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Passive Investing, Diversification Risk and Financial Stability

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Abstract

This paper studies whether the rise of passive investing has reduced the equity market's capacity to absorb aggregate shocks. Using a valuation-adjusted Bartik instrument, I show that a one-standard-deviation increase in a stock's passive ownership raises its average pairwise return correlation by 9 percentage points. A structural demand-system counterfactual reveals two opposing forces: common, price-insensitive passive demand synchronizes returns while dampening firm-specific volatility. For the market as a whole, synchronization dominates: with passive investors, the minimum volatility attainable in a long-only portfolio is 3.3% higher and diversification benefits are 2.1% lower, and about half of the loss stems from the growth of passive investing since the late 1990s. Active institutions, whose portfolios are more concentrated, bear about 5% less risk and gain slightly in certainty-equivalent terms, but lose 12% of their diversification benefits as risk shifts from firm-specific to common components. Passive investing thus trades lower private risk for a higher market-wide risk floor.

Keywords: Passive investing; Index funds; Exchange-traded funds; Diversification benefits; Stock return comovement; Systematic risk; Financial stability

JEL Classification: G01, G11, G12, G23

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1 Introduction

Over the past two decades, passive investing has grown dramatically, reshaping equity markets (Haddad et al., 2025). Index funds and exchange-traded funds (ETFs) now manage about half of the assets of U.S. equity funds, fundamentally altering the structure of asset management (Investment Company Institute, 2025). While this transformation has lowered management costs and broadened market access, both practitioners and academics have begun to question the potential risks associated with this growing dominance of passive investors. In particular, concerns have emerged that the rise of passive investing may affect price discovery, market efficiency, and the ability of investors to diversify risk.

This paper examines how the rise of passive investing affects financial stability through the lens of risk-sharing capacity: the ability of the equity market to absorb aggregate shocks through diversification under realistic portfolio constraints. I measure it by the minimum risk attainable within the market, the volatility of the long-only global minimum variance portfolio, and by the share of risk that diversification removes. Passive investors trade primarily on index weights rather than individual stock fundamentals, generating common demand shocks that increase return correlations across equities. I document how rising passive ownership shifts the composition of risk from idiosyncratic towards common components. This limits the diversification achievable through portfolio construction and raises the market's risk floor, even when the risk of individual portfolios does not rise. From a policy perspective, this matters because it affects the resilience of the entire financial system: when diversification benefits erode, aggregate shocks propagate more uniformly across portfolios, potentially amplifying the need for coordinated interventions during stress periods.

The literature on systemic risk has studied financial stability through several lenses: the probability and severity of joint tail losses (Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017), contagion through interconnected balance sheets (Allen and Gale, 2000), and amplification through fire sales and liquidity spirals (Brunnermeier and Pedersen, 2009; Greenwood et al., 2015). The notion of risk-sharing capacity used

in this paper is complementary to these. It concerns the covariance structure of returns in normal times as well as in crises, and asks how much of a given shock the equity market can absorb through diversification, rather than how likely extreme outcomes are or how shocks propagate once they occur. The distinction matters for passive investing: even if the probability of a crisis is unchanged, a decline in risk-sharing capacity means that shocks, whenever they occur, are spread more uniformly across portfolios and less of them can be diversified away. The two notions are also connected: when a larger share of risk is common across assets, fire sales and other amplification mechanisms are more likely to affect many institutions at once.

Using institutional holdings from SEC 13F filings and CRSP–Compustat data, I construct a valuation-adjusted Bartik-like instrument based on exogenous variation in passive fund flows, and document that increased passive ownership leads to stronger stock correlations and a measurable erosion of diversification benefits, thereby increasing exposure to aggregate shocks. A one–standard–deviation rise in passive ownership increases average pairwise stock correlations by 9 percentage points. Part of this increase survives the removal of common factor variation, indicating synchronization beyond shared risk-factor exposure. Consistent with a price-insensitive demand channel, this residual component is absent in the pre-1997 period, when passive ownership was low and stable, and is concentrated in periods of aggregate stress.

In a structural framework following Koijen and Yogo (2019), I decompose diversification benefits and portfolio volatility and show that passive investing entails opposing risk effects. I show analytically how characteristics-based demand maps into the covariance matrix of returns: passive ownership lowers the elasticity with which prices absorb demand shocks, and passive flows load almost uniformly across the stocks passive funds hold, generating a common component in returns. By increasing return correlations, it erodes diversification benefits, while by dampening idiosyncratic price movements it smooths stock-level risk. Compared to a model-implied counterfactual that removes passive investors and reallocates

their AUM to active investors, diversification benefits in a global minimum variance portfolio are about 2.1% smaller, and the minimum volatility achievable in a long-only portfolio is higher by 3.3%. A qualitatively similar result is obtained looking at the risk parity portfolio: diversification benefits reduce by 5.1% and the volatility increases by 19.8%.

Turning to the cross-section, the effects scale monotonically with passive ownership: relative to the counterfactual, idiosyncratic variance is 7.5% lower in the least passively held decile and 49.5% lower in the most passively held, while average pairwise correlation rises from 0.5 to 6.3 percentage points. Scaling passive assets down rather than removing them shows that these effects grow steadily with the size of the passive sector: roughly half of the loss in diversification benefits, and about 60% of the cross-sectional risk reallocation, is attributable to the growth of passive investing since the late 1990s.

The rise of passive investing has altered not only the level of risk in equity markets, but also its composition, shifting risk away from idiosyncratic fluctuations and toward aggregate, non-diversifiable components. Finally, I show that active institutions' own risk falls slightly and their certainty equivalent rises, most for those with concentrated portfolios, for which the dampening of firm-specific volatility matters most. Institutions more exposed to passive ownership, and larger ones, do not bear more total risk, but a larger share of their risk comes from comovement.

Literature review This paper contributes to three strands of literature: *i*) the effect of passive investing on stock co-movement and market efficiency, *ii*) demand-system approaches to asset pricing, and *iii*) the systemic-risk implications of common ownership and ETFs.

Among many contributions, this paper is most closely related to Fang et al. (2024), who use exogenous variation in Russell 2000 index constituents to identify the causal effect of passive ownership on return correlations, and show that rising passive ownership increases stocks' return comovement across a variety of measures. My approach differs in three key ways. First, I exploit continuous variation in passive fund flows through a valuation-adjusted

Bartik instrument, capturing the gradual diffusion of passive ownership across the market rather than a local index discontinuity. Second, rather than focusing solely on return correlations, my contribution is on estimating the extent to which higher comovement translates into diversification benefits, quantifying the loss in risk-sharing capacity of increased synchronicity. Finally, while Fang et al. (2024) focus on firms around the Russell 2000 cutoff, I examine the broader cross-section of U.S. equities, linking passive ownership to the economy's aggregate capacity for risk sharing and financial stability.

Similarly, Pavlova and Sikorskaya (2023) show that benchmarking generates inelastic demand for benchmark constituents—captured by their benchmarking-intensity (BMI) measure—and that benchmark reconstitutions provide quasi-exogenous variation in benchmarked ownership; I build on this inelastic-demand logic but study its implications for the covariance structure (comovement and diversification benefits) rather than prices/expected returns and extend the analysis to a broader identification strategy, not limited to Russell 1000/2000 cutoff.

Most closely related on the volatility dimension is Jiang et al. (2025), who show that passive flows raise the prices and idiosyncratic volatility of the largest firms, as active investors absorb more of these firms' idiosyncratic risk through their short positions. My focus differs: I study how the level of passive ownership reshapes the covariance structure of returns and diversification benefits across the cross-section, rather than the marginal response to flows. In my long-only demand system this short-selling channel is absent, and removing passive ownership raises idiosyncratic volatility on average: passive investing dampens firm-specific risk while synchronizing returns. The two results are complementary: passive ownership raises idiosyncratic volatility at the margin near observed levels but lowers it relative to a counterfactual with substantially less passive ownership.

This paper contributes to understanding the effect of passive investors on market volatility. Lochstoer and Muir (2026) argue that U.S. stock market volatility has sharply increased in the last 70 years and should not be attributed to changes in fundamentals, but

rather to the central role that index trading has gained. Differently from their contribution which mostly focuses on aggregate volatility I study how passive investing has induced a reallocation from idiosyncratic to systematic risk. Furthermore, I provide a portfolio perspective on market volatility by quantifying these effects in terms of diversification benefits and equity market risk floor, namely the volatility of the global minimum variance portfolio.

This paper is also related to Da and Shive (2018), who document that ETF ownership increases stock return correlations through the mechanical trading of baskets of securities. My analysis differs in several respects. First, I study the broader phenomenon of passive investing—encompassing both ETFs and index funds—and focus on ownership-induced, rather than trading-induced, effects on return comovement. Second, I exploit exogenous variation in passive fund flows through a valuation-adjusted Bartik instrument, allowing for a causal interpretation of the link between passive ownership and correlations. Finally, I extend the analysis to portfolio-level implications, quantifying how increased synchronicity erodes diversification benefits and amplifies systemic risk using a structural approach.

Bond and Garcia (2022) study indexing in a rational-expectations equilibrium, where lower indexing costs increase indexing participation and thereby affect equilibrium price informativeness and welfare; my focus is complementary but distinct, in that I consider the expansion of passive ownership as a source of more inelastic demand across many stocks and quantify how this common-demand component reshapes the composition of risk and ultimately financial stability by increasing the long-only equity "risk floor" (i.e., the minimum achievable variance within equities) even absent explicit crisis dynamics.

This paper also relates to the demand-system approach to asset pricing (Koijen and Yogo, 2019; Haddad et al., 2025), which emphasizes that financial prices depend on the type of investor holding the asset and on the elasticity of investor demand. I borrow their empirical framework to identify passive investors based on estimated price elasticities from portfolio holdings, providing an economically grounded measure of passive ownership. Unlike these studies, which examine how investor inelasticity affects equilibrium prices and competition

in asset markets, I show that it also shapes the covariance structure of returns. By linking investor demand inelasticity to higher stock comovement and lower diversification benefits, I highlight a novel macro-financial implication of the demand-system paradigm.

Finally, the analysis complements rather than replaces traditional systemic risk measures. Studies examining ETF-related fire sales (Pagano et al., 2019), liquidity spillovers (Bhattacharya and O'Hara, 2020), and trading-induced volatility (Ben-David et al., 2018) focus on crisis amplification mechanisms—how shocks propagate once they occur. In contrast, I examine the baseline covariance structure of returns in the presence of passive investors, which affects risk-sharing capacity during both normal times and stress periods. Similarly, while work on common ownership and corporate decision-making (Appel et al., 2016) emphasizes real effects through governance channels, my focus is on financial effects through portfolio diversification. These channels are not mutually exclusive—increased return comovement may interact with fire-sale dynamics during crises, and both governance effects and diversification effects may operate simultaneously. My contribution is to isolate and quantify the diversification channel specifically.

The remainder of the paper is structured as follows: Section 2 presents the data and the construction of the main variables. Section 3 describes the reduced-form identification strategies and the instrumental variables regression estimates. Section 4 turns to the structural model: Section 4.1 constructs the counterfactual economy without passive investors, Section 4.2 decomposes the resulting changes in diversification benefits and portfolio volatility into correlation and marginal-risk components, and Section 4.3 documents their dynamics over the sample. Section 4.4 examines which stocks drive these effects in the cross-section, Section 4.5 studies the intensive margin by scaling passive capital down rather than removing it, and Section 5 quantifies the welfare consequences across investors. Finally, Section 6 concludes.

2 Data

I use monthly and quarterly data from CRSP and Compustat to obtain returns and stocks' characteristics for US ordinary shares traded on the New York Stock Exchange, American Stock Exchange, and Nasdaq. I merge these data with quarterly institutional holdings from 13F SEC filings, which report the positive holdings of all investors with more than $100 million assets under management. I exploit the cross-section of investors' holdings to identify passive investors and their investment universe to quantify how increased correlation affects investors' risk and welfare. Overall, my sample runs from March 1982 to December 2022.[1]

Passive ownership Passive investors are those whose portfolio weights are insensitive to price changes. For instance, a pure index fund mechanically rebalances toward market weights, exhibiting near-zero sensitivity to price changes within their mandate. Hence, the set of passive investors ($\mathcal{P}$) is identified from demand elasticities following Haddad et al. (2025) and includes all the investors whose demand elasticity to prices is sufficiently small. The details and robustness checks on the estimation of the demand function and identification of active and passive investors are provided in Appendix A.

Passive ownership is defined as the share of stock's market capitalization held by passive investors:

$$PO_{n,t} = \sum_{k \in \mathcal{P}} \frac{w_{k,n,t} \text{AUM}_{k,t}}{me_{n,t}} \tag{1}$$

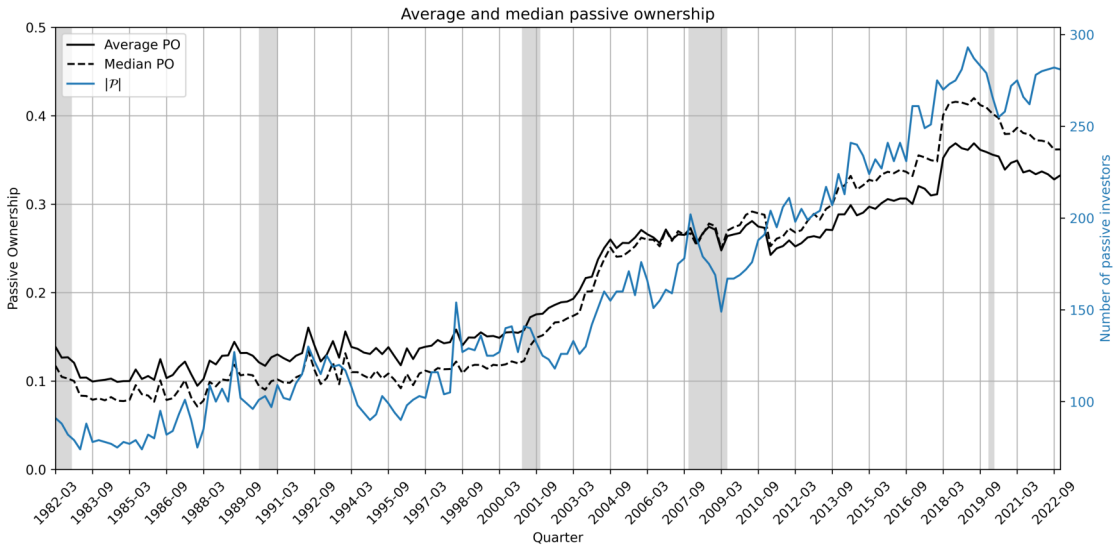
where $\text{AUM}_{k,t}$ denotes the assets under management of investor k at time t, $w_{k,n,t}$ is the portfolio weight of investor k at time t on asset n and $me_{n,t}$ is the market capitalization of asset n at time t.

Figure 1 reports the cross-section average and median passive ownership across stocks (left axis) and the number of passive investors (right axis). Average passive ownership has

[1]The sample ends in December 2022 due to data availability. While this predates some recent market events, it encompasses four decades of passive investing growth and multiple market stress episodes, providing sufficient variation to identify the effects of interest.

remained stable during the 80s and 90s, with an average PO of around 12% (see Table 1). The documented rise of passive investing is consistent with the literature (Da and Shive, 2018; Haddad et al., 2025, among others): the average ownership in the hands of this type of investors has doubled between 1998Q1 and 2022Q4.

Figure 1: Passive investors' ownership



Notes: This figure reports the cross-section average and median passive ownership PO (solid and dashed black lines, left axis) and the number of passive investors $|\mathcal{P}|$ (solid blue line, right axis). Passive ownership is defined as the share of ownership held by passive investors. Passive investors are identified as those with price elasticity smaller than 0.06, estimated according to Eq. A1. Shaded areas indicate NBER recession periods.

Stocks comovement A common belief is that passive investing increases stocks comovement, as assets held by passive investors respond more to common shocks (e.g. passive funds flows) and less to idiosyncratic information. In this paper, I construct two measures of comovement. The first is the average pairwise stocks' returns correlation:

$$\bar{\rho}_t = \frac{2}{N(N-1)} \sum_{i<j} \rho_{i,j,t} \tag{2}$$

where $\rho_{i,j,t}$ is the correlation of the returns of stocks i and j over a window of 24 months. The second is the average pairwise *excess* correlation, defined as the average correlation of

Table 1: Descriptive Statistics by Sample Period

	Passive Ownership	Correlation	Excess correlation	Diversification Benefit
Panel A: Full sample				
Mean	0.209	0.153	0.029	0.792
Median	0.188	0.137	0.029	0.790
Std. Dev.	0.085	0.070	0.013	0.078
10th pct.	0.109	0.067	0.013	0.679
90th pct.	0.334	0.265	0.047	0.889
Panel B: Pre-1997				
Mean	0.123	0.129	0.027	0.827
Median	0.126	0.129	0.027	0.844
Std. Dev.	0.016	0.071	0.011	0.084
10th pct.	0.101	0.059	0.014	0.680
90th pct.	0.140	0.266	0.039	0.921
Panel C: Post-1997				
Mean	0.263	0.166	0.031	0.773
Median	0.266	0.147	0.030	0.769
Std. Dev.	0.065	0.066	0.014	0.067
10th pct.	0.155	0.088	0.012	0.678
90th pct.	0.349	0.263	0.049	0.867

Notes: This table reports the mean, median, time-series standard deviation of the cross-sectional average, 10th and 90th percentile of cross-section average passive ownership PO, average pairwise correlation $\bar{\rho}$, excess pairwise correlation $\bar{\rho}^{\text{ex}}$ — defined as the average correlation of CAPM residuals net of common market factor co-movement — and global minimum variance (GMV) portfolio diversification benefits $\mathcal{DB}$ in full, pre-1997 and post-1997 samples.

market model (CAPM) residuals (Bekaert et al., 2009):

$$\bar{\rho}_t^{\text{ex}} = \frac{2}{N(N-1)} \sum_{i<j} \rho_{i,j,t}^{\text{ex}} \tag{3}$$

where $\rho_{i,j,t}^{\text{ex}}$ is the correlation of the residuals $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ from stock-level market model regressions estimated over the same 24-month window. By construction, $\bar{\rho}_t^{\text{ex}}$ nets out co-movement driven by common exposure to aggregate market dynamics, such as globalization or macro-fundamentals synchronization, isolating the component of return synchronicity unexplained by shared market factor (Campbell et al., 2001; Pukthuanthong and Roll, 2009). I also compute the stock-level analogue $\rho_{n,t}$, the average correlation of stock n with all other stocks in the sample, following Pollet and Wilson (2010). Summary statistics on both measures are provided in Table 1. In the post-1997 period, raw comovement has increased by almost 30% (0.166 *vs.* 0.129), while excess correlation has increased by 15% (0.031 *vs.* 0.027), suggesting that a non-trivial component of the rise in synchronicity is not accounted for by common fundamentals alone.

Diversification benefits The stylized facts on stocks comovement are in line with Fang et al. (2024), who claim a causal link between passive investing and stocks' returns synchronicity. What remains unexplored in the literature is how more correlated asset returns translate into investors' risk, welfare and financial stability. I contribute to the literature on passive investing by bridging this gap. Following Choueifaty (2008) and Billio et al. (2017), I construct diversification benefits, i.e. the reduction in portfolio risk that can be achieved by a well-diversified portfolio relative to the weighted average risk of its constituents:

$$\mathcal{DB}_t = 1 - \frac{\sqrt{\mathbf{w}_t' \Sigma_t \mathbf{w}_t}}{\mathbf{w}_t' \sigma_t} \tag{4}$$

where $\mathbf{w}_t$ is the vector of portfolio weights with elements w_n. Throughout, the variance-covariance matrix Σ_t is estimated using the shrinkage estimator of Ledoit and Wolf (2004).

While diversification benefits can be constructed for any portfolio, I focus on two benchmark portfolios that span the trade-off between theoretical optimality and empirical relevance. The first is the *Global Minimum Variance* (GMV) portfolio, which solves:

$$\mathbf{w}_t^{GMV} = \arg\min_{\mathbf{w}} \mathbf{w}'\Sigma_t\mathbf{w} \qquad \text{s.t.} \quad \mathbf{w}'\mathbb{1} = 1, \quad w_n \geqslant 0. \tag{5}$$

The GMV portfolio delivers the lowest attainable risk among all fully invested long-only portfolios, providing a theoretical lower bound on portfolio risk. When its diversification benefits decline, no feasible reallocation can offset the increase in aggregate risk, so changes in GMV-based diversification benefits directly capture shifts in the economy's capacity to absorb aggregate shocks, rather than changes driven by investor preferences or portfolio tilts.

The second benchmark is the *Risk Parity* (RP) portfolio, which allocates weights such that each asset contributes equally to total portfolio variance:

$$\mathbf{w}_t^{RP} = \arg\min_{\mathbf{w}} \sum_i \sum_j \left(w_i(\Sigma_t\mathbf{w})_i - w_j(\Sigma_t\mathbf{w})_j\right)^2 \qquad \text{s.t.} \quad \mathbf{w}'\mathbb{1} = 1, \quad w_n \geqslant 0. \tag{6}$$

Risk parity has been widely adopted by institutional investors as a practical alternative to mean-variance optimization (Asness et al., 2012; Anderson et al., 2012), making it a natural benchmark for assessing the real-world costs of eroded diversification. Unlike GMV, which endogenously tilts toward low-volatility and low-correlation assets, risk parity spreads risk uniformly across assets and is therefore more exposed to the correlation-increasing effects of passive ownership. As a result, GMV provides a conservative lower bound on diversification losses, while RP reflects the experience of a broad class of institutional investors.[2]

The statistics on aggregate $\mathcal{DB}$ are shown in Table 1. Unlike return correlations, which tend to increase sharply during periods of market stress, diversification benefits de-

[2]The link between return comovement and diversification benefits follows directly from the portfolio variance-covariance structure. Differentiating Eq. (4) with respect to an individual pairwise correlation ρ_{ij} yields $\frac{\partial \mathcal{DB}}{\partial \rho_{ij}} = -\frac{w_i w_j \sigma_i \sigma_j}{(\mathbf{w}^\top \sigma)\sqrt{\mathbf{w}_t'\Sigma_t\mathbf{w}_t}} < 0$, showing that higher return comovement mechanically reduces diversification benefits by increasing portfolio variance relative to the weighted average marginal risk of its constituents.

clined in the most recent years, reflecting the growing dominance of systematic shocks over idiosyncratic risk. The percentage decline between the pre- and post-1997 period is around 6.5%. Note that this is the diversification benefit for an unrestricted investment universe. Empirically, investors hold much more restricted sets of assets, either because of preferences or investment mandates, so investor-specific diversification benefits are likely to be smaller than the aggregate measure described here.

3 Reduced form analysis

In this section, I discuss the identification strategy to measure the causal impact of passive investing on stocks comovement. Then, by means of two-stage least squares I estimate how an increase in passive ownership changes the average pairwise correlation.

3.1 Identification strategy

A simple regression of return comovement on passive ownership is unlikely to identify a causal effect, for three reasons. First, reverse causality and mechanical selection: passive funds hold stocks in proportion to their index weights, so passive ownership is mechanically higher for large, liquid index constituents, whose returns load more heavily on the market factor regardless of who owns them. Second, omitted variables: characteristics such as size, liquidity, index membership and analyst coverage plausibly drive both passive ownership and comovement. Third, measurement error: passive ownership is a generated regressor, built on investor-level price elasticities estimated from the demand system (Appendix A), so classification error attenuates OLS estimates toward zero.

To address these concerns, I employ a shift-share (Bartik) instrument that combines heterogeneous, predetermined baseline exposure to passive investors with investor-level flow shocks that are plausibly orthogonal to stock-level characteristics. The key identifying assumption is that passive fund flows are driven by external forces such as household savings

decisions, retirement contributions, and market-wide sentiment rather than individual stock fundamentals—an assumption standard in demand-based asset pricing (e.g. Koijen and Yogo, 2019; Haddad et al., 2025). For each stock n and quarter t, the instrument is

$$Z_{n,t-h} = \sum_{k \in \mathcal{P}} \underbrace{PO_{n,k,t-h}}_{\text{baseline exposure}} \underbrace{f^{(-n)}_{k,t-h}}_{\text{flow shifter}}, \tag{7}$$

where $PO_{n,k,t-h}$ is the fraction of stock n held by passive investor k in the baseline period $t-h$, and $f^{(-n)}_{k,t-h}$ is investor k's value-adjusted net flow rate over $[t-h, t]$. Following the standard definition of fund flows net of valuation effects (Coval and Stafford, 2007), I compute it from assets under management, with the modification that the valuation adjustment uses fund returns excluding stock n:

$$f^{(-n)}_{k,t-h} = \frac{AUM_{k,t} - \left(1 + R^{(-n)}_{k,t}\right) AUM_{k,t-h}}{AUM_{k,t-h}}. \tag{8}$$

Excluding stock n's return from $R^{(-n)}_{k,t}$ removes any mechanical link between the flow shifter and outcomes for stock n, ensuring the instrument captures only fund-level demand shocks.[3]

I set $h = 8$ quarters (two years) to balance instrument relevance and exogeneity. This lag choice ensures the baseline exposure is predetermined and cannot be influenced by current or anticipated stock characteristics, mitigating concerns about reverse causality. At shorter lags, passive and active fund flows exhibit high correlation (0.64 at $h = 4$), suggesting they respond to similar short-term factors such as momentum and market timing that may violate the exclusion restriction. At longer lags, the baseline becomes too distant to meaningfully predict current passive ownership, weakening the instrument. The two-year lag provides sufficient temporal separation while maintaining predictive power: the correlation between passive and active instruments drops to 0.37, and the instrument exhibits strong first-stage predictive power.

[3]Section 4 shows that $Z_{n,t-h}$ is the lagged-share counterpart of the passive-flow component of demand shocks in the structural model (Lemma 1), so that the reduced-form and structural analyses exploit the same source of variation.

The maintained exclusion restriction is that, conditional on firm and time fixed effects, variation in $Z_{n,t-h}$ affects stock n's return comovement only through its impact on passive ownership. With time fixed effects, identification exploits within-quarter cross-sectional differences: stocks with higher predetermined exposure to passive funds experiencing positive flow shocks see larger increases in passive ownership. Time fixed effects absorb market-wide shocks, ensuring the instrument captures idiosyncratic variation orthogonal to aggregate comovement trends. Regressing $Z_{n,t-h}$ on lagged stock characteristics yields an R^2 of only 3%, confirming the instrument provides independent variation beyond observables.

To validate the exclusion restriction, I conduct two sets of tests. First, I construct an analogous instrument using active fund exposure and flows, as placebo test. If the identifying variation merely reflected general institutional demand rather than passive-specific flows, this placebo should also predict passive ownership. Instead, it yields an insignificant first stage, confirming the variation is passive-specific.[4] Second, I show that passive fund flows load on aggregate macroeconomic conditions: they rise with consumption and disposable-income growth and fall with market volatility, and their response to income, saving-rate and volatility shocks differs from that of active flows, consistent with predominantly aggregate rather than firm-specific drivers.[5]

The first-stage regression reads as:

$$PO_{n,t} = \pi_0 + \pi_1 Z_{n,t-h} + X'_{n,t}\delta + \alpha_n + \gamma_{j(n),t} + u_{n,t}, \tag{9}$$

where $PO_{n,t}$ denotes the fraction of shares of stock n held by passive investors at time t, $Z_{n,t-h}$ is the instrument constructed as baseline exposure to passive investors interacted with subsequent AUM growth, $X'_{n,t}$ are control variables, α_n are stock fixed effects, $\gamma_{j(n),t}$ are industry $\times$ time (quarter) fixed effects and $u_{n,t}$ is the error term.

[4] At shorter lags ($h = 4$), the placebo instrument exhibits strong predictive power, indicating correlated institutional flows. At $h = 8$, the placebo becomes insignificant while the main instrument maintains strength, demonstrating successful isolation of passive flows.

[5] Detailed analysis of the macroeconomic determinants of passive flows is provided in Appendix B.

Table 2: First-Stage IV Estimates of Passive Ownership

	Full sample (1)	S&P 500 (2)
Z	0.837***	0.883***
	(0.169)	(0.141)
Excluded-instrument F	24.529	39.218
Observations	174,760	124,346
Adj. R^2	0.680	0.660

Notes: Dependent variable is passive ownership $PO_{n,t}$. The instrument $Z_{n,t-h}$ is the valuation-adjusted shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters. Column (1) uses the full cross-section of stocks; Column (2) restricts the sample to S&P 500 constituents. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2 shows that the instrument strongly predicts passive ownership. In both the full cross-section and the S&P 500 subsample, the coefficient on $Z_{n,t-h}$ is positive, and highly significant, indicating a strong correlation between the instrument and passive ownership. The inclusion of firm and time fixed effects alongside controls for lagged market equity, book equity, profitability, and asset growth does not limit the statistical significance of the instrument. The excluded-instrument F-statistic is 24.5 in the full sample and 39.2 in the S&P 500 subsample, above the Stock and Yogo (2005) critical value of 16.38 for 10% maximal size, confirming that weak-instrument concerns do not affect inference. The consistency of the estimates across the two samples is noteworthy: despite S&P 500 constituents being more capitalized, more liquid, and already subject to higher passive ownership, the instrument retains strong predictive power, suggesting that the identifying variation is not confined to smaller or less liquid stocks.

3.2 Reduced form evidence

I estimate the causal effect of passive ownership on stock return comovement using a two-stage least squares (2SLS) specification. In the second stage, I regress my measures of

stock-level comovement on the instrumented measure of passive ownership:

$$y_{n,t} = \beta \widehat{\mathrm{PO}}_{n,t} + \alpha_n + \gamma_{j(n),t} + X'_{n,t}\delta + \varepsilon_{n,t} \tag{10}$$

where $y_{n,t}$ is alternatively the average pairwise correlation ($\bar{\rho}_{n,t}$) or excess correlation ($\bar{\rho}^{ex}_{n,t}$), $\widehat{PO}_{n,t}$ is the fitted value of passive ownership from the first-stage regression (Eq. 9), $X_{n,t}$ is a matrix of stock's characteristics including lagged book, and market equity, profitability and the growth rate of assets, α_n and $\gamma_{j(n),t}$ denote stock and industry $\times$ time fixed effects, respectively.

Table 3: Second-Stage IV Estimates: Effect of Passive Ownership on Return Comovement

	Correlation		*Excess Correlation*	
	(1)	(2)	(3)	(4)
Passive Ownership	0.534***	0.522***	0.065***	0.064***
	(0.027)	(0.033)	(0.012)	(0.020)
1-SD Effect	0.093	0.090	0.011	0.011
Observations	174,760	124,346	174,760	124,346
R^2	0.812	0.812	0.291	0.228
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Full sample	✓	–	✓	–
S&P 500	–	✓	–	✓

Notes: Dependent variable is stock return comovement, proxied either by *i*) average pairwise return correlations or by *ii*) average pairwise excess correlations of market-model residuals. Columns (2) and (4) restrict the sample to S&P 500 constituents; Columns (1) and (3) use the full cross-section. Passive ownership is instrumented by the valuation-adjusted shift-share Bartik instrument $Z_{n,t-h}$ (Eq. 7) with $h = 8$ quarters. *1-SD Effect* $= \hat{\beta} \times \sigma_{PO}$ measures the change in comovement for a one-standard-deviation increase in passive ownership, where σ_{PO} is the standard deviation of stock-level passive ownership. All specifications use IV-2SLS. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry $\times$ time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3 reports the second-stage IV estimates of the effect of passive ownership on stock return comovement, using both raw pairwise correlations and excess correlations of market-model residuals as dependent variables. All specifications include controls and industry $\times$ time and stock fixed effects.

Columns (1) and (2) report estimates for raw pairwise correlations. The coefficient

on instrumented passive ownership is positive, and highly significant in both the full cross-section and the S&P 500 subsample, with estimates of 0.534 and 0.522 respectively. A one-standard-deviation increase in passive ownership raises average pairwise correlations by 9 percentage points in both samples. The near-identical estimates across the two samples indicate that the effect is not driven by small or illiquid stocks — it is equally present among the large-cap, highly liquid constituents of the S&P 500, where passive ownership is already high and stocks are already highly correlated, leaving if anything less room for passive-induced comovement to appear.

Columns (3) and (4) repeat the analysis using excess correlations, defined as average pairwise correlations of market-model residuals (Bekaert et al., 2009). By construction, excess correlations capture return synchronization orthogonal to aggregate market movements, isolating the component of comovement that cannot be attributed to common factor exposure. The coefficient on passive ownership remains positive and highly significant in both samples, with estimates of 0.065 and 0.064, implying a one-standard-deviation effect of 1.1 percentage points. While a smaller magnitude than the raw correlation estimates is expected since excess correlations strip out common factor variation, the persistence of a significant effect indicates that the correlation increase documented in columns (1)–(2) is not entirely driven by passive investors loading on the same risk factors. Passive ownership also generates some return synchronization beyond what common factor exposure alone would predict, consistent with the price-insensitive demand channel described above. This second component is the smaller of the two, and two pieces of evidence delimit when it operates. It loses significance once NBER recession quarters are excluded, while the effect on raw correlations remains (Table C6), so it is concentrated in periods of aggregate stress. It is also absent before 1997: in a sample restricted to the period in which passive ownership was low and stable, passive ownership still raises raw correlations but has no effect on excess correlations (Table C4). The ownership-induced synchronization channel is therefore specific to the era of large-scale passive investing, rather than a mechanical feature of institutional ownership

at any level.

The reduced-form analysis establishes a causal link between passive ownership and return comovement. However, three key questions remain unanswered. First, while I document increased correlations, I have not yet quantified how this translates into economy-wide diversification losses. Second, the reduced-form estimates capture only the off-diagonal (correlation) channel; passive investing may also affect individual stock volatilities (the diagonal), with ambiguous net effects on portfolio risk. Third, passive ownership simultaneously affects multiple dimensions of the return distribution, and the portfolio-level implications require a general equilibrium perspective that accounts for all stocks and the full covariance matrix.

To address these limitations, I turn to a structural demand-system approach. This framework allows me to: *i*) compute counterfactual equilibrium prices and returns for the full cross-section of stocks under alternative ownership structures, *ii*) decompose changes in portfolio risk into correlation versus idiosyncratic-volatility components, and *iii*) quantify the overall impact on the economy's risk-sharing capacity through changes in diversification benefits and minimum achievable portfolio volatility.

4 A structural approach on passive ownership

The reduced-form evidence in Section 3 documents that passive ownership causally increases stock return correlations. However, this correlation-increasing effect is only one channel through which passive investing affects portfolio risk. This section uses the demand-system framework of Koijen and Yogo (2019) to study the full general equilibrium effects on the covariance structure of returns.

4.1 Demand system and counterfactual construction

Unlike the reduced-form analysis, which exploits exogenous variation in passive ownership for identification, the structural counterfactual is an accounting exercise that evaluates

how the observed growth of passive assets under management reshapes equilibrium risk. Essentially, the question is: "*what would have been the covariance structure of asset prices if passive investing didn't exist?*". Importantly, this removes the propagation channel (passive demand), not aggregate shocks themselves. I further assume that assets under management of passive investors are reallocated proportionally to active ones, in order to maintain the total size of the market unchanged.[6]

To construct the counterfactual and study the impact of passive investing I exploit investors holding data from the SEC 13F filings and estimate, for each investor-quarter, the following demand function:

$$\delta_{k,t,n} = \frac{w_{k,t,n}}{w_{k,t,0}} = \exp\left\{\beta_{0,k,t}\, me_{t,n} + \sum_{m=1}^{M-1} \beta_{m,k,t}\, x_{t,n} + \beta_{M,k,t}\right\} \epsilon_{k,t,n} \tag{11}$$

where $\delta_{k,n,t}$ is the portfolio allocation of investor k in asset n at time t relative to the outside asset, which collects all holdings that are not U.S. common stocks in the sample, such as non-equity securities, foreign stocks and derivatives, $\log me_{n,t}$ is the market capitalization, and $x_{t,n}$ is a vector of stock characteristics including log book equity, profitability, investment growth, dividend-to-book equity and the market beta. $\epsilon_{k,t,n}$ is the latent demand of stock n at time t, representing investor's k sentiment and private information. Each investor portfolio choice is modelled as function of observable stock characteristics (market equity, book equity, investment growth, profitability, dividend to book equity, and market beta) and an unobserved demand component $\epsilon_{k,t,n}$. The estimated coefficients represent the demand elasticities relative to asset characteristics. To address potential endogeneity, I follow Koijen and Yogo (2019) and instrument the market equity $me_{t,n}$ by the counterfactual market equity as if every investor held an equal weighted portfolio within its investment universe.

Exploiting the estimated coefficients and taking investors' assets under management and investment universe as exogenously given I compute counterfactual prices by imposing

[6] In Appendix D I show that the results are driven by a change in stocks' ownership from passive to active investors and not by the reallocation, which only determines the magnitude of the effect.

market clearing:

$$\underbrace{\mathbf{p}_t + \mathbf{s}_t}_{\text{supply}} = \underbrace{\log\left(\sum_{k=1}^{K} AUM_{k,t}^{cf}\, \mathbf{w}_{k,t}(\mathbf{p}_t)\right)}_{\text{demand}} \tag{12}$$

where $AUM_{k,t}^{cf}$ is the counterfactual assets under management after setting the assets under management of passive investors to zero and reallocate it to active ones proportionally to their size at each quarter. Market clearing requires that supply equals aggregate demand at each quarter, as expressed in Eq. (12), which I solve for counterfactual prices p_t^{cf} given $AUM_{k,t}^{cf}$ and the estimated demand elasticities.

I structurally identify the mapping from ownership to the variance-covariance matrix of returns and compute a partial-equilibrium counterfactual removing passive AUM: given $AUM_{k,t}^{cf}$ and the estimated demand elasticities, I solve the Koijen and Yogo (2019) market-clearing system at each quarter to obtain counterfactual prices p_t^{cf} and counterfactual stock returns. These returns yield the counterfactual variance–covariance matrix Σ_t^{cf}. The structural analysis covers 1997Q1-2022Q4. The earlier part of the sample is used to estimate the demand system and to initialise the 24-quarter rolling windows underlying Σ, so the first counterfactual equilibrium that can be compared with observed data is 1997Q1.

Importantly, the counterfactual variance-covariance matrix changes are not estimated, but rather implied by the composition of stocks demand. The counterfactual covariance matrix is obtained by solving the nonlinear market-clearing condition in Eq. (12) quarter by quarter and estimating Σ_t^{cf} from the resulting returns. To make explicit how the demand system shapes Σ_t, and in particular how covariances across stocks arise from demand functions that depend only on each stock's own characteristics, I linearize market clearing around the observed equilibrium (Appendix H). Let $\theta_{k,n,t} = AUM_{k,t}\, w_{k,n,t}/ME_{n,t}$ denote the share of stock n held by investor k, so that $\sum_k \theta_{k,n,t} = 1$ once the household sector is included, and collect these shares in the diagonal matrix $\Theta_{k,t}$. Let $f_{k,t}$ denote investor k's valuation-adjusted flow, i.e. the change in log assets under management not explained by the return

on its equity holdings, as in Eq. (8). Time subscripts are omitted when unambiguous.

Lemma 1 (Linearized equilibrium returns)**.** *Holding shares outstanding fixed, to a first-order approximation the vector of stock returns satisfies*

$$M\,\mathbf{r} = \mathbf{u}, \qquad M \equiv I - \sum_k \Theta_k \big(\beta_{0,k}\, I + (1-\beta_{0,k})\, \boldsymbol{\iota}\, \mathbf{w}_k'\big), \tag{13}$$

$$\mathbf{u} \equiv \sum_k \Theta_k \Big[\boldsymbol{\iota}\, f_k + G_k\big(d\mathbf{X}\, \boldsymbol{\beta}_k + \mathbf{X}\, d\boldsymbol{\beta}_k + \mathbf{me}\, d\beta_{0,k} + d\log \boldsymbol{\epsilon}_k\big)\Big], \qquad G_k \equiv I - \boldsymbol{\iota}\, \mathbf{w}_k', \tag{14}$$

where $\boldsymbol{\iota}$ is a vector of ones, $\mathbf{X}$ stacks the non-price characteristics in Eq. (11) including the constant, and $\boldsymbol{\beta}_k$ collects the corresponding coefficients. Consequently,

$$\Sigma = M^{-1}\, \Omega_u\, M^{-1\prime}, \qquad \Omega_u \equiv \mathrm{Var}(\mathbf{u}). \tag{15}$$

Equation (15) separates two objects. The matrix M governs how elastically aggregate demand absorbs shocks. Its diagonal entries,

$$M_{nn} = \eta_n \equiv \sum_k \theta_{k,n}\,(1-\beta_{0,k})\,(1-w_{k,n}), \tag{16}$$

coincide, up to the factor $(1-w_{k,n})$, with the ownership-weighted elasticity in Eq. (E2), while its off-diagonal entries are of the order of individual portfolio weights. The vector $\mathbf{u}$ collects demand shocks (flows, news about characteristics, changes in investors' tilts and latent demand) each loading on stock n in proportion to the ownership shares of the investors who experience it. Covariances across stocks therefore arise even though each investor's demand for a stock depends only on that stock's characteristics: two stocks covary when they are held by the same investors, or by investors whose demand shocks are correlated. Dropping terms of the order of portfolio weights,

$$r_n \approx \frac{1}{\eta_n} \sum_k \theta_{k,n} \big(f_k + \boldsymbol{\beta}_k' d\mathbf{x}_n + \mathbf{x}_n' d\boldsymbol{\beta}_k + me_n\, d\beta_{0,k} + d\log \epsilon_{k,n}\big), \tag{17}$$

so that the flow-driven component of the covariance between stocks n and m is

$$\mathrm{Cov}^{\mathrm{flow}}(r_n, r_m) \approx \frac{\boldsymbol{\theta}_n' \, \Sigma_f \, \boldsymbol{\theta}_m}{\eta_n \, \eta_m}, \tag{18}$$

where $\boldsymbol{\theta}_n = (\theta_{1,n}, \ldots, \theta_{K,n})'$ and Σ_f is the covariance matrix of flows across investors. Up to the elasticity terms, this is the cross-stock analogue of the fragility measure of Greenwood and Thesmar (2011); see also Anton and Polk (2014) on common ownership and comovement.

Passive investors enter the two objects in Eq. (15) through different features of their demand. Their effect on M depends only on their price elasticity. Splitting the elasticity in Eq. (16) between passive holders and the remaining ones,

$$\eta_n = PO_n \, \bar{\eta}_n^{P} + (1 - PO_n) \, \bar{\eta}_n^{-P}, \qquad \bar{\eta}_n^{P} \equiv \sum_{k \in \mathcal{P}} \frac{\theta_{k,n}}{PO_n} (1 - \beta_{0,k})(1 - w_{k,n}), \tag{19}$$

where $\bar{\eta}_n^{-P}$ is defined analogously over non-passive holders, including households. Investors classified as passive have a price elasticity below 0.06 in the demand specification of Appendix A, an order of magnitude below that of active investors, so $\bar{\eta}_n^{P}$ is correspondingly small. Replacing elastic with passive ownership therefore lowers η_n roughly in proportion to PO_n, and every demand shock moves the price of a heavily passively held stock by more (Gabaix and Koijen, 2021; Haddad et al., 2025). This holds regardless of whether passive investors tilt towards characteristics, since characteristic coefficients do not enter M.

Their effect on $\mathbf{u}$ depends instead on which stocks they hold, and here passive investors are heterogeneous. For broad-market index funds, $\theta_{k,n}$ is approximately constant across index constituents. Their flows are strongly correlated across funds and driven by aggregate conditions (Appendix B), so their contribution to Eq. (18) is approximately $PO_n^{\mathrm{mkt}} \, PO_m^{\mathrm{mkt}} \, \sigma_f^2 / (\eta_n \eta_m)$, where PO_n^{mkt} is ownership by broad-market funds and σ_f^2 the variance of their common flow. This is a common component that raises correlations among all stocks they hold. Style, factor and sector index funds, which the elasticity-based classification also identifies as passive, hold stocks according to characteristic-based index weights.

Their flows load more heavily on stocks sharing those characteristics, and index reconstitutions act as changes in their tilts $d\boldsymbol{\beta}_k$, so they generate comovement concentrated within styles rather than across the market as a whole. In both cases flows are transmitted through ownership shares rather than through stock-specific information, which is what distinguishes passive demand shocks from the largely stock-specific latent demand of active investors. The latter loads mainly on the diagonal of Σ and governs the marginal-risk channel. Finally, the passive-flow component of u_n, $\sum_{k\in\mathcal{P}} \theta_{k,n,t} f_{k,t}$, is the contemporaneous counterpart of the instrument in Eq. (7), which evaluates the same object at ownership shares lagged h quarters: the reduced-form and the structural analyses exploit the same source of variation.

I compute diversification benefits and the volatility of the global minimum variance and risk parity portfolios in an economy where passive investors' assets under management are set to zero and reallocate proportionally to active ones. This exercise isolates the portion of the decline in diversification specifically attributable to the growth in passive fund flows, rather than to changes in investor composition, mandates, or return-driven AUM dynamics. This approach allows one to study the impact of passive investing on the whole US market, overcoming both the limitations of the reduced-form analysis discussed at the end of Section 3 and the computational burden that restricts the pairwise analysis to S&P 500 stocks (Appendix C.2), and quantifies the contribution of passive fund flows to changes in the equilibrium covariance structure of returns, without relying on instrumental-variable variation or assumptions about the exogeneity of flows. Importantly, this exercise does not remove aggregate shocks from the economy; rather, it removes one specific propagation channel through which such shocks affect prices, namely the accumulation of assets by passive investors.

4.2 Aggregate effects on risk-sharing capacity

Table 4 reports the percentage change in diversification benefits ($\Delta\mathcal{DB}$) and portfolio volatility ($\Delta\sigma$) in the counterfactual market with no passive investors, for two benchmark portfolios. Negative $\Delta\mathcal{DB}$ indicates that diversification benefits are lower in the observed

data (with passive investors) than in the counterfactual (without passive investors). Positive $\Delta\sigma$ indicates that minimum portfolio volatility is higher in the observed data than in the counterfactual.

Table 4: Summary statistics on counterfactual analysis

Panel A: Diversification benefits, $\Delta\mathcal{DB}$ (%)			
	Total	Correlation	Marginal risk
GMV	-2.093	-1.514	-0.580
Risk Parity	-5.101	-4.439	-0.662
Panel B: Portfolio volatility, $\Delta\sigma$ (%)			
	Total	Correlation	Marginal risk & rebalancing
GMV	3.320	20.220	-16.900
Risk Parity	19.802	35.360	-15.558

Notes: This table reports the percentage change in diversification benefits ($\Delta\mathcal{DB}$, Panel A) and portfolio volatility ($\Delta\sigma$, Panel B) between the observed data and the counterfactual in which passive investors are removed and their assets under management reallocated to active ones, for two benchmark portfolios. Percentage changes are defined as $\Delta\mathcal{DB} = (\mathcal{DB}^{obs} - \mathcal{DB}^{cf})/\mathcal{DB}^{cf}$ and $\Delta\sigma = (\sigma^{obs} - \sigma^{cf})/\sigma^{cf}$. Each total is decomposed into a correlation component and a marginal risk component, according to Eq. 20. For portfolio volatility a third, rebalancing component arises and it is reported jointly with marginal risk (see Eq. 21. Components are scaled by the counterfactual level and therefore sum to the corresponding total.

The implied equilibrium prices generate substantially lower stock-return correlations and, consequently, higher diversification benefits throughout the sample. For the GMV portfolio, the observed-counterfactual gap in diversification benefits is approximately 2.1%, while minimum portfolio volatility is higher by around 3.3% in the presence of passive investors. The Risk Parity portfolio shows substantially larger effects: diversification benefits are lower by 5.1% and portfolio volatility is higher by 19.80%. This difference across the two benchmarks is intuitive. The GMV portfolio endogenously tilts toward low-volatility and low-correlation assets, partially insulating itself from the correlation-increasing effects of passive ownership and thus providing a conservative lower bound on diversification losses. Risk parity, by contrast, spreads risk uniformly across assets and is therefore more exposed to passive-induced synchronization, reflecting the experience of a broad class of institutional investors (Asness et al., 2012; Anderson et al., 2012).

Passive investing reallocates risk from firm-specific to aggregate components. One manifestation of this shift is increased return comovement, which mechanically reduces diversification benefits. However, the impact on minimum portfolio risk is substantially larger than the decline in diversification benefits alone would suggest: for both GMV and Risk Parity, the percentage increase in portfolio volatility far exceeds the percentage decline in diversification benefits. This asymmetry points to the presence of opposing forces operating simultaneously through the covariance structure of returns, which the aggregate counterfactual cannot disentangle on its own. To shed light on these offsetting effects, I propose a decomposition of diversification benefits and portfolio volatility into their correlation and marginal risk components.

Diversification benefits depend on both covariances of stock returns and individual volatility. Eq. 20 decomposes the change in diversification benefits into a correlation and marginal risk (or individual volatility) components.

$$\Delta\mathcal{DB}_t = \mathcal{DB}_t^{obs} - \mathcal{DB}_t^{cf} = \underbrace{\mathcal{DB}(\Sigma_t^{obs}) - \mathcal{DB}(\Sigma_t^{\rho})}_{\text{correlation}} + \underbrace{\mathcal{DB}(\Sigma_t^{\rho}) - \mathcal{DB}(\Sigma_t^{cf})}_{\text{marginal risk}} \tag{20}$$

The correlation component measures the contribution of the change in return correlations arising from removing the common, price-insensitive demand of passive investors. Formally, $\Sigma_t^{\rho} = D_t^{obs} R_t^{cf} D_t^{obs}$, where D is the diagonal matrix of individual volatilities and R the correlation matrix. Practically, it is the difference between observed diversification benefits and those obtained when only correlations move to their counterfactual values (i.e., using counterfactual correlations but observed individual volatilities), in percent of counterfactual diversification benefits. The marginal risk component captures the change in individual volatilities when stock-specific information plays a larger role in price formation, and is scaled in the same way. The latter is measured by the difference of diversification benefits in the counterfactual market with no passive funds and when only stock returns correlation adjusts.

The volatility of the portfolio depends both on the individual risk and the correlation structure. Additionally, a rebalancing effect accounts for the change in portfolio positions due to changes in the covariance matrix.

$$\Delta\sigma_t = \sigma_t^{obs} - \sigma_t^{cf} = \underbrace{\sqrt{\left(w_t^{obs}\right)' \Sigma_t^{obs} w_t^{obs}} - \sqrt{\left(w_t^{\rho}\right)' \Sigma_t^{\rho} w_t^{\rho}}}_{\text{correlation}} + \underbrace{\sqrt{\left(w_t^{\rho}\right)' \Sigma_t^{\rho} w_t^{\rho}} - \sqrt{\left(w_t^{\rho}\right)' \Sigma_t^{cf} w_t^{\rho}}}_{\text{marginal risk}} + \underbrace{\sqrt{\left(w_t^{\rho}\right)' \Sigma_t^{cf} w_t^{\rho}} - \sqrt{\left(w_t^{cf}\right)' \Sigma_t^{cf} w_t^{cf}}}_{\text{rebalancing}} \tag{21}$$

Eq. 21 shows the decomposition, where w_t^{ρ} are the global minimum variance portfolio weights under off-diagonal changes in the variance covariance matrix, w^{obs} are portfolio weights computed using the observed variance-covariance matrix and w^{cf} are the portfolio weights when both off-diagonal and individual volatilities adjust to a market without passive investors. When passive investors are absent, prices are determined by more elastic investors that respond to asset-specific information, increasing the sensitivity of prices to idiosyncratic shocks. As a result, individual return volatilities rise, leading to higher marginal risk. These two opposite effects induce investors to rebalance their portfolios but the binding short-selling constraints limit their ability to hedge risk, giving rise to the rebalancing component.

The remaining columns of Table 4 report the contribution of the correlation, marginal risk and rebalancing on the change in diversification benefits and portfolio volatility between the observed and counterfactual markets. For both portfolios, the correlation component dominates over marginal risk: it accounts for roughly 72% of the total erosion of GMV diversification benefits (-1.514 out of -2.093) and for more than 85% in the risk parity case (-4.439 out of -5.101). The contrast between the two benchmarks is informative about the mechanism. GMV endogenously tilts toward low-volatility and low-correlation names, which partially insulates it from passive-induced synchronisation and leaves a comparatively larger role for the marginal-risk channel. Risk parity, which spreads risk uniformly across the cross-section, has no such defence: almost the entire loss in diversification benefits is attributable to the off-diagonal entries of the covariance matrix.

Note that in Panel A the two channels reinforce each other, whereas in Panel B they work in opposite directions. Removing passive investors raises individual stock volatilities, which by itself would push counterfactual portfolio volatility up and therefore contributes negatively to $\Delta\sigma$. For the GMV portfolio the marginal risk and rebalancing component reduce the portfolio volatility by 16.900% against a positive correlation component of 20.220%. Overall, the volatility of the GMV portfolio falls by 3.320% after removing passive investors and reallocating their AUM to active ones. For risk parity the offset is substantial: the correlation channel alone would imply a 35.360% increase in portfolio volatility, of which 15.558 percentage points are undone by higher counterfactual idiosyncratic volatility and the associated reweighting, leaving a net increase of 19.802%.

4.3 The dynamics of risk-sharing capacity

Figure 2 reports the time-series decomposition of ΔDB for the global minimum variance (Panel A) and risk parity (Panel B) portfolios. The qualitative picture is the same in both: diversification benefits would have been systematically higher in an economy without passive investors, and the gap widens markedly during and after recessions. Quantitatively, the two benchmarks differ in both scale and composition. The risk parity gap is roughly three times as large at its trough (about -16% in 2013-2014 against -5.5% for GMV) consistent with the aggregates in Table 4, and it is almost entirely a correlation phenomenon: the marginal-risk component (yellow bars) never accounts for more than a thin share of the total, while the correlation component (blue bars) traces the black line closely throughout.

For GMV the correlation component also dominates on average, but the marginal-risk share is materially larger than for risk parity, and it becomes more prominent in the last part of the sample: from 2016 onward the yellow bars account for a growing fraction of a gap that is itself narrower than in 2010–2015. This is what one expects from a variance-minimising rule, which endogenously reweights away from the most synchronised names and therefore retains comparatively more exposure to the individual-volatility channel; risk

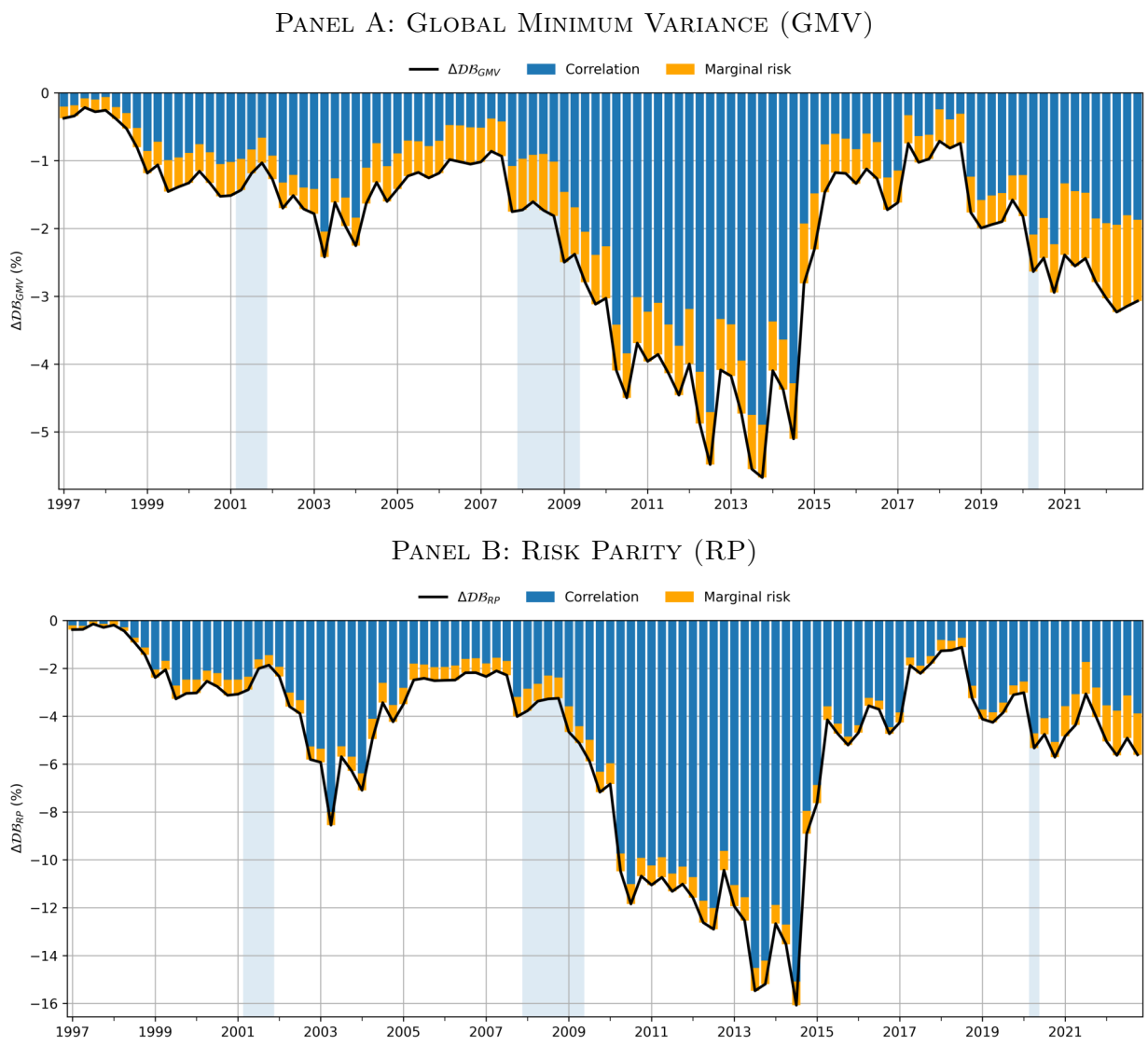
parity, by spreading weights uniformly, has no such defence against the off-diagonal entries of the covariance matrix.

The correlation component is also the more variable of the two in both panels: its time-series standard deviation is almost five times that of the marginal-risk component (1.2% against 0.24% for GMV), so that almost all of the movement in $\Delta\mathcal{DB}$ over the sample is attributable to changes in return comovement. The correlation gap widens sharply during and after recessions — most visibly in the post-2008 period, where it stays elevated until the abrupt narrowing in 2015 — while the marginal-risk component is comparatively stable. Both the level and the timing of the erosion of diversification benefits are therefore governed primarily by return synchronisation, with individual volatilities contributing a steadier, second-order share that matters most for the portfolio best placed to avoid high-correlation assets.

With prices set by investors who trade on heterogeneous information and beliefs and exploit firm-specific information, return comovement declines, weakening the common factor structure that characterizes markets with large passive participation. As a result, assets again provide insurance against each other, and portfolio diversification becomes more effective. On the other hand, through their common trades shocks, passive investors have dampened individual volatilities. Removing their demand from the market suggests a reallocation from aggregate to idiosyncratic risk.

Figure 3 reports the decomposition of $\Delta\sigma$ into a correlation component and a combined marginal-risk and rebalancing component, for the global minimum variance (Panel A) and risk parity (Panel B) portfolios. The two panels tell the same story at different scales. In both, the correlation component (blue bars) is positive throughout the sample: passive ownership raises minimum attainable portfolio volatility by synchronising returns, so that removing passive investors would reduce correlations, make diversification more effective and lower the equity risk floor. The combined marginal-risk and rebalancing component (yellow bars) is negative and works in the opposite direction. When passive investors are absent,

Figure 2: Decomposition of $\Delta\mathcal{DB}$



Notes: This figure reports the decomposition of the difference between observed and counterfactual diversification benefits $\Delta\mathcal{DB}$ (Eq. 20) for the Global Minimum Variance (Panel A) and Risk Parity (Panel B) portfolios. Counterfactual diversification benefits are computed on equilibrium returns after removing passive investors and reallocating their assets under management to active ones. The correlation component (blue bars) lets only return correlations move to their counterfactual values, holding individual volatilities at their observed level. The marginal risk component (yellow bars) then lets individual volatilities move to their counterfactual values, holding correlations at their counterfactual level. The marginal risk component (yellow bars) lets only individual volatilities move, holding the off-diagonal entries at their counterfactual values. The two components sum to the total change in diversification benefits, denoted by the black line, and are expressed as a percentage of the counterfactual level. Shaded areas indicate NBER recession periods. Covariance matrices are estimated over a 24-quarter rolling window with Ledoit and Wolf (2004) linear shrinkage.

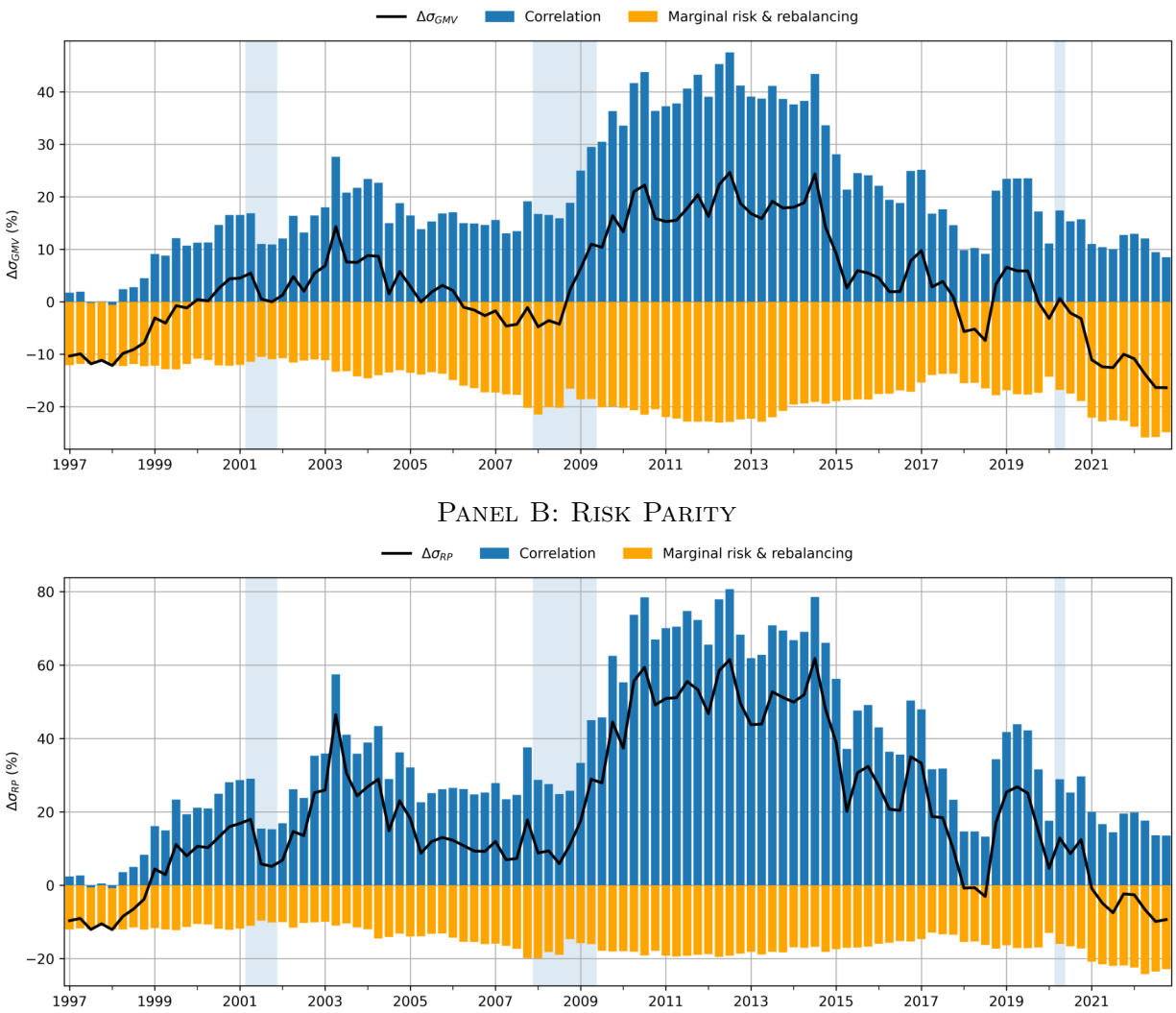
prices are set by more elastic investors that respond to firm-specific information, individual return volatilities rise, and this increase in marginal risk pushes counterfactual portfolio volatility up; the associated reweighting of the portfolio partially offsets the effect, but is limited by the short-selling constraint.

The net effect, given by the black line, is positive over most of the sample and is dominated by the correlation channel. It is largest during and after periods of financial stress: both panels peak in the years following the global financial crisis, with $\Delta\sigma_{GMV}$ reaching roughly 20% in 2012–2013 and $\Delta\sigma_{RP}$ close to 60% over the same window, before narrowing sharply after 2015. The risk parity decomposition is the more extreme of the two on both sides: the correlation component is larger, consistent with a rule that spreads weights uniformly and therefore has no defence against passive-induced synchronisation, and the offsetting marginal-risk and rebalancing component is larger in absolute value as well, in line with the aggregate figures reported in Table 4. The global minimum variance portfolio, which endogenously tilts toward low-volatility and low-correlation assets, is partially insulated from both channels.

The final years of the sample are an exception worth noting. From 2021 onwards the black line turns negative in both panels, so that observed portfolio volatility falls below its counterfactual counterpart. In this period the rise in individual volatilities implied by removing passive demand is large enough to dominate the decorrelation benefit, reversing the sign of the total effect. The full-sample averages in Table 4 therefore mask meaningful time variation, and the erosion of risk-sharing capacity documented here is concentrated in, rather than uniform across, the post-crisis period.

In conclusion, passive investing reshapes the composition of risk in financial markets. By generating common, price-insensitive demand across a broad set of assets, passive funds compress idiosyncratic price movements and lower firm-level volatility. At the same time, this common demand synchronizes asset returns, increasing return comovement and reducing diversification benefits. As a result, risk becomes increasingly concentrated in the aggregate

Figure 3: Decomposition of $\Delta\sigma$



Notes: This figure reports the decomposition of the difference between observed and counterfactual portfolio volatility $\Delta\sigma$ (Eq. 21) for the Global Minimum Variance portfolio (Panel A) and the Risk Parity portfolio (Panel B). Counterfactual volatility is computed on equilibrium returns after removing passive investors and reallocating their assets under management to active ones. The correlation component (blue bars) lets only return correlations move to their counterfactual values, holding individual volatilities at their observed level. The remaining change is reported as a single marginal risk and rebalancing component (orange bars), combining the change arising from individual volatilities moving to their counterfactual values with the change arising from portfolio weights adjusting to the counterfactual variance-covariance matrix. The total change in portfolio volatility is denoted by the black line. Shaded areas indicate NBER recession periods. Covariance matrices are estimated over a 24-quarter rolling window with Ledoit and Wolf (2004) linear shrinkage.

dimension, weakening the economy's capacity to absorb aggregate shocks: losses become more simultaneous across assets and harder to diversify precisely when diversification is most valuable. From a financial stability perspective, the expansion of passive investing therefore entails a trade-off between lower idiosyncratic volatility and higher systematic risk.

Importantly, the counterfactual exercise maintains the identifying assumption that investors' demand elasticities remain constant when passive flows are removed. In general equilibrium, active investors might respond to the absence of passive competition by adjusting their own strategies. However, Haddad et al. (2025) document that the strategic interaction of investors, i.e. the extent to which investors respond to changes in market aggregate elasticity by adjusting their trading strategy, is limited by many forces. For instance, costly information acquisition, bounded rationality and strategic complementarities might place a limit on investors' ability and willingness to change their trading aggressiveness in response to the disappearance of passive investors. Consequently, my counterfactual should be interpreted as a partial equilibrium exercise that isolates the mechanical effect of passive fund flows on the covariance structure, holding investor behaviour fixed, providing a bound on the true impact.

A second limitation concerns the scope of the demand system itself. Portfolio weights in Eq. 11 are estimated on 13F long positions and, under the logit specification of Koijen and Yogo (2019), are restricted to be non-negative. The counterfactual therefore cannot accommodate active investors taking short or effectively negative positions in individual stocks. This matters for comparison with Jiang et al. (2025), whose amplification mechanism operates precisely through this margin: passive inflows into large firms with high non-fundamental demand force active investors to scale up short positions, and the resulting increase in the risk borne on those positions raises equilibrium prices further and amplifies absolute idiosyncratic price movements. This channel is absent from my framework by construction. As a consequence, the counterfactual likely understates any volatility-amplifying effect of passive demand for the small set of mega-capitalisation stocks that active investors hold at

substantial underweights. Short positions are, however, small relative to passive holdings: short interest averages 3.7% of shares outstanding over the sample, against a value-weighted passive ownership of 41%, and the cross-sectional patterns documented below are similar for stocks with low and high short interest (Appendix F).

4.4 Which stocks become riskier?

The decomposition in Section 4.2 shows that passive investors raise the volatility of the global minimum-variance and risk parity portfolios because of increased correlation risk. This aggregate result, however, leaves open an important question: which stocks in the cross-section contribute more to marginal risk and correlation. To understand which stocks drive these effects, I examine how individual stock risk characteristics change when passive investors are removed. Following the literature on return comovement and idiosyncratic volatility (Campbell et al., 2001; Morck et al., 2000; Lochstoer and Muir, 2026), I decompose each stock's return variance into systematic and idiosyncratic components. For each stock n and quarter t, I estimate a market model regression using a 24-quarter rolling window:

$$R_{n,t} = \alpha_n + \beta_n R_{mkt,t} + \varepsilon_{n,t} \tag{22}$$

where $R_{n,t}$ is stock n's return in quarter t, $R_{mkt,t}$ is the value-weighted market return including all stocks in my sample, and $\varepsilon_{n,t}$ is the idiosyncratic component orthogonal to the market factor. The market return is constructed as the value-weighted portfolio of all stocks in the sample, using beginning-of-period market capitalizations as weights.

From this regression, I extract four key statistics. First, the idiosyncratic variance $\sigma^2_{\varepsilon,n}$ captures firm-specific risk unrelated to aggregate market movements. Second, the systematic variance component $\beta_n^2 \sigma^2_{mkt}$ measures exposure to the common market factor. Third, the market model R^2 summarizes the fraction of return variance explained by the market, providing a scalar measure of comovement with the aggregate factor. Fourth, I compute the

average pairwise correlation $\bar{\rho}_n$ as the mean correlation between stock n and all other stocks in the sample, following Pollet and Wilson (2010).

These statistics relate to the portfolio-level decomposition in a natural way. The idiosyncratic variance $\sigma^2_{\varepsilon,n}$ corresponds to the marginal risk component: stocks with higher firm-specific volatility contribute more to portfolio variance when held in diversified portfolios. The R^2 and average correlation $\bar{\rho}_n$ capture exposure to common factors, corresponding to the correlation component. The market model framework is standard in the comovement literature (Morck et al., 2000; Jin and Myers, 2006; Fang et al., 2024) and provides a transparent decomposition of variance into systematic and idiosyncratic components without imposing equilibrium restrictions.

I compute these statistics for both observed and counterfactual returns. In the counterfactual, I use equilibrium prices from the demand system estimation in Section 4, which removes passive investors while reallocating their assets under management to active investors. Critically, the counterfactual market return $R^{cf}_{mkt,t}$ is endogenous: it reflects both the direct effect of changed individual stock prices and the compositional shift in market weights. This ensures that the market model decomposition captures the general equilibrium effects of removing passive ownership.

For each stock n, I compute the change in each risk statistic as the difference between its observed and counterfactual values, so that a negative change indicates that the statistic is lower in the presence of passive investors. I construct passive ownership deciles each quarter by sorting all stocks into ten equal-sized groups based on their passive ownership $PO_{n,t}$. For each decile d and quarter t, I compute the median change in each risk measure across all stocks in that decile, and report the time-series median of these quarterly decile medians. Sorting within each quarter ensures that differences across deciles are not driven by the upward trend in passive ownership over the sample. This procedure, which resembles the portfolio sorting approach common in asset pricing (Fama and French, 1993), provides a nonparametric assessment of how risk changes scale with passive ownership without imposing

functional form assumptions. Table 5 reports these decile medians alongside the median passive ownership within each decile.

Table 5: Stock-Level Risk Changes by Passive Ownership Decile

PO Decile	Median PO	InstHHI	Changes (Observed - Counterfactual)						
			$\Delta\sigma^2$ (%)	$\Delta\sigma^2_\varepsilon$ (%)	$\Delta(\beta^2\sigma^2_{mkt})$	ΔR^2	$\Delta\bar{\rho}$	$\Delta\bar{\rho}^{ex}$	$\Delta\beta$
1	0.037	0.694	-9.1	-7.5	-0.0002	-0.000	0.005	-0.002	-0.064
2	0.111	0.503	-9.5	-7.7	-0.0003	0.001	0.019	0.002	-0.061
3	0.189	0.349	-10.3	-10.7	-0.0003	-0.001	0.025	0.008	-0.094
4	0.250	0.232	-13.0	-14.5	-0.0002	0.006	0.034	0.012	-0.055
5	0.306	0.158	-15.5	-21.5	-0.0002	0.021	0.043	0.013	-0.040
6	0.353	0.115	-18.5	-26.8	-0.0001	0.027	0.048	0.013	-0.026
7	0.397	0.096	-21.3	-31.1	-0.0000	0.038	0.053	0.015	0.005
8	0.438	0.082	-25.9	-35.4	-0.0000	0.045	0.053	0.016	0.006
9	0.483	0.070	-29.9	-41.2	0.0001	0.054	0.059	0.016	0.027
10	0.560	0.061	-39.3	-49.5	0.0004	0.070	0.063	0.016	0.067

Notes: This table reports median changes in stock-level risk characteristics by passive ownership decile when passive investors are removed in the counterfactual. InstHHI is the institutional ownership Herfindahl–Hirschman index computed over institutional investors reporting in SEC 13F filings. σ^2 is total return variance, σ^2_ε is idiosyncratic variance from market model $R_i = \alpha + \beta R_{mkt} + \varepsilon$, $\beta^2\sigma^2_{mkt}$ is systematic variance component, R^2 is market model R-squared, $\bar{\rho}$ is average pairwise raw correlation with other stocks, $\bar{\rho}^{ex}$ is average pairwise excess correlation of market-model residuals, and β is market beta. All statistics are computed using 24-quarter rolling windows. Stocks are sorted into deciles within each quarter; the table reports time-series medians of the quarterly decile medians of observed minus counterfactual values. Sample: 1997Q1–2022Q4.

Table 5 reports median changes in stock-level risk characteristics by passive ownership decile. The effects scale strongly with passive ownership. Both total and idiosyncratic variance are lower in the observed economy than in the counterfactual in every decile, and the gap widens monotonically with passive ownership: idiosyncratic variance σ^2_ε is 7.5% lower in the lowest PO decile and 49.5% lower in the highest. This pattern directly validates the marginal risk channel: price-insensitive demand substantially compresses the firm-specific volatility of stocks with high passive ownership. In contrast, the systematic variance component $\Delta(\beta^2\sigma^2_{mkt})$ is close to zero in all deciles, indicating that passive investing primarily affects firm-specific rather than market-wide risk.

Comovement moves in the opposite direction. The market-model R^2 is essentially unchanged for the three lowest PO deciles and then rises steadily, reaching 7.0 percentage points in the highest decile, so that passive ownership strengthens the comovement of individual stocks with the market factor. Average pairwise correlation $\Delta\bar{\rho}$ increases with passive

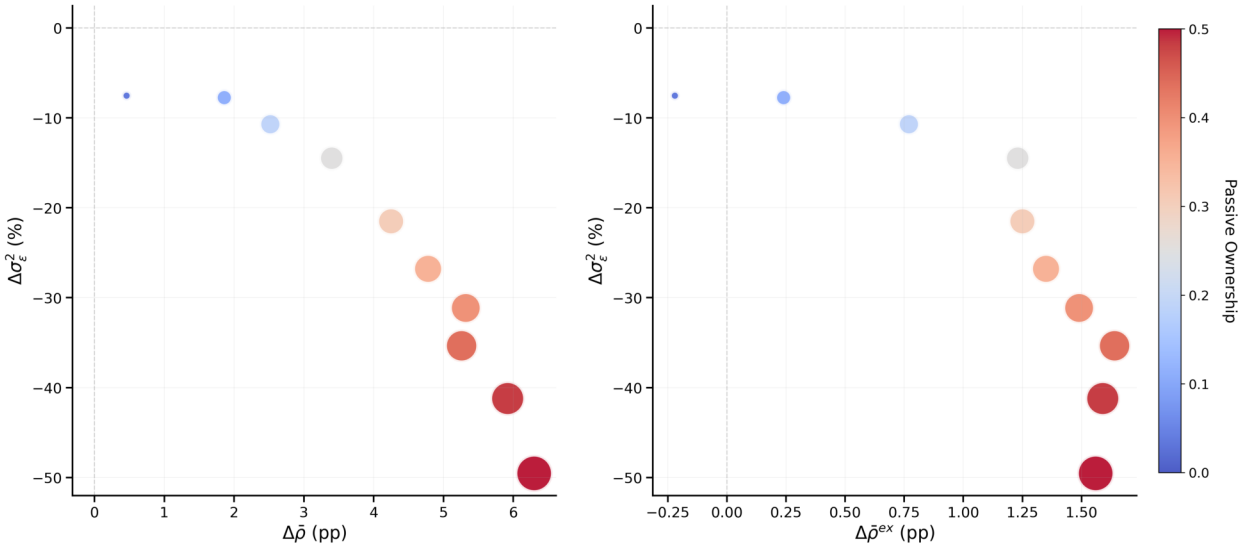
ownership across the whole distribution, from 0.5 percentage points in the lowest decile to 6.3 percentage points in the highest. This captures the correlation channel: passive ownership increases return synchronization through common demand shocks.

Market beta $\Delta\beta$ is lower in the observed economy for low- and mid-PO stocks and higher for high-PO stocks (+0.067 in the highest decile). This reflects the endogenous reweighting of the market portfolio: when passive investors are removed, high-PO stocks receive less weight in the market return, which mechanically reduces their measured beta in the counterfactual.

Table 5 also reveals a monotonic decline in institutional ownership concentration (InstHHI) across passive ownership deciles, from 0.694 in the lowest decile to 0.061 in the highest. This gradient reflects a fundamental shift in the identity of the marginal price-setter. When a stock is held predominantly by concentrated active investors, prices respond to firm-specific information, such as earnings surprises and competitive dynamics, keeping idiosyncratic volatility high and return synchronization low. As passive ownership increases, the marginal price-setter shifts to funds that trade on index weights rather than fundamentals, so firm-specific news is incorporated into prices more slowly and less completely. The result is a simultaneous compression of idiosyncratic volatility and increase in return synchronization. Moving from the lowest to the highest passive ownership decile, the reduction in idiosyncratic variance grows from 7.5% to 49.5%, while the increase in average pairwise correlation grows from 0.5 to 6.3 percentage points. The two effects push diversification benefits in opposite directions, and which one prevails depends on how a portfolio weights individual stocks. The portfolio-level decomposition in Section 4.2 shows that, for the benchmark portfolios, the correlation channel dominates.

Figure 4 visualizes the trade-off between correlation and volatility changes. Each circle represents a passive ownership decile, with size and colour intensity proportional to its median passive ownership. In both panels, the vertical axis shows the change in idiosyncratic variance, while the horizontal axis shows the change in average pairwise correlation, raw (left

Figure 4: Risk reallocation by passive ownership



This figure reports the changes in correlation and idiosyncratic variance ($\Delta\sigma_\varepsilon^2$) between the observed economy and the counterfactual in which passive investors are removed and their assets under management are reallocated to active investors (observed minus counterfactual). The left panel plots the change in average pairwise raw correlation ($\Delta\bar{\rho}$) against $\Delta\sigma_\varepsilon^2$. The right panel plots the change in average pairwise excess correlation ($\Delta\bar{\rho}^{ex}$), defined as the average pairwise correlation of market-model residuals, against $\Delta\sigma_\varepsilon^2$. The idiosyncratic variance σ_ε^2 is computed from the market model $R = \alpha + \beta R_{mkt} + \varepsilon$. Each circle represents a passive ownership decile, with size and colour intensity proportional to median passive ownership. Values are the time-series medians of quarterly decile medians reported in Table 5. Sample: 1997Q1–2022Q4.

panel) and excess (right panel). The left panel shows that as passive ownership increases (larger, red circles), deciles move steadily towards the bottom-right: stocks with more passive ownership display both higher return correlations and lower idiosyncratic variance than in the counterfactual. The right panel shows that the trade-off persists after removing common factor variation. Excess correlations are slightly negative for the lowest passive ownership decile, increase up to the seventh decile, and remain at about 1.6 percentage points in the highest deciles, while the compression of idiosyncratic variance keeps deepening. This is consistent with passive ownership generating some return synchronization through price-insensitive demand, in addition to the larger component that operates through common factor exposure. Table E1 shows that this residual gradient survives the inclusion of an industry factor in the market model. Overall, the figure summarizes the risk reallocation induced by passive investors: removing passive ownership shifts risk from the correlation dimension back to the idiosyncratic dimension, and both shifts are largest for the stocks

most held by passive funds.

Table 6: Passive Ownership and Stock-Level Risk Changes

	(1) $\Delta\sigma^2$ (%)	(2) $\Delta\sigma^2_\varepsilon$ (%)	(3) $\Delta(\beta^2\sigma^2_{mkt})$	(4) ΔR^2	(5) $\Delta\bar{\rho}$	(6) $\Delta\bar{\rho}^{ex}$	(7) $\Delta\beta$
Panel A: Cross-sectional regressions							
PO	-57.634***	-97.948***	0.016**	0.234***	0.211***	-0.020**	0.671***
	(6.8528)	(6.8756)	(0.0075)	(0.0254)	(0.0159)	(0.0093)	(0.1128)
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	5,239	5,239	5,239	5,239	5,239	5,239	5,239
R^2	0.097	0.141	0.027	0.047	0.095	0.044	0.016
Panel B: Panel regressions							
PO (lagged)	-13.038***	-28.416***	-0.002	0.120***	0.076***	0.008*	0.485***
	(2.7535)	(2.8124)	(0.0028)	(0.0136)	(0.0077)	(0.0042)	(0.0417)
Controls	✓	✓	✓	✓	✓	✓	✓
Stock FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Observations	161,173	161,173	161,173	161,173	161,173	161,173	161,173
R^2	0.002	0.009	0.002	0.009	0.013	0.002	0.016

Notes: This table reports regression results of stock-level risk changes on passive ownership. Panel A shows cross-sectional regressions on stock-level time-series medians. Panel B shows panel regressions with stock and time fixed effects and lagged passive ownership (8 quarters). Dependent variables are changes between observed and counterfactual values. Controls include institutional ownership (IO), institutional HHI, market equity (log), liquidity, and effective elasticity. Standard errors in parentheses are heteroskedasticity-robust (Panel A) or clustered at the stock level (Panel B). Passive ownership is expressed as a fraction (0–1), so coefficients give the change for a one-unit (100 percentage point) increase in PO; a 10 percentage point increase corresponds to one tenth of the reported coefficient. Dependent variables in columns (1)–(2) are in percent; those in columns (3)–(7) are in levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 reports regressions of stock-level risk changes on passive ownership. Panel A shows cross-sectional regressions on stock-level time-series medians, while Panel B presents panel regressions with stock and time fixed effects and passive ownership lagged eight quarters. All specifications control for institutional ownership, institutional concentration, market equity, Amihud liquidity, and effective elasticity, whose construction is described in Appendix E. Since the dependent variables are differences between observed and counterfactual values, the coefficients measure how the effect of passive investors on each risk characteristic varies with a stock's passive ownership, holding the controls fixed. The results confirm the patterns documented in the decile analysis: stocks with higher passive ownership display a larger reduction in idiosyncratic variance and a larger increase in comovement.

A 10 percentage point increase in passive ownership is associated with an additional 9.8% reduction in idiosyncratic variance in the cross-section and 2.8% in the panel specification (column 2). High-PO stocks therefore exhibit substantially compressed firm-specific volatility in the observed data, as common demand shocks from passive funds smooth firm-specific price movements. The panel estimates are smaller than the cross-sectional ones because fixed effects absorb time-invariant stock characteristics, yielding a more conservative within-stock comparison. The systematic variance component in column (3) is economically negligible in both specifications (0.016 in Panel A and -0.002 in Panel B), confirming that the effect operates through firm-specific rather than market-wide risk.

The comovement effects in columns (4) and (5) are precisely estimated and economically meaningful. A 10 percentage point increase in passive ownership raises the market-model R^2 by about 2.3 percentage points in the cross-section and 1.2 percentage points in the panel, and average pairwise correlation by 2.1 and 0.8 percentage points, respectively. This is consistent with passive ownership increasing return synchronization through common demand shocks. Column (7) shows that the change in market beta also increases with passive ownership, in line with the reweighting of the market portfolio discussed above.

Evidence on excess correlations in column (6) is mixed. In the panel specification, a 10 percentage point increase in passive ownership raises the average pairwise correlation of market-model residuals by 0.08 percentage points, significant only at the 10% level. In the cross-section, the coefficient is negative and significant at the 5% level, although economically small (0.2 percentage points for a 10 percentage point increase). Most of the synchronization induced by passive ownership therefore operates through comovement with the market factor, with at most a limited role for correlation beyond it. Where that residual component appears, in the decile sorts of Table 5, it is not explained by industry exposure (Table E1). Consistently, in the reduced-form analysis the effect of passive ownership on excess correlations is concentrated in recession periods (Table C6).

4.5 The intensive margin of passive investing

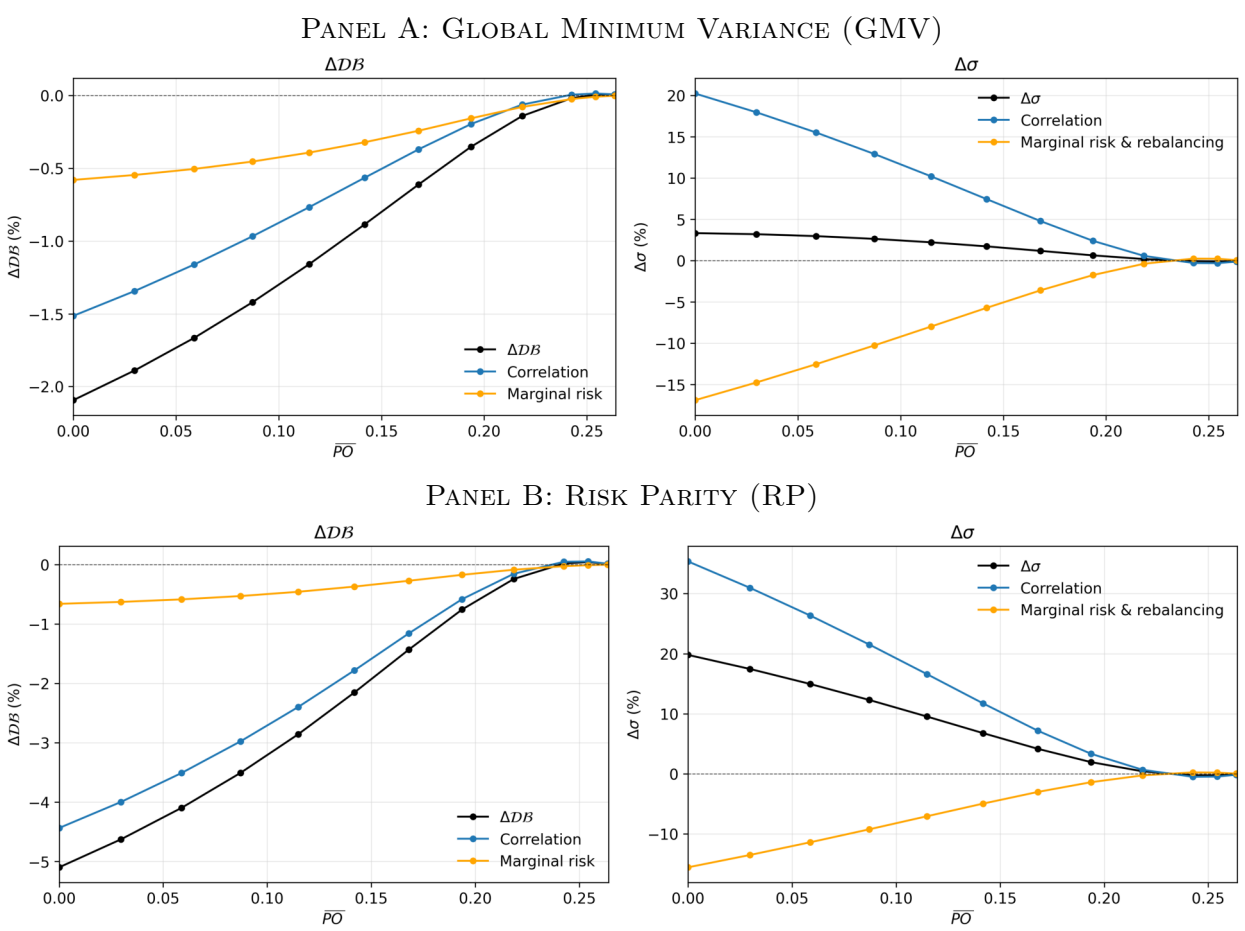
Section 4.2 studies the extensive margin, removing passive investors altogether. This section studies the intensive margin: passive investors remain in the counterfactual economy, but with less capital.[7] Specifically, I scale the assets under management of each passive investor by a factor $\phi \in [0, 1]$ and reallocate the remaining $(1 - \phi)$ share to active investors in proportion to their assets under management, as in the baseline counterfactual. The case $\phi = 0$ corresponds to the counterfactual of Section 4.2, and $\phi = 1$ to the observed economy.

Figure 5 reports the results. For each value of ϕ, I solve for the counterfactual equilibrium and compute the percentage change in diversification benefits and portfolio volatility, together with their components, exactly as in Table 4. Rather than plotting these changes against ϕ, I plot them against the average passive ownership that each counterfactual implies, $\overline{PO}(\phi)$, defined as the time-series average of the cross-sectional mean of passive ownership in the counterfactual economy. This choice allows a direct comparison with the historical level of passive ownership. The mapping from ϕ to $\overline{PO}$ is monotone: $\overline{PO}(0) = 0$ corresponds to the baseline counterfactual, $\overline{PO}(1) = 0.263$ to the observed economy, and intermediate values lie slightly above $\phi\,\overline{PO}(1)$ because counterfactual prices, and hence the ownership shares implied by a given amount of passive capital, adjust with ϕ. The pre-1997 average passive ownership of 12.3% corresponds to $\phi \approx 0.43$. Reading the figure from left to right therefore traces the growth of the passive sector from zero to its observed size, and the vertical distance between a curve and zero measures how much of the total effect is attributable to the growth of passive ownership beyond that level, that is, the part that would have been avoided had passive ownership stopped there.

The effects scale smoothly with the size of the passive sector, and the pattern is similar across the two benchmark portfolios. Losses in diversification benefits grow almost linearly with $\overline{PO}$, somewhat faster between 10% and 20% passive ownership, and the correlation

[7] The exercise differs from studying the marginal effect of additional passive flows at current ownership levels, as in Jiang et al. (2025).

Figure 5: Decomposition of $\Delta\mathcal{DB}$ and $\Delta\sigma$



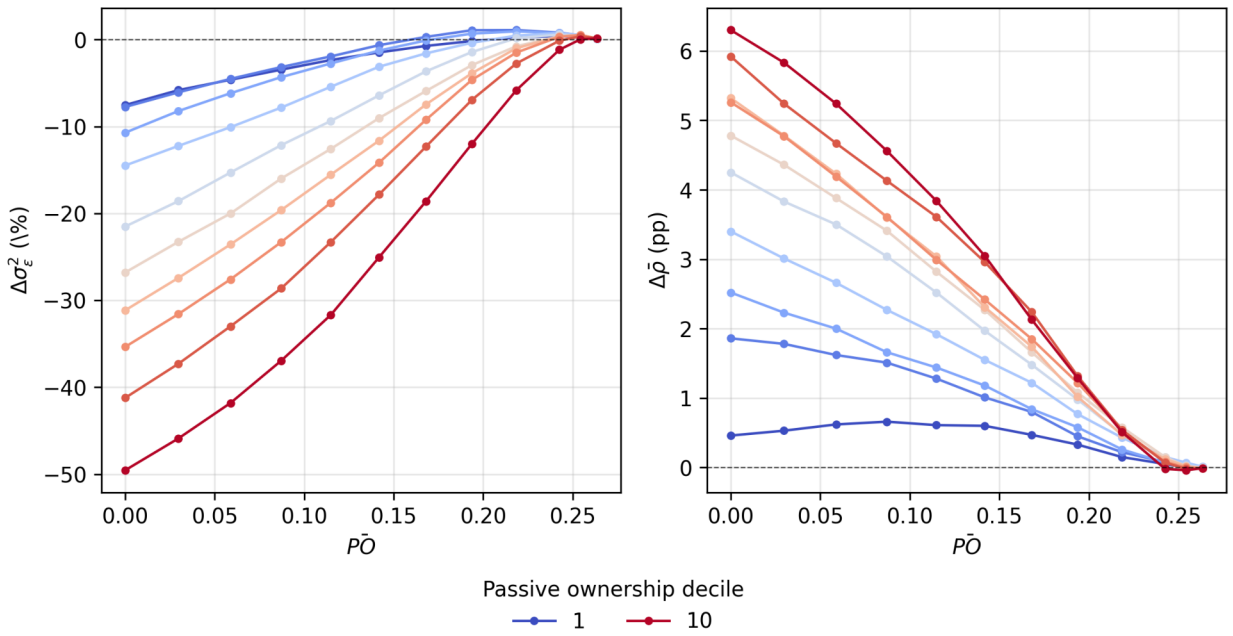
Notes: This figure reports the percentage change in diversification benefits $\Delta\mathcal{DB}$ (left) and portfolio volatility $\Delta\sigma$ (right) between the observed economy and counterfactual economies in which the assets under management of each passive investor are scaled by $\phi \in [0,1]$, with the remaining $(1-\phi)$ share reallocated to active investors in proportion to their size, for the Global Minimum Variance (Panel A) and Risk Parity (Panel B) portfolios. Each point corresponds to one value of ϕ and is placed at the average passive ownership implied by that counterfactual, $\overline{PO}(\phi)$, defined as the time-series average of the cross-sectional mean of passive ownership in the counterfactual economy. $\phi = 0$ corresponds to the baseline counterfactual of Table 4 and $\phi = 1$ to the observed economy. Totals are decomposed into a correlation and a marginal risk component for $\Delta\mathcal{DB}$ (Eq. 20), and into a correlation and a combined marginal risk and rebalancing component for $\Delta\sigma$ (Eq. 21). Components are scaled by the counterfactual level. Covariance matrices are estimated over a 24-quarter rolling window with Ledoit and Wolf (2004) linear shrinkage. Sample: 1997Q1–2022Q4.

channel accounts for most of the loss at every level. For the GMV portfolio, the loss rises from about 1.2% at the pre-1997 level of passive ownership to 2.1% under full removal; for the risk-parity portfolio, from about 2.8% to 5.1%. In both cases, the growth of passive investing since the late 1990s accounts for roughly half of the total effect. The marginal-risk component is small and varies little with $\overline{PO}$, especially for the risk-parity portfolio, so the mechanism identified in Section 4.2 does not hinge on the extreme scenario in which passive investors disappear.

Portfolio volatility shows a sharper difference between the two benchmarks. For both portfolios, the correlation component rises steadily as passive ownership grows, reaching about 20% for GMV and 35% for risk parity under full removal, and is partly offset by the combined marginal-risk and rebalancing component. For the risk-parity portfolio the offset is less than half of the correlation effect at every level, so volatility increases substantially with passive ownership: by about 9% at the pre-1997 level and 20% under full removal. For the GMV portfolio the offset grows almost one-for-one with the correlation effect, because variance minimisation reweights away from stocks whose idiosyncratic volatility falls less; the net increase in minimum volatility therefore remains small throughout, at about 2% at the pre-1997 level and 3% under full removal. Finally, the curves flatten as PO approaches its observed level, indicating that the marginal effect of passive capital declines with the size of the passive sector: the effects documented in this paper stem from the cumulative growth of passive ownership rather than from its most recent increments.

The cross-sectional patterns documented in Section 4.4 scale in the same way. Figure 6 reports, for each passive ownership decile, the changes in idiosyncratic variance and average pairwise correlation as a function of the average passive ownership implied by each counterfactual. At every level of $\overline{PO}$, stocks with higher passive ownership display a larger compression of idiosyncratic variance and a larger increase in return correlation, and the ranking across deciles is preserved as the counterfactual economy approaches the observed one. The cross-sectional gradient documented in Table 5 is therefore not an artefact of

Figure 6: Stock-level changes



Notes: This figure reports, for each passive ownership decile, the change in idiosyncratic variance ($\Delta\sigma^2_\varepsilon$, left) and in average pairwise correlation ($\Delta\bar{\rho}$, right) between the observed economy and counterfactual economies in which the assets under management of each passive investor are scaled by $\phi \in [0, 1]$, with the remainder reallocated to active investors (observed minus counterfactual). Each point corresponds to one value of ϕ and is placed at the average passive ownership implied by that counterfactual, $\overline{PO}(\phi)$. Stocks are sorted into deciles within each quarter on observed passive ownership, from decile 1 (blue) to decile 10 (red); values are time-series medians of quarterly decile medians. Covariance matrices are estimated over a 24-quarter rolling window with Ledoit and Wolf (2004) linear shrinkage. Sample: 1997Q1–2022Q4.

removing passive investors altogether. Its magnitude, however, grows with the size of the passive sector. Relative to a counterfactual in which passive ownership had remained at its pre-1997 level, observed idiosyncratic variance in the highest passive ownership decile is about 30% lower and average correlation about 3.6 percentage points higher, roughly 60% of the corresponding effects under full removal. The growth of the passive sector since the late 1990s therefore accounts for about 60% of the cross-sectional risk reallocation documented in Table 5. Stocks with the lowest passive ownership, in contrast, are barely affected at any level of $\overline{PO}$: their average correlation changes by less than one percentage point throughout.

5 Welfare analysis

The preceding analysis establishes that passive investing reallocates risk from idiosyncratic to common components, lowering diversification benefits and raising the market's risk floor. This section asks what this reallocation implies for the institutions that actually hold stocks: how it changes their risk and welfare, and which of them gain or bear more comovement risk.

5.1 Welfare measure

Koijen and Yogo (2019) emphasize that the demand system determines prices, but that welfare questions cannot be answered without taking an explicit stance on investors' preferences, beliefs and constraints. I take this stance by evaluating welfare with the objective from which characteristics-based demand is derived, so that the welfare measure is consistent with the estimated demand system. The characteristics-based demand in Eq. (11) can be interpreted as the portfolio of a mean-variance investor whose beliefs about expected returns and risk are functions of stock characteristics (Koijen and Yogo, 2019). Suppose investor k maximizes $\mathbf{w}'\boldsymbol{\mu}_k - \frac{\gamma_k}{2}\mathbf{w}'\Sigma_k\mathbf{w}$ subject to $\mathbf{w} \geqslant 0$, and perceives a factor structure $\Sigma_k = B_k\Omega_k B_k' + D_k$, with D_k diagonal. Appendix I shows that the weight on any stock the investor holds is

$$w_{k,n} = \frac{\mu_{k,n} - \mathbf{b}_{k,n}'\boldsymbol{\lambda}_k}{\gamma_k\,\sigma_{k,n}^2}, \qquad \boldsymbol{\lambda}_k \equiv \gamma_k\,\Omega_k B_k'\mathbf{w}_k, \tag{23}$$

where $\mathbf{b}_{k,n}$ and $\sigma_{k,n}^2$ are stock n's factor loadings and idiosyncratic variance. The covariance matrix enters each weight only through the stock's own loadings and idiosyncratic variance and through the investor-level vector $\boldsymbol{\lambda}_k$. When $\mu_{k,n}$, $b_{k,n}$ and $\sigma_{k,n}^2$ are functions of stock characteristics (which include market beta), $w_{k,n}$ depends on stock n's characteristics and on investor-level constants absorbed by the investor-quarter coefficients. Eq. (11) approximates this function with an exponential, as in Koijen and Yogo (2019), and the latent demand $\epsilon_{k,n}$ captures beliefs not spanned by observed characteristics. Since 13F filings report only

long positions, latent demand is restricted to be non-negative, so that portfolio weights are non-negative as well (Appendix F assesses how restrictive this is). Mean-variance utility is therefore the objective that rationalizes the estimated demand, not an additional assumption. The same framework nests the benchmark portfolios of Section 4.2: the GMV portfolio is the mean-variance optimum when expected returns are equal across stocks, and the risk parity portfolio when Sharpe ratios are equal and correlations constant (Maillard et al., 2010).

The benchmark portfolios and active investors differ in what they know. GMV and risk parity are computed from Σ itself and re-optimize when it changes: the change in their certainty equivalent measures how passive investing affects the *opportunity set* available to an investor who observes the covariance matrix. Active investors' beliefs are instead encoded in their characteristic coefficients, which the counterfactual holds fixed: their portfolios respond to counterfactual prices through Eq. (11) but not to the change in Σ, which their beliefs do not register. For them I measure *experienced* welfare, the certainty equivalent of their own mean-variance objective evaluated under the equilibrium distribution of returns:

$$CE_{k,t} = (w_{k,t})' \mu_t - \frac{\gamma}{2} (w_{k,t})' \Sigma_t w_{k,t}, \tag{24}$$

computed with observed weights, moments and prices in the observed economy and with counterfactual ones in the counterfactual. The gap between the two concepts is the cost of portfolio rules that do not respond to the covariance matrix. Writing $\Delta CE_{k,t} = CE^{obs}_{k,t} - CE^{cf}_{k,t}$,

$$\Delta CE_{k,t} = \underbrace{\left(w^{obs}_{k,t} - w^{cf}_{k,t}\right)' \mu_t}_{\text{portfolio reallocation}} - \frac{\gamma}{2}\Big(\underbrace{\Delta\sigma^{2,\rho}_{k,t}}_{\text{correlation}} + \underbrace{\Delta\sigma^{2,m}_{k,t}}_{\text{marginal risk}} + \underbrace{\Delta\sigma^{2,r}_{k,t}}_{\text{rebalancing}} \Big), \tag{25}$$

where

$$\Delta\sigma^{2,\rho}_{k,t} = \left(w^{obs}_{k,t}\right)' \Sigma^{obs}_t w^{obs}_{k,t} - \left(w^{obs}_{k,t}\right)' \Sigma^{\rho}_t w^{obs}_{k,t},$$
$$\Delta\sigma^{2,m}_{k,t} = \left(w^{obs}_{k,t}\right)' \Sigma^{\rho}_t w^{obs}_{k,t} - \left(w^{obs}_{k,t}\right)' \Sigma^{cf}_t w^{obs}_{k,t},$$
$$\Delta\sigma^{2,r}_{k,t} = \left(w^{obs}_{k,t}\right)' \Sigma^{cf}_t w^{obs}_{k,t} - \left(w^{cf}_{k,t}\right)' \Sigma^{cf}_t w^{cf}_{k,t}.$$

These are the variance counterparts of the components in Eq. (21), with Σ^{ρ}_t defined as in Eq. (20). Because investors' weights respond to counterfactual prices but not to the covariance matrix, the weights under Σ^{ρ}_t coincide with the observed ones, $w^{\rho}_{k,t} = w^{obs}_{k,t}$. Because utility is linear in variance, the three risk components map additively into welfare.[8]

Welfare is evaluated under the true distribution of returns, so expected returns are common across investors; heterogeneity enters through weights. I do not use historical average returns, which over 24-quarter windows are dominated by sampling noise. I set $\mu_{n,t} = \hat{\beta}_{n,t}\bar{\lambda}$, where $\hat{\beta}_{n,t}$ is stock n's beta with respect to the value-weighted market portfolio of the sample, computed from Σ^{obs}_t, and $\bar{\lambda}$ is the full-sample average quarterly market excess return, following Calvet et al. (2007). Betas and market weights are computed in the observed economy and used in both economies, so that ΔCE isolates the change in risk and the reallocation of portfolio weights.

Risk aversion is not separately identified from beliefs in the demand system, since both are absorbed in the investor-specific coefficients of Eq. (11). I set $\gamma = 1$, which corresponds to the log-utility investor from which Koijen and Yogo (2019) derive characteristics-based demand. Because expected returns are the same in the two economies, the reallocation term in Eq. (25) does not depend on γ, while the risk components scale linearly with it: a higher risk aversion magnifies their contribution to ΔCE but does not change their sign.

[8] Holding expected returns fixed across the two economies excludes the effect of passive demand on price levels, which transfers wealth between buyers and sellers rather than changing risk-sharing capacity.

5.2 Aggregate results

Table 7 decomposes the change in active investors' portfolio volatility and diversification benefits, in percent of the counterfactual level. Observed quantities are computed with investors' observed portfolio weights, counterfactual quantities with the weights they would hold at counterfactual prices. Panel A shows that portfolio volatility is about 5% lower in the presence of passive investors (−4.8% AUM-weighted, −4.0% equal-weighted). This small net change is the sum of two larger effects of opposite sign: higher correlations raise volatility by 8.7%, while lower individual volatilities reduce it by 13.9%; rebalancing contributes 0.4%.[9] Panel B shows that the pattern holds for every investor type. The correlation component ranges from 6.2% for insurance companies to 10.5% for mutual funds, the marginal-risk component from −11.5% to −14.9%, and the net change is negative throughout, from −1.2% for pension funds to −5.1% for banks.

Panels C and D show that diversification benefits are nonetheless lower when passive investors are present: by 11.9% AUM-weighted and 11.4% equal-weighted, with declines between 10.0% and 13.1% across investor types. About four fifths of the decline comes from higher correlations (−9.6% of −11.9%), the remainder from lower individual volatilities. The decline is much larger than for the global minimum variance (2.1%) and risk parity (5.1%) portfolios (Table 4): the portfolios active investors actually hold are more exposed to passive-induced synchronization than either benchmark.

Volatility nonetheless falls for active investors, while it rises for the benchmark portfolios, mainly because active portfolios are far less diversified. The median active investor holds the equivalent of about 55 to 85 equally weighted positions, against 100 to 500 for the benchmark portfolios (Figure G1). Firm-specific risk therefore accounts for a larger share of their portfolio variance, and this is exactly the component that passive investing dampens. In addition, their weights follow their demand for stock characteristics rather than a

[9] Rebalancing components have opposite signs in Tables 7 and 8 for every investor-quarter; their averages can share a sign because the welfare table, in variance units, weights riskier investors and volatile quarters more.

risk-minimization rule: unlike the benchmark portfolios, they do not re-optimize against the counterfactual covariance matrix and therefore do not exploit its lower correlations. Diversification benefits fall in both cases, since their sign does not depend on whether a portfolio responds to the covariance matrix.

Table 7: Decomposition of the change in investors' portfolio volatility and diversification benefits

	Level		Change (% of counterfactual)			
	Observed	Counterfactual	Total	Correlation	Marginal risk	Rebalancing
Panel A: Portfolio volatility σ, all active investors						
AUM-weighted	6.699	7.026	-4.84	8.66	-13.90	0.40
Equal-weighted	6.941	7.228	-4.01	8.05	-12.18	0.11
Panel B: Portfolio volatility σ, by investor type (AUM-weighted)						
Mutual funds	6.919	7.178	-3.43	10.52	-14.89	0.94
Insurance companies	6.984	7.301	-4.66	6.19	-11.45	0.61
Pension funds	5.850	6.048	-1.19	10.10	-13.27	1.99
Other	5.100	5.288	-2.73	7.31	-11.46	1.41
Banks	6.614	6.976	-5.08	8.99	-13.31	-0.75
Investment advisors	6.864	7.203	-4.83	8.13	-13.49	0.53
Panel C: Diversification benefits $\mathcal{DB}$, all active investors						
AUM-weighted	0.497	0.560	-11.95	-9.57	-2.38	—
Equal-weighted	0.497	0.557	-11.44	-8.96	-2.47	—
Panel D: Diversification benefits $\mathcal{DB}$, by investor type (AUM-weighted)						
Mutual funds	0.493	0.564	-13.12	-10.69	-2.43	—
Insurance companies	0.497	0.550	-10.39	-7.92	-2.47	—
Pension funds	0.502	0.571	-12.73	-10.01	-2.72	—
Other	0.492	0.542	-9.98	-7.64	-2.34	—
Banks	0.502	0.566	-12.08	-9.64	-2.44	—
Investment advisors	0.495	0.556	-11.68	-9.38	-2.30	—

Notes: This table decomposes the change in active investors' portfolio volatility (Panels A and B) and diversification benefits (Panels C and D) between the observed data and the counterfactual where passive investors are removed and their assets under management reallocated to active ones. Levels are in percentage points for volatility; changes are in percent of the counterfactual level. Panels A and C weight investors by observed AUM and, alternatively, equally; Panels B and D report AUM-weighted averages within investor type. The household sector is excluded. The sample runs from 1997Q1 to 2022Q4.

Table 8 reports the change in active investors' certainty equivalent and its decomposition, in basis points per quarter. Over the full sample, the AUM-weighted change is 4.4 basis points: active investors are slightly better off in the presence of passive investors, by about 18 basis points per year in certainty-equivalent return. This small net gain is the sum of two larger risk effects of opposite sign. Higher return correlations lower the certainty equivalent by 4.3 basis points, while the compression of individual volatilities raises it by 7.9. The reweighting of portfolios at counterfactual prices contributes little, 0.2 basis points

through risk and 0.6 through expected returns. The equal-weighted average is similar (3.3 basis points), with the same pattern across components. Because the risk components scale linearly with risk aversion, a higher γ magnifies both channels without changing the sign: with $\gamma = 3$, the gain is about 12 basis points per quarter.

Panel B shows that this pattern is common to all institutional sectors. For every investor type the correlation component is negative, the marginal-risk component positive and larger, and the net change positive, ranging from 2.4 basis points for other institutions to 6.1 for banks. Mutual funds bear the largest cost from higher correlations (-5.2 basis points), consistent with their larger correlation component in Table 7, but this is more than offset by the dampening of firm-specific volatility. The larger gain of banks partly reflects rebalancing: the portfolios they would hold at counterfactual prices are riskier under the counterfactual covariance matrix, which lowers their counterfactual certainty equivalent.

For active investors, welfare and risk-sharing capacity therefore move in opposite directions: their certainty equivalent rises slightly, while their diversification benefits fall by about 12% (Table 7). The private gain of concentrated investors and the higher risk floor of the market are two sides of the same reallocation of risk: individual portfolios become less exposed to firm-specific shocks, while the market as a whole retains less capacity to absorb aggregate ones.

5.3 Investor-level analysis

The aggregate results in Tables 7 and 8 mask heterogeneity across investors. To describe which institutions gain and which bear more comovement risk, I estimate

$$\begin{aligned}\Delta Y_{k,t} = \beta\, PO\ exposure_{k,t-1} + \delta\, HHI_{k,t-1} + \theta \log(N\ assets_{k,t-1}) + \eta \log(aum_{k,t-1}) \\ + \psi\, \text{Outside-asset share}_{k,t-1} + \alpha' Type_k + \tau_t + \epsilon_{k,t},\end{aligned} \tag{26}$$

where $\Delta Y_{k,t}$ is either the change in investor k's portfolio volatility, or one of its correlation, marginal-risk and rebalancing components (Eq. 21), all in percent of the investor's counter-

Table 8: Welfare effects of passive investing: certainty-equivalent decomposition

			Risk, $-\frac{\gamma}{2}\Delta\sigma^2$		
	ΔCE	Reallocation	Correlation	Marginal risk	Rebalancing
Panel A: All active investors					
AUM-weighted	4.4	0.6	-4.3	7.9	0.2
Equal-weighted	3.3	0.3	-4.2	7.1	0.0
Panel B: By investor type (AUM-weighted)					
Mutual funds	3.1	0.7	-5.2	8.0	-0.4
Insurance companies	3.2	0.6	-3.3	6.3	-0.3
Pension funds	5.2	1.2	-3.5	7.5	0.0
Other	2.4	0.6	-2.3	4.0	0.2
Banks	6.1	0.6	-4.4	8.3	1.6
Investment advisors	3.9	0.4	-4.1	7.7	-0.1

Notes: This table reports the change in active investors' certainty equivalent, $\Delta CE = CE^{obs} - CE^{cf}$ (Eq. 24), between the observed economy and the counterfactual in which passive investors are removed and their assets under management reallocated to active ones, and its decomposition according to Eq. 25. Positive values indicate that investors are better off with passive investors present; the four components sum to ΔCE. Expected returns are $\mu_{n,t} = \hat{\beta}_{n,t}\bar{\lambda}$ in both economies, with $\bar{\lambda} = 0.98\%$ per quarter, the average value-weighted market price return in excess of the Treasury-bill rate. Risk aversion is $\gamma = 1$, and the risk components scale linearly with γ. Values are in basis points per quarter: within each quarter investors are averaged, and quarterly averages are then averaged over the sample. Panel A weights investors by observed AUM and, alternatively, equally; Panel B reports AUM-weighted averages within investor type. The household sector is excluded. Sample: active investors, 1997Q1–2022Q4.

factual volatility, or the change in its certainty equivalent $\Delta CE_{k,t}$ (Eq. 25), in basis points. Expressing the volatility terms relative to the counterfactual level removes their mechanical dependence on the share of assets held in equities; for ΔCE, this dependence is absorbed by the outside-asset share. Because portfolio characteristics and outcomes are built from the same holdings, the coefficients describe how the effects of passive investing vary across investors, conditional on the other characteristics, rather than causal effects.

Table 9 relates investor-level changes to portfolio characteristics, following Eq. 26. Three results stand out.

First, portfolio concentration is the main determinant of who gains. The coefficient of HHI on the change in volatility is -21.6 and highly significant: moving from the equivalent of 100 to 50 equally weighted positions, which raises the HHI by 0.01, lowers volatility in the presence of passive investors by an additional 0.2% of its counterfactual level and raises the certainty equivalent by 0.7 basis points per quarter (column 5). Both risk channels contribute: concentrated portfolios are less exposed to the rise in correlations (-13.3) and

Table 9: Passive ownership and investor-level risk and welfare

	Volatility (% of counterfactual)				Welfare (bp)
	(1) $\Delta\sigma_{k,t}$	(2) $\Delta\sigma^{\rho}_{k,t}$	(3) $\Delta\sigma^{m}_{k,t}$	(4) $\Delta\sigma^{r}_{k,t}$	(5) $\Delta CE_{k,t}$
PO exposure	10.49	18.40***	-29.54***	21.63***	10.84
	(8.67)	(4.73)	(7.73)	(2.83)	(26.40)
HHI	-21.58***	-13.34***	-10.82***	2.58***	69.32***
	(3.48)	(1.77)	(3.25)	(0.89)	(14.65)
log(N assets)	0.13	0.11	0.20	-0.18***	1.21*
	(0.22)	(0.14)	(0.19)	(0.06)	(0.64)
log(AUM)	0.10	0.35***	-0.37***	0.12***	0.23
	(0.09)	(0.07)	(0.09)	(0.03)	(0.23)
Outside-asset share	6.40	6.47***	-15.07***	15.00***	6.85
	(3.96)	(2.19)	(3.61)	(1.47)	(11.87)
Observations	36,166	36,166	36,166	36,166	36,166
Quarter FE	✓	✓	✓	✓	✓
Investor type FE	✓	✓	✓	✓	✓

Notes: This table reports estimates of Eq. (26) on investor-level changes between the observed economy and the counterfactual where passive investors are removed and their assets under management reallocated to active ones. Columns (1)–(4) report the change in portfolio volatility, $\sigma_{k,t} = \sqrt{w'_{k,t}\Sigma_t w_{k,t}}$, and its correlation, marginal-risk and rebalancing components (Eq. 21), in percent of the investor's counterfactual volatility; the components sum to column (1). Column (5) reports the change in the certainty equivalent (Eq. 25), in basis points per quarter, with $\gamma = 1$. Explanatory variables are lagged one quarter: PO exposure is the average passive ownership of the investor's holdings weighted by portfolio weights, HHI is portfolio concentration, log(N assets) is the log number of holdings, log(AUM) is the log of assets under management, and Outside-asset share is the share of assets held in the outside asset, i.e. in holdings other than U.S. common stocks in the sample. Because characteristics and outcomes are built from the same holdings, the coefficients are descriptive. Standard errors, two-way clustered at the investor and quarter level, are in parentheses. Sample: active investors, 1997Q1–2022Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

benefit more from the dampening of firm-specific volatility (-10.8). This is the investor-level counterpart of the comparison with the benchmark portfolios: the less diversified a portfolio, the larger the share of its risk that passive investing dampens.

Second, exposure to passive ownership reshapes the composition of risk without changing its level. PO exposure does not predict the total change in volatility or in the certainty equivalent, but it strongly predicts each component. Investors whose holdings are more heavily owned by passive funds bear more correlation risk (18.4) and benefit more from the compression of firm-specific volatility (-29.5), with the reweighting at counterfactual prices (21.6) absorbing the remainder. For these investors, passive investing changes what kind of risk they bear rather than how much: firm-specific volatility is replaced by

exposure to comovement, the risk that diversification cannot remove.

Third, larger institutions display the same shift on a smaller scale. A higher log(AUM) raises the correlation component (0.35) and lowers the marginal-risk component (-0.37) by similar amounts, with no effect on total volatility or welfare. Once concentration is controlled for, the number of holdings and the outside-asset share do not predict the change in total volatility, and the number of holdings has at most a weak effect on welfare.

6 Conclusions

This paper studies how the rise of passive investing has affected the equity market's capacity to share risk. Using a valuation-adjusted Bartik instrument, I show that passive ownership causally raises stock return comovement: a one-standard-deviation increase in stock-level passive ownership raises average pairwise correlations by 9 percentage points. Part of this effect survives the removal of common factor variation. This residual synchronization is absent before 1997, when passive ownership was low and stable, and it is concentrated in periods of aggregate stress. It is therefore specific to the era of large-scale passive investing rather than a mechanical feature of institutional ownership.

A structural demand-system counterfactual shows that this synchronization is only one side of the story. Passive investing moves risk along two opposing margins: it raises return correlations through common, price-insensitive demand, and it dampens firm-specific volatility. For the market as a whole, the correlation effect dominates. Relative to an economy in which passive assets are reallocated to active investors, the minimum volatility attainable in a long-only equity portfolio is 3.3% higher and the volatility of the risk parity portfolio 19.8% higher, while diversification benefits are 2.1% and 5.1% lower, respectively. These averages mask substantial time variation. The erosion of risk-sharing capacity is concentrated in the years after the global financial crisis, and in the final years of the sample the dampening of firm-specific volatility is large enough to reverse the sign of the effect on

portfolio volatility.

A cross-sectional analysis at the stock level shows that the risk reallocation is strongest where passive ownership is highest. Moving from the least to the most passively held decile of stocks, the compression of idiosyncratic variance grows from 7.5% to 49.5%, while the increase in average correlation grows from 0.5 to 6.3 percentage points. Scaling passive capital down rather than removing it shows that these effects build up gradually with the size of the passive sector. About half of the loss in diversification benefits, and about 60% of the cross-sectional risk reallocation, is attributable to the growth of passive investing since the late 1990s.

For the portfolios that active investors actually hold, the balance between the two forces is different. Because these portfolios are far more concentrated than the benchmarks, the dampening of firm-specific volatility outweighs the rise in correlations: their volatility is about 5% lower in the presence of passive investors, and their certainty equivalent slightly higher. Their diversification benefits nonetheless fall by about 12%, mostly through the correlation channel. The gain is largest for the most concentrated investors, while those most exposed to passive ownership, and the largest institutions, do not bear more total risk but a larger share of comovement risk. Passive investing thus lowers the private risk of concentrated portfolios while raising the risk floor of the market as a whole.

While my analysis focuses on diversification capacity rather than on crisis probability or amplification mechanisms, the structural changes I document have broader implications for financial stability. They concern the composition of risk rather than simply its level. As firm-specific risk is replaced by exposure to common movements, a larger share of any aggregate shock cannot be diversified away within the equity market, and losses are likely to be more uniform across portfolios. Because passive ownership also lowers the elasticity with which prices absorb demand shocks, the same composition of ownership that compresses firm-specific volatility makes prices more sensitive to common shocks. These features may interact with the amplification mechanisms studied in the systemic-risk literature: when a

larger share of risk is common across assets, fire sales and other spillovers are more likely to affect many institutions at once. Lower protection from equity diversification may also lead investors to seek alternative hedging strategies that carry different forms of systemic risk.

The analysis has several limitations. The counterfactual is a partial-equilibrium exercise that holds investors' demand elasticities fixed. Active investors could in principle respond to the disappearance of passive competition by trading more aggressively. However, Haddad et al. (2025) show that such strategic responses, while present, are limited in the data, because costly information acquisition and other frictions constrain how much investors adjust their trading behaviour. The counterfactual also restricts portfolio weights to be non-negative, and therefore abstracts from the short-selling channel emphasized by Jiang et al. (2025), although short positions are an order of magnitude smaller than passive holdings and flat across the most passively held stocks (Appendix F). Finally, I do not study whether passive investing changes the probability or severity of crises, how it interacts with fire sales and liquidity spirals (Brunnermeier and Pedersen, 2009; Pagano et al., 2019; Bhattacharya and O'Hara, 2020), or its real effects through corporate governance (Appel et al., 2016). These channels are likely to interact with the diversification effects documented here and are natural avenues for future research.

The results highlight a trade-off inherent in the growth of passive investing. Index funds have lowered costs and broadened market access, but they have also changed how risk is distributed in the equity market. Supervisors could track aggregate diversification metrics alongside traditional systemic-risk indicators, since an erosion of risk-sharing capacity can build up even when tail risk is not elevated. Stress-test scenarios could likewise account for the lower protection that equity diversification offers in a market where a large share of ownership is price-insensitive. Understanding how passive investing reshapes the composition of risk is essential for preserving financial stability without giving up the efficiency gains that index investing has delivered.

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A Measuring passive investing

In this section I describe the strategy to identify passive investors in my sample. Intuitively, passive investors are those insensitive to prices (Koijen and Yogo, 2019; Haddad et al., 2025). At each quarter I estimate a demand system similar to the one of Koijen and Yogo (2019). This equation relates investors' portfolio shares to stock characteristics and market size, allowing me to infer their price elasticity of demand:

$$\log \delta_{k,n,t} - \log p_{n,t} = d_{0,k,t} + d_{1,k,t}^{\top} X_{n,t} - \mathcal{E}_{k,t} \log me_{n,t} + \epsilon_{k,n,t} \tag{A1}$$

where $\delta_{k,n,t}$ is the portfolio allocation of investor k in asset n at time t relative to the outside asset, which collects all holdings that are not U.S. common stocks in the sample, such as non-equity securities, foreign stocks and derivatives; $\log me_{n,t}$ is the market capitalization of stock n at time t and $X_{n,t}$ includes stock characteristics of stock n at time t. The coefficient $\mathcal{E}_{k,t}$ identifies the price elasticity of investor k at time t. As in Haddad et al. (2025) I define investors whose elasticity $\mathcal{E}_{k,t}$ is smaller than 0.06 in a given quarter as passive. Formally the set of passive investors is $\mathcal{P} = \left\{ k \in \mathcal{I} : \mathcal{E}_k < 0.06 \right\}$.

Economically, the threshold $\mathcal{E}_{k,t} < 0.06$, indicates investors whose demand function is insensitive to prices. In other words the portfolio weights mechanically adjust, without any active trade. On the contrary, active investors exploit perceived mispricing and generate non-zero demand elasticity. The choice of the particular value of the threshold is motivated by Haddad et al. (2025), who document that this cutoff cleanly separates index-tracking behaviour from active portfolio management.

B Determinants of active and passive fund flows

This appendix analyses the macroeconomic determinants of aggregate fund flows and compares the sensitivity of active and passive investors to macroeconomic shocks. The objective is twofold: *i*) to document systematic differences in how active and passive flows respond to macroeconomic conditions, and *ii*) to motivate the use of macro-driven passive flows as a source of common demand shocks in the main analysis.

First, I compute investor i flow as:

$$Flow_{i,t} = AUM_{i,t} - AUM_{i,t-1}(1 + R_{i,t})$$

where $R_{i,t}$ is the portfolio return of investor i between time t and $t-1$. The dependent variable of the analysis is the aggregate flow rate:

$$\widetilde{Flow}_{j,t} = \frac{\sum_{i=1}^{\mathcal{I}\in j} Flow_{i,t}}{\sum_{i=1}^{\mathcal{I}\in j} AUM_{i,t-1}}$$

where $j = \{\mathcal{A}, \mathcal{P}\}$ denotes the set of active and passive investors, respectively.

I first estimate flow regressions separately for active and passive funds:

$$\widetilde{Flow}_{j,t} = \alpha_j + \beta_j' X_t + \varepsilon_{j,t}, \quad j \in \{\text{Active}, \text{Passive}\} \tag{B1}$$

where $\widetilde{Flow}_{j,t}$ denotes the aggregate flow rate of fund type j at time t. The vector $\mathbf{X}_t$ includes macroeconomic variables such as real personal consumption expenditures (Real PCE), real disposable income, the personal saving rate, and market volatility (VIX). Real macro variables enter in log differences. All variables have been retrieved from FRED database and span the period from 1993Q4 – 2022Q4. Standard errors are corrected for heteroscedasticity and autocorrelation up to 8 lags.

Table B1: Determinants of active and passive flow rates

	Active	Passive
Constant	0.0060	0.0075*
	(0.81)	(1.88)
Real PCE	1.0352	2.9866***
	(0.84)	(5.49)
Real Disposable Income	0.6609	2.6961***
	(0.73)	(4.33)
Personal Saving Rate	-0.0380***	-0.0107
	(-3.91)	(-0.93)
VIX	-0.1364***	-0.0833***
	(-6.11)	(-3.04)
Obs.	117	117
R^2	0.235	0.239

Notes: This table reports the regression results of active and passive investors aggregate flow rate on macroeconomic variables. Flow rate is defined as $\frac{Flow_t}{AUM_{t-1}}$. All macroeconomic variables enter as logarithmic difference. Standard errors are corrected for heteroskedasticity and autocorrelation up to 8 lags. T-statistics are reported in parenthesis. Sample: 1993Q4 – 2022Q4. *** p < 0.01, ** p < 0.05, * p < 0.1.

The results reveal pronounced differences between active and passive investors. Passive fund flows exhibit a strong and statistically significant sensitivity to real economic activity: both Real PCE growth and Real Disposable Income growth load positively and significantly in the passive-flow regressions, while the corresponding coefficients for active flows are small and statistically insignificant. Quantitatively, the estimated elasticities for passive flows are several times larger than those for active flows.

The personal saving rate enters negatively in both regressions, but the effect is economically meaningful only for active flows. This pattern suggests that active investors partially offset changes in household saving by reallocating across assets, whereas passive flows are less directly affected. In contrast, increases in market uncertainty, proxied by the VIX, are associated with significant outflows from both active and passive funds, indicating that volatility shocks trigger broad-based reductions in equity exposure.

Table B2: Pooled Regressions: Flow-Rate Sensitivity (Passive vs Active)

	Real PCE	Real Disposable Income	Personal Saving Rate	VIX
Constant	0.0050	0.0111**	0.0107**	0.0099**
	(0.97)	(2.18)	(2.43)	(2.34)
Macro shock	1.5060	-0.5559	-0.0429***	-0.1657***
	(1.63)	(-0.91)	(-3.87)	(-7.06)
Passive dummy	0.0146***	0.0090**	0.0125***	0.0138***
	(4.25)	(2.05)	(3.42)	(4.42)
Macro × Passive	-0.2242	1.7735*	0.0518**	0.0539**
	(-0.37)	(1.71)	(2.11)	(2.02)
Obs.	234	234	234	234
R^2	0.070	0.066	0.072	0.139

Notes: This table reports the pooled regression results of investors aggregate flow rate on macroeconomic variables. Passive is a dummy variable equal to one for passive investors. Flow rate is defined as $\frac{Flow_t}{AUM_{t-1}}$. All macroeconomic variables enter as logarithmic difference. Standard errors are corrected for heteroskedasticity and autocorrelation up to 8 lags. T-statistics are reported in parenthesis. Sample: 1993Q4 – 2022Q4. *** p < 0.01, ** p < 0.05, * p < 0.1.

To formally test whether passive flows respond differently to macroeconomic shocks, I estimate pooled regressions of the form:

$$\widetilde{Flow}_{i,t} = \alpha + \beta\,\text{Macro}_t + \gamma\,\text{Passive}_i + \delta\,(\text{Macro}_t \times \text{Passive}_i) + \varepsilon_{i,t}, \tag{B2}$$

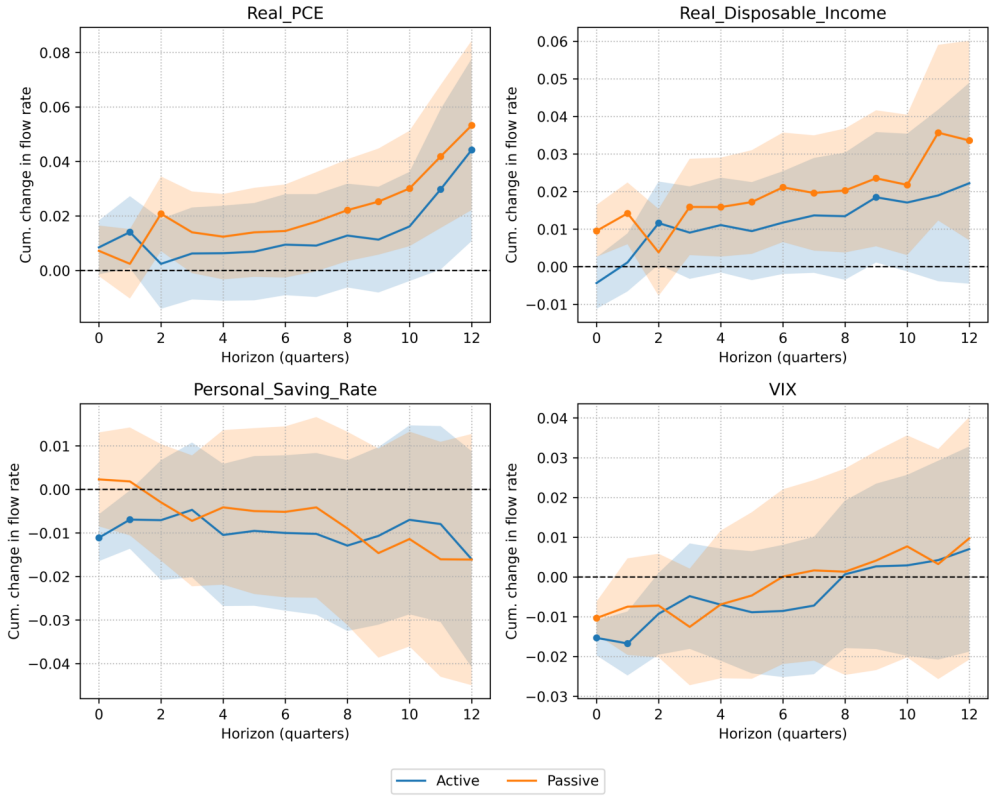
where Passive_i is a dummy variable equal to one for passive funds and zero for active funds. The interaction coefficient δ captures the differential sensitivity of passive flows to macroeconomic shocks relative to active flows.

The pooled regressions confirm and sharpen these findings. The passive dummy is positive and statistically significant across specifications, indicating higher average flow rates for passive funds. More importantly, the interaction terms reveal that passive flows respond differently from active flows to several macroeconomic shocks.

In particular, the interaction between the passive dummy and real disposable income growth is positive and statistically significant, implying that income-driven shocks translate disproportionately into passive fund inflows. Similarly, the interaction terms for the personal saving rate and the VIX are positive and significant, indicating that passive flows respond

differently from active flows to changes in household saving behavior and aggregate uncertainty. Since both shocks reduce flows, the positive differential implies that passive flows contract less than active ones.

Figure B1: Impulse response function of flow rates on macroeconomic variables



Notes: This figure plots impulse response functions of cumulative fund flow rates for active and passive investors following one–standard–deviation shocks to macroeconomic variables (Real PCE growth, Real Disposable Income growth, Personal Saving Rate, and VIX) in Eq. B3. Responses are estimated using local projections following Jordà (2005) over horizons up to 12 quarters. Solid lines denote point estimates. Shaded areas represent 90% confidence intervals.

To complement the static regressions, I study the dynamic response of active and passive fund flows to macroeconomic shocks using impulse response functions (IRFs). The IRFs are estimated from local projections in the spirit of Jordà (2005), which allow for flexible dynamics and avoid imposing strong parametric restrictions. For each macroeconomic variable and horizon $h = 0, 1, \ldots, H$, I estimate the following specification separately for

active and passive flows:

$$\sum_{s=0}^{h} \widetilde{Flow}_{j,t+s} = \alpha_{j,h} + \beta_{j,h}\, Shock_t + \varepsilon_{j,t+h}, \quad j \in \{\text{Active}, \text{Passive}\} \tag{B3}$$

where Shock_t denotes a one–standard–deviation innovation to a macroeconomic variable (Real PCE, Real Disposable Income, Personal Saving Rate, or VIX). The left-hand side is the cumulative flow rate up to horizon h. No additional controls or lagged variables are included, so the coefficients $\beta_{j,h}$ capture the unconditional dynamic response of fund flows to macroeconomic shocks. Standard errors are heteroscedasticity-robust.

The impulse response functions reveal systematic differences in the dynamic behaviour of active and passive flows. Following positive shocks to real economic activity, both active and passive flows increase gradually. For disposable income, the passive response exceeds the active one from about two quarters onward and is significantly positive at most horizons, whereas the active response is not. For consumption, the two responses are similar for the first two years, with the passive response somewhat larger at longer horizons. Confidence bands overlap at all horizons.

Shocks to the personal saving rate reduce active flows on impact, while passive flows do not respond on impact and decline only gradually; by twelve quarters the cumulative responses are similar, and confidence bands include zero at most horizons. This timing is consistent with passive flows adjusting slowly to changes in household saving rather than through short-run portfolio rebalancing.

In response to increases in market volatility, both active and passive flows decline on impact. The passive decline is smaller, and it reverts to zero within about six quarters, against about eight for active flows.

Taken together, the regression and impulse response evidence shows that passive fund flows are more tightly linked to aggregate macroeconomic conditions than active flows.Passive flows respond more strongly to income shocks, and differ from active flows in their response

to saving and uncertainty shocks, reacting less on impact. These results are consistent with a transmission mechanism in which macroeconomic shocks translate into aggregate savings reallocations that are channelled through passive investment funds. This tighter linkage between passive flows and macroeconomic conditions provides a natural source of common demand shocks.

C Robustness checks

In this section I discuss some robustness checks on the reduced form regressions. First, I conduct a placebo test using active funds flows in the construction of the Bartik instrument. Second, I estimate the impact of passive ownership on pairwise rather than average correlation using a sample of S&P 500 stocks. Third, I test the robustness of the results in the pre-1997 period where passive investors ownership was low and stable. Fourth, I re-estimate the main specification excluding recession periods. Finally, I use an alternative classification of passive investors.

C.1 Placebo tests.

To validate that the instrument isolates passive-specific variation, I construct a placebo instrument using active fund exposure and flows: $Z_{n,t}^{Placebo} = \sum_{k \in \mathcal{A}} AO_{n,k,t-h} \times f_{k,\text{active},t-h}^{(-n)}$. If the main instrument merely captured correlated institutional flows rather than passive-specific effects, this placebo should also predict passive ownership. At $h = 8$, the placebo yields an insignificant first stage, confirming the identifying variation is passive-specific (see Table C1). This demonstrates that the two-year lag successfully isolates passive flows from correlated institutional demand, validating the exclusion restriction.

Table C1: Placebo First-Stage IV Estimates of Passive Ownership

	Full sample (1)	S&P 500 (2)
$Z^{Placebo}$	-0.001	-0.015
	(0.003)	(0.018)
Excluded-instrument F	0.111	0.694
Observations	174,760	124,346
Adj. R^2	0.664	0.641

Notes: Dependent variable is passive ownership $PO_{n,t}$. The instrument $Z_{n,t-h}$ is the valuation-adjusted placebo shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters constructed from active investors' baseline exposure. Column (1) uses the full cross-section of stocks; Column (2) restricts the sample to S&P 500 constituents. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C.2 Pair-wise correlation

This section shows that passive ownership causally raises pairwise return correlations, validating the off-diagonal channel used in the structural counterfactual. I compute, for each pair of stocks (i, j), their pairwise correlation $\rho_{ij,t}$ and a measure of pairwise passive ownership $PO_{ij,t}$, defined as the arithmetic average of the passive ownership shares of individual stocks.

I estimate the causal effect of passive investing on pairwise stock correlations using the following.

$$\rho_{ij,t} = \beta \widehat{PO}_{ij,t} + \alpha_{ij} + \gamma_t + X'_{ij,t}\delta + \varepsilon_{ij,t}, \tag{C1}$$

where $PO_{ij,t}$ is instrumented with $Z_{ij,t}$, α_{ij} denotes pair-fixed effects, γ_t are time (quarter) fixed effects, and $X'_{ij,t}$ is the matrix of observable stock characteristics for pair (i, j).[10]

Because constructing these measures for every stock pair is computationally intensive, the analysis is restricted to S&P 500 stocks. The restriction to S&P 500 stocks likely produces conservative estimates. These stocks already exhibit high passive ownership, so if the effect of passive ownership on correlation is concave, the estimates capture the relationship where it is flattest. Moreover, large-cap stocks are already highly correlated due to common factor exposures and broad institutional coverage, leaving less room for passive-induced comovement to appear.

[10]The pair-wise instrument $Z_{ij,t}$ is constructed following the same logic as Eq. 7.

Table C2: IV Estimates: Effect of Passive Ownership on Pairwise Return Correlations

	Panel A: First Stage	*Panel B: Second Stage*	
		Correlation	*Excess Correlation*
	(1)	(2)	(3)
Z	8.671***		
	(1.194)		
Excluded-instrument F	52.775		
Observations	13,848,439		
Adj. R^2	0.501		
Passive Ownership		0.746***	0.044***
		(0.002)	(0.002)
1-SD Effect		0.036	0.002
Observations		13,848,439	13,848,439
R^2		0.681	0.008
Estimator	IV-2SLS	IV-2SLS	IV-2SLS

Notes: This table reports two-stage least squares (2SLS) estimates of the effect of passive ownership on pairwise stock return correlations. *Panel A* reports the first-stage regression results where the instrument $Z_{ij,t-h}$ is the pairwise valuation-adjusted shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters. *Panel B* reports second-stage estimates. Column (2) uses pairwise return correlations as the dependent variable; Column (3) uses pairwise excess correlations of market-model residuals. *1-SD Effect* $= \hat{\beta} \times \sigma_{PO_{i,j}}$ measures the change in comovement for a one-standard-deviation increase in passive ownership, where $\sigma_{PO_{i,j}}$ is the standard deviation of pair (i, j) passive ownership. Stock-pair and time fixed effects are included in all specifications. Standard errors (in parentheses) are clustered at the stock-pair and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C2 reports the results of the two–stage least squares estimation of the effect of passive ownership ($PO_{i,j}$) on pairwise return correlations ($\rho_{i,j}$), including firm–pair and time fixed effects. In the first stage, the instrument based on baseline exposure to passive investors and investor-level passive AUM growth strongly predicts pairwise passive ownership, with a partial F–statistic far exceeding conventional relevance thresholds.

In the second stage, the coefficient on instrumented passive ownership is positive and highly significant, indicating that an increase in passive ownership causally raises stock return comovement. Quantitatively, a one–standard–deviation rise in PO_{ij} (around 4.9%) increases the average pairwise correlation by roughly 3.6 percentage points. The inclusion of firm–pair and time fixed effects ensures that identification relies exclusively on within–pair variation over time, reinforcing the interpretation of the estimates as causal. Overall, the results provide evidence that greater passive ownership amplifies common return components

and erodes diversification opportunities across equities.

C.3 Pre-1997 subsample

I re-estimate the model restricting the sample to observations up to December 1997, a period during which passive ownership was low and stable — averaging around 12% with little cross-sectional variation (see Table 1). If the main results reflect a genuine causal effect of passive ownership on return synchronization, the effect should be attenuated or absent in this subsample.

Tables C3 and C4 report the results. The first stage remains strong in the full sample (F = 25.7)but is weaker in the SP 500 subsample (F = 10.8), below the Stock and Yogo (2005) critical value of 16.38, so the SP 500 estimates should be interpreted with caution. In the second stage, however, a striking pattern emerges. For raw correlations, the coefficient on passive ownership is positive and significant (1.680 and 1.845 in the full sample and S&P 500 respectively), suggesting that even in this early period passive ownership was associated with higher return synchronization. For excess correlations, by contrast, the coefficient is small, statistically insignificant, and essentially zero in both samples (0.015 and −0.192).

This contrast is the key result. In the pre-1997 period, the correlation increase associated with passive ownership is entirely accounted for by common factor exposure, once market-level comovement is removed, passive ownership has no additional explanatory power. This stands in sharp contrast to the full sample results in Table 3, where passive ownership significantly raises excess correlations even after purging common factor variation. The pre-1997 pattern is consistent with a world where passive ownership was too small to generate genuine price-insensitive demand shocks, so that the raw correlation increase reflected fundamentals co-moving rather than passive-induced synchronization. Taken together, the pre- and post-1997 results suggest that the ownership-induced synchronization channel documented in the main analysis is specific to the era of large-scale passive investing.

Table C3: First-Stage IV Estimates of Passive Ownership (Pre-1997)

	Full sample (1)	S&P 500 (2)
Z	0.775***	0.500***
	(0.153)	(0.152)
Excluded-instrument F	25.658	10.821
Observations	73,763	57,844
Adj. R^2	0.801	0.803

Notes: Dependent variable is passive ownership $PO_{n,t}$. The instrument $Z_{n,t-h}$ is the valuation-adjusted shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters. Column (1) uses the full cross-section of stocks; Column (2) restricts the sample to S&P 500 constituents. The sample is restricted to observations up to December 1997. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C4: Second-Stage IV Estimates: Effect of Passive Ownership on Return Comovement (Pre-1997)

	Correlation		*Excess Correlation*	
	(1)	(2)	(3)	(4)
Passive Ownership	1.680***	1.845***	0.015	-0.192
	(0.412)	(0.527)	(0.072)	(0.142)
1-SD Effect	0.088	0.096	0.001	-0.010
Observations	73,763	57,844	73,763	57,844
R^2	0.456	0.277	0.276	0.066
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Full sample	✓	–	✓	–
S&P 500	–	✓	–	✓

Notes: Dependent variable is stock return comovement, proxied either by *i*) average pairwise return correlations or by *ii*) average pairwise excess correlations of market-model residuals. Columns (2) and (4) restrict the sample to S&P 500 constituents; Columns (1) and (3) use the full cross-section. The sample is restricted to observations up to December 1997. Passive ownership is instrumented by the valuation-adjusted shift-share Bartik instrument $Z_{n,t-h}$ (Eq. 7) with $h = 8$ quarters. *1-SD Effect* $= \hat{\beta} \times \sigma_{PO}$ measures the change in comovement for a one-standard-deviation increase in passive ownership, where σ_{PO} is the standard deviation of stock-level passive ownership. All specifications use IV-2SLS. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

C.4 Excluding recession periods

As a further robustness test, I re-estimate the model after excluding all NBER recession quarters to verify that the main results are not driven by crisis episodes. Tables C5

and C6 report the first- and second-stage IV estimates respectively. The first stage remains strong in the full cross-section (F = 24.9) but is weak in the S&P 500 subsample (F = 6.1), so the S&P 500 estimates in columns (2) and (4) of Table C6 should be interpreted with caution. For excess correlations, the effect loses significance in both the full sample and the S&P 500 subsample (columns (3) and (4)), with coefficients of 0.039 and 0.008 respectively, neither statistically distinguishable from zero. This suggests that the ownership-induced synchronization above and beyond common factor exposure documented in the main analysis is concentrated in periods of aggregate stress, rather than reflecting a purely structural feature of passive ownership. While raw correlations remain significantly elevated outside recessions, consistent with passive ownership generating persistent return synchronization through common demand shocks, the excess correlation channel appears to operate primarily during downturns, when passive-induced comovement is amplified by the heightened sensitivity of prices to aggregate shocks. These findings call for a more cautious interpretation of the diversification channel: the erosion of risk-sharing capacity documented in Section 4 may be more severe during stress periods than the full-sample estimates suggest.

Table C5: First-Stage IV Estimates of Passive Ownership

	Full sample (1)	S&P 500 (2)
Z	0.364***	0.333**
	(0.073)	(0.135)
Excluded-instrument F	24.863	6.084
Observations	153,284	110,697
Adj. R^2	0.672	0.656

Notes: Dependent variable is passive ownership $PO_{n,t}$. The instrument $Z_{n,t-h}$ is the valuation-adjusted shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters. Column (1) uses the full cross-section of stocks; Column (2) restricts the sample to S&P 500 constituents. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. NBER recessions are excluded from the sample.***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C6: Second-Stage IV Estimates: Effect of Passive Ownership on Return Comovement

	Correlation		*Excess Correlation*	
	(1)	(2)	(3)	(4)
Passive Ownership	0.508***	0.310**	0.039	0.008
	(0.105)	(0.127)	(0.037)	(0.053)
1-SD Effect	0.088	0.054	0.007	0.001
Observations	153,284	110,697	153,284	110,697
R^2	0.813	0.794	0.293	0.203
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Full sample	✓	–	✓	–
S&P 500	–	✓	–	✓

Notes: Dependent variable is stock return comovement, proxied either by *i*) average pairwise return correlations or by *ii*) average pairwise excess correlations of market-model residuals. Columns (2) and (4) restrict the sample to S&P 500 constituents; Columns (1) and (3) use the full cross-section. Passive ownership is instrumented by the valuation-adjusted shift-share Bartik instrument $Z_{n,t-h}$ (Eq. 7) with $h = 8$ quarters. *1-SD Effect* $= \hat{\beta} \times \sigma_{PO}$ measures the change in comovement for a one-standard-deviation increase in passive ownership, where σ_{PO} is the standard deviation of stock-level passive ownership. All specifications use IV-2SLS. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. NBER recessions are excluded from the sample.***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

C.5 Alternative classification of passive investors

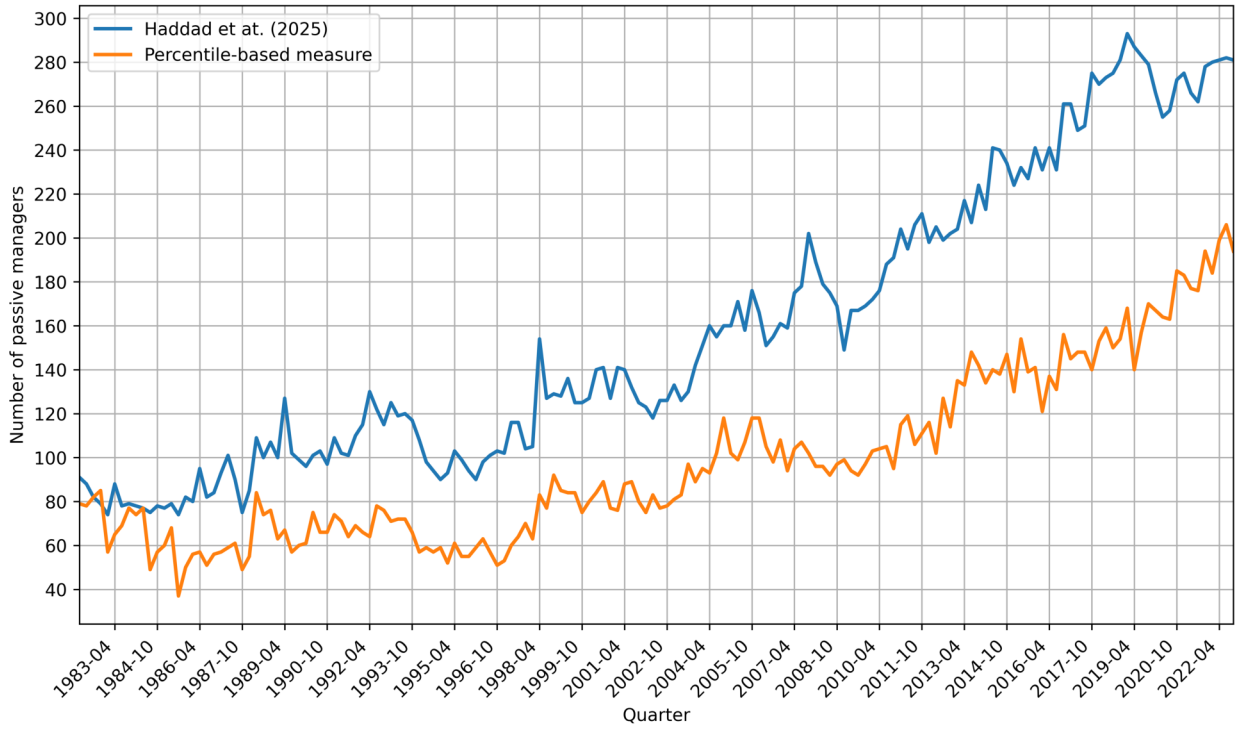
The elasticity-based classification using the Haddad et al. (2025) threshold could in principle be sensitive to crisis-period price volatility inflating measured elasticities. As a robustness test, I follow a similar approach and define as passive all investors whose demand elasticity with respect to prices in each quarter is within the 15th percentile. Using the demand-system of Koijen and Yogo (2019) I estimate:

$$\frac{w_{k,t,n}}{w_{k,t,0}} = \exp\left\{ \beta_{0,k,t}\, me_{t,n} + \sum_{m=1}^{M-1} \beta_{m,k,t}\, x_{t,n} + \beta_{M,k,t} \right\} \epsilon_{k,t,n} \tag{C2}$$

where $1 - \beta_{0,k,t}$ denotes the price elasticity of demand of investor k at quarter t. A value of one indicates that portfolio weights adjust in the same proportion as market capitalization.

Figure C1 shows the number of passive investors using the definition of Haddad et al.

Figure C1: Number of passive investors



Notes: This figure reports the number of passive investors according the definition of Haddad et al. (2025) (blue line) and using the percentile-based measure (orange line). Following Haddad et al. (2025), investors are classified as passive if their demand elasticity to price $\mathcal{E}k,t$ estimated from Eq. A1 is smaller than 0.06. The percentile based measure identifies passive investors as those whose demand elasticity to price $\mathbf{1} - \beta_{0,k,t}$ from Eq. C2 is within the 15th percentile.

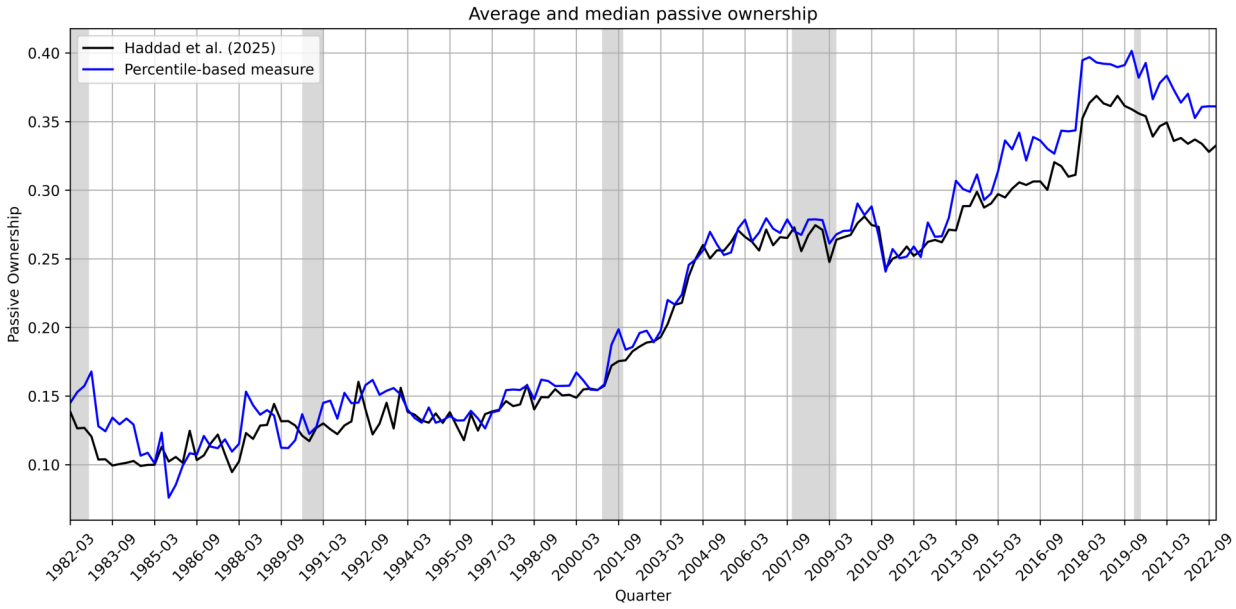
(2025) and the percentile-based measures. It demonstrates that the elasticity-based classifications closely track the trend in the number of passive investors, but is more conservative in the active-passive classification.

The percentile-based alternative (classifying the bottom 15% by elasticity) tracks both series closely, confirming that 0.06 represents a stable empirical separator rather than an arbitrary cutoff.

The passive ownership implied by the two measures is shown in Figure C2. Despite the number of passive investors according to the percentile-based measure is smaller compared to Haddad et al. (2025)'s classification, the cross-sectional average of passive ownership is very similar. Actually some slight difference is reported in the post-GFC.

Traditional passive investor identification relies on fund names or prospectus language

Figure C2: Passive ownership



(Ben-David et al., 2018; Appel et al., 2016; Becker et al., 2026). While straightforward, these textual approaches have limitations: they miss "closet indexers" (active in name only), cannot classify institutional investors lacking public prospectuses, and fail to capture index-like behaviour by non-traditional vehicles.

Specifically, I classify as passive all investors whose demand elasticity to price is within the 15th percentile each quarter. This measure is by construction immune to the crisis-induced rebalancing concern: even if market-wide volatility mechanically shifts estimated elasticities upward for all investors during stress periods, the percentile-based classification continues to identify the most price-insensitive investors by ranking them relative to the cross-sectional distribution each quarter.

Tables C7 and C8 report the results. The first stage remains strong across both samples, with excluded-instrument F-statistics of 25.9 and 38.3 for the full cross-section and S&P 500 respectively, comparable to the baseline in Table 2. The second stage estimates are also close to the baseline: a one-standard-deviation increase in passive ownership raises raw pairwise correlations by 9.2 and 8.9 percentage points in the full sample and S&P 500 respectively, and excess correlations by 1.2 percentage points in both samples. The

consistency of these estimates with Table 3 confirms that the main results are not sensitive to the specific threshold used to classify passive investors.

Table C7: First-Stage IV Estimates of Passive Ownership

	Full sample (1)	S&P 500 (2)
Z	0.886***	0.953***
	(0.174)	(0.154)
Excluded-instrument F	25.928	38.295
Observations	174,760	124,346
Adj. R^2	0.680	0.660

Notes: Dependent variable is passive ownership $PO_{n,t}$. The instrument $Z_{n,t-h}$ is the valuation-adjusted shift-share Bartik instrument (Eq. 7) with $h = 8$ quarters. Column (1) uses the full cross-section of stocks; Column (2) restricts the sample to S&P 500 constituents. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C8: Second-Stage IV Estimates: Effect of Passive Ownership on Return Comovement

	Correlation		*Excess Correlation*	
	(1)	(2)	(3)	(4)
Passive Ownership	0.512***	0.491***	0.064***	0.066***
	(0.026)	(0.029)	(0.011)	(0.016)
1-SD Effect	0.092	0.089	0.012	0.012
Observations	174,760	124,346	174,760	124,346
R^2	0.815	0.818	0.292	0.229
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Full sample	✓	–	✓	–
S&P 500	–	✓	–	✓

Notes: Dependent variable is stock return comovement, proxied either by *i*) average pairwise return correlations or by *ii*) average pairwise excess correlations of market-model residuals. Columns (2) and (4) restrict the sample to S&P 500 constituents; Columns (1) and (3) use the full cross-section. Passive ownership is instrumented by the valuation-adjusted shift-share Bartik instrument $Z_{n,t-h}$ (Eq. 7) with $h = 8$ quarters. *1-SD Effect* $= \hat{\beta} \times \sigma_{PO}$ measures the change in comovement for a one-standard-deviation increase in passive ownership, where σ_{PO} is the standard deviation of stock-level passive ownership. All specifications use IV-2SLS. Controls include lagged market equity, book equity, profitability, and asset growth. Firm and industry × time fixed effects are included. Standard errors (in parentheses) are two-way clustered at the stock and time level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

D Counterfactual AUM without reallocation

In this section I show that the decomposition results in Section 4.2 are not driven by the reallocation of funds from passive to active investors, but rather by changing the investor base determining the price of assets. To this end, I construct counterfactual assets under management assuming no passive investors, without reallocating them to existing active investors.

Table D1: Summary statistics on counterfactual analysis

Panel A: Diversification benefits, $\Delta\mathcal{DB}$ (%)			
	Total	Correlation	Marginal risk
GMV	-2.028	-1.570	-0.459
Risk Parity	-5.114	-4.583	-0.531
Panel B: Portfolio volatility, $\Delta\sigma$ (%)			
	Total	Correlation	Marginal risk & rebalancing
GMV	5.122	20.821	-15.699
Risk Parity	21.477	36.106	-14.628

Notes: This table reports the percentage change in diversification benefits ($\Delta\mathcal{DB}$, Panel A) and portfolio volatility ($\Delta\sigma$, Panel B) between the observed data and the counterfactual in which passive investors are removed for two benchmark portfolios. Differently than in Table 4, passive investors' AUM are not reallocated to active ones. Percentage changes are defined as $\Delta\mathcal{DB} = (\mathcal{DB}^{obs} - \mathcal{DB}^{cf})/\mathcal{DB}^{cf}$ and $\Delta\sigma = (\sigma^{obs} - \sigma^{cf})/\sigma^{cf}$. Each total is decomposed into a correlation component and a marginal risk component, according to Eq. 20. For portfolio volatility a third, rebalancing component arises and it is reported jointly with marginal risk (see Eq. 21. Components are scaled by the counterfactual level and therefore sum to the corresponding total. Covariance matrices are estimated over a 24-quarter rolling window with Ledoit and Wolf (2004) linear shrinkage.

Table D1 reports the change in diversification benefits $\Delta\mathcal{DB}$ and portfolio volatility $\Delta\sigma$. Negative values of $\Delta\mathcal{DB}$ indicate that diversification benefits are lower in the observed data than in the counterfactual, while positive values of $\Delta\sigma$ indicate that portfolio volatility is higher. The numbers closely mirror those in Table 4. Diversification benefits are essentially unaffected by the reallocation assumption: the loss is 2.0% for the GMV portfolio and 5.1% for risk parity, against 2.1% and 5.1% in the baseline, and in both cases the correlation channel accounts for around 80 to 90% of the total. Portfolio volatility effects are somewhat larger without reallocation, 5.1% versus 3.3% for the GMV portfolio and 21.5% versus 19.8%

for risk parity. The decomposition shows where this difference originates: the correlation components are almost identical across the two counterfactuals (20.8 against 20.2 for GMV and 36.1 against 35.4 for risk parity), while the offsetting marginal risk and rebalancing component is smaller in absolute value when passive assets are not redistributed. When passive AUM is removed without reallocation, aggregate demand for equities contracts, so counterfactual prices adjust further and individual volatilities rise by less than under proportional reallocation, leaving less scope for the offset. The baseline in Table 4 is therefore conservative with respect to portfolio volatility and, for diversification benefits, essentially invariant to the reallocation rule.

The robustness of these findings across reallocation assumptions indicates that the main results are not driven by the mechanical redistribution of passive AUM to active investors. Whether assets are reallocated or simply removed from the market, the counterfactual consistently shows that passive ownership erodes diversification benefits and raises the minimum achievable portfolio risk by increasing return correlations. Both specifications deliver the same economic message: passive investing compresses the economy's capacity to absorb aggregate shocks by shifting risk from idiosyncratic to systematic dimensions, and this reallocation of risk depends on the investor composition determining prices rather than on the ultimate distribution of assets.

E Additional results on stock-level risk analysis

Additional variables construction This appendix provides complementary details on the construction of control variables used to study the cross-sectional effects of passive ownership. Institutional ownership concentration is measured using a Herfindahl–Hirschman index computed over institutional investors reporting in SEC 13F filings. For each stock i and quarter t, institutional holdings are constructed as the product of investor assets under management and portfolio weights. The institutional HHI is defined as:

$$\text{InstHHI}_{i,t} = \sum_k \left(\frac{\text{Holdings}_{k,i,t}}{\sum_j \text{Holdings}_{j,i,t}} \right)^2 \tag{E1}$$

Note that, as I do not observe all investors' positions, the index does not represent the overall ownership concentration of a stock. Rather, it measures how institutional investors reporting their investment position in SEC 13F filings concentrate in stocks.[11]

Finally, I compute a measure of stock's demand elasticity. To characterize the elasticity of the marginal price-setting investor for each stock, I construct an ownership-weighted elasticity measure. Let $\beta_{0,k,t}$ denote the demand elasticity to log market equity of investor k at quarter t estimated according to Eq. (C2). Following Koijen and Yogo (2019), the elasticity of demand can be expressed as $\epsilon_{k,t} = 1 - \beta_{0,k,t}$. Demand elasticity for stock i in quarter t is defined as:

$$\text{EffElasticity}_{i,t} = \sum_k \hat{\varepsilon}_{k,t} \frac{\text{Holdings}_{k,i,t}}{\sum_j \text{Holdings}_{j,i,t}} \tag{E2}$$

This measure is similar to the stock-level aggregate elasticity in Haddad et al. (2025) and captures the average price sensitivity of investors holding a given stock, weighting each investor's elasticity by their share of ownership. Higher values indicate that a stock is priced by more elastic (active) investors, while lower values reflect greater exposure to inelastic

[11] Although a household sector is constructed to close the market clearing, it mechanically includes positions of smaller funds and retail investors. Thus, the household sector is excluded from the construction of institutional ownership concentration.

(passive) demand.

Industry-adjusted market model As a robustness check, I augment the market model with an industry factor to verify that the cross-sectional patterns in Table 5 are not driven by passive investors concentrating in specific industries. Specifically, for each stock n I estimate:

$$R_{n,t} = \alpha_n + \beta_n R_{mkt,t} + \gamma_n R_{ind,t} + \varepsilon_{n,t} \tag{E3}$$

where $R_{ind,t}$ is a leave-one-out value-weighted industry return, constructed by excluding stock n from its own industry portfolio to avoid mechanical correlation between the dependent variable and the industry factor. Industries are defined using the Fama-French 12 industry classification. The leave-one-out construction ensures that the industry factor captures genuine sectoral comovement rather than the stock's own contribution to industry returns.

Table E1: Stock-Level Risk Changes by Passive Ownership Decile (Industry-Adjusted Market Model)

PO Decile	Median PO	InstHHI	Changes (Observed - Counterfactual)						
			$\Delta\sigma^2$ (%)	$\Delta\sigma^2_\varepsilon$ (%)	$\Delta(\beta^2\sigma^2_{mkt})$	ΔR^2	$\Delta\bar{\rho}$	$\Delta\bar{\rho}^{ex}$	$\Delta\beta$
1	0.037	0.694	-9.1	-8.3	-0.0002	0.001	0.005	-0.007	-0.138
2	0.111	0.503	-9.5	-9.2	-0.0002	0.005	0.019	-0.004	-0.147
3	0.189	0.349	-10.3	-12.4	-0.0001	0.010	0.025	-0.001	-0.122
4	0.250	0.232	-13.0	-16.6	-0.0002	0.018	0.034	0.004	-0.145
5	0.306	0.158	-15.5	-23.1	-0.0002	0.036	0.043	0.006	-0.098
6	0.353	0.115	-18.5	-28.5	-0.0002	0.050	0.048	0.006	-0.087
7	0.397	0.096	-21.3	-32.9	-0.0003	0.056	0.053	0.008	-0.090
8	0.438	0.082	-25.9	-37.5	-0.0005	0.060	0.053	0.010	-0.079
9	0.483	0.070	-29.9	-43.5	-0.0006	0.080	0.059	0.010	-0.065
10	0.560	0.061	-39.3	-51.7	-0.0006	0.099	0.063	0.012	0.003

Notes: This table reports median changes in stock-level risk characteristics by passive ownership decile when passive investors are removed in the counterfactual. Unlike Table 5, the market model includes a leave-one-out value-weighted industry return as an additional factor, where industries are defined using the Fama-French 12 industry classification; the industry return is computed from observed returns in the observed economy and from counterfactual returns in the counterfactual. InstHHI is the institutional ownership Herfindahl–Hirschman index computed over institutional investors reporting in SEC 13F filings. σ^2 is total return variance, σ^2_ε is idiosyncratic variance from the augmented market model $R_i = \alpha + \beta R_{mkt} + \gamma R_{ind} + \varepsilon$, $\beta^2\sigma^2_{mkt}$ is the market component of systematic variance, R^2 is the augmented model R-squared, $\bar{\rho}$ is average pairwise raw correlation with other stocks, $\bar{\rho}^{ex}$ is average pairwise excess correlation of the augmented-model residuals, and β is market beta. All statistics are computed using 24-quarter rolling windows. Stocks are sorted into deciles within each quarter; the table reports time-series medians of the quarterly decile medians of observed minus counterfactual values. Sample: 1997Q1–2022Q4.

Table E1 reports the decile-level results. The patterns documented in Table 5 are robust to the inclusion of the industry factor. Idiosyncratic variance is 8.3% lower in the observed economy in the lowest passive ownership decile and 51.7% lower in the highest, slightly larger in magnitude than the baseline estimates (-7.5% and -49.5%), since the augmented model attributes a smaller share of return variation to the idiosyncratic component. The increase in the augmented-model R^2 is now monotonic across deciles, from 0.1 to 9.9 percentage points, compared with 7.0 percentage points in the highest decile of the baseline. The change in average pairwise raw correlation $\Delta\bar{\rho}$ does not depend on the factor model and is therefore identical to the baseline, rising from 0.5 to 6.3 percentage points.

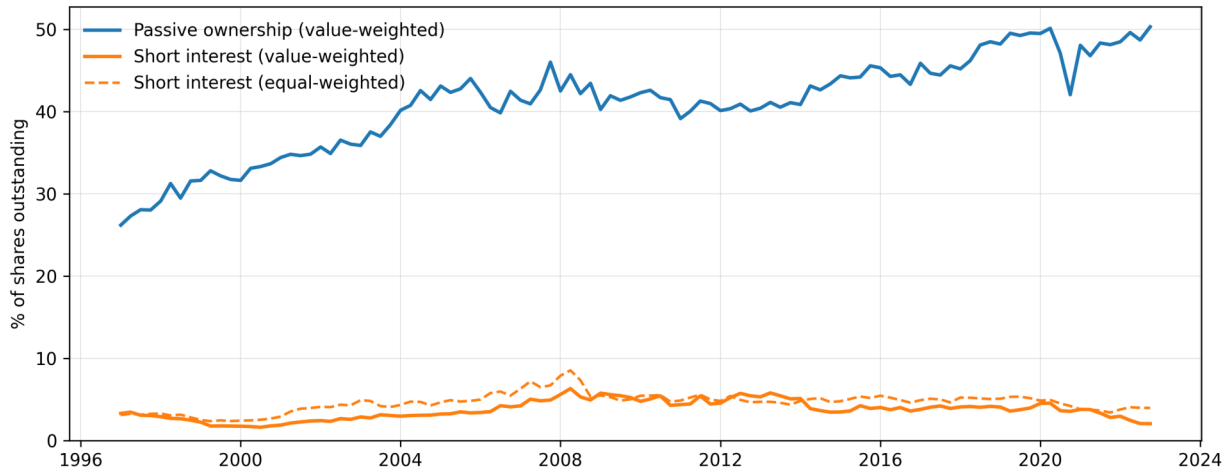
Excess correlations, now computed from residuals that also remove industry comovement, increase monotonically with passive ownership: $\Delta\bar{\rho}^{ex}$ is slightly negative for the three lowest deciles (-0.7 percentage points in the lowest) and rises to 1.2 percentage points in the highest. The correlation-increasing effect of passive ownership therefore operates above and beyond both market-wide and industry-level comovement, consistent with a genuine ownership-induced synchronization channel. The main difference with the baseline concerns market beta, which is lower in the observed economy for all but the highest decile once the industry factor is included, suggesting that part of the beta pattern in Table 5 reflects industry exposure. Overall, these results confirm that the risk reallocation documented in Table 5 is not driven by industry composition but reflects an ownership-induced compression of firm-specific risk accompanied by stronger return synchronization.

F Short positions

Portfolio weights in the demand system are estimated on 13F long positions and are non-negative. To assess how restrictive this is, I measure short interest from the Compustat Supplemental Short Interest file. I take the last report in each quarter, match it to CRSP by 8-digit CUSIP (historical CUSIP first, then CUSIPs that map to a single PERMNO over the sample), and divide it by shares outstanding. Short interest is available for 89% of market capitalization over 1997–2022; coverage of Nasdaq stocks starts in 2003, so before then it is available for about 37% of stock-quarters.

Figure F1 compares short interest with passive ownership over time. Short interest averages 3.7% of shares outstanding value-weighted and 4.6% equal-weighted, against a passive ownership of 41% and 28%, respectively. It has no upward trend: it rises from about 2% around 2000 to about 5.5% in 2008–2013 and falls back to 2.4% by 2022, while passive ownership grows steadily from 27% to 49%.

Figure F1: Short interest and passive ownership



Notes: This figure reports value-weighted passive ownership and value- and equal-weighted short interest, in percent of shares outstanding, by quarter. Short interest is from the Compustat Supplemental Short Interest file, matched to CRSP by CUSIP; coverage of Nasdaq stocks starts in 2003. Sample: 1997Q1–2022Q4.

Table F1 sorts stocks into passive-ownership deciles each quarter, as in Table 5. The first columns report passive ownership and short interest within each decile. Short interest

Table F1: Short interest and stock-level risk changes by passive ownership decile

		Short interest		Split within decile by short interest			
				$\Delta\sigma_\varepsilon^2$ (%)		$\Delta\bar{\rho}$ (pp)	
PO decile	Median PO	Median	Mean	Low SI	High SI	Low SI	High SI
1	3.7	0.2	1.2	-7.7	-6.5	0.1	0.8
2	11.1	0.9	2.2	-8.5	-7.0	1.6	1.8
3	18.9	1.8	3.4	-11.4	-10.4	2.6	2.1
4	25.0	2.7	4.7	-16.1	-14.8	3.6	3.0
5	30.6	3.1	5.5	-22.3	-20.7	4.7	3.5
6	35.3	3.2	5.8	-27.6	-25.1	4.9	4.9
7	39.7	3.0	5.4	-31.7	-30.3	5.5	4.8
8	43.8	3.1	5.5	-36.0	-32.7	5.9	4.9
9	48.3	3.2	5.6	-41.0	-38.2	7.1	4.9
10	56.0	3.7	6.6	-51.3	-46.2	7.4	6.0

Notes: This table reports passive ownership (PO) and short interest (SI), in percent of shares outstanding, and the change in idiosyncratic variance $\Delta\sigma_\varepsilon^2$ (in percent) and in average pairwise correlation $\Delta\bar{\rho}$ (in percentage points) between the observed economy and the counterfactual, as in Table 5, by passive ownership decile. Stocks are sorted into deciles within each quarter; within each decile and quarter, stocks with short interest above the decile median form the high-short-interest group (High SI) and the remaining stocks the low-short-interest group (Low SI); stocks without short-interest data are excluded from the split. The table reports time-series medians of the quarterly decile (or group) medians, and of the quarterly decile means for Mean SI. Short interest is from the Compustat Supplemental Short Interest file, matched to CRSP by CUSIP, and is measured at the last report of each quarter. Over the sample, short interest averages 3.7% (value-weighted) and 4.6% (equal-weighted) of shares outstanding, against a passive ownership of 40.9% and 27.9%, respectively. Sample: 1997Q1–2022Q4.

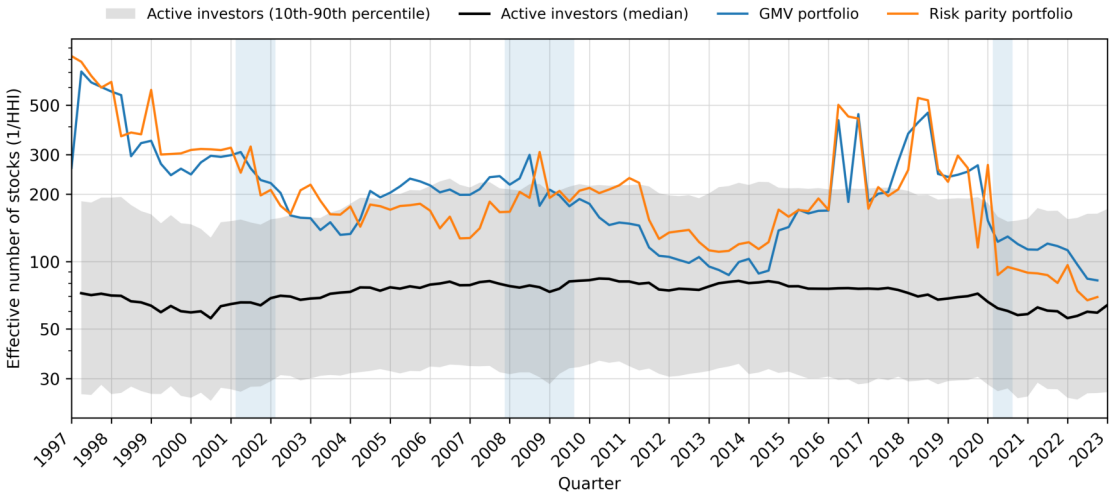
rises with passive ownership in the lower deciles, from 0.2% of shares outstanding in the first to 3.1% in the fifth (median across stocks), consistent with the role of passive funds as securities lenders (Palia and Sokolinski, 2024; von Beschwitz et al., 2025). The average cross-sectional rank correlation between the two is 0.43. Above the median, however, short interest is essentially flat, between 3.0% and 3.7%, while the compression of idiosyncratic variance and the increase in return correlation in Table 5 keep growing across these deciles.

The last four columns split each decile and quarter into stocks with short interest above and at or below the decile median, and report the changes in idiosyncratic variance and average correlation separately for the two groups. Because the demand system ignores short positions, the concern is that it misrepresents heavily shorted stocks: stocks with low short interest are those for which this restriction is least binding. Among them, the cross-sectional gradient is at least as strong as in Table 5: idiosyncratic variance falls by 7.7% in the lowest decile and 51.3% in the highest, and average correlation rises by 0.1 and 7.4 percentage points. Among stocks with high short interest the pattern is the same but somewhat weaker, at 6.5% and 46.2%, and 0.8 and 6.0 percentage points. Omitted short positions are therefore an order of magnitude smaller than passive holdings, and the cross-sectional results hold where ignoring them is closest to correct.

G Portfolio concentration

Figure G1 compares the portfolio concentration of active investors with that of the two benchmark portfolios, measured as the effective number of stocks held, i.e. the inverse of the Herfindahl-Hirschman index of portfolio weights. The median active investor holds the equivalent of about 55 to 85 equally weighted positions, with little variation over time. The GMV and risk parity portfolios are more diversified than the median investor in every quarter, typically holding the equivalent of 100 to 500 positions, although their concentration varies considerably and rises markedly after 2020. The 10th–90th percentile band shows that the most diversified investors reach levels comparable to the benchmarks, but most active investors hold substantially more concentrated portfolios. This supports the interpretation in Section 5 that firm-specific risk accounts for a larger share of active investors' portfolio risk than of the benchmark portfolios'.

Figure G1: Effective number of stocks held



Notes: This figure reports the effective number of stocks held, defined as the inverse of the Herfindahl–Hirschman index of portfolio weights, $1/\sum_n w_{k,n}^2$, with weights on stocks normalized to sum to one. The black line is the cross-sectional median across active investors and the grey band the range between the 10th and 90th percentiles; the blue and orange lines refer to the global minimum variance and risk parity portfolios. The vertical axis is on a logarithmic scale. Shaded areas indicate NBER recession periods. Sample: 1997Q1–2022Q4.

H Linearized equilibrium and the covariance matrix

This appendix derives Lemma 1. All quantities are evaluated at the observed equilibrium in quarter t; d denotes a small change, for instance from one quarter to the next, and time subscripts are omitted. Vectors stack the N stocks; Θ_k is diagonal with entries $\theta_{k,n}$, and $\mathbf{w}_k$ is investor k's vector of portfolio weights on stocks.

Step 1: market clearing. Including the household sector, market clearing for stock n is $ME_n = \sum_k AUM_k\, w_{k,n}$. Taking the total differential, factoring out each holding and dividing by ME_n,

$$d\,me_n = \sum_k \frac{AUM_k\, w_{k,n}}{ME_n}\left(\frac{dAUM_k}{AUM_k} + \frac{dw_{k,n}}{w_{k,n}}\right) = \sum_k \theta_{k,n}\big(da_k + d\log w_{k,n}\big), \tag{H1}$$

where $a_k = \log AUM_k$. In vector form,

$$d\,\mathbf{me} = \sum_k \Theta_k\big(\boldsymbol{\iota}\, da_k + d\log \mathbf{w}_k\big). \tag{H2}$$

Step 2: logit weights. From $w_{k,n} = \delta_{k,n}/(1+\sum_m \delta_{k,m})$,

$$d\log w_{k,n} = d\log \delta_{k,n} - \sum_m w_{k,m}\, d\log \delta_{k,m} \quad\Longrightarrow\quad d\log \mathbf{w}_k = G_k\, d\log \boldsymbol{\delta}_k, \qquad G_k = I - \boldsymbol{\iota}\,\mathbf{w}_k'. \tag{H3}$$

Step 3: demand. From Eq. (11), $\log \boldsymbol{\delta}_k = \beta_{0,k}\,\mathbf{me} + \mathbf{X}\boldsymbol{\beta}_k + \log \boldsymbol{\epsilon}_k$, hence

$$d\log \boldsymbol{\delta}_k = \beta_{0,k}\, d\,\mathbf{me} + \mathbf{me}\, d\beta_{0,k} + d\mathbf{X}\,\boldsymbol{\beta}_k + \mathbf{X}\, d\boldsymbol{\beta}_k + d\log \boldsymbol{\epsilon}_k. \tag{H4}$$

Step 4: assets under management and returns. Investor k's assets change with the return on its equity holdings and with everything else, which defines the valuation-adjusted

flow f_k (net flows plus the return on the outside asset, as in Eq. (8)):

$$da_k = \mathbf{w}_k'\mathbf{r} + f_k. \tag{H5}$$

With shares outstanding fixed, $me_n = p_n + s_n$ implies $d\,\mathbf{me} = \mathbf{r}$, abstracting from dividends.

Step 5: solving. Substituting $d\,\mathbf{me} = \mathbf{r}$ into Eq. (H4), the result into Eq. (H3), and Eqs. (H3) and (H5) into Eq. (H2), and writing $\boldsymbol{\iota}(\mathbf{w}_k'\mathbf{r}) = (\boldsymbol{\iota}\mathbf{w}_k')\mathbf{r}$,

$$\mathbf{r} = \sum_k \Theta_k \Big[(\boldsymbol{\iota}\mathbf{w}_k')\mathbf{r} + \boldsymbol{\iota} f_k + \beta_{0,k} G_k \mathbf{r} + G_k \big(\mathbf{me}\, d\beta_{0,k} + d\mathbf{X}\boldsymbol{\beta}_k + \mathbf{X}\, d\boldsymbol{\beta}_k + d\log \boldsymbol{\epsilon}_k \big) \Big]. \tag{H6}$$

Collecting the terms in $\mathbf{r}$ on the left-hand side and using $\beta_{0,k}G_k + \boldsymbol{\iota}\mathbf{w}_k' = \beta_{0,k} I + (1-\beta_{0,k})\boldsymbol{\iota}\mathbf{w}_k'$ gives $M\mathbf{r} = \mathbf{u}$ with M and $\mathbf{u}$ as in Eqs. (13)–(14). Treating M as constant over the estimation window, $\Sigma = \mathrm{Var}(\mathbf{r}) = M^{-1}\Omega_u M^{-1\prime}$.

Diagonal of M. Using $\sum_k \theta_{k,n} = 1$, $M_{nn} = 1 - \sum_k \theta_{k,n}\big[\beta_{0,k} + (1-\beta_{0,k})w_{k,n}\big] = \sum_k \theta_{k,n}(1-\beta_{0,k})(1-w_{k,n}) = \eta_n$, and for $n \neq m$, $M_{nm} = -\sum_k \theta_{k,n}(1-\beta_{0,k})\, w_{k,m}$. If assets under management are instead held fixed within the quarter, as in the counterfactual of Section 4.1, $M_0 = I - \sum_k \beta_{0,k}\Theta_k G_k$ and f_k is replaced by da_k; the two versions agree to first order in portfolio weights.

Scalar approximation and flow covariance. Neglecting terms of the order of portfolio weights, $M \approx \mathrm{diag}(\eta_1, \ldots, \eta_N)$ and $G_k \approx I$, so that row n of $M\mathbf{r} = \mathbf{u}$ yields Eq. (17). Its flow component is $r_n^{\text{flow}} = \eta_n^{-1}\boldsymbol{\theta}_n'\mathbf{f}$ with $\mathbf{f} = (f_1, \ldots, f_K)'$. Since $\mathrm{Cov}(\mathbf{a}'\mathbf{f}, \mathbf{b}'\mathbf{f}) = \mathbf{a}'\,\mathrm{Var}(\mathbf{f})\,\mathbf{b}$ for constant $\mathbf{a}, \mathbf{b}$, Eq. (18) follows, and

$$\boldsymbol{\theta}_n'\Sigma_f\boldsymbol{\theta}_m = \sum_k \sum_l \theta_{k,n}\,\theta_{l,m}\,\mathrm{Cov}(f_k, f_l). \tag{H7}$$

Treating the flow term as a separate component of Σ assumes that flows are uncorrelated with the other shocks in $\mathbf{u}$; otherwise the corresponding cross terms must be added. The approximation is least accurate for concentrated investors and for the largest stocks, whose portfolio weights are not small; the exact expression in Eq. (15) applies in all cases.

I Mean-variance foundation of the demand system

Koijen and Yogo (2019) derive characteristics-based demand from the portfolio choice of an investor with log utility over terminal wealth, approximated by mean-variance utility, who faces short-sale constraints and perceives a one-factor structure in returns in which expected returns and factor loadings are functions of stock characteristics (their Assumption 1). Under these assumptions the optimal weight on each stock held depends only on that stock's characteristics and on investor-level constants (their Proposition 1), and a coefficient restriction yields the exponential form in Eq. (11) (their Corollary 1). I restate their argument with an explicit risk-aversion coefficient, which the welfare analysis requires, and allow for several factors and stock-specific idiosyncratic variance.

Investor k chooses $\mathbf{w} \geqslant 0$ to maximize $\mathbf{w}'\boldsymbol{\mu}_k - \frac{\gamma_k}{2}\mathbf{w}'\Sigma_k\mathbf{w}$, with $\Sigma_k = B_k\Omega_k B_k' + D_k$.[12] Abstracting from the leverage constraint in Koijen and Yogo (2019), the Karush–Kuhn–Tucker conditions are $\gamma_k\Sigma_k\mathbf{w}_k = \boldsymbol{\mu}_k + \boldsymbol{\nu}_k$, $\boldsymbol{\nu}_k \geqslant 0$, $\nu_{k,n}w_{k,n} = 0$. For any stock held, row n gives Eq. (23) with $\boldsymbol{\lambda}_k = \gamma_k\Omega_k B_k'\mathbf{w}_k$. If $\mu_{k,n}$, $\mathbf{b}_{k,n}$ and $\sigma^2_{k,n}$ are functions of $\mathbf{x}_n$, the weight is a function of the stock's own characteristics and of investor-level constants, as in Proposition 1 of Koijen and Yogo (2019).

[12] Here γ_k denotes risk aversion; Koijen and Yogo (2019) use $\gamma_{i,t}$ for idiosyncratic variance.