a doubling of systematic risk over the sample. Thus, we conclude that the majority of the rise in volatility we document is coming from market risk but that this pattern is not equally mirrored in idiosyncratic risk.

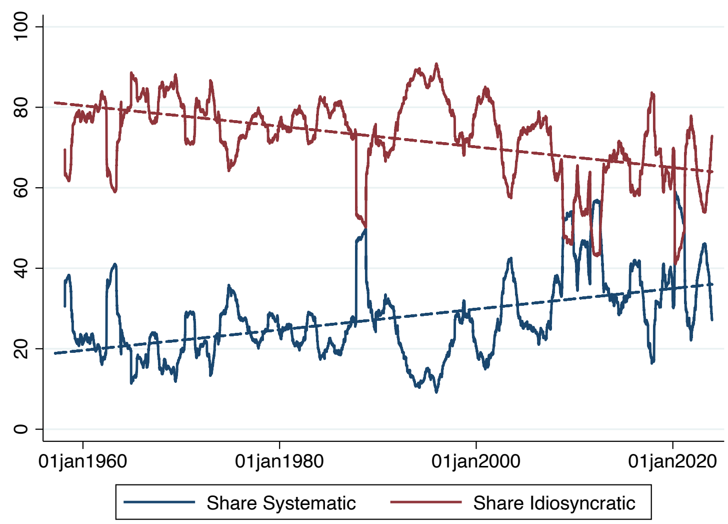

Figure 4: The share of systematic vs idiosyncratic risk.

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These results do not say that idiosyncratic volatility has not changed (Campbell et al., 2001). They are consistent with updates to this work in Campbell et al. (2022) and Chiah et al. (2020) that market volatility has increased by substantially more than idiosyncratic volatility in the last 50 years.

2.2.4 Additional Results on Horizon Effects and Return Autocorrelations

Figure 5 plots the increase in volatility as a function of return horizon, going from 1 day out to 1 quarter (13 weeks). The increase is significant out to around 6 weeks, though the point estimate is positive for all return horizons. The gradual decay is consistent with short-run mean reversion or reversals in returns.

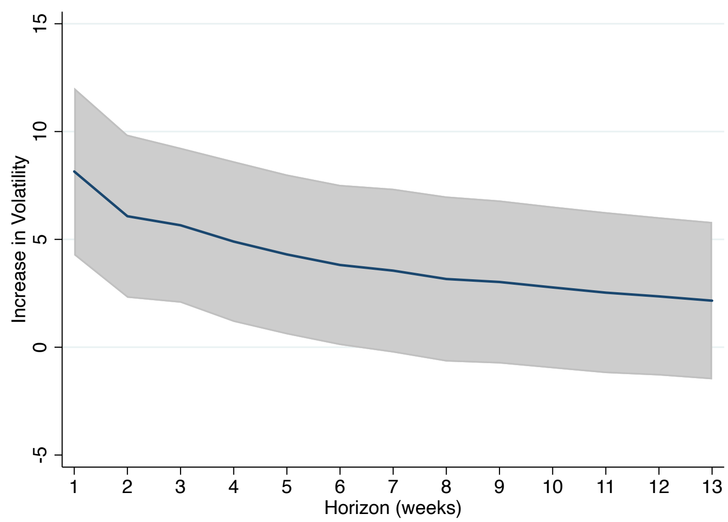

Figure 5: Increase in Volatility by Return Horizon.

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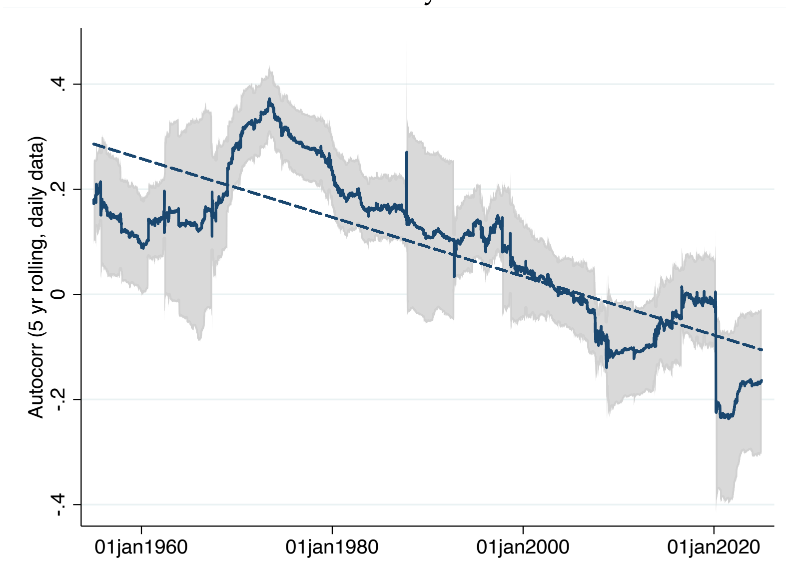
Figure 6 shows the autocorrelation of returns using 5-year rolling windows over our sample. Panel A uses daily return data, while Panel B uses weekly return data. Both panels show a similar pattern with return autocorrelations trending downward throughout the sample and switching signs from positive to negative. This decreased autocorrelation pattern mechanically implies that relatively shorter horizon return volatility will increase compared to returns at longer horizons. This is because the variance of log compounded returns is equal to the sum of the variances of per period returns plus all autocovariances of returns – hence the variance ratio of long to short horizon returns is intimately tied to return autocorrelation.

Panel A: Daily Returns



Panel B: Weekly Returns

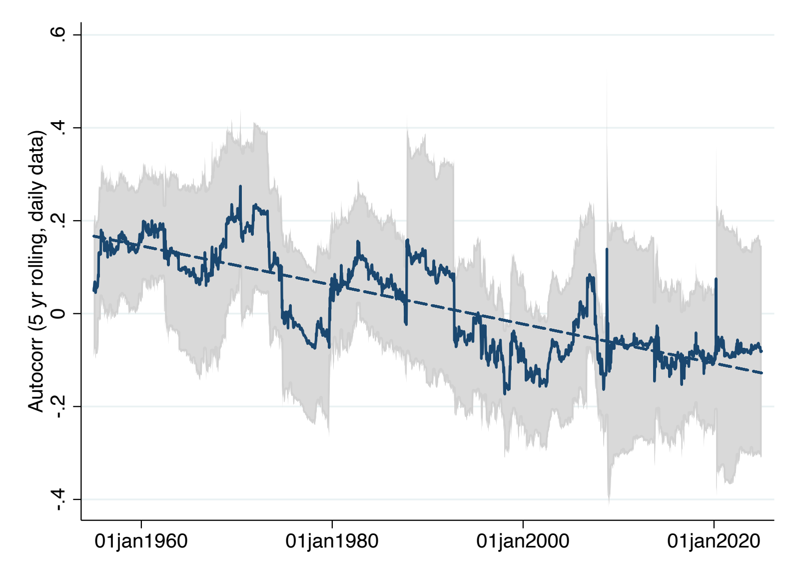


Figure 6: Return autocorrelation over time for the market return.

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3. Volume and Volatility: Stylized Facts and Causal Evidence

We propose that the market is more volatile because investors trade the overall market a lot more than they used to. That is, with the rise of S&P500 index funds, S&P500 futures, or similar products, it has become increasingly easy and prevalent over the past 50 years to trade in and out of the overall market rather than in individual stocks.

This concentration of trading volume in the overall stock market means that investors facilitating trade – e.g., arbitrageurs and liquidity provides – will have to absorb market risk, rather than idiosyncratic risk of individual stocks. Their compensation is given by the degree of short-term reversal, which higher reversal leading to more volatility of high frequency returns.

To explore the prevalence for "trading the market" we propose a simple measure that assesses how much volume for individual stocks can be explained by volume of trade in the overall stock market. More specifically, suppose all volume activity in a given day came from flows in and out of the overall stock market – for example flows in and out of market index funds. Then volume on that day for all stocks would be proportional to their weights in the market index – that is, their market capitalization.

This motivates the following cross-sectional regression. For a given time period t, we run

$$\frac{Volume_{i,t}}{Total\ Volume_t} = a_t + b_t \times MktWeight_{i,t-1} + \varepsilon_{i,t} \quad i = 1, ..., N \tag{2}$$

where $Volume_{i,t}$ represents the dollar volume in stock i in day t, *Total Volume* represents the total dollar volume across all stocks, and $MktWeight_{i,t-1}$ represents stock i's weight in the market portfolio. If all trading on a given day was trading by market index funds, then we would have $b_t = 1$ because volume in every stock would be proportional to that stocks market capitalization.

We run the regression in (2) daily, collect estimates b_t, and then compute rolling averages of the time-series of b_t.

Figure 7 plots the rolling 5 year average of volume coming from trading the market along with market volatility. Market volume betas double over this period from around 0.4 in 1960 to around 0.8 today, coinciding with the rise in market volatility. Recall that a market volume beta of 1 is consistent with all trades being trades in and out of the market portfolio, which suggests that today a huge fraction of trading volume in the stock market may be driven by trading the market index.

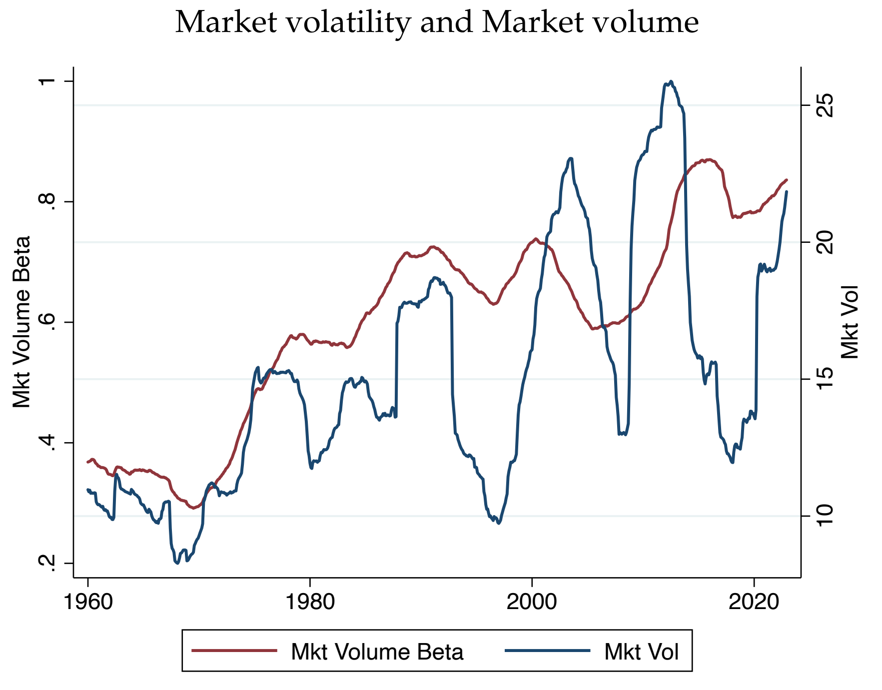

Figure 7: Plot of Market volatility and market volume.
See text and equation 2.

3.1 Causal Evidence: Volume and Volatility

While the link between the volatility of the overall market and volume in the stock market are suggestive, they of course do not point to a causal channel. We argue that it is natural that the prevalence and easy of trading in market index products drove significant trading activity in the market itself which increased volatility. We now exploit quasi-natural experiments that test this view. The first uses changes in the trading hours of the NYSE as an instrument for trading volume. The second exploits the E-mini futures as a popular way to trade the market index.

3.1.1 Changes in Trading Hours as an Instrument for Volume

We exploit changes in NYSE trading hours and trading days, as instruments for trading activity. The basic idea goes back to work by French and Roll (1986). They exploited a paperwork backlog at the NYSE in 1968 which led the NYSE to close on Wednesdays from June-December 1968. The amount of information content relevant for stock prices presumably did not change because of this closure. During the closure period, the return on Thursdays is now a 2-day cumulative return – that is, the return Thursday reflects the price movements from the close on Tuesday to the close on Thursday.

Strikingly, however, French and Roll (1986) find that the *variance* of the Thursday return did not change due to the closure, when in fact it should double.[6] As a result, total weekly variance (the sum of squared returns in a week) *falls* during the closure period by around 20% (one-fifth, given one in five trading days is removed). This decrease in variance is relative to the period of January through May of 1968 (the first half of the year) before the Wednesday closure was in place. Further, the variance on other days (i.e., Tuesday) did not change during the closure period, so that it does not appear there were any general changes in the level of volatility.

We take these results and push them further. Specifically, we exploit 8 changes in trading hours on NYSE, 1952-1985. These include: the 1952 cut from 6 to 5 trading days per week (trading used to occur on Saturdays), the 1968 Wednesday closure, and

[6] If the returns on any two days are roughly uncorrelated, variance of a 2-day return will be twice the variance of a 1-day return. Letting r_t be the log daily return, we have $var(r_t + r_{t+1}) = 2var(r)(1 + \rho)$ where ρ is the autocorrelation of returns.

the subsequent extensions of the trading day from 4 hours of trading per day in 1969 to eventually 6.5 hours today.

We compute the total trading hours per week as our instrument. The first stage runs log total stock market volume on the log of trading hours. The second stage then estimates the relationship between log volatility and log volume. Volatility is computed as the squared weekly realized return on the value-weighted market portfolio.

$$\ln \sigma_t = a_w + a_e + b \times \ln VM_t + \varepsilon_t \tag{3}$$

$$\ln VM_t = a_w + a_e + \gamma \times \ln \textit{trading hours}_t + \nu_t. \tag{4}$$

We use trading hours *only* in 6 month windows before and after a change in trading hours as the instrument for weekly volume (VM) to see how trading activity affects volatility (σ). Restricting to shorter windows around changes in trading hours is important because trading hours have generally trended up over time along with volatility and volume. Further, the levels of volume and of volatility are different around each of these changes. To deal with this, we include event dummies, a_e, (equal to 1 in the 6 months before and after a change in trading hours). We thus estimate how the relative change in trading hours affects relative volume and volatility. In addition, we include week fixed effects, a_w, to control for seasonal patterns in volume and/or volatility.

Our identifying assumptions are as follows. First, increases in trading hours only affect volatility through increased trading activity. Second, the decision to increase trading hours does not depend on an expected increase in volume 6 months before / after the official change in hours. We do not assume that increased demand for trading doesn't affect trading hours in general, but that a decision to permanently increase trading hours does not depend on a predicted spike in volume during the event window. The second assumption is most appropriate when the event window is relatively

Table 3: IV: Instrumenting volume with trading hours

Notes.

	(1) OLS	(2) IV	(3) First Stage	(4)
	σ on VM	σ on VM	VM on Hours	σ on Hours
Log Volume	0.72***	1.42**		
	(0.12)	(0.72)		
Log Trading Hours			1.02***	1.45**
			(0.31)	(0.67)
Observations	326	326	326	326
R-squared	0.54	0.49	0.90	0.49
FE: Week & Event	Y	Y	Y	Y

narrow – our baseline uses 6 months because we face a tradeoff in statistical precision in using realized volatility. Our results are robust to a tighter 3-month window, at the expense of slightly larger standard errors.

Table 3 presents the results. Column 3 presents the first stage. Trading hours increase volume nearly one to one – when the stock market is open, people trade more. A coefficient of 1 means that if trading hours increase 10%, volume also increases by 10%. The first stage shows that trading hours are a strong instrument for volume, consistent with prior work. This increase in volume translates to increased market volatility, demonstrating a causal effect of trading activity on market volatility. Column 2 finds a positive causal effect of volume on volatility. A 10% increase in trading hours increases volume by 10% and leads to a 14% increase in volatility. The coefficient of 1.4 in Column 2 is statistically significant at the 5% level. Column 1 presents OLS estimates of volatility on volume and finds a strong positive relationship as well. Column 4 regresses volatility directly on trading hours. Since the first stage coefficient was 1, the coefficient in column 4 is about the same as that in column 2. The relatively similar statistical significance in columns 4 vs 2 highlights that the first stage is strong, but the relationship between changes in trading hours and volatility is slightly noisier.

Overall, the evidence strongly supports a positive causal relationship whereby increased trading activity drives significantly higher volatility of the overall stock market.

3.1.2 The E-mini Futures as a Natural Experiment

We exploit the introduction of the E-mini futures on Sept 9, 1997, which led to a large amount of trading on the S&P500 index. Importantly, the E-mini could be traded during non-trading hours, unlike individual stocks at the time it was introduced. We exploit this differential trading by comparing the variance of the S&P500 overnight vs intraday relative to the same comparison for individual stocks in the S&P500 (idiosyncratic vol). We make this comparison before and after the E-mini is introduced. The idea is that more trading activity overnight results in more volatility for the market overnight but not for individual stocks. The relative comparison controls for overall news coming out at night that would move stocks in general, and other factors that would move the overall volatility of the market during this period (either during the day or night).

We use close to open and open to close returns as measures of overnight and intraday returns, respectively.[7] We compute the sum of squared returns within a rolling 22 day period (roughly 1 month). For individual stocks, we aggregate into a single measure of volatility by value weighting the resulting overnight and intraday variances at the stock level. We then compute $\left(var(r_{mkt}^{night})/var(r_{mkt}^{day}\right) / \left(var(r_{stock}^{night})/var(r_{stock}^{day}\right)$. This represents the ratio of the two variance ratios.

Figure 8 plots the results. Panel A shows the increase in this variance ratio. The first vertical line represents the introduction of the E-mini in September 1997. Since our variance computations use 22 day rolling windows, the full effect is not felt until the second vertical line, which then only uses data since the E-mini introduction. The red dashed line estimates the means before and after using the 3-month window in the plot, with a linear transition between to reflect the transition window induced

[7]Thus, we also use weekend returns.

by rolling returns. It is clear from the plot that the relative variance of the S&P500 increased overnight after the introduction of the E-mini.

However, for our story to be correct, we also need that the E-mini generated significant trading in the S&P500 when it was introduced. Panel B adds the (log) total volume of S&P500 futures contracts and shows they indeed rise with the introduction of the E-mini. We use a 22 day rolling average of total volume in S&P500 futures contracts to match the window at which volatility is computed. Thus, we see the rise in relative volatility coinciding with a large increase in trading activity in the S&P500, consistent with our story.

More generally, the volume of the E-mini futures has exploded since it was introduced, leading to a huge amount of trading volume in the market index. Because futures are traded nearly 24 hours a day, this can also contribute to a general increase in volatility in overnight returns due to increased trading activity. Figure 9 plots the volatility of the market return using 5-year rolling windows as in our main plots earlier, but it splits returns into overnight (close to open) and intraday (open to close). We can see that a substantial amount of the increase in volatility over the past 30 years comes from increased volatility of overnight returns.

4. A model of index investing and market returns

In this section, we present a simple model of the impact of increased index investment on market outcomes. The model borrows features from Merton (1987) and Campbell, Grossman and Wang (1993; henceforth, CGM).

Following Merton, we assume that each investor only knows about a subset of the financial assets and therefore only trades these. This assumption is motivated by the fact that investors empirically only hold a few assets.[8] When an index fund is intro-

[8]Merton writes: "The prime motivation for this assumption is the plain fact that the portfolios held by actual investors (both individual and institutional) contain only a small fraction of the thousands of traded securities available. ... Because this behavior can be derived from a variety of underlying structural

Panel A: Variance Ratio with E-mini introduction

Panel B: Volume in S&P futures lines up with increased volatility

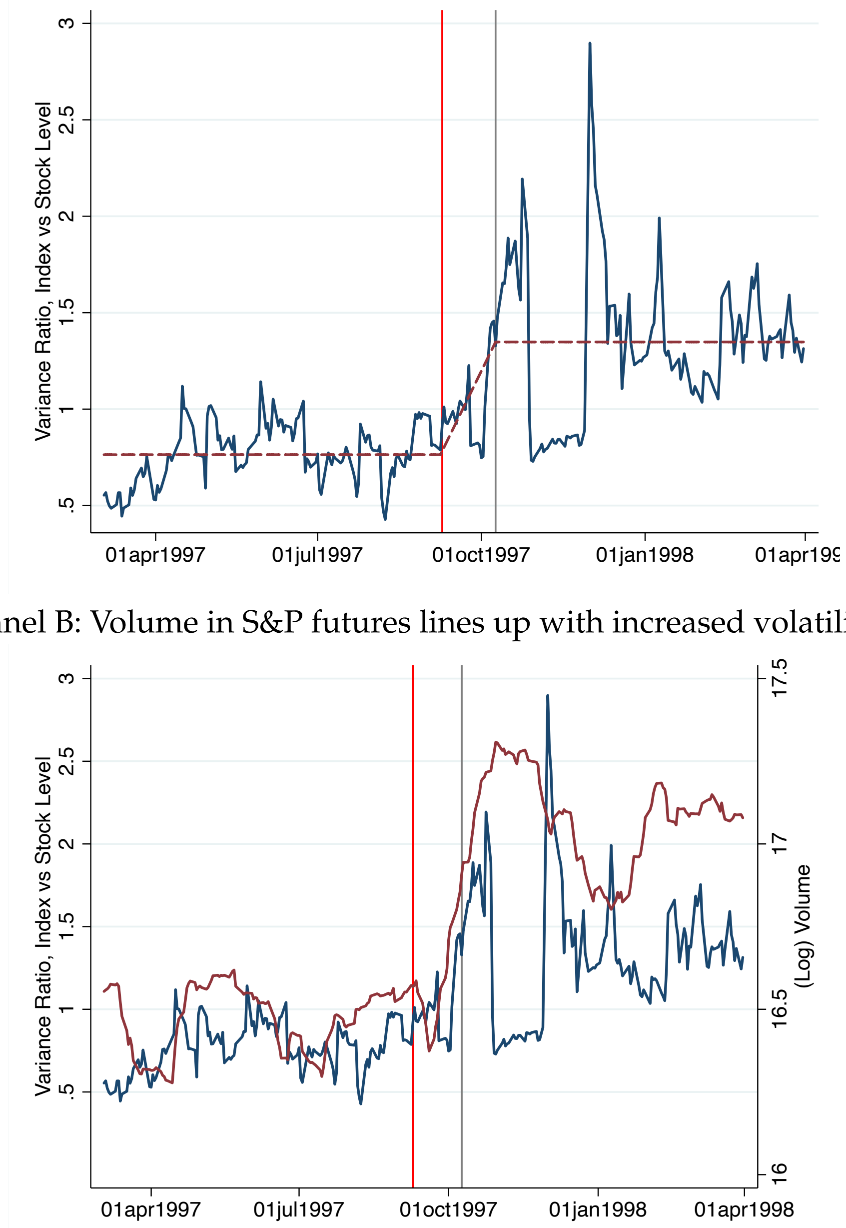

Figure 8: The Introduction of the E-mini Futures and the Effects on Volatility.

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assumptions, the formally derived equilibrium-pricing results are the theoretical analog to reduced-form equations."

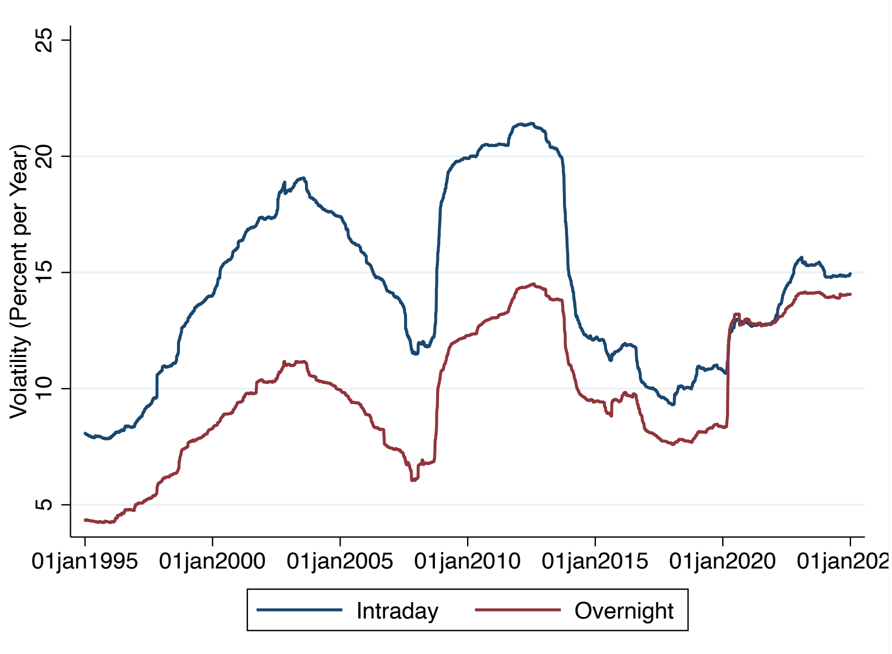

Figure 9: The Rise of Overnight Volatility on the Market.

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duced, these investors shift their attention and investment to this more efficient asset. Following CGM, risk averse arbitrageurs accommodate buying and selling pressure arising from investors' demand shocks.

4.1 Market structure

There are N assets with per share dividends $D_{it} \sim N\left(\mu, \sigma_D^2\right)$. The correlation between any two assets' dividends is ρ_D. Stock i is in supply x_i. There are N investors and 1 arbitrageur. Every agent acts competitively as a price taker. The investors have extrapolative beliefs, where their beliefs about future dividends is extrapolated based on the dividends of the assets they hold. The arbitrageur is rational and can frictionlessly invest in all assets. The risk-free rate has gross return $R_f > 1$ and is supplied elastically. Each agent has CARA utility over next period wealth, which implies that they are one-period mean-variance optimizers. Investors have risk aversion a, while the arbitrageur has risk aversion $\tilde{a}$.

Let P_{it} refer to the share price of the claim with dividends D_{it}, and let D_t and P_t be the $N \times 1$ vectors of the corresponding dividends and prices for all individual stocks. Let X denote the $N \times 1$ vector of supply with row i equal to x_i, normalized such that $\sum_{i=1}^{N} x_i = 1$. The value of the market portfolio is the sum of all stock prices times the supply, $P_{mt} = X'P_t = \sum_{i=1}^{N} P_{it}x_i$, while market dividends are $D_{mt} = X'D_t = \sum_{i=1}^{N} D_{it}x_i$.

4.1.1 Asset market without an index fund

In this economy, each investor is assumed to only invest in one stock in addition to the risk-free asset. For notational simplicity, we assume investor i invests in stock i. For the asset they hold, investor i believes that:

$$E_t^i\left(D_{it+1}\right) = \mu\left(1-\phi\right) + \phi D_{it}, \tag{5}$$

where $1 > \phi > 0$. That is, they erroneously extrapolate from past dividends of the asset they hold when forming beliefs about future dividends. This time-variation in beliefs create demand shocks that are not due to information. The rational arbitrageurs correctly believe expected dividends equal μ.

Proposition 1. *The equilibrium prices in the case where no index fund is traded are given by*

$$P_t = m + AX + BD_t, \tag{6}$$

where

$$A = \begin{bmatrix} \alpha & \delta & \cdots & \delta \\ \delta & \alpha & \cdots & \delta \\ \vdots & \vdots & \ddots & \vdots \\ \delta & \delta & \cdots & \alpha \end{bmatrix}, \quad B = \begin{bmatrix} \beta & \gamma & \cdots & \gamma \\ \gamma & \beta & \cdots & \gamma \\ \vdots & \vdots & \ddots & \vdots \\ \gamma & \gamma & \cdots & \beta \end{bmatrix}, \tag{7}$$

$m \propto \mu$, $\alpha < \delta < 0$, and $\beta > \gamma > 0$. Further, β and γ are increasing in the degree of extrapolation, ϕ. See the Appendix for derivations.

The equilibrium prices are lower when the supply of the asset is higher and, to a lesser extent, if the supply of other assets is higher. This is because higher asset supply means more risk has to be borne in equilibrium. Further, the extrapolative beliefs of the investors imply assets temporarily get over- or undervalued depending on the level of current dividends. The arbitrageur does lean against investors' demand shocks, but only partially accommodate them due to risk aversion. The fact that $\gamma > 0$ means asset *i*'s price increases if asset *j* experiences positive demand shocks. The high price of asset *i* in this case comes from arbitrageur demand. The high investor demand for asset *j* means the arbitrageur will decrease their position in asset *j*. However, it is then, all else equal, optimal to increase their positions in the other risky assets to maintain an optimal amount of risk taking.

As in CGM, these demand-shocks lead to trading volume and autocorrelation in asset returns. While the extrapolation is based on firm-specific dividends, this bias also affect the market portfolio as dividends are correlated. The excess return on the market claim are

$$R^e_{mt+1} = P_{mt+1} + D_{mt+1} - R_f P_{mt}. \tag{8}$$

Let C_D be the dividend correlation matrix, with ρ_D in the off-diagonal entries. The appendix shows that the market return variance and autocorrelation are given by

$$Var\left(R^e_{mt+1}\right) = X'\left(B + I_N\right)\sigma^2_D C_D \left(B + I_N\right) X + R^2_f X' B \sigma^2_D C_D B X, \tag{9}$$

and

$$Corr\left(R^e_{mt}, R^e_{mt+1}\right) = -R_f \frac{X' B \sigma^2_D C_D \left(B + I_N\right) X}{X'\left(B + I_N\right)\sigma^2_D C_D \left(B + I_N\right) X + R^2_f X' B \sigma^2_D C_D B X}.$$

The variance is increasing and the autocorrelation is decreasing in the degree of extrapolation, as this makes B "bigger." This is intuitive, and consistent with the analysis in CGM, as the demand shocks in this case temporarily push prices further away from fundamental value.

Finally, we consider the average fraction of market risk in individual asset returns:

$$\bar{R}^2 = \frac{\frac{1}{N}\sum_{i=1}^{N} Cov\left(R^e_{mt}, R^e_{it}\right)^2}{Var\left(R^e_{mt}\right) Var\left(R^e_{it}\right)}, \tag{10}$$

and trading volume:

$$dv_t = \left|\left(X^A_t - X^A_{t-1}\right) \odot P_t\right|, \tag{11}$$

where dv denotes the dollar volume vector across assets and where $\odot$ is the Hadamard product (element-by-element multiplication).[9] In the empirical section, we show that, relative to an asset market with more index trading, the level of market risk in asset returns is relatively low. Further, we also show that the cross-sectional regression

$$dv_{it} = a_t + b_t \frac{x_i P_{it}}{P_{mt}} \sum_{i=1}^{N} dv_{it} + \varepsilon_{it}, \tag{12}$$

yields a relatively low slope coefficient, b_t. In fact, the appendix shows that b_t is lower when, in the cross-section, larger-weight names have lower per-dollar-of-market weight share of aggregate volume. That is, when

$$q_{it} = \frac{dv_{it}}{\sum_{i=1}^{N} dv_{it}} \frac{\sum_{j=1}^{N} x_j P_{jt}}{x_i P_{it}} \tag{13}$$

is lower. If all investors trade the index, the share of total volume equals the market share of the firm and so in this special case $q_{it} = 1$. This economy, where investors trade individual assets with corresponding strong idiosyncratic components to their

[9] As is well-known, prices can go negative in the CARA-Normal setup, which is awkward for the interpretation of the volume calculations. A sufficiently high mean level of dividends, μ, makes the probability of this negligible.

demand shocks, is a case where typically $q_{it} << 1$ for a large stock i and thus b_t is low.

4.1.2 Asset market with an index fund

We now introduce an index fund that buys the market index. Aggregate market dividends are:

$$D_{mt} = \sum_{i=1}^{N} x_i D_{it}. \tag{14}$$

The mean market dividends is thus μ and the variance is $\sigma_{Dm}^2 = X' C_D X \sigma_D^2$. The arbitrageurs offer the index fund to investors competitively with no fees. It is ex ante optimal for the investors, who only can trade one asset, to now trade the fund instead of an individual asset.

The investors' again have an extrapolation-bias based on the dividends of the asset they hold. In this case, that is the index fund, so their expectation about future market dividends are given by

$$E_t^i \left(D_{mt+1} \right) = \mu \left(1 - \phi \right) + \phi D_{mt}, \tag{15}$$

for all investors i.

Proposition 2. *The price of the market in the economy with an index fund is*

$$P_{mt} = a_m + b_m D_{mt}, \tag{16}$$

where $a_m = \frac{(b_m+1)\mu\left(1-\frac{N\phi}{N+a/\tilde{a}}\right)-\frac{a\sigma_{\tilde{m}}^2}{N+a/\tilde{a}}}{R_f-1}$ *and* $b_m = \frac{\phi}{R_f(N+a/\tilde{a})N^{-1}-\phi}$.

It is immediate that b_m is increasing in the level of extrapolation, ϕ, and arbitrageur risk aversion, $\tilde{a}$. This economy differ from the case without an index fund in two critical manners. First, all trade is along the market dimension, which immediately implies that $b_t = 1$ in the cross-sectional volume regressions. Further, investors trade more aggressively in the index fund than they did in individual assets as the Sharpe ratio of the index fund is (on average) higher than that of individual stocks due to better diversification. This forces the arbitrageur to take on more risk from the correlated component of the demand shocks, which they again only partially accommodate due to risk aversion. In sum, when an index fund is introduced the market portfolio return becomes more sensitive to the extrapolation bias.

The variance of these excess market returns is:

$$\sigma_m^2 = \left((b_m + 1)^2 + R_f^2 b_m^2 \right) \sigma_{Dm}^2. \tag{17}$$

Since b_m is relatively high, market returns are more volatile than in the no-index-fund-case. The autocorrelation is

$$Corr\left(R_{mt+1}^e, R_{mt}^e\right) = -R_f \frac{b_m\left(b_m + 1\right)}{\left(b_m + 1\right)^2 + R_f^2 b_m^2}, \tag{18}$$

which of the same reason is more negative than in the no-index-fund-case.

From the equilibrium expressions for the individual market prices, we infer that average systematic risk, $\bar{R}^2$, increases when the index fund is introduced as asset returns are more highly correlated with the market. See the appendix for derivations.

4.2 Calibration and results

To get a sense of quantities, we calibrate the model and report key moments across the two economies. We let there be 503 firms, consistent with the current number of firms in the S&P500, with supply set equal to the market weight of each stock so that we mimic the size distribution. Table 4 gives the parameters of the model. They key parameter is ϕ, which is set to 0.6.

Figure 10 shows the standard deviation of market returns across the two economies. In the case without an index fund, the standard deviation is 13%, whereas in the case with an index fund the standard deviation is 22%. This is a substantial increase and

Table 4: Model Calibration

The table gives the main of the model calibration. Here, μ is the mean of dividends, ρ_D is the dividend correlation, N is the number of shares and investors, $\tilde{a}$ is the arbitrageur risk aversion, R_f is the gross risk-free rate, a is the investor risk aversion, $sigma_D$ is the dividend volatility, and ϕ is the extrapolation bias parameter.

Model Calibration			
μ	0.05	R_f	1.02
ρ_D	0.20	a	1
N	503	$\tilde{a}$	0.05
σ_D	0.18	ϕ	0.60

on par with what we find in the data.

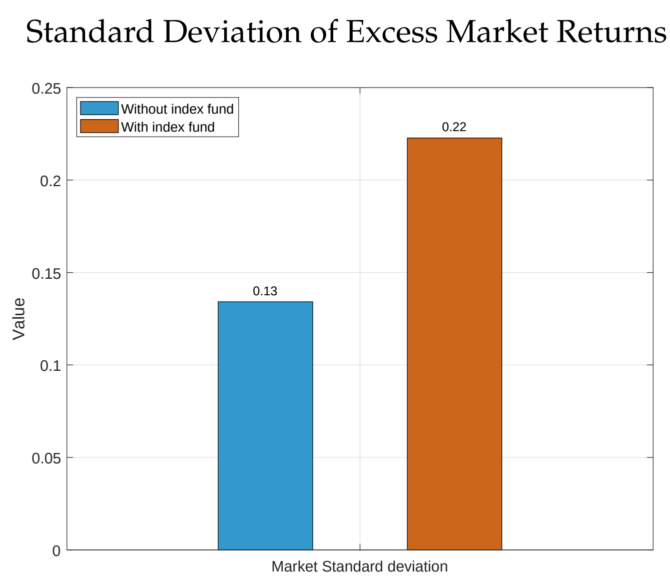

Figure 10: Model-implied Market Volatility.
The figures shows the standard deviation of excess market return for the economy without an index fund and the economy with an index fund.

Next, Figure 11 shows the change in the autocorrelation of excess market returns, the share of average systematic risk, and the slope coefficient on the volume regression. The changes in these are -0.12, 0.24, and 1.00, respectively. Again this is of similar magnitudes to those in the data, although the model is of course too simple to account for all empirical values. For instance, the volume regression in the index fund case yields $b_t = 1$ since all trade is along the market dimension, but this is not true in the data. That said, empirically, we do find this coefficient doubles from about 0.4 to 0.8 over the sample we consider.

Change in Autocorrelation, Systematic Risk, and Volume Regression Slope

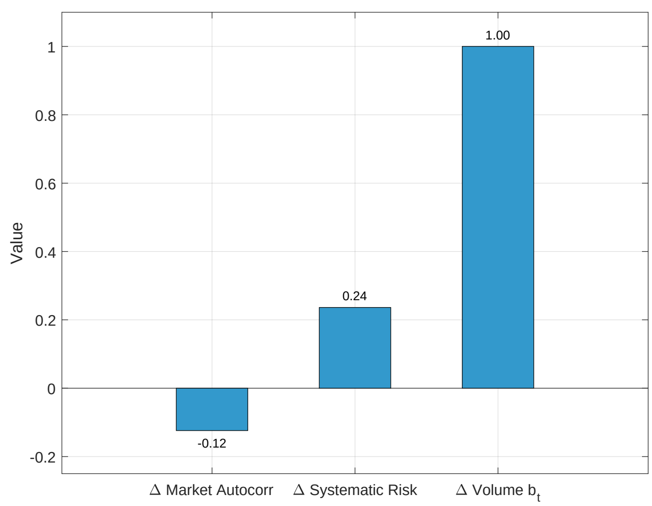

Figure 11: Change in Autocorrelation, Systematic Risk, and Volume Regression Slope. The figures shows the change in key market outcomes as the economy goes from no index fund traded to having an index fund traded. The moments are the change in the autocorrelation of excess market returns, the average amount of systematic (market) risk in individual stock returns, and the slope coefficient in the volume regressions discussed in the main table.

In sum, a simple model based on well-accepted concepts from classic papers delivers both qualitative and quantitative predictions that line up with our main empirical arguments. Increased index trading increases market return variance, but decreases market autocorrelation so the volatility effect is less pronounced at lower return frequencies. Index trading further increases the fraction of systematic risk in individual stock returns and lines volume up more strongly along the market dimension.

5. Conclusion

The stock market has transformed over the past 60 years, with the proliferation of index products (index futures, index ETFs, and passive mutual fund products). Far from being "passive", the volume of trade in these products is enormous. We provide causal evidence that this volume has contributed substantially to increased volatility of the overall stock market.

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