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Monetary transmission and portfolio rebalancing: A cross-sectional approach☆

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ABSTRACT

We show that institutional portfolio rebalancing across asset classes plays a key role in transmitting monetary shocks to the stock market. Around FOMC announcements, *ceteris paribus*, a stock with 10-percentage-point higher ownership by rebalancing institutions experiences an additional 3.7-basis-point loss following a 10-basis-point surprise rate hike. We corroborate our mechanism by exploiting within-firm variations for dual shares, showing stronger price reactions at quarter- and month-ends when rebalancing is more imminent, and presenting placebo tests contrasting rebalancing institutions with other institutions. A concluding calibration suggests rebalancing could contribute roughly one-third to two-thirds of the aggregate stock market excess return response to monetary shocks.

1. Introduction

A central question in macro-finance is how monetary policy transmits to financial markets. Standard economic models suggest that the effects of monetary shocks are transitory (Christiano et al., 2005; Smets and Wouters, 2007). According to this view, the prices of long-term financial assets should not respond significantly to monetary shocks. However, extensive empirical research shows that monetary shocks lead to substantial price changes in the stock market. Bernanke and Kuttner (2005) document that a 10-basis-point unexpected rate hike reduces the aggregate stock market value by about 40 basis points. Importantly, these reactions are largely driven by shifts in expected returns, rather than changes in expected future cash flows or the risk-free rate, suggesting that fundamentals alone cannot fully explain the magnitude of the aggregate stock market reaction.

This paper highlights how institutional portfolio rebalancing across asset classes contributes to stock price responses to monetary policy shocks. We focus on *rebalancers*, the investors with stable equity-share targets who systematically rebalance between stocks and bonds, following Chien et al. (2012), Gabaix and Koijen (2022) and Parker et al. (2023). A large literature shows that monetary policy shocks substantially revalue long-term bonds (Shiller et al., 1983; Mankiw and Summers, 1984; Cochrane and Piazzesi, 2002; Gürkaynak et al., 2005b; Hanson and Stein, 2015; Giglio and Kelly, 2018; Hanson et al., 2021).

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Our mechanism is that, as a positive monetary policy shock lowers bond prices, rebalancers sell stocks and buy bonds to restore their targeted equity shares, driving down the stock prices. Empirically, we show that, all else equal, a stock with 10-percentage-point higher ownership by rebalancing institutions loses an additional 3.7 basis points following a 10-basis-point surprise rate hike — a relationship we term the *cross-sectional sensitivity*. We use this cross-sectional sensitivity to gauge the potential aggregate implication of the rebalancing channel, shedding light on the Bernanke and Kuttner (2005) puzzle.

In addition to our finding of the cross-sectional sensitivity across all common stocks, we present three additional tests to further corroborate the rebalancing mechanism. To start, to minimize the concern that differences in stock price reactions may arise from factors unrelated to rebalancing, we exploit within-firm price reaction differences for dual shares with the same fundamentals. Second, we show that both the cross-sectional sensitivity and the aggregate stock market reaction to FOMC announcements are stronger when rebalancing events are more imminent, confirming the role of rebalancing demand in driving prices. Finally, we demonstrate in placebo tests that ownership by rebalancing institutions predicts stock price reactions, whereas ownership by other institutions does not.

In practice, pensions, sovereign wealth funds, and target-date funds fit our definition of rebalancers. For instance, Norges Bank Investment Management sets a target equity allocation of 70% for the Government Pension Fund Global, commonly referred to as the "Oil Fund" (NBIM, 2021). It further highlights that "the choice of equity proportion will probably constitute the single most important decision" (NBIM, 1997). Similarly, U.S. pension funds are required to comply with asset-class-allocation targets set by state and local pension trustees (Jung and Rhee, 2013), while target-date funds are governed by systematic rebalancing policies (Parker et al., 2023). In addition to these allocation mandates, it is also documented that asset managers may tilt their portfolios toward assets with higher returns (such as stocks) when interest rates are low, a phenomenon referred to as "reaching for yield" (Lian et al., 2019; Becker and Ivashina, 2015; Hanson and Stein, 2015). By end-2019, FactSet data suggest that these rebalancers owned over 20% of the U.S. stock market, making portfolio rebalancing a potentially important channel for monetary transmission to equities.

Based on these observations, we introduce a model in Section 2 to analyze the implications of institutional rebalancing demand for monetary transmission. The baseline model features two stocks with identical fundamentals held by two types of investors. A rebalancer allocates funds between a single stock and a long-term bond, and a risk-averse equity market arbitrageur trades across both stocks and a short-term risk-free bond. A tightening monetary shock devalues long-term bonds, which would raise the rebalancer's equity share relative to its target. To restore the target equity share, the rebalancer sells stocks and buys bonds. If, in addition, the rebalancer reaches for yield — that is, its desired equity share increases when yields fall and decreases when yields rise — it sells even more stocks. With limits to arbitrage, these rebalancing trades have price impact: the stock more directly exposed to rebalancer demand falls more in price, and some of the pressure spills over to the other stock depending on the arbitrageur's demand elasticity between the two stocks. This generates the cross-sectional sensitivity we document.

The model formalizes the null hypothesis of this paper — in the absence of rebalancers, the stock price reactions will only be attributed to changes in the risk-free rate and dividends due to the arbitrageur's demand. As a result, stocks with the same fundamentals will have the same price reactions to monetary shocks. The model suggests that, if they react differently due to rebalancing flows, their price gap reflects changes in excess returns and informs the aggregate stock market reaction beyond fundamentals.

Next, we test the cross-sectional predictions against the null hypothesis that rebalancer ownership does not affect returns. Testing that presents two key identification challenges. First, as noted by Gürkaynak et al. (2005a) and Nakamura and Steinsson (2018), monetary policy announcements are often anticipated and endogenous to changes in economic fundamentals. To address this challenge, following the high-frequency identification literature, we use unexpected changes in the policy rate estimated over 30-minute windows surrounding FOMC announcements and analyze the high-frequency changes in asset prices during these same windows.

Second, monetary shocks affect stock prices through multiple channels, such as changes in dividends or the risk-free rate. An ideal test of the rebalancing channel would compare stocks that differ solely in their exposure to rebalancing demand. In Section 4, we exploit a quasi-experimental setting using dual-share firms with highly liquid share classes. These dual shares have identical fundamentals but different investor bases, allowing us to identify *within-firm* variation attributable to rebalancing. We measure rebalancing demand using the share-class-level rebalancer ownership data from FactSet. We find that rebalancers tend to hold more shares with lower voting rights, likely to avoid involvement in corporate governance. After a tightening monetary shock, the share class with higher rebalancer ownership loses significantly more value than the other class, regardless of whether we use raw rebalancer ownership or voting-right-instrumented rebalancer ownership.

While the dual-share evidence most effectively mitigates concerns about omitted variables, it is limited to a subset of common stocks. In Section 5, we demonstrate that our findings generalize to the cross-section of all common stocks after controlling for stock characteristics. The results in Section 5.1 show that, in response to a 10-basis-point rate hike, a stock with 10% (or one standard deviation) higher rebalancer ownership experiences an additional price decline of approximately 3.7 basis points (or 2.5 basis points).

By adopting a high-frequency identification strategy, we estimate the effects of monetary shocks using narrow windows around FOMC announcements, rather than until actual rebalancing dates. Anecdotal evidence suggests that pensions and mutual funds typically rebalance at the end of each quarter or month, rather than continuously adjusting to their target allocations. Although rebalancing may not occur immediately after monetary shocks, arbitrageurs incorporate expected future rebalancing demand into prices instantaneously. As arbitrageurs trade more aggressively to front-run more imminent flows, monetary shocks closer to quarter- and month-end dates should lead to larger cross-sectional sensitivity and stronger aggregate market reactions. We formalize this intuition in a model with delayed rebalancing in Section 2.2 and test the implications in Section 5.2. Supporting this mechanism, we find that the cross-sectional sensitivity is approximately 1.55 times larger for monetary shocks from quarter-end FOMC meetings compared to the full-sample average, and the aggregate stock market reaction is larger as well. This provides the first evidence on how the timing of portfolio rebalancing affects asset prices and, in particular, shapes the aggregate stock market reaction to monetary shocks.

In addition, we present placebo tests that contrast rebalancing institutions with pure-equity institutions to validate the mechanism further. Ownership by rebalancing institutions predicts stock price reactions to monetary shocks, whereas ownership by pure-equity institutions does not. Our main measure of rebalancer ownership is constructed from FactSet, which covers all institutions but only provides broad institutional categories. We construct an alternative proxy for rebalancer ownership using fund-level holdings from Morningstar mutual fund data, as detailed in Section 5.3, to corroborate our tests. We identify balanced funds based on fund names and their complete portfolio holdings. We show that stocks more heavily held by balanced funds respond more strongly to monetary shocks, while pure-equity fund ownership lacks such predictive power.

Beyond the pricing evidence, we provide quantity evidence that the institutions we classify as rebalancers adjust portfolios following target equity shares. First, using U.S. public pension plan data, we find that their equity shares are far more stable than a CRRA-implied equity-share benchmark. Their equity shares are explained by reported target shares, but not by measures of expected stock excess returns, or by counterfactual equity shares of a buy-and-hold portfolio without active adjustment. Additionally, using weekly CFTC futures positions, we show that institutional asset managers rotate out of equity index futures and into Treasury futures after tightening monetary shocks, while arbitrageurs trade in the opposite direction. Finally, we confirm active post-monetary-shock rebalancing using portfolio-level mutual fund holdings for balanced funds: funds farther from target equity shares due to revaluation cut equity exposure more after tightening shocks. Together, these results provide consistent quantity evidence for the rebalancing channel.

Finally, in a concluding back-of-the-envelope calibration, we gauge the quantitative importance of the rebalancing channel in explaining the Bernanke and Kuttner (2005) puzzle. Consistent with the literature, we find that a sizeable share (about 63% in our benchmark decomposition) of the aggregate market reaction is attributed to changes in expected excess returns. In our model, we show that the excess aggregate stock market reaction relates to the cross-sectional sensitivity via a ratio of the micro elasticity (the demand elasticity of individual stocks) to macro elasticity (the demand elasticity of the aggregate stock market) à la Gabaix and Koijen (2022). Intuitively, our model implies that the cross-sectional sensitivity multiplied by the micro elasticity recovers the rebalancing flow. This implied flow is then scaled by the macro elasticity to yield the corresponding aggregate stock market reaction. We calibrate the portion of the aggregate market reaction driven by the rebalancing channel using various estimates of micro and macro elasticities from the literature. We suggest that the rebalancing channel could plausibly account for approximately one-third to two-thirds of the aggregate market reaction that is due to changes in expected excess returns.

Literature review. This paper contributes to the intermediary asset pricing literature (He and Krishnamurthy, 2013), in which the demands of financial intermediaries take center stage. Our model draws from Chien et al. (2011, 2012) and Gabaix and Koijen (2022), which emphasize the role of institutions with stable equity shares. In the presence of limits to arbitrage (Shleifer and Vishny, 1997; Vayanos and Vila, 2021), we make unique cross-sectional predictions of our rebalancing channel for equity prices. Our empirical test using stock price reactions to monetary shocks complements tests of intermediary leverage or wealth as determinants of *unconditional* expected returns, such as Adrian et al. (2014) and He et al. (2017). Our reduced-form evidence highlights the importance of investor demand in asset pricing, complementing the structural approach (Koijen and Yogo, 2019).

Our results speak to the growing literature showing that long-horizon investors rebalance toward target allocations and, in doing so, move asset prices (see, for example, Merton 1971, Chien et al. 2011, 2012). Our findings relate closely to emerging research on target-date funds (TDFs), a rapidly growing class of rebalancers (Mitchell and Utkus, 2021; Elton et al., 2015; Balduzzi and Reuter, 2019; Duarte et al., 2021; Parker et al., 2022, 2023). Parker et al. (2023) show that TDFs actively rebalance in response to differential returns across asset classes, and stocks with higher TDF ownership have lower returns when equities outperform bonds.

While we share a focus on rebalancing demand, this paper makes several distinct contributions from Parker et al. (2023) and others. First, we examine the transmission of shocks from the bond market to the stock market, rather than contrarian flows driven by stock market fluctuations. Second, we use monetary shocks for causal identification, instead of relying on general market movements. Third, we demonstrate that the rebalancing effect extends beyond TDFs, manifesting across a broad range of institutions — including wealth management and pension funds — that collectively hold a significant share of the stock market. And last, we highlight that rebalancing timing contributes to the seasonality of the cross-section of stock prices and aggregate stock market reactions, a finding confirmed by Harvey et al. (2025) beyond monetary-policy-driven price movements.

Related papers by Hanson and Stein (2015), Becker and Ivashina (2015), and Lian et al. (2019) document that investors reach for yield — that is, they exhibit a greater propensity to take risk when interest rates are low. We highlight, using cross-sectional evidence, that reaching for yield across both stock and bond asset classes may affect stock prices, and this effect occurs via rebalancers' demand.

We build on the high-frequency identification literature, pioneered by Cook and Hahn (1989). Specifically, we use monetary shocks estimated from five short-term interest rate futures from Gürkaynak et al. (2005a) and Nakamura and Steinsson (2018). The exogeneity of these shocks with respect to economic fundamentals remains debated. Some argue that these shocks may reflect a Fed information effect, revealing private information held by the Federal Reserve (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018; Ai et al., 2022), while others suggest they capture the Fed's response to contemporaneous news (Cieslak, 2018; Bauer and Swanson, 2023a). This debate, while important, is less central to our analysis, as Bauer and Swanson (2023b) show that orthogonalizing monetary shocks with respect to macroeconomic and financial news does not materially change their effects on asset prices. For robustness, we show that our findings of cross-sectional sensitivity hold on a subsample of monetary shocks less susceptible to the Fed information effect selected by Jarociński and Karadi (2020).

We use a cross-sectional approach to test the rebalancing channel of monetary transmission. In explaining the Bernanke and Kuttner (2005) puzzle, the literature suggests a few mechanisms, including shifts in risk-bearing capacity (Kekre and Lenel, 2022; Pflueger and Rinaldi, 2022) and changes in investor beliefs (Bianchi et al., 2022). Because aggregate time-series evidence has limited power to distinguish these, we combine high-frequency monetary policy shocks with detailed institutional holdings of the cross-section of stocks. This approach allows us to test predictions that are specific to rebalancing and to assess their implications for the aggregate equity response.

A related literature shows that firm fundamentals — such as price stickiness (Gorodnichenko and Weber, 2016), financial frictions (Ozdagli, 2018; Chava and Hsu, 2020; Gürkaynak et al., 2022), dividend yield (Daniel et al., 2021), and a composite index developed by Ozdagli and Velikov (2020) of several firm characteristics called monetary policy exposure (MPE) — predict individual stock price reactions to monetary shocks. Our mechanism differs in that it is based on investor demand, and generates excess returns that cannot be explained by these fundamental-based channels. To isolate our rebalancing channel, we control for the MPE index, along with other firm characteristics and industry-level sensitivities. Furthermore, in Appendix E.7, we confirm that our rebalancer-ownership factor is not spanned by the established asset-pricing factors in Haddad et al. (2020) and Jensen et al. (2021).

2. A model of the rebalancing channel

We develop a model of the rebalancing channel to guide our empirical analysis. The model predicts that a stock with higher ownership by rebalancers is more exposed to rebalancing flows and thus experiences greater revaluation in response to monetary shocks. We refer to this dependence of a stock's price reaction on its rebalancer ownership as the *cross-sectional sensitivity*. Our model further illustrates that such a cross-sectional sensitivity connects to the aggregate stock market reaction attributed to changes in the excess returns resulting from portfolio rebalancing, shedding light on the Bernanke and Kuttner (2005) puzzle.

In Section 2.1, we present a simple static model that yields these predictions. In Section 2.2, we extend the model to a multi-period environment to take into account that rebalancers typically rebalance at a lower frequency. This extension predicts that both the cross-sectional sensitivity and the aggregate market reaction decline as the time gap between monetary shocks and rebalancing events widens. In

Section 2.3, we discuss our empirical strategies to test these theoretical predictions. Last, in Section 2.4, we summarize various extensions of our model that are presented in Appendix B. Appendix C collects all the proofs.

2.1. The baseline static model

As a baseline, we consider a static environment with two stocks, one long-term bond and one short-term risk-free bond whose return η is set by the central bank. We examine how stock prices respond to monetary shocks $\mathrm{d}MS$ that change bond prices. The stocks, indexed by $i = 1, 2$, are imperfect substitutes and each is in unit supply. They have the same pre-shock dividend $\bar{D}$ and price $\bar{P}$ but differ in their investor bases, which expose them differentially to rebalancing flows. Suppose that the long-term bond's price change from its pre-shock price $\bar{P}_B$ following a monetary shock $\mathrm{d}MS$ is $r_B = P_B/\bar{P}_B - 1$, with $\frac{\mathrm{d}r_B}{\mathrm{d}MS} < 0$. A vast literature has established the long-term bond price exhibits a large response to monetary shocks (Shiller et al., 1983; Mankiw and Summers, 1984; Cochrane and Piazzesi, 2002; Gürkaynak et al., 2005b; Hanson and Stein, 2015; Giglio and Kelly, 2018; Hanson et al., 2021).[1] We *take as given* the bond price reaction r_B and study how rebalancing flows between the stock and bond asset classes drive the changes in stock prices $r_i = P_i/\bar{P} - 1$ relative to their pre-shock price $\bar{P}$. Our predictions of stock price reactions are based on the stock market clearing conditions only, *given any bond revaluation* r_B, regardless of how the long-term bond price is determined.[2]

There are two investors, a rebalancer (R) who holds stock 1 and the long-term bond and an equity arbitrageur (E) who trades both stocks and the short-term bond. Their demand pins down the stock prices. We assume that the expected stock dividend changes in response to the monetary shock by the same sensitivity $\frac{\mathrm{d}D}{\mathrm{d}MS} < 0$ across two stocks. Throughout, we take first-order approximations of investors' demand, since monetary shocks are small. We index investors by superscripts and assets by subscripts.

Rebalancer's demand. In the absence of a monetary shock, the rebalancer holds ω share of stock 1, implying an aggregate market share of $\bar{\omega} = \omega/2$, since two stocks have the same market capitalization. As the bond price rises by r_B, the bond expected return falls. Suppose that the rebalancer targets an equity share of

$$\vartheta \equiv \frac{W_1^R}{W^R} = \theta \mathrm{e}^{\chi(1-\theta) r_B} \tag{1}$$

where $\theta = \omega\bar{P}/\bar{W}^R$ is their pre-shock equity share, and $\chi \geq 0$ parametrizes a potential incentive to reach for yield across asset classes *à la* Lian et al. (2019) — in response to a positive bond revaluation r_B (which means a lower bond return), the investor tilts their portfolio towards stock. If $\chi = 0$, the rebalancer targets a fixed equity share θ as in Gabaix and Koijen (2022) and Parker et al. (2023). With $\chi > 0$, the parametrization ensures that the reaching-for-yield incentive to adjust equity share only applies when the fund holds both the equity and bond asset classes, i.e., $\theta \in (0, 1)$. Further, the more extreme the equity share θ, the smaller margin of adjustment.[3]

As the prices of stock 1 and bond change by r_1, r_B respectively, the log change in the rebalancer's wealth is $\frac{\Delta W^R}{\bar{W}^R} = \theta r_1 + (1-\theta) r_B$. Using Eq. (1), the log change in the rebalancer's wealth invested in equity is thus $\frac{\Delta W_1^R}{\bar{W}_1^R} = \frac{\Delta\vartheta}{\theta} + \frac{\Delta W^R}{\bar{W}^R} = \theta r_1 + (1-\theta)(1+\chi) r_B$. Therefore, the change in stock demand $\Delta Q_1^R = \frac{\bar{W}_1^R + \Delta W_1^R}{\bar{P}(1+r_1)} - \omega$ is

$$\Delta Q_1^R = -\omega(1-\theta) r_1 + \underbrace{\omega(1-\theta)(1+\chi) r_B}_{\text{rebalancing flow}} \tag{2}$$

In the limiting case, if a fund only invests in stock ($\theta = 1$) or bond ($\theta = 0$ hence $\omega = 0$), their stock demand does not respond to price changes. When they invest in both stock and bond, i.e., $\theta \in (0, 1)$, their stock demand responds to both price changes as follows. If the stock price changes by r_1, they sell stock according to an elasticity $\omega(1-\theta)$. If the bond price falls ($r_B < 0$) and its expected return rises, this generates two sources of rebalancing flow to sell stock 1. First, the bond is worth less, which raises the equity share of the rebalancer's portfolio and triggers them to sell stocks, captured by $\omega(1-\theta) r_B$. Second, the expected bond return is higher, which means the rebalancer wants to lower their equity share with a reach-for-yield incentive across asset classes, with strength $\omega(1-\theta)\chi r_B$.

Arbitrageur's demand. The equity arbitrageur trades both stocks and the short-term bond, according to the following demand function with $\psi^A, \psi^C \in (0, \infty)$, microfounded from a canonical mean–variance optimization in Appendix A.1,

$$\Delta Q_i^E = -\psi^A (r_i - \check{r}) - \psi^C (r_i - r_{-i}), \quad i \in \{1, 2\} \tag{3}$$

in which $\check{r} = \frac{\Delta D - \bar{P}\Delta\eta}{(1+\eta)\bar{P}}$ indicates the stock revaluation due to changes in fundamentals (i.e., dividend and the risk-free rate) and hence $r_i - \check{r}$ captures the "excess" stock revaluation from a change in the excess return. The arbitrageur's demand for each stock has two terms: they sell the stock if its price exceeds its fundamental value $\check{r}$ (ψ^A term) and if its price exceeds the other stock (ψ^C term).

Following the literature on the excess sensitivity of long-term rates to monetary shocks, we assume that $\frac{\mathrm{d}r_B}{\mathrm{d}MS} < \frac{\mathrm{d}\check{r}}{\mathrm{d}MS} < 0$. That is, the long-term bond revaluates more than the fundamental-driven stock market revaluation.

Stock market clearing. The stock prices are determined by market clearing conditions

$$\Delta Q_1 = \Delta Q_1^R + \Delta Q_1^E = 0$$
$$\Delta Q_2 = \Delta Q_2^E = 0$$

The equilibrium stock price reactions are as follows.

Proposition 1 (*Stock Price Reactions Due to Rebalancing*)**.** *We consider a monetary shock* $\mathrm{d}MS$ *in this baseline static model.*

(a) The stock price reactions are

$$\frac{\mathrm{d}(r_1 - \check{r})}{\mathrm{d}MS} = \left(\psi^A + \psi^C\right) R\omega \left[(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} - \frac{\mathrm{d}\check{r}}{\mathrm{d}MS}\right] < 0 \tag{4}$$

$$\frac{\mathrm{d}(r_2 - \check{r})}{\mathrm{d}MS} = \psi^C R\omega \left[(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} - \frac{\mathrm{d}\check{r}}{\mathrm{d}MS}\right] < 0 \tag{5}$$

with $R = \frac{1-\theta}{\psi^A(\psi^A + 2\psi^C) + (\psi^A + \psi^C)\omega(1-\theta)}$, $\frac{\mathrm{d}r_B}{\mathrm{d}MS}$ *being the long-term bond price reaction, and* $\frac{\mathrm{d}\check{r}}{\mathrm{d}MS} = \frac{1}{(1+\eta)\bar{P}}\frac{\mathrm{d}D}{\mathrm{d}MS} - \frac{1}{1+\eta}\frac{\mathrm{d}\eta}{\mathrm{d}MS}$ *being the stock price reaction due to changes in fundamentals (dividends and the risk-free rate). The stock price reactions differ from* $\check{r}$ *only in the presence of rebalancer* ($\omega > 0$).

(b) With rebalancer ownership $\omega > 0$*, there is a price gap between the two stocks proportional to* ω*, with the cross-sectional sensitivity* $\gamma \equiv \omega^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right)$ *satisfying*

$$\gamma = \psi^A R \left[(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} - \frac{\mathrm{d}\check{r}}{\mathrm{d}MS}\right] < 0 \tag{6}$$

which means the stock with higher rebalancer ownership exhibits a stronger price response to monetary shocks.

[1] The existing literature has proposed various mechanisms that might contribute to the excess sensitivity of long-term rates to movements in short-term rates, such as mortgage refinancing, investor extrapolation, and investor reaching for yield in the bond market (Hanson et al., 2021).

[2] One could embed our model of portfolio rebalancing across stock and bond classes into a richer model with bond market demand frictions developed by previous papers to jointly determine the stock and bond price reactions.

[3] In Appendix B.3, we consider further flexibility in the targeted equity share by small amounts based on the equity-bond excess return following Gabaix and Koijen (2022) and show that our main message carries through.

(c) *The aggregate stock market reaction* $\bar{r} = \frac{r_1+r_2}{2}$ *satisfies, with the aggregate rebalancer ownership* $\bar{\omega} = \omega/2$,

$$\frac{\mathrm{d}(\bar{r} - \check{r})}{\mathrm{d}MS} = \left(1 + \frac{2\psi^C}{\psi^A}\right)\gamma\bar{\omega} < 0 \tag{7}$$

which exceeds its fundamental value $\check{r}$ *only in the presence of rebalancer* ($\omega > 0$).

This proposition illustrates the effects of portfolio rebalancing on the stock price reactions to monetary shocks, and in particular, their excess return components. To understand the mechanism, we start with the benchmark with no portfolio rebalancing, and then explain how rebalancing leads to a cross-sectional price gap and contributes to the change in excess return for the aggregate stock market.

Benchmark with no rebalancer ($\omega = 0$) *and null hypothesis.* If there exists no rebalancer, according to Eqs. (4) and (5), both stocks will revaluate only due to changes in fundamentals (dividends and the risk-free rate), i.e., $r_1 = r_2 = \check{r}$. It happens because the arbitrageur's position depends only on the stock excess returns relative to the short-term bond, as seen from Eq. (3). In order for them to hold their positions after monetary shocks, the excess returns have to be unchanged. As both stocks experience the same changes in fundamentals, there will be no price gap between them. Further, the aggregate stock market revaluation will be entirely attributed to changes in fundamentals with no changes in the excess returns, following Eq. (7), which is at odds with Bernanke and Kuttner (2005).

Cross-sectional and aggregate implications of rebalancing. Conversely, the existence of rebalancers can be detected by its cross-sectional price implications, to the extent that they hold different stocks with the same fundamentals by different amounts. Our theory not only predicts that there is a price gap between stocks, it also implies that such a price gap increases in the rebalancing ownership gap. We call this the *cross-sectional sensitivity* $\gamma \equiv \omega^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right)$. Assuming realistically that long-term bonds have excessive price reactions to monetary shock, i.e., $\frac{\mathrm{d}r_B}{\mathrm{d}MS} < \frac{\mathrm{d}\check{r}}{\mathrm{d}MS} < 0$, we predict $\gamma < 0$. That is, the stock with higher rebalancer ownership exhibits a stronger price response to monetary shocks.

To understand this prediction of γ, recall that if there is no rebalancer, both stocks will revaluate by $\check{r}$ due to changing fundamentals, which should be small as monetary shocks are short-lived. Under $\frac{\mathrm{d}r_B}{\mathrm{d}MS} < \frac{\mathrm{d}\check{r}}{\mathrm{d}MS} < 0$ (i.e., excess movement of long-term bond), in response to a contractionary monetary shock, the long-term bond loses more value than stock 1 and hence the rebalancer's equity share would go up. Thus the rebalancer needs to sell stock 1 and buy long-term bond to restore their equity share. Further, if they reach for yield ($\chi > 0$), they would like to lower their equity share given that the bond return is higher now, hence an additional incentive to sell stock 1. As the rebalancer sells stock 1, its price has to drop to induce the equity arbitrageur to trade. Since stock 1 is directly exposed to the rebalancing flow and stock 2 is only indirectly affected by the arbitrageur's trade, stock 1 has a larger price reaction to monetary shocks.

A negative cross-sectional sensitivity γ supports the rebalancing channel and further implies that the aggregate stock market reaction exceeds the extent warranted by changes in fundamentals (dividends and the risk-free rate), as indicated by Eq. (7). Hence the rebalancing channel contributes to the component of aggregate stock market reaction due to excess returns, i.e., the Bernanke and Kuttner (2005) puzzle. A cross-sectional price gap points to an excess aggregate reaction because the expected changes in fundamentals $\check{r}$ are equal across two stocks and thus netted out in the difference in price changes $r_1 - r_2$. Any price difference only results from the rebalancing flow, which also contributes to the aggregate stock market reaction in excess of fundamental changes.

2.2. Delayed rebalancing in multi-period environment

The baseline model in Section 2.1 assumes instantaneous rebalancing between stock and bond following monetary shocks by the rebalancer. Although this assumption simplifies the analysis, investors such as pension funds are known to rebalance their portfolios only periodically. Here, we enrich the baseline model to accommodate delayed rebalancing, yet the market price is forward-looking to price future flows. This generates another unique and testable prediction that monetary shocks closer to rebalancing times lead to a larger cross-sectional sensitivity γ and trigger a larger aggregate stock market reaction $\bar{r}$.

Assume there are $T+1$ periods, indexed by $t = 0, \dots, T$, the last of which is like the baseline model, and two stocks $i = 1, 2$. Assume a monetary shock $\mathrm{d}MS_0$ in period 0 triggers a predictable long-term bond revaluation of $\mathrm{d}r_{BT}$ in period T. We assume that $\frac{\mathrm{d}|r_{BT}|}{\mathrm{d}MS_0}$ weakly declines in T, as the effects of monetary shocks on asset prices fade away over time.

As in the baseline model, since fundamental changes are common to both stocks, any price gap will only reflect the excess return components of stock price changes caused by portfolio rebalancing. For simplicity, here we assume that the monetary shocks do not change stock fundamentals to abstract away from the $\check{r}$ terms, but our message is robust to that.

Let $r_{it} = P_{it}/\bar{P} - 1$ denote the change in the time-t price of stock i. As before, we analyze demand of the rebalancer and the arbitrageur to pin down the stock price reactions.

Rebalancer's demand. The rebalancer holds ω share of stock 1 unchanged, i.e., $\Delta Q^R_{1t} = 0$ for $t = 0, \dots, T-1$, until they rebalance in period T according to

$$\Delta Q^R_{1T} = -\omega(1-\theta)r_{1T} + \omega(1-\theta)(1+\chi)r_{BT} \tag{8}$$

which is the same as Eq. (2).

Arbitrageur's demand. The equity arbitrageur is forward-looking and adjusts their position every period as follows, subject to discount rate η with $\psi^A, \psi^C \in (0, \infty)$, which we microfound from a period-by-period mean–variance optimization in Appendix A.2, for $i = 1, 2,\ t = 0, \dots, T-1$,

$$\Delta Q^E_{it} = -\psi^A\left(r_{it} - \frac{r_{i,t+1}}{1+\eta}\right) - \psi^C\left[r_{it} - \frac{r_{i,t+1}}{1+\eta} - \left(r_{-i,t} - \frac{r_{-i,t+1}}{1+\eta}\right)\right] \tag{9}$$

Stock market clearing. The stock prices are pinned down by period-by-period market clearing, $t = 0, \dots, T$

$$\Delta Q_{1t} = \Delta Q^R_{1t} + \Delta Q^E_{1t} = 0$$
$$\Delta Q_{2t} = \Delta Q^E_{2t} = 0$$

We characterize the instantaneous stock price reactions to monetary shocks driven by anticipated future rebalancing flows as follows.

Proposition 2 (*Delayed Rebalancing*). *We consider a monetary shock and normalize the fundamental-driven stock revaluation* $\check{r}$ *to zero in this multi-period model with delayed rebalancing.*

(a) *The period-*t *stock price reactions are*

$$\frac{\mathrm{d}r_{1t}}{\mathrm{d}MS_0} = \frac{1}{(1+\eta)^{T-t}}\left(\psi^A + \psi^C\right)R\omega(1+\chi)\frac{\mathrm{d}r_{BT}}{\mathrm{d}MS_0} < 0 \tag{10}$$

$$\frac{\mathrm{d}r_{2t}}{\mathrm{d}MS_0} = \frac{1}{(1+\eta)^{T-t}}\psi^C R\omega(1+\chi)\frac{\mathrm{d}r_{BT}}{\mathrm{d}MS_0} < 0 \tag{11}$$

with $R = \frac{1-\theta}{\psi^A(\psi^A+2\psi^C)+(\psi^A+\psi^C)\omega(1-\theta)}$ *and* r_{BT} *being the time-*T *revaluation of long-term bond triggered by the monetary shock.*

(b) Both the time-0 cross-sectional sensitivity $\gamma_0 = \omega^{-1}\left(\frac{\mathrm{d}r_{10}}{\mathrm{d}MS_0} - \frac{\mathrm{d}r_{20}}{\mathrm{d}MS_0}\right)$ *and the aggregate price reaction* $\bar{r}_0 \equiv \frac{r_{10}+r_{20}}{2}$ *decline in magnitude in the time gap T between the monetary shock and the rebalancing event,*

$$\frac{\partial|\gamma_0|}{\partial T} < 0 \tag{12}$$

$$\frac{\partial|\mathrm{d}\bar{r}_0/\mathrm{d}MS_0|}{\partial T} < 0 \tag{13}$$

(c) The time-0 aggregate stock market reaction $\bar{r}_0$ *satisfies, with the aggregate rebalancer ownership* $\bar{\omega} = \omega/2$,

$$\frac{\mathrm{d}\bar{r}_0}{\mathrm{d}MS_0} = \left(1 + \frac{2\psi^C}{\psi^A}\right)\gamma_0\bar{\omega} < 0 \tag{14}$$

Proposition 2(a) suggests that when rebalancing is delayed, the time-0 prices partially incorporate future rebalancing, due to the forward-looking arbitrageur. The dampening rate is the short-term rate η which serves as the arbitrageur's discount rate to front-run future rebalancing flows. More realistically, the discount rate η may also reflect other frictions, such as inattention (Gabaix, 2019).

Proposition 2(b) suggests a new testable prediction that both the aggregate stock market reaction $\bar{r}_0$ and the cross-sectional sensitivity γ_0 should be smaller, when the delay is longer.

Last, Proposition 2(c) establishes that, in this multi-period environment, the implied time-0 aggregate stock market reaction due to rebalancing still relates to the measured cross-sectional sensitivity γ_0, parallel to Proposition 1(c).

2.3. Empirical implications

We now take stock of our theoretical predictions to guide the empirical strategy.

The null hypothesis across stocks. When there exists no rebalancers whose demand follows Eq. (2), the stock price reactions will only depend on changes in the risk-free rate and dividends. Empirically, if our measure of rebalancer ownership does not capture true rebalancer ownership or if rebalancer ownership does not affect prices, there will be no price gaps across stocks with the same fundamentals, which is our null hypothesis.

A cross-sectional test: dual shares and all common stocks. Proposition 1(b) presents a unique prediction of the rebalancing channel — all else equal, a stock with higher rebalancer ownership revalues more in response to monetary shocks. Empirically, we test whether the regression coefficient γ in the relationship $r_{it} = \gamma MS_t \cdot \omega_{it} + \cdots$ is negative, where MS_t denotes monetary shock on announcement day t, r_{it} is the return of stock i on announcement day t, and ω_{it} denotes rebalancer ownership share (i.e., the proportion of stock i held by rebalancers on announcement day t).

In reality, stock prices may respond differently to monetary shocks due to different responses in stock fundamentals (e.g., dividends), rather than differences in exposure to rebalancing flows. Therefore, the ideal test of the rebalancing channel should compare two stocks with identical fundamentals but different investor bases. In Section 4, we analyze a sample of dual-share firms, where the dual shares ($s = 1, 2$) of the same firm f have identical fundamentals but differ in their investor composition, and show that the share with higher rebalancer ownership revalues more in response to monetary shocks.

While the dual shares are closest to the ideal test, they are a small sample. We generalize our findings to the cross-section of all common stocks, acknowledging that their prices may react differently to monetary shocks for reasons other than rebalancing (e.g., duration, dividends). Therefore, when testing whether the regression coefficient γ from the regression of r_{it} on $MS_t \cdot \omega_{it}$ is negative, we control for additional firm characteristics that may capture alternative channels of monetary transmission into stock prices. These controls and the full empirical specification are detailed in Section 5.1.

The timing of shocks. Once we acknowledge that rebalancing is often delayed rather than immediately following FOMC announcements, Proposition 2(b) offers another prediction of the rebalancing channel based on this institutional feature — when the rebalancing event is further away from the monetary policy announcement date, the cross-sectional sensitivity γ_0 and the aggregate stock market reaction $\frac{\mathrm{d}\bar{r}_0}{\mathrm{d}MS}$ are both smaller in magnitude. Anecdotally, rebalancers adjust portfolios routinely at the end of each quarter or month. To test this prediction, in Section 5.2, we split the sample based on the proximity of the monetary policy announcement dates to the month and quarter ends. On subsamples of month- and quarter-ends, we test whether the aggregate stock market reaction to monetary shocks and the cross-sectional sensitivity are larger in magnitude.

Different types of investors and placebo tests. In our baseline model, we consider only one rebalancer and suggest that their ownership predicts stock price reactions. We conduct placebo tests in Sections 5.1 and 5.3 to show that ownership by institutional investors who invest solely in stocks does not exhibit predictive power, which highlights the unique role of rebalancers. We further support our theory by showing the ownership of two different types of rebalancers, constructed from FactSet and Morningstar respectively, both as valid predictors of stock price reactions in Sections 5.1 and 5.3.[4]

Rebalancing quantities and the relative revaluation of stock and bond. We examine high-frequency price responses to shed light on the Bernanke and Kuttner (2005) puzzle. Our model also predicts quantities — rebalancers actively trade to lower their equity shares (relative to their counterfactual equity shares if they hold quantities fixed) after a rate hike, as formalized in Proposition 4(a) in Appendix B.1. In Section 5.4, we confirm that rebalancers have stable equity shares that trace targeted shares and trade in directions as predicted by the model after monetary shocks.

An advantage of our cross-sectional approach using price reactions is that the cross-sectional sensitivity γ directly informs the aggregate stock market reaction as in Proposition 1(c). γ has already incorporated the underlying rebalancing flow, the bond revaluation r_B, and other demand parameters. If one is interested in measuring the underlying parameter (for example, the reaching-for-yield incentive χ), that could be informed by the difference in price reactions $\bar{r} - r_B$.[5] Proposition 4(b) in Appendix B.1 demonstrates that, in the absence of reaching for yield ($\chi = 0$), we would observe $\frac{\mathrm{d}r_B}{\mathrm{d}MS} < \frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} < 0$. That is, the aggregate stock market revalues less than the long-term bond. Further, the difference $\frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} - \frac{\mathrm{d}r_B}{\mathrm{d}MS}$ decreases in χ, meaning that the stock revaluates more if χ is sufficiently high. We provide evidence on market-wide revaluations following monetary shocks for equity and bond markets in Appendix F.3 using traded ETFs that track these markets, and we cannot reject that the stock market revalues less than the bond market.

Mismeasurement of rebalancer ownership. A key empirical challenge is measuring rebalancer ownership. First, the classic measurement error in rebalancer ownership could attenuate the estimated cross-sectional sensitivity γ. Because FactSet reports equity holdings at the management-firm level, our proxy can be measured with error — for example, if a firm includes rebalancing and pure-equity subsidiaries —

[4] Different types of rebalancers may differ in their equity shares θ, reaching-for-yield incentive χ, or other demand parameters, which we formally accommodate in Appendix B.3. Such heterogeneity may affect the magnitude of the cross-sectional sensitivity γ when using their ownership share as predictor, which we discuss further in Section 5.3, but not the sign of γ.

[5] Alternatively, one could measure these parameters by examining rebalancers' portfolios. Unfortunately, this is not feasible with our primary data from FactSet, which does not contain the bond holdings. Merging bond holdings data (e.g., eMAXX) with FactSet is known to be challenging (Koijen and Yogo, 2019).

so both the cross-sectional estimates and the calibrated aggregate implication may be affected. We discuss the construction and limitations of this empirical measure in Section 3. Additionally, Proposition 5 in Appendix B.2 notes a narrow special case: if the ownership measure is overstated by the same proportion across all stocks, then the coefficient γ scales down by the same proportion but keeps the negative sign. As a result, the aggregate implication in Proposition 1(c) is invariant to this specific mis-scaling. We emphasize that this is not a general robustness result: more realistic forms of mismeasurement need not cancel.

2.4. Model extensions

Here we summarize extensions to the baseline model in Appendices B.3 and B.4. We also show that, across these extensions, the cross-sectional sensitivity γ still only reflects rebalancing flows and informs the aggregate stock market reaction $\bar{r}$.

Heterogeneous rebalancers and more flexible demand. In the baseline model we assume a representative rebalancer who trades stock 1 but not stock 2. In Appendix B.3, we consider a more general environment with heterogeneous rebalancers and more flexible demand. In particular, rebalancers indexed by $n \in \mathcal{R}$ could differ in their pre-shock equity share θ^n, shares owned ω_1^n, ω_2^n of stock 1 and 2, as well as reaching-for-yield incentive χ^n. Further, each rebalancer can adjust their equity share according to the excess return of stock relative to bond by flexibility κ^n, and trade two stocks to take advantage of their return difference by elasticity ϕ^n. Proposition 6 shows the cross-sectional sensitivity $\gamma \equiv \frac{\frac{dr_1}{dMS} - \frac{dr_2}{dMS}}{\omega_1 - \omega_2}$ and the aggregate stock market reaction in this more general environment. Proposition 7 suggests that, in a particular case with proportional holdings ($\frac{\omega_1^n}{\sum_n \omega_1^n} = \frac{\omega_2^n}{\sum_n \omega_2^n}$), the aggregate stock market reaction relates to the cross-sectional sensitivity in a way proportional to $\gamma\bar{\omega}$ as in the baseline model.

Many stocks. The baseline model considers two stocks, providing the minimal setting to introduce and connect the cross-sectional sensitivity γ and the aggregate stock market reaction $\bar{r}$. In Appendix B.4, we extend this model to an environment with many stocks. In this setting, the cross-sectional sensitivity γ becomes the regression coefficient of r_i on $\omega_i \cdot MS$ across all stocks, and the aggregate stock market reaction $\bar{r}$ is an average of all stocks' price reactions. Proposition 8 establishes that, to the leading order, the cross-sectional sensitivity γ informs the aggregate stock market reaction $\bar{r}$ in the same proportional way as in the baseline two-stock model.

3. Holdings and prices data

3.1. Institutional equity holdings

Ideally, we would observe each investor's complete stock and bond holdings and their equity-share targets. This would allow us to identify *rebalancers* as investors who manage portfolios around stable equity-share targets and therefore trade predictably in response to relative revaluations across stocks and bonds. Our theory predicts that stocks with greater ownership by such rebalancers have stronger price responses to monetary policy surprises. If rebalancers are heterogeneous — for example, in target equity shares or the frequency of rebalancing — then ownership by different rebalancer types should predict price reactions to different extents. With the ideal data, we could measure ownership by rebalancer type directly and estimate these heterogeneous effects.

In practice, actual and target equity shares are not observed for most investors. Our main empirical exercise therefore uses FactSet to construct a stock-level measure of *rebalancer ownership*. FactSet collects equity holdings of major U.S. institutions, which together owned over 70% of the market by the end of 2019. This allows us to construct detailed stock-level ownership measures. Following Koijen et al.

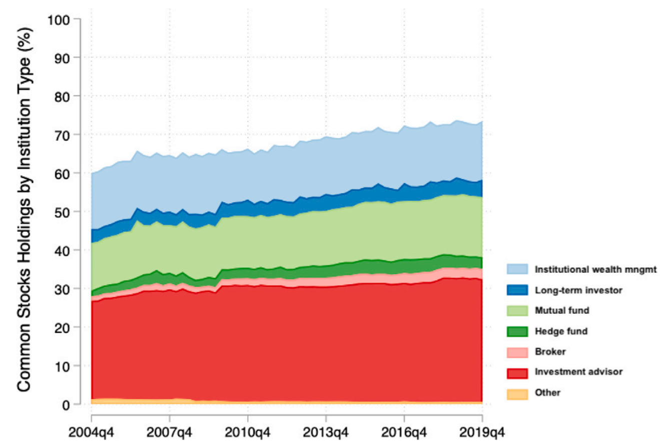

Fig. 1. Equity holdings by institution types.
This graph plots the equity market coverage by institution types in FactSet from 2004Q4 to 2019Q3. Stocks in the sample are the common stocks (share codes 10, 11, and 12) listed on the three major exchanges (NYSE, NYSE MKT, and NASDAQ). For each institution category at any given time, we compute the equity market share by dividing the market value of all the stocks held by the institutions by the market value of all outstanding stocks.

(2022), we categorize these institutions into six groups: *institutional wealth management*, *long-term investors*, *investment advisors*, *hedge funds*, *mutual funds*, and *brokers*. The categorization uses FactSet's *subtype* field, supplemented by its *entity_type* mapping and our manual review of unclassified entities. The complete cleaning and classification process is detailed in Appendix D.1. Fig. 1 shows the share of total institutional holdings by group from 2004 to 2019.

FactSet provides comprehensive equity holdings across investor sectors, but it does not report bond holdings or explicit equity-share targets. We proxy rebalancers using investor classification. Specifically, we focus on the *long-term investors* and *institutional wealth management* categories and define rebalancer ownership as their combined equity ownership. We focus on these categories because they are most likely associated with rebalancing targets.[6] First, sovereign wealth funds are classified as *long-term investors* in FactSet. As in the NBIM example discussed in the introduction, such investors often operate with explicit strategic allocation targets. Second, pensions, another class of investors known to have rebalancing incentives, appear across multiple categories: in-house assets are typically recorded under *long-term investors*, while outsourced mandates are recorded under *institutional wealth management* (Fender, 2003). In Appendix D.1, we summarize the largest institutions within the *institutional wealth management* and *long-term investors* categories. The former primarily includes wealth management firms and their subsidiaries, while the latter consists mostly of in-house pension and endowment fund managers.

Table 1 reports the summary statistics for the holdings data in our sample period with year-end holdings. For *institutional wealth management* and *long-term investors*, the markets are quite concentrated, with the top 10 institutions holding around 60% of the total assets under management in that category. We measure active portfolio management for each category of institutions using *active share*. It is defined as one-half times the sum of the absolute value of active weights, which are portfolio weights minus market weights within the set of stocks held

[6] In FactSet, mutual funds encompass all fund types, of which balanced funds are a small subset holding approximately 0.3% of the aggregate stock market. We therefore exclude mutual funds from the rebalancer classification in FactSet.

Table 1
Summary statistics for institutions and funds.

		N	Asset under management					Concentration		Active share (%)		
			Mean (bn)	SD (bn)	10th %tile (mn)	Median (bn)	90th %tile (bn)	HHI	CR10	Mean	SD	Median
Institutional Wealth Management	**2004**	**683**	**34.33**	**276.3**	**201.3**	**2.565**	**30.95**	**961.4**	**62.74**	**49**	**18.8**	**48.7**
	2009	**892**	**22.87**	**198.5**	**147.1**	**1.806**	**21.33**	**855.0**	**62.33**	**46.9**	**18.9**	**47.6**
	2014	**1401**	**28.77**	**308.4**	**91.55**	**1.765**	**22.15**	**826.8**	**57.63**	**45.7**	**20**	**47.2**
	2019	**1947**	**28.68**	**375.4**	**133.3**	**1.475**	**18.32**	**884.7**	**60.04**	**45.2**	**18.3**	**44.3**
Long-Term Investor	**2004**	**113**	**53.29**	**117.1**	**54.6**	**3.757**	**177.8**	**512.4**	**64.29**	**28.4**	**22.2**	**24.5**
	2009	**112**	**55.87**	**129.3**	**87.72**	**5.109**	**169**	**563.0**	**60.64**	**28.5**	**24.3**	**23.9**
	2014	**124**	**96.28**	**252.5**	**145.9**	**13.03**	**214.3**	**630.8**	**59.83**	**27.9**	**21.2**	**27.4**
	2019	**127**	**129**	**402.2**	**150**	**16.34**	**244.1**	**837.9**	**65.16**	**31.9**	**22.7**	**30.4**
Investment Advisor	2004	1784	23.2	159.4	41.79	1.506	34.51	270.1	36.72	47.2	19	47.3
	2009	2083	21.24	126.5	34.89	1.146	31.34	175.1	30.83	45.7	19.2	45.6
	2014	3306	23.87	167.3	31.68	0.9059	30.62	151.5	29.61	43.7	19.4	44.4
	2019	3691	30.94	247	45.32	1.109	28.55	175.4	33.11	43.6	18.8	44.1
Broker	2004	35	51.07	87.18	107.9	4.172	190.2	1094	90.88	40.2	22.9	42.2
	2009	68	34.49	75.53	85.64	2.369	128.7	842.2	80.21	43.6	20.3	43.7
	2014	95	63.08	161	85.74	3.784	189.2	783.6	79.07	45	21.2	43.5
	2019	82	116.8	270.3	943.3	8.09	419.1	767.2	77.50	43.3	17.7	39.4
Hedge Fund	2004	569	5.529	10.84	124.4	2.008	13.56	85.05	20.81	53.7	20.1	57.2
	2009	722	6.692	18.93	104	1.506	13.54	124.5	27.41	51.2	19.8	54.3
	2014	1118	10.08	30.65	127.4	1.999	21.79	91.59	23.57	44.9	23.9	49.8
	2019	1139	11.78	49.35	166.8	2.163	21.26	162.7	31.29	48.4	22.6	51.6
Mutual Fund	2004	212	91.02	318.5	26.68	0.6942	207.5	622.0	65.19	44.4	20.3	45.6
	2009	257	75.87	336	22.48	0.5497	138.4	799.0	66.67	45.6	21.3	45.2
	2014	393	92.5	690	24.5	0.5092	59.91	1438	78.69	43.7	19.9	45.4
	2019	380	144.5	1431	34.62	0.6731	51.13	2603	88.45	42.5	20.7	44.3

This table summarizes assets under management and active share for institutional investors in the sample and concentration for each investor category, which is based on FactSet codes *entity_type* and *entity_subtype*. We report the Herfindahl–Hirschman index and the concentration ratio $CR10$, defined as the market share (in percentage) for the ten largest institutions for each category. Active share is one-half times the sum of the absolute value of active weights, which are portfolio weights minus market weights within the set of stocks held for each manager (Koijen et al., 2022). Institutions and funds with less than $1 million in assets under management are excluded. Data is shown for the end of the years 2004, 2009, 2014, and 2019.

for each manager (Koijen et al., 2022).[7] The active portfolio management style suggests large variations in security-level ownership. Table 2 confirms that for the common stocks in the sample, considerable variation exists in ownership for both *institutional wealth management* and *long-term investors*.

3.2. Mutual fund holdings across asset classes

We supplement FactSet equity holdings with Morningstar monthly database of U.S. open-end mutual funds which contains their holdings across all asset classes. We link each security's CUSIP to the CUSIP Master File to determine its asset class. We then identify balanced funds by scanning fund names for keywords such as "Target Date" and by checking their underlying asset-allocation mixes. Our sample covers 2004Q4 through 2019Q3. For every common stock, we compute the ownership shares by balanced funds and pure-equity funds respectively. Detailed data-cleaning procedures and coverage statistics appear in Appendix D.2.

3.3. High-frequency shocks and prices

To separate the exogenous changes in monetary policy from endogenous responses of monetary policy to the economy, we use the high-frequency monetary shocks from Nakamura and Steinsson (2018), extracted from five Fed Funds futures and Eurodollar futures using 30-minute windows around FOMC meetings.[8] We use a subsample of the updated monetary shocks from Acosta and Saia (2020), including all the scheduled FOMC meetings from 2004 to 2019 to match the availability of high-frequency TAQ data below.[9]

We align stock returns by extracting intraday data from the Millisecond Trade and Quote (TAQ) database via WRDS. TAQ consolidates trades and quotes for all securities listed on the NYSE, AMEX, NASDAQ NMS, and Arca. We extract common stock prices for the period from 2004Q4 to 2019Q3. To mitigate market-microstructure noise at the 30-minute frequency, we apply filters described in Appendix D.3. Our final sample comprises roughly 532 firms per quarter (about half of all listed tickers), covering over 90% of total market capitalization. For each FOMC announcement, following Gürkaynak et al. (2005a) and Ozdagli and Velikov (2020), we define the pre-announcement price for a stock as the last valid trade price from 10 min before the FOMC announcement (and no more than 90 min before that), and the end price from the first valid trade 20 min after the FOMC announcement (and no more than 90 min after that). We compute market returns using S&P 500 ETF returns (from the ETF with ticker SPY, the most liquid ETF tracking the S&P 500 index).

3.4. Stock characteristics

We construct a variety of security characteristics, such as equity duration (Dechow et al., 2004; Weber, 2018; Gormsen and Lazarus, 2022), monetary policy exposure (MPE) index (Ozdagli and Velikov, 2020), firm size (Koijen and Yogo, 2019), dividend yield (Daniel et al., 2021; Jensen et al., 2021), and market beta (Frazzini and Pedersen, 2014) from CRSP and IBES database, accessed through WRDS. We construct the MPE index for securities in the sample following (Ozdagli and Velikov, 2020). They survey the literature on cross-sectional stock

[7] Conventionally, practitioners use tracking-error volatility to measure active management. Cremers and Petajisto (2009) show active share is a better measure than tracking-error volatility regarding stock selection.

[8] Specifically, the authors use the 30-minute windows from 10 min before scheduled FOMC announcements to 20 min after and use the price changes of two fed funds futures for the fed funds rate immediately following the FOMC meeting and the expected fed funds rate following the next FOMC meeting, and three Eurodollar futures for expected three-month Eurodollar interest rates at horizons of two, three, and four quarters. These shocks are normalized based on the daily treasury yield around FOMC dates.

[9] We have access to tick-level futures data from the CME group until mid-2018, which is outdated by the publicly available series from Acosta and Saia (2020). Within the overlapping period, our replication of monetary shocks from Nakamura and Steinsson (2018) is mostly consistent with (Acosta and Saia, 2020).

Table 2
Summary statistics for common stocks in FactSet holdings.

	Variables	N	Mean	Median	SD	p10	p90
2004	Advisor %	4913	22.00	20.50	16.20	1.52	44.60
	Broker %	4662	0.94	0.54	1.33	0.03	2.20
	Hedge Fund %	4322	5.59	3.23	6.63	0.46	13.60
	Long-Term Investor %	4516	2.15	1.38	2.02	0.15	4.84
	Mutual Fund %	4291	9.92	8.22	8.33	0.81	21.90
	Institutional Wealth Mgmt %	4849	10.10	8.92	8.34	0.56	20.90
	Market Value ($ million)	4938	2536	355.20	8444	36.23	4742
	β	3838	0.918	0.800	0.647	0.170	1.850
	DSS Duration (year)	1110	18.41	17.53	9.548	14.98	19.26
	Weber Duration (year)	1137	18.98	21.14	11.31	15.26	23.60
2009	Advisor %	4398	24.80	24.30	18.10	1.42	49.50
	Broker %	3919	1.23	0.85	1.49	0.08	2.53
	Hedge Fund %	4085	6.72	4.14	7.48	0.68	16.20
	Long-Term Investor %	3996	2.47	2.13	2.03	0.21	5.15
	Mutual Fund %	3914	10.40	9.11	8.14	0.94	21.70
	Institutional Wealth Mgmt %	4230	9.77	9.07	7.60	0.68	18.80
	Market Value ($ million)	4328	2774	320.94	9075	23.67	5260
	β	3329	0.911	0.843	0.563	0.218	1.681
	DSS Duration (year)	1336	18.47	16.65	12.76	13.13	20.11
	Weber Duration (year)	1381	16.64	19.30	14.88	10.23	23.35
2014	Advisor %	4220	25.70	26	17.70	1.79	49.90
	Broker %	4101	1.43	0.89	1.62	0.08	3.41
	Hedge Fund %	4056	9.60	6	10.10	0.91	23.90
	Long-Term Investor %	3678	2.79	2.51	2.28	0.22	5.84
	Mutual Fund %	3954	11.20	10.30	8.34	1.40	23.00
	Institutional Wealth Mgmt %	4171	11.30	10.70	8.54	0.84	21.20
	Market Value ($ million)	4170	4798	666.39	12,860	47.39	10,560
	β	2936	1.329	1.338	0.617	0.438	2.111
	DSS Duration (year)	1554	19.27	17.40	12.32	14.94	20.22
	Weber Duration (year)	1604	18.35	20.86	15.39	14.86	23.86
2019	Advisor %	4149	25.50	25.90	17.80	1.30	49.00
	Broker %	4016	1.66	1.28	1.62	0.12	3.58
	Hedge Fund %	3995	10	6.42	10.40	1.04	24.70
	Long-Term Investor %	3417	2.90	2.68	2.37	0.21	6.04
	Mutual Fund %	3827	11.20	10.30	8.32	1.22	22.90
	Institutional Wealth Mgmt %	4072	11.80	11.80	8.37	0.93	20.80
	Market Value ($ million)	4104	5950	761.93	14,960	34.75	14,830
	β	2835	0.929	0.933	0.428	0.351	1.469
	DSS Duration (year)	1971	19.42	17.65	11.26	14.30	22.46
	Weber Duration (year)	2018	19.35	20.95	12.08	14.11	24.79

This table reports summary statistics for the US publicly traded common stocks in the FactSet Holdings data, including the number of securities, statistics on their market value, estimated equity durations (DSS duration and Weber duration; based on parameter values from Dechow et al. (2004), and Weber (2018) respectively), market β (Frazzini and Pedersen, 2014), and average institutional holdings by type at each year end of 2004, 2009, 2014, and 2019. The percentage of market value owned by institutions is from SEC regulatory filings accessed via FactSet and reported by category in percentage points. Market values are computed from end-of-year adjusted prices and shares outstanding from CRSP. Stocks with a SIC code between 4900 and 5000, or 6000 and 7000, are excluded from duration computation. Variables are winsorized at 1% and 99% cutoffs. The sample only includes common stocks listed on NYSE, NYSE MKT, and NASDAQ.

price reactions to monetary shocks and propose a composite measure of monetary exposure using firm characteristics. The index is a linear combination of a measure of financial constraints, cash and short-term investments, equity duration, cash-flow volatility, and operating profitability. In particular, we note that equity duration is not as easily measured as bond duration. For robustness, we compute equity duration using three measures in the literature (Dechow et al., 2004; Weber, 2018; Gormsen and Lazarus, 2022). We detail the construction of duration, MPE, and other stock characteristics in Appendix D.4.

4. A quasi-experiment: Dual shares

Monetary shocks affect stock prices through multiple channels. Ideally, to test the rebalancing channel, one would compare stocks with identical fundamentals, so that any differential response to monetary shocks can be attributed solely to differences in exposure to rebalancing demand. In this section, we exploit *within-firm* variation using dual shares. We demonstrate that, for a given firm, the share class with higher exposure to rebalancing demand exhibits greater sensitivity to monetary shocks.

4.1. *The sample of dual shares*

We focus on dual-share firms, i.e., firms with two publicly traded share classes. Although each share class generally represents proportional economic interests in the firm, they often differ in voting rights, which can result in price discrepancies between the classes (Larcker and Tayan, 2015; Cox and Roden, 2002). Most dual-share firms adopt the dual-share capital structure before IPO (Gompers et al., 2010), including many large-cap companies such as Alphabet Inc., Meta Platforms Inc., and Berkshire Hathaway Inc.

To our knowledge, no existing panel dataset provides detailed share-class-level information on voting and dividend rights for our sample period. We outline the construction of our dual-share sample in Appendix D.5. The final sample comprises 68 dual-share firms. Within each firm f, these share classes have identical economic fundamentals, providing an ideal quasi-experimental setting for our analysis. Moreover, they are highly liquid: typical deviations in price gaps between share classes halve within 15 min.

4.2. Empirical design and results

Proposition 1(b) predicts that stocks with higher rebalancer ownership exhibit stronger price responses to monetary shocks. To test this, we construct rebalancer ownership on announcement day t for share class s of firm f by aggregating holdings of that share class across all rebalancers j:

$$\omega_{sft} = \sum_{j=1}^{N} \omega_{sfjt},$$

where ω_{sfjt} denotes the holdings of share class s of firm f by rebalancer j before announcement day t, summed across a total number N of rebalancers in FactSet. Each ω_{sfjt} is calculated as the ratio of shares of class s of firm f held by rebalancer j to the total shares outstanding of class s for firm f before t. We use holdings from the last available filing period before the announcement day to mitigate concerns about endogeneity in holding choices responding to monetary shocks.

Our baseline specification identifies *within-firm* price reactions to monetary shocks driven by differences in rebalancer ownership:

$$r_{sft} = \gamma^{dual}\omega_{sft} \cdot MS_t + \nu\omega_{sft} + \delta_{ft} + \epsilon_{sft}, \tag{15}$$

where r_{sft} denotes the 30-minute return of share class s of firm f around FOMC announcement t, MS_t represents the high-frequency monetary shock of Nakamura and Steinsson (2018), and ω_{sft} is the rebalancer ownership. δ_{ft} captures firm-meeting fixed effects, and ϵ_{sft} is the residual.[10]

The dual-share estimation exploits the *within-firm* variation of rebalancer ownership at each announcement date. Across firms, stock price reactions may be different because of changes in fundamentals (e.g., cash flows), date-specific news (e.g., shifts in risk aversion), or their interaction (e.g., firm-specific investor beliefs varying over time). A negative cross-sectional sensitivity γ^{dual} suggests that within a firm-meeting cell (given δ_{ft}), a larger rebalancer ownership induces a larger price response.

Our identification assumes that monetary shocks are exogenous to market fundamentals, and that differences in the high-frequency price reactions between share classes of the same firm arise solely from differential exposure to rebalancing-induced trading. Since dual shares of a given firm reflect identical fundamentals and differ only in their voting rights and liquidity, we address the potential concern that observed differences might come from liquidity variations between share classes with additional liquidity checks in Appendix D.5.

Voting rights and rebalancer ownership. Many rebalancers are passive investors, and in the dual-share setting, favor share classes with limited voting rights systematically (Bebchuk et al., 2017). In addition to the ordinary least squares (OLS) analysis in Eq. (15), we employ a two-stage least squares (2SLS) approach to instrument the rebalancer ownership using voting rights.

Specifically, we use $I_{High\ Voting\ Rights,sft}$, an indicator equal to one if share class s of firm f in the quarter $t-1$ before announcement day has higher voting rights, and zero otherwise, as an instrument for rebalancer ownership ω_{sft}. The exclusion restriction assumes that any effect of monetary shocks on return gaps between dual shares is not driven by voting rights per se, but only through their link to rebalancer ownership. One potential concern is that the voting rights premium might respond to monetary shocks. Prior research shows that the value of voting rights for individual firms can fluctuate significantly during periods of control threats or special shareholder meetings (Kalay et al., 2014). However, given the relatively small magnitude of monetary shocks (typically only a few basis points), it is unlikely that such shocks would trigger these major corporate governance events.[11]

We estimate the following first-stage regression:

$$\begin{pmatrix} \omega_{sft} \cdot MS_t \\ \omega_{sft} \end{pmatrix} = \boldsymbol{\Phi} \begin{pmatrix} I_{High\ Voting\ Rights,sft} \cdot MS_t \\ I_{High\ Voting\ Rights,sft} \end{pmatrix} + \delta_{ft} + \epsilon^1_{sft}, \tag{16}$$

where $I_{High\ Voting\ Rights,sft} \cdot MS_t$ and $I_{High\ Voting\ Rights,sft}$ are the instruments, and δ_{ft} are the firm-meeting fixed effects which control for trends across firms over time. The second stage estimates regress returns on the predicted $\widehat{\omega_{sft} \cdot MS_t}$ and $\widehat{\omega_{sft}}$ from the first stage:

$$r_{sft} = \gamma^{dual}_{2SLS}\widehat{\omega_{sft} \cdot MS_t} + \nu_{2SLS}\widehat{\omega_{sft}} + \delta_{ft} + \epsilon^2_{sft}. \tag{17}$$

Empirical results. Table 3 presents the instrumented regressions for dual shares and compares them with OLS results. Column (1) regresses rebalancer ownership on the high voting rights dummy, and Columns (2) and (3) display the first-stage regression results.

Columns (1) and (2) show that the indicator variable $I_{High\ Voting\ Rights,sft}$ negatively predicts rebalancer ownership, with statistical significance at the 1% level. These estimates suggest that a share class with more voting rights on average has 6.4% less rebalancer ownership compared to the other share class. Similarly, column (3) shows that the interaction term $MS_t \cdot \omega_{sft}$ is negatively predicted by $MS_t \cdot I_{High\ Voting\ Rights,sft}$ at the 1% level. Columns (4) and (5) report the second-stage and OLS estimates from Eqs. (15) and (17).

For the 2SLS specification, the Stock-Yogo F-statistic of 12.08 exceeds the weak instrument threshold of 7.03 (Stock and Yogo, 2005). The interaction coefficient from 2SLS (or OLS) implies that the share class with 10-percentage-point higher rebalancer ownership reacts about 37 basis points (or 17 basis points) more than the other class in response to a 10 basis point short-rate shock, statistically significant at the 1% (or 1%) level.

The estimated coefficient from 2SLS for dual shares is significantly larger than the OLS coefficient. One potential reason is that the OLS coefficient is subject to attenuation bias from measurement error. Besides that, the larger estimate from 2SLS could also be because this instrumented ownership estimates the local average treatment effect (Angrist and Imbens, 1995). Rebalancers may choose to hold a share class for reasons other than lower voting rights. In that case, the 2SLS estimate reflects the effect of rebalancer ownership for the rebalancers who choose to hold a share class because of the voting rights, while the OLS estimate presents the average effect for all rebalancers.

Fig. 2 plots the coefficients of the instrumented interaction term $\widehat{\omega_{sft} \cdot MS}$ for the dual shares, from the main estimation window up to 90 min after FOMC announcements. The cross-sectional sensitivity to monetary shocks driven by rebalancing becomes significant within 5 min of announcements, and persists throughout the trading day.[12] However, the cross-sectional sensitivity is no longer significant the next day or at even lower frequency (not shown). This reflects a well-known limitation of high-frequency identification in monetary economics: the identified monetary shocks are extremely small — the average size of Nakamura and Steinsson (2018) shocks from 2004 to 2019 is about 2 basis points. As time goes by and other shocks come in, the effects of these small monetary shocks are swamped.

[10] It is important to use the fully saturated model that controls for firm-meeting fixed effects, rather than a restricted fixed-effect model that only controls for firm fixed effects interacted with monetary shocks. The latter can be biased as we discuss further in Appendix E.1.

[11] When we include an indicator for high voting rights and its interaction with monetary shocks as controls in our OLS regression (15), the coefficient on the rebalancer ownership interaction, γ^{dual}, remains unchanged. This suggests that the effect is driven by rebalancing activity, rather than by the value of voting rights.

[12] In Appendix E.1, we present additional empirical results using the uninstrumented interaction $\omega_{sft} \cdot MS$. The persistence of our results stands in contrast to the high cointegration between dual-share prices, indicating that the effects we document are not short-lived liquidity effects.

Table 3
Dual shares: rebalancer ownership and returns.

	OLS	1st Stage		2SLS	OLS
	(1)	(2)	(3)	(4)	(5)
	$\text{Ownership}_{Rebalancer}$	$\text{Ownership}_{Rebalancer}$	$\text{MS}\times\text{Ownership}_{Rebalancer}$	Returns	Returns
$I_{HighVotingRights}$	−0.0641***	−0.0619***	0.000150*		
	(0.00344)	(0.0203)	(0.0000892)		
$\text{MS}\times I_{HighVotingRights}$		0.117*	−0.0739***		
		(0.0675)	(0.0214)		
$\text{Ownership}_{Rebalancer}\ \times\text{MS}$				−37.83***	−17.19***
				(12.23)	(5.582)
$\text{Ownership}_{Rebalancer}$				−0.454	−0.0622
				(0.366)	(0.133)
Firm-Meeting FE	N	Y	Y	Y	Y
N	4164	4164	4164	4164	
Adj. R^2	0.0780	0.627	0.869		0.840
F-statistics				12.08	

This table summarizes the instrumented regressions for dual shares and compares the results with OLS regressions. Ownership_{sft} is the rebalancer ownership for share class s of firm f before announcement day t. $I_{HighVotingRights}$ is an indicator function that equals one when the share class s of firm f has higher voting rights before t than the other share class $-s$ of firm f, and zero otherwise. Columns (1)–(3) show the relevance of instruments. Columns (4) and (5) report the 2SLS estimate of returns on instrumented ownership variables ($\widehat{\text{Ownership}_{sft}}$ and $\widehat{\text{Ownership}_{sft}\cdot MS}$), and the OLS estimate of returns on raw ownership variables (Ownership_{sft} and $\text{Ownership}_{sft}\cdot MS$).
Standard errors are clustered at the firm by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

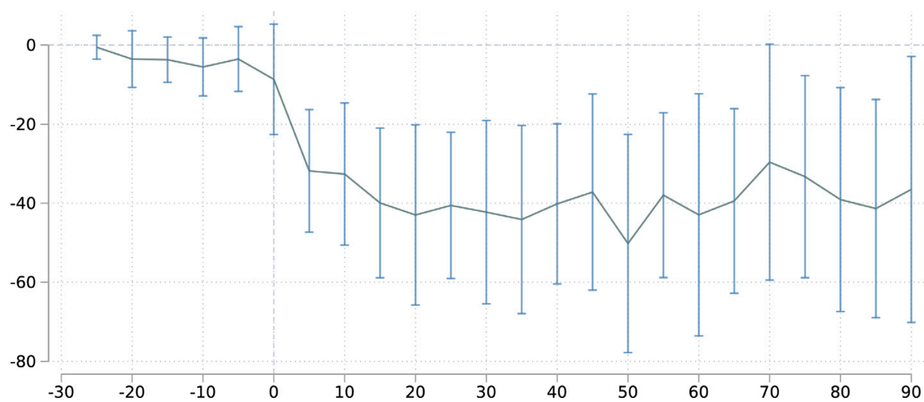

Fig. 2. Returns for dual shares around FOMC announcements under 2SLS.
This figure plots the cross-sectional sensitivity to monetary shocks $\gamma^{dual,h}_{2SLS}$ of dual shares around FOMC announcements from the second stage in the 2SLS empirical model $r^h_{sft} = \gamma^{dual,h}_{2SLS}\widehat{\omega_{sft}\cdot MS_t} + \nu^h_{2SLS}\widehat{\omega_{sft}} + \delta^h_{ft} + \epsilon^{2SLS,h}_{sft}$. r^h_{sft} is the cumulative return from 30 min before the FOMC announcements to $(h\times 5)$-minute after for share class s of firm f at FOMC announcement t. $\widehat{\omega_{sft}}$ is the instrumented rebalancer ownership from the first stage. δ^h_{ft} collects firm-meeting fixed effects. The standard errors are two-way clustered at the firm-meeting level, and 95% confidence intervals are displayed.

5. Empirical design and results on all common stocks

This section extends the quasi-experimental findings to the cross-section of all common stocks. Section 5.1 presents the main empirical result: stocks with higher rebalancer ownership exhibit stronger responses to monetary shocks, other things equal. It further contains a placebo test that shows no predictive power of ownership by other institutions. Section 5.2 tests the prediction on delayed rebalancing, showing that monetary shocks from FOMC meetings closer to routine rebalancing dates lead to larger price reactions. Section 5.3 leverages Morningstar data to show additional evidence using balanced fund ownership and a placebo test with pure-equity fund ownership. Finally, Section 5.4 presents quantity evidence of rebalancing.

5.1. Cross-sectional tests and results

Similar to Section 4, we construct security-level institutional ownership for stock i before announcement day t by aggregating the institution-level holdings of stock i:

$\omega_{it} = \Sigma_{j=1}^{N}\omega_{ijt}$,

where ω_{ijt} is the ratio between shares of stock i held by rebalancer j over shares outstanding for stock i at the quarter before announcement day t (again, we use the last filing period to mitigate endogeneity concerns about holding choices made in response to monetary shocks), added across a total number N of rebalancers in the FactSet dataset.

The main empirical model for intraday returns around FOMC meetings is specified as:

$$r_{it} = \gamma\omega_{it}\cdot MS_t + \boldsymbol{\phi}'\boldsymbol{X}_{it}\cdot MS_t + \nu\omega_{it} + \boldsymbol{\varphi}'\boldsymbol{X}_{it} + \delta_t + \epsilon_{it}, \quad (18)$$

where r_{it} denotes the 30-minute return of stock i around FOMC announcements, and MS_t represents high-frequency monetary shocks (Nakamura and Steinsson, 2018). δ_t captures meeting fixed effects, absorbing the stand-alone impact of monetary shocks. ω_{it} is the rebalancer ownership at the security level, $\boldsymbol{X}_{it}$ includes controls discussed below, and ϵ_{it} is the residual. Coefficient γ captures how an individual stock's price reaction to a monetary shock MS_t depends on its rebalancer ownership ω_{it}, directly corresponding to the cross-sectional sensitivity in Proposition 1 which predicts $\gamma < 0$.

As variation in fundamentals can also drive differential price reactions to monetary shocks across common stocks, our identification rests on two key assumptions: first, monetary shocks are exogenous; and second, institutions do not sort into stocks based on unobserved fundamentals that systematically alter sensitivity to monetary shocks beyond what our control variables capture. We introduce a set of

Table 4
Does rebalancing demand affect monetary transmission to stock prices?

(a) Stocks with higher rebalancer ownership are more responsive to monetary shocks

	Aggregate	Rebalancers					
	(0)	(1)	(2)	(3)	(4)	(5)	(6)
MS	−8.900***	×	×	×	×	×	×
	(1.200)						
$\text{Ownership}_{Rebalancers}$×MS		−2.817*	−3.295**	−3.363**	−3.684**	−3.734**	−3.811**
		(1.561)	(1.585)	(1.585)	(1.548)	(1.560)	(1.556)
$\text{Ownership}_{Rebalancers}$		×	×	×	×	×	×
MPE			×	×	×	×	×
MPE×MS			×	×	×	×	×
Dividend			×	×	×	×	×
Dividend×MS			×	×	×	×	×
DSS Duration×MS				×	×	×	×
DSS Duration				×	×	×	×
β×MS					×	×	
β					×	×	
Size×MS						×	×
Size						×	×
FF4 Factors ×MS							×
FF4 Factors							×
Meeting FE	N	Y	Y	Y	Y	Y	Y
I_ind.× MS	N	Y	Y	Y	Y	Y	Y
N	110	58,497	58,497	58,497	58,497	58,497	58,497
Adj. R^2	0.267	0.592	0.593	0.593	0.594	0.594	0.596

(b) Non-rebalancer ownership does not affect monetary sensitivities

	Non-Rebalancers					
	(1)	(2)	(3)	(4)	(5)	(6)
MS	×	×	×	×	×	×
$\text{Ownership}_{NonRebalancers}$×MS	0.332	0.385	0.396	0.848	0.943	0.664
	(0.770)	(0.775)	(0.775)	(0.764)	(0.783)	(0.784)
$\text{Ownership}_{NonRebalancers}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
Dividend		×	×	×	×	×
Dividend×MS		×	×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
Size×MS					×	×
Size					×	×
FF4 Factors ×MS						×
FF4 Factors						×
Meeting FE	Y	Y	Y	Y	Y	Y
I_ind.× MS	Y	Y	Y	Y	Y	Y
N	58,497	58,497	58,497	58,497	58,497	58,497
Adj. R^2	0.592	0.592	0.592	0.594	0.594	0.596

This table reports the results of the regressions of 30-minute equity returns around FOMC announcements on institutional ownership (of rebalancers or other institutions) $Ownership_{it}$ interacted with high-frequency monetary shocks MS_t of Nakamura and Steinsson (2018):

$$r_{it} = \gamma Ownership_{it} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + \nu Ownership_{it} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it},$$

where i indexes stocks and t indexes the date in quarters. Equity returns around FOMC announcements are the log returns between the beginning price, as the last valid trade price 10 min before the FOMC announcement (and no more than 90 min before that time), and the end price, the first valid trade 20 min after the FOMC announcement (and no more than 90 min after that time). Monetary shocks are estimated as the principal component of five fed funds futures and Eurodollar futures using 30-minute windows around FOMC announcements; these shocks are normalized based on the daily treasury yield around FOMC dates (Nakamura and Steinsson, 2018). Institutional ownership is collected from FactSet; $Ownership_{it}$ in Panel (a) sums up the quarterly ownership of institution categories *institutional wealth management* and *long-term investors* for security i before quarter t, and $Ownership_{it}$ in Panel (b) sums up the quarterly ownership of the rest of the institution categories for security i. The sample period runs from 2004Q4 to 2019Q3.
Standard errors are clustered at the industry by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

controls for alternative transmission channels of monetary policy, including security-level cash-flow duration (Dechow et al., 2004; Weber, 2018; Gormsen and Lazarus, 2022), systematic risk (Frazzini and Pedersen, 2014), momentum, firm size proxied by the logarithm of book equity (Koijen and Yogo, 2019), and 12-month dividend yield (Daniel et al., 2021; Jensen et al., 2021), as well as the monetary policy exposure (MPE) index (Ozdagli and Velikov, 2020), each interacted with monetary shocks. We further include 3-digit SIC industry fixed effects and their interactions with monetary shocks to absorb sectoral heterogeneity in price stickiness (Gorodnichenko and Weber, 2016) and high-frequency risk factors (Pelger, 2020).

Results using rebalancer ownership. Table 4 presents the main pricing results based on Eq. (18). A 10 basis point positive monetary shock reduces the aggregate market return by approximately 89 basis points from panel (a) column (0). Column (1) reports the regression of returns on monetary shocks, institutional ownership, and their interaction, controlling for meeting and industry fixed effects interacted with monetary shocks. Columns (1) through (6) incrementally add controls to the empirical model, including equity duration, beta, the MPE index, size, dividend yield, and the Fama–French and Carhart asset pricing factors, along with their interactions with monetary shocks. We find γ to be negative with high statistical significance across these specifications.[13]

In a saturated model in column (5), a 10% (/1 standard deviation) increase in rebalancer ownership corresponds to an additional 3.7 basis point (/2.5 basis point) decline in equity prices following a 10 basis point increase in the short rate. The sign of γ confirms the prediction of Proposition 1.

Placebo test using other institutions' ownership. In contrast, when rebalancer ownership is replaced with the ownership of other institutional investors in the regression, the interaction with monetary shocks becomes insignificant across all specifications (panel (b)). Section 5.3 further presents a placebo test using Morningstar data, which distinguishes between balanced funds and pure-equity funds. We find that ownership by balanced funds significantly predicts cross-sectional price reactions to monetary shocks, whereas ownership by pure-equity funds does not.

Discussion of other channels. Although we control for various fundamental and market-based factors, there may be additional mechanisms that influence stock price reactions to monetary shocks, which we discuss here.

First, the Federal Reserve may possess superior information about the economy relative to the private sector (Romer and Romer, 2000; Nakamura and Steinsson, 2018; Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020). Consequently, monetary policy actions can reveal new information that was not previously known to market participants. This "information effect" implies that monetary tightening may signal positive economic news, thereby dampening the negative impact on equity prices. Applying this to our cross-sectional framework, if institutional investors are better at processing information than retail investors, the information effect would predict that stocks with higher institutional ownership, regardless of institution type, are less sensitive to monetary shocks. This information effect prediction runs counter to our findings that rebalancer ownership negatively predicts stock price reactions but pure-equity institution ownership does not. If anything, such an effect would imply that the rebalancing channel is stronger

[13] Besides cash-flow duration and other channels mentioned above, Appendix E.2 shows that our result is robust to alternative duration measures (Gormsen and Lazarus, 2022; Weber, 2018), an alternative proxy of rebalancer ownership using cross-sectional ranks, weighted OLS, and on subsamples of stocks. Our estimate is also robust to including firm fixed effects.

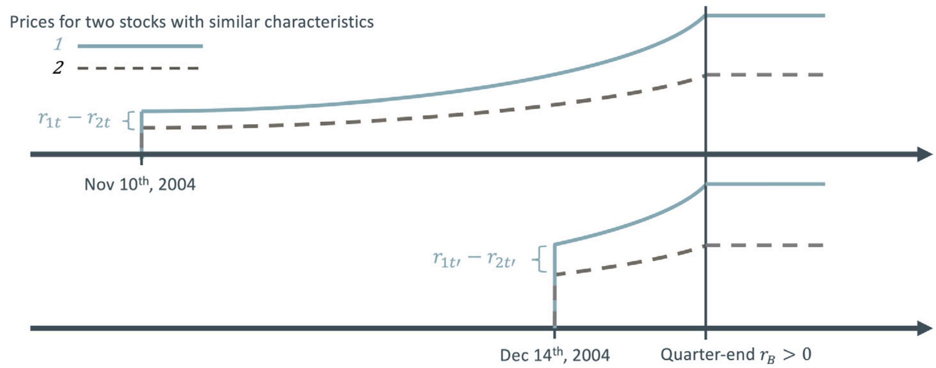

Fig. 3. An illustration of delayed rebalancing.
This graph demonstrates the different pricing implications for monetary shocks at the beginning and the end of a quarter, using two surprise rate cuts in the last quarter of 2004 as examples. For the surprise rate cut on November 10, 2004, to front-run the rebalancing trades at the end of the quarter, the arbitrageur would face considerable risk in buying and holding for nearly two months. In contrast, for the surprise rate cut on December 14, 2004, the arbitrageur could expect to profit from its front-running strategy faster, in which case we expect the arbitrageur to be more active and prices to adjust closer to its eventual levels.

than our estimates suggest. Nonetheless, Appendix E.3 provides additional robustness checks, using a subsample of FOMC meetings less likely to exhibit strong information effects (Jarociński and Karadi, 2020).

Additionally, one might argue that because institutions react faster to macroeconomic news than retail investors, stocks with higher institutional ownership could be more responsive to monetary shocks in the short run. However, our placebo test comparing rebalancers to other institutions in FactSet does not support this, unless different types of institutions differ significantly in their reaction speeds. Further, an additional placebo test in Section 5.3 suggests that, even within the same type of institutional investors, namely mutual funds, only balanced funds' ownership predicts cross-sectional price reactions.

Comparison with dual shares. The cross-sectional sensitivity γ estimated on all common stocks is smaller in magnitude than its counterpart γ^{dual} on dual-share sample. This may be driven by heterogeneity of rebalancers (as captured in Appendix B.3) or difference in arbitrageur's demand across these two samples.[14]

Margins of rebalancing. In principle, rebalancers can adjust either the weights of stocks within their existing portfolios (the intensive margin) or the composition of their holdings by adding or removing stocks (the extensive margin). Our findings that rebalancers' ownership predicts cross-sectional stock reactions rely on the assumption that rebalancing occurs primarily through the intensive margin. Two key institutional features justify this assumption. First, rebalancers hold a narrow subset of stocks. In the *institutional wealth management* category (the majority of our rebalancers), the median institution holds only 60–70 stocks, and even at the 90th percentile the count is just 300–400, one to two orders of magnitude smaller than the total number of publicly traded U.S. stocks. Second, rebalancers' investment universes remain stable in response to monetary shocks. Appendix E.4 shows that rebalancers do not systematically add or remove stocks in response to monetary shocks.

5.2. The timing of shocks

Our empirical estimates rely on the assumption that prices immediately adjust to reflect rebalancing demand following monetary policy announcements. In practice, large pension funds rebalance at the end of quarters and months.[15] Despite that rebalancing might be delayed, arbitrageurs may front-run future rebalancing flows, causing prices to move immediately, formalized by Proposition 2. That proposition further predicts that both the cross-sectional sensitivity and the aggregate stock market reactions are larger in magnitude when FOMC announcements happen closer to quarter- and month-ends.

Fig. 3 offers an illustration of the differing pricing implications of monetary shocks at the beginning versus the end of a quarter, using two surprise rate cuts from the last quarter of 2004 as examples. After the November 10 cut, an arbitrageur seeking to front-run end-of-quarter rebalancing would need to hold positions for nearly two months. By contrast, the December 14 cut allows the arbitrageur to capitalize on anticipated rebalancing flows in just a few weeks. Consequently, we expect more intense arbitrage activity and larger price responses following the December cut.

In Table 5, we divide FOMC meetings based on their proximity to quarter- and month-ends and apply the same empirical specification (18) to these subsamples. An FOMC announcement during the final month of a quarter is classified as a *quarter-end* announcement, while announcements in the last two weeks of any month are labeled *month-end* announcements. Comparing column (1) (respectively, column (5)) with column (9) of Table 5, we find that the aggregate market reaction for the quarter-end (month-end) subsample is approximately 1.14 (1.10) times larger than in the full sample, which, to our knowledge, has not been documented in the literature. Moreover, column (4) (column (8)) shows that the estimated cross-sectional sensitivity γ at quarter-end (month-end) is about 1.55 (1.27) times larger than its full-sample counterpart in column (10). Additionally, the ratio of γ to the

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[14] Such heterogeneity may arise since institutions are generally against dual-share structures due to corporate governance concerns; see ISS Benchmark Policy Recommendations (https://www.issgovernance.com/file/policy/active/americas/US-Voting-Guidelines.pdf, last retrieved on September 5, 2022). S&P Dow Jones Indices no longer add companies with multiple share class structures (https://press.spglobal.com/2017-07-31-S-P-Dow-Jones-Indices-Announces-Decision-on-Multi-Class-Shares-and-Voting-Rules, last retrieved on September 5, 2022).

[15] For more anecdotal evidence, see media coverage on some rebalancing activities:
– Bloomberg, last retrieved on October 25, 2021: https://www.bloomberg.com/news/articles/2021-10-25/bonds-are-about-to-reap-5-billion-from-a-pension-rebalance-wave;
– Reuter, last retrieved on March 25, 2021: https://www.reuters.com/business/quarter-end-rebalancing-could-present-headwinds-wall-street-2021-03-25/;
– Zero-edge, last retrieved on November 18, 2020: https://www.zerohedge.com/markets/goldman-warns-massive-36bn-month-end-pension-selling-4th-largest-record.

Table 5
Stronger price reactions at month and quarter ends.

	Quarter-End				Month-End				Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MS	−10.14***	×	×	×	−9.820***	×	×	×	−8.900***	×
	(1.518)				(1.112)				(1.200)	
Ownership of Rebalancers×MS		−4.850***	−5.862***	−5.802***		−3.725**	−4.770***	−4.730***		−3.734**
		(1.855)	(1.821)	(1.823)		(1.750)	(1.724)	(1.732)		(1.560)
Ownership of Rebalancers		×	×	×		×	×	×		×
Duration×MS			×	×			×	×		×
DSS Duration			×	×			×	×		×
MPE			×	×			×	×		×
MPE×MS			×	×			×	×		×
β×MS			×	×			×	×		×
β			×	×			×	×		×
Dividend				×				×		×
Dividend×MS			×	×			×	×		×
Size×MS				×				×		×
Size				×				×		×
Meeting FE	N	Y	Y	Y	N	Y	Y	Y	N	Y
$I\_ind.\times$ MS	N	Y	Y	Y	N	Y	Y	Y	N	Y
N	55	29,329	29,329	29,329	70	37,270	37,270	37,270	110	58,497
Adj. R^2	0.391	0.626	0.631	0.631	0.444	0.584	0.588	0.588	0.267	0.594

This table reports the results of the regressions of 30-minute equity returns around FOMC announcements on institutional ownership interacted with high-frequency monetary shocks (Nakamura and Steinsson, 2018): $r_{it} = \gamma \text{Ownership}_{it} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + v\text{Ownership}_{it} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, where i indexes stocks and t indexes date in quarters. Equity returns around FOMC announcements are the log returns between the beginning price, as the last valid trade price 10 min before the FOMC announcement (and no more than 90 min before that time), and the end price, the first valid trade 20 min after the FOMC announcement (and no more than 90 min after that time). The monetary shocks are estimated as the principal component of five fed funds futures and Eurodollar futures using 30-minute windows around FOMC announcements; these shocks are normalized based on the daily treasury yield around FOMC dates (Nakamura and Steinsson, 2018). $Ownership_{it}$ sums up the quarterly ownership of institutions in the rebalancer categories (*institutional wealth management* and *long-term investors*) for portfolio i before announcement day t.
The sample period runs from 2004Q4 to 2019Q3; the quarter-end subsample includes only the FOMC announcements that occur in the last month of a quarter, and the month-end subsample includes only the FOMC announcements that occur in the second half of each month.
Standard errors are clustered at the industry by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

aggregate market reaction is higher at quarter- and month-ends than in the full sample. It suggests that the contribution of portfolio rebalancing to the aggregate stock market reaction is larger when rebalancing is more imminent. This is expected since the aggregate stock market reaction due to changes in fundamentals does not feature such time variation. Together, these results support the prediction of Proposition 2 that monetary shocks occurring closer to routine rebalancing times generate stronger cross-sectional sensitivity and aggregate stock market reaction.[16]

In Appendix E.6, we report placebo regressions that replace rebalancer ownership with ownership by other institutional categories. In every specification, the interaction coefficient is statistically insignificant. These placebo tests further support our mechanism by showing that the pronounced price reactions around quarter- and month-ends cannot be driven by general market conditions but instead reflect our delayed rebalancing channel.

5.3. Evidence from mutual funds

Thus far, our analysis relies on FactSet classifications and SEC filings to infer whether an institution engages in rebalancing, as we do not directly observe their bond holdings. For an alternative, we introduce a proxy based on mutual funds using Morningstar data of detailed holdings of all assets by mutual funds. Crucially, we distinguish between balanced funds and pure-equity funds. We use the following specification to test the effect of ownership by balanced funds and pure-equity funds, similar to Eq. (18):

$$r_{it} = \gamma \omega^F_{it} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + v\omega^F_{it} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it}, \tag{19}$$

where ω^F_{it} represents the share of stock i held by balanced funds.[17] For a placebo test, we also calculate the ownership share of stock i held by pure-equity mutual funds. As before, r_{it} denotes the 30-minute return of stock i around FOMC announcements, MS_t captures high-frequency monetary shocks from Nakamura and Steinsson (2018), $\boldsymbol{X}_{it}$ includes control variables, δ_t is a meeting fixed effect, and ϵ_{it} is the error term. Table 6 summarizes the results. In the balanced fund panel, stock prices load negatively on monetary shocks interacted with balanced fund ownership ($\omega^F_{it} \cdot MS_t$). Column (4) presents the fully saturated specification, controlling for interactions with monetary shocks of stock duration, the MPE index, market equity, beta, dividend yield, and industry fixed effects. In this specification, a 10 bp surprise rate hike is associated with an additional 55 bp decline in prices for stocks with 10-percentage-point higher balanced fund ownership.

Columns (5) and (6) report placebo tests using pure-equity fund ownership. These regressions fail to reject the null hypothesis, indicating no significant effect of pure-equity fund ownership on cross-sectional sensitivity to monetary shocks.

Comparison of FactSet and morningstar results. The estimated cross-sectional sensitivity is larger in magnitude with Morningstar balanced fund ownership than with FactSet rebalancer ownership. It may arise because the two rebalancer groups have different demand parameters (as considered in Appendix B.3's model extension). Unfortunately, we cannot quantify these differences without observing the complete portfolios of rebalancers.

Another possibility is measurement issues. We note that FactSet collects only institutional stock holdings aggregated at the management-company level (e.g., BlackRock). Each company has both balanced funds and pure-equity funds that operate separately, leading to potential overstatement of rebalancer ownership. An overstatement of rebalancer ownership will bias the estimated cross-sectional sensitivity γ downward. In contrast, Morningstar reports both stock and bond positions, allowing for a more precise identification of rebalancers.

[16] For future research, it may be promising to further examine arbitrageurs' front-running behavior and to quantify the roles of arbitrage frictions (Andersen et al., 2019) and inattention (Gabaix, 2019).

[17] We construct ω^F_{it} using direct stock holdings of balanced funds from Morningstar. We exclude indirect stock holdings through balanced funds' investment in tactical-allocation funds, as these may actively adjust to monetary shocks via extensive margin adjustments (adding or deleting stocks), potentially contaminating ownership as a measure of rebalancing exposure.

Table 6
Identifying the effect of rebalancing: evidence from mutual funds.

	Balanced funds				Pure-Equity funds	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Ownership}_{BalancedFunds}$×MS	−59.55**	−59.55**	−54.93*	−55.49*		
	(29.64)	(29.64)	(29.54)	(29.52)		
$\text{Ownership}_{BalancedFunds}$	×	×	×	×		
$\text{Ownership}_{EquityFunds}$×MS					2.701	3.175
					(2.563)	(2.642)
$\text{Ownership}_{EquityFunds}$					×	×
Size & Size×MS			×	×		×
Duration & Duration×MS			×	×		×
β&β×MS				×		×
MPE & MPE×MS				×		×
Dividend & Dividend×MS				×		×
Meeting FE	Y	Y	Y	Y	Y	Y
$I\_ind.$× MS	Y	Y	Y	Y	Y	Y
N	27,182	27,182	27,182	27,182	27,182	27,182
Adj. R^2	0.593	0.593	0.595	0.595	0.593	0.597

This table reports the results of the regressions of 30-minute equity returns around FOMC announcements on mutual fund ownership interacted with high-frequency monetary shocks (Nakamura and Steinsson, 2018): $r_{it} = \gamma\omega^F_{it} \cdot MS_t + \boldsymbol{\phi}'\boldsymbol{X}_{it} \cdot MS_t + \nu\omega^F_{it} + \boldsymbol{\varphi}'\boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, where i indexes stocks, j indexes types of mutual funds, and t indexes the date. Equity returns around FOMC announcements are the log returns between the beginning price, as the last valid trade price 10 min before the FOMC announcement (and no more than 90 min before that time), and the end price, the first valid trade 20 min after the FOMC announcement (and no more than 90 min after that time). Monetary shocks are estimated as the principal component of five fed funds futures and Eurodollar futures using 30-minute windows around FOMC meetings; these shocks are normalized based on the daily treasury yield around FOMC dates (Nakamura and Steinsson, 2018). Mutual funds' ownership is collected from Morningstar; we use a sample of securities with more than 0.1% ownership by balanced funds since stocks with negligible ownership by balanced funds are unlikely to be meaningfully affected by demands of these funds. ω^F_{it} in columns (1)–(4) sums up the quarterly ownership of balanced funds (identified from names containing keywords for balanced funds or target-date funds) for security i before announcement day t, and ω^F_{it} in columns (5)–(6) sums up the quarterly ownership of equity funds (funds except for balanced funds or target-date funds) for security i; both are denoted by ownership shares out of share outstanding between 0 and 1. The sample period runs from 2004Q4 to 2019Q3.
Standard errors are clustered at the industry by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

However, Morningstar systematically underestimates mutual fund holdings, as managers often run parallel vehicles with identical asset allocations that are not reported to Morningstar (Huang et al., 2023), which introduces an upward bias on γ.

5.4. Quantity evidence on rebalancing

A premise of our mechanism is that certain institutional investors rebalance their portfolios based on equity-share targets, in response to price fluctuations of stocks and bonds. Ideally, we would identify rebalancers by examining equity shares of all investors and determining those whose portfolio shares are stable. In FactSet data, as we do not observe bond holdings, we determine rebalancers based on investor categories. Here we provide complementary quantity-based evidence from alternative datasets for rebalancing. Using public pension plan data, we show that pension equity shares are stable and track reported policy targets. Using CFTC futures positions, we show that institutional asset managers rotate out of equity index futures and into Treasury futures after positive monetary policy shocks. Using Morningstar fund holdings, we show that balanced funds adjust equity shares back following target equity shares after monetary shocks.

We begin with U.S. public pension plans, one of the FactSet rebalancer types, which report both actual and target equity shares at annual frequency. Figure A-8 replicates Gabaix and Koijen (2022) using the Center for Retirement Research Public Plans Data and shows that actual equity shares are far more stable than the CRRA-implied equity share, whose optimal allocation would vary with perceived expected excess returns.

We then test the rebalancing channel against two alternatives using panel regressions to address potential compositional changes. Under rebalancing, the investor sets a policy equity target $\theta^T_{i,t}$ and trades so that the actual equity share $\theta_{i,t}$ tracks the target. Thus, variation in $\theta^T_{i,t}$ should map into variation in $\theta_{i,t}$. Under a CRRA-implied allocation, the equity share $\theta_{i,t}$ should instead depend on the expected excess stock returns. Alternatively, if the investor does not trade actively, their actual equity shares should follow a buy-and-hold benchmark we construct. Specifically, we initialize the buy-and-hold benchmark $\theta^{BH}_{i,t}$ at the plan's first observed actual equity share and then compound forward using fiscal-year equity and bond gross returns $(1 + r^e_t)$ and $(1 + r^b_t)$: $\theta^{BH}_{i,t} = \frac{\theta^{BH}_{i,t-1}(1+r^e_t)}{\theta^{BH}_{i,t-1}(1+r^e_t)+(1-\theta^{BH}_{i,t-1})(1+r^b_t)}$.

Table 7 summarizes the results. Column (1) shows that actual equity shares comove strongly with reported targets. Column (2) adds plan fixed effects to absorb time-invariant plan differences and shows that the target share remains a strong predictor. Columns (3) and (4) imply that a 10-percentage-point higher target share is associated with roughly a 7-percentage-point higher actual equity share, while equity risk premium proxies are statistically indistinguishable from zero. Column (5) adds the buy-and-hold drift, defined as $\theta^{BH}_{i,t} - \theta_{i,t-1}$, together with lagged actual equity share $\theta_{i,t-1}$ to separate mechanical revaluation-driven drift from the persistence in portfolio shares. The buy-and-hold drift term adds no explanatory power once targets are included, whereas the target coefficient remains statistically significant. Taken together, the evidence supports active rebalancing toward policy targets and is inconsistent with both the CRRA-implied allocation and the buy-and-hold benchmark.

Second, we provide higher-frequency evidence of rebalancing using weekly futures positions around FOMC announcements. As discussed by Harvey et al. (2025), large institutions often implement rebalancing via index futures because futures allow fast, capital-efficient adjustments to aggregate market exposure without immediately trading the underlying cash securities. We use the CFTC Traders-in-Financial-Futures (TFF) futures-only reports, which measure weekly (Tuesday-to-Tuesday) long and short positions by trader category in E-mini S&P 500 equity index futures (ES) and 10-year Treasury note futures (TY). Following Harvey et al. (2025), we construct a cross-asset net trading measure as the change in a group's net position (long minus short) in ES minus the change in TY, scaling each leg by open interest so the measure is comparable across markets and time. With this sign convention, negative values indicate rotation out of equities and into Treasuries. Table A-11 shows that a positive monetary policy shock predicts a more negative cross-asset net trading measure for rebalancer-type traders (asset managers in TFF), with effects that strengthen markedly in month-end and quarter-end weeks when rebalancing is more imminent. In contrast, leveraged funds (often relative-value/arbitrage-oriented) move in the opposite direction after

Table 7
Rebalancing vs. CRRA-implied and buy-and-hold allocations.

	(1)	(2)	(3)	(4)	(5)
Target share	0.793***	0.709***	0.708***	0.709***	0.427***
	(0.032)	(0.045)	(0.045)	(0.045)	(0.056)
Equity risk premium (CFO survey)			−0.111		
			(0.329)		
Equity risk premium (Shiller/CAPE)				−0.020	
				(0.032)	
Buy-and-hold drift					0.089
					(0.069)
Lagged equity share					0.525***
					(0.063)
N	2400	2400	2400	2400	2400
Plan FE	N	Y	Y	Y	Y
Adj. R^2	0.657	0.740	0.740	0.741	0.807

The dependent variable is the actual equity share $EqShare_{i,t}$ of public pension plan i in fiscal year t, computed from reported equity and fixed-income allocations in the Center for Retirement Research (Boston College) Public Plans Data. Equity risk premium (CFO survey) is the Duke CFO survey one-year-ahead expected excess return on the S&P 500 (expected S&P 500 return net of the one-year risk-free rate, GS1 from FRED) in decimal units. Equity risk premium (Shiller/CAPE) is the Shiller/CAPE-yield-based expected excess return proxy net of GS1 in decimal units. Target share $\theta^T_{i,t}$ is constructed from reported target allocations to equity and fixed income, rescaled to sum to one over these two asset classes. For the buy-and-hold benchmark, we initialize $\theta^{BH}_{i,t}$ at the plan's first observed actual equity share and then compound forward using fiscal-year equity and bond gross returns $(1+r^e_t)$ and $(1+r^b_t)$: $\theta^{BH}_{i,t} = \frac{\theta^{BH}_{i,t-1}(1+r^e_t)}{\theta^{BH}_{i,t-1}(1+r^e_t)+(1-\theta^{BH}_{i,t-1})(1+r^b_t)}$. In Column (5), we include the implied buy-and-hold drift, defined as $\theta^{BH}_{i,t} - \theta_{i,t-1}$ and the lagged actual equity share $\theta_{i,t-1}$ to capture mechanical return-driven drift and persistence in portfolio shares. Fiscal years run from July to June. Equity returns r^e_t are the value-weighted total returns (including distributions) of all U.S. equity securities from the CRSP database, compounded monthly over each fiscal year. Bond returns r^b_t are the total returns of the Bloomberg U.S. Aggregate Bond Index over the fiscal year. Plans with only equity or only fixed income are excluded. Standard errors (in parentheses) are clustered at the plan and year levels. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

tightening shocks, consistent with intermediaries partially absorbing rebalancers' equity-to-Treasury rotation.

Finally, using Morningstar mutual fund holdings, we focus on balanced funds as a small but relatively clean class of rebalancers and provide evidence that they actively adjust quantities in response to monetary policy shocks. Because holdings are observed at the security level, we can separate active reallocation from passive changes in equity shares driven by post-shock price movements. We compare each fund's actual equity share to a counterfactual share that holds pre-shock quantities fixed and only revalues them at post-shock prices, so the difference isolates trading rather than valuation. Appendix E.5 shows that tightening shocks lead to a significant decline in equity exposure for funds with stronger rebalancing needs (i.e., those further away from targets), consistent with managers selling equity and rotating toward bonds after a rate hike.

Together, the evidence on pension funds' equity shares, trading of futures, and active adjustments by balanced funds provides quantity-based support for the rebalancing channel of monetary transmission.

6. From cross-sectional sensitivity to aggregate reaction

In Section 5, we have estimated the cross-sectional sensitivity γ across all common stocks in response to monetary shocks. Here we determine the implied aggregate stock market reaction from the cross-sectional sensitivity using our model-implied relation and estimates of stock market elasticities in the literature.

6.1. From cross-section to aggregate via two elasticities

We show how the estimated cross-sectional sensitivity γ connects into the aggregate stock market reaction to monetary shocks. We illustrate this in the baseline model of Section 2.1, but the same connection holds in the multi-period model of Section 2.2. To draw this connection, following Gabaix and Koijen (2022), we distinguish between the "macro" and "micro" demand elasticities of stock measured in the literature and map them to our model parameters.

The macro elasticity is defined as the demand elasticity of the aggregate stock market. Consider in the baseline static model a price change of both stocks by $r_1 = r_2 = r$. The aggregate stock demand from Eqs. (2) and (3) changes by $\Delta\bar{Q} = \frac{\Delta Q_1 + \Delta Q_2}{2} = -\bar{\omega}(1-\theta)r - \psi^A r + \bar{\omega}[(1-\theta)+\chi]r_B$, and thus the macro elasticity is

$$\zeta \equiv -\frac{\partial \Delta\bar{Q}}{\partial r} = \underbrace{\bar{\omega}(1-\theta)}_{\text{rebalancer contribution}} + \underbrace{\psi^A}_{\text{arbitrageur contribution}} \tag{20}$$

The micro elasticity captures how relative demand for two stocks responds to changes in their relative prices.[18] The relative demand is $\Delta Q_1 - \Delta Q_2 = -\omega(1-\theta)r_1 - (\psi^A + 2\psi^C)(r_1 - r_2) + \omega[(1-\theta)+\chi]r_B$. We define the micro elasticity in a symmetric way as

$$\begin{aligned} \zeta^{\perp} &\equiv \frac{1}{2}\left[-\frac{\partial\left(\Delta Q_1 - \Delta Q_2\right)}{\partial r_1} + \frac{\partial\left(\Delta Q_1 - \Delta Q_2\right)}{\partial r_2}\right] \\ &= \underbrace{\bar{\omega}(1-\theta)}_{\text{rebalancer contribution}} + \underbrace{\psi^A + 2\psi^C}_{\text{arbitrageur contribution}} \end{aligned} \tag{21}$$

A large literature has estimated these micro and macro elasticities $\zeta^{\perp}, \zeta$, which we review in Table A-15. We express the aggregate stock market reaction using these elasticities and the cross-sectional sensitivity γ as follows.[19]

Proposition 3 (*Aggregate Stock Market Reaction*). *The aggregate stock market reaction $\bar{r} \equiv \frac{r_1 + r_2}{2}$ to a monetary shock MS due to a change in the excess return satisfies*

$$\frac{\mathrm{d}(\bar{r}-\check{r})}{\mathrm{d}MS} = \frac{\zeta^{\perp} - \bar{\omega}(1-\theta)}{\zeta - \bar{\omega}(1-\theta)}\gamma\bar{\omega} = \frac{\zeta^{\perp}}{\zeta}\gamma\bar{\omega} + O\left(\frac{\bar{\omega}(1-\theta)}{\zeta^{\perp}}\gamma\bar{\omega}\right) + O\left(\frac{\bar{\omega}(1-\theta)}{\zeta}\gamma\bar{\omega}\right) \tag{22}$$

[18] Chang et al. (2015) and Pavlova and Sikorskaya (2023) estimate the micro elasticity using offsetting demand shocks in the cross-section of stocks from index inclusion/deletion. They improve on the previous literature (Shleifer, 1986; Harris and Gurel, 1986) with better benchmarks for the added/dropped stocks from the indices to identify the effect of relative demand.

[19] The empirical estimates of $\zeta^{\perp}, \zeta$ in the literature may or may not incorporate the rebalancer's contribution, depending on the time horizon of the study. In our model, it corresponds to the static model (with rebalancer trading) and period 0 in the dynamic model (without rebalancer trading) respectively. In Eqs. (20) and (21), for completeness, we include the rebalancer's contribution, but it is small and quantitatively immaterial for our next proposition.

where $\check{r}$ is the stock revaluation due to changes in dividends and the risk-free rate as in Proposition 1, $\zeta^{\perp}, \zeta$ are the micro and macro elasticities, γ is the cross-sectional sensitivity, $\bar{\omega} = \omega/2$ is the rebalancer ownership of the aggregate stock market, and θ is the equity share of the rebalancer.

This proposition suggests that we can determine the aggregate stock market reaction in excess of fundamental changes $\bar{r} - \check{r}$ using the cross-sectional sensitivity γ. Quantitatively, the correction of $\bar{\omega}(1-\theta)$ relative to $\zeta^{\perp}, \zeta$ is unimportant.[20] Hence, Eq. (22) approximates

$$\frac{\mathrm{d}(\bar{r} - \check{r})}{\mathrm{d}MS} \approx \frac{\zeta^{\perp}}{\zeta} \gamma \bar{\omega} \tag{23}$$

Intuitively, in terms of flows, $\gamma\omega$ multiplied by the micro elasticity $\zeta^{\perp}$ gives the magnitude of rebalancing flows to stock 1, and thus $\zeta^{\perp}\gamma\bar{\omega}$ corresponds to the rebalancing flow relative to the aggregate stock market. We then use this aggregate flow and the macro elasticity ζ to back out the implied aggregate market reaction $\bar{r}$ in excess of fundamental changes. The reason that this calculation yields the excess part of the aggregate stock market reaction is that the cross-sectional sensitivity γ only captures the component of stock price reactions due to excess returns, as discussed in Section 2. While we derive Eq. (23) from the baseline static model, it applies to the multi-period model with delayed rebalancing as well regarding the time-0 aggregate stock market reaction and the time-0 cross-sectional sensitivity.

This proposition implies that to determine the aggregate stock market reaction according to Eq. (23), the only things we need are the cross-sectional sensitivity γ and aggregate rebalancer ownership $\bar{\omega}$, which is a nice property of our cross-sectional approach. In this baseline model, we do not need to know the actual change in bond price r_B, the pre-shock equity share of the rebalancer θ, or their reaching-for-yield incentive χ, which are all reflected in the cross-sectional sensitivity γ. This property is generally true in extended models presented in Appendix B, where many additional primitive parameters are also reflected in γ. In particular, while we consider 2 stocks for simplicity, Eq. (23) holds in a more general environment with many stocks studied in Appendix B.4.

6.2. Calibration

We study high-frequency stock price reactions to monetary shocks, yet macro and micro elasticity estimates in the literature are typically derived from longer time windows. A limitation of our calibration is that both elasticities may depend on the horizon of interest (Duffie, 2010), which is outside of our model. Absent data on the time variation of these elasticities, our best recourse is to use estimates of ζ and $\zeta^{\perp}$ measured over comparable horizons for consistency and employing two separate sets of estimates for robustness. Further, we draw on estimates from information-free events, so that they only reflect demand forces.

First, we use the elasticities estimated around dividend *payment* dates. Dividend payouts are typically announced weeks in advance, which cleanly separates the news effect from the price pressure due to reinvestment. Schmickler and Tremacoldi-Rossi (2022) exploit this by examining prices of connected stocks on the payment day for U.S. common stocks and recover a micro demand elasticity of about 1.25. Hartzmark and Solomon (2022) use dividend payout dates to estimate the macro elasticity for U.S. common stocks, finding a value between 0.43 and 0.66. Taking the midpoint of that range implies a micro-to-macro-elasticity ratio $\frac{\zeta^{\perp}}{\zeta}$ of around 2.3.

Second, we use the elasticities from Lou (2012) and Gabaix and Koijen (2022), both of which use idiosyncratic demand shocks from institutional investors' flows for estimation. Lou (2012) aggregates flow-induced trading across all funds for each stock and finds a micro elasticity of 0.83. Gabaix and Koijen (2022) use a granular instrumental variable approach and find a macro elasticity of 0.17. Together, these imply $\frac{\zeta^{\perp}}{\zeta}$ of around 4.9.

Our estimate from column (5) in Table 4(a) suggests that $\gamma = -3.7$ (which means, in response to a 10 bp surprise short rate hike, a stock with 10-percentage-point higher ownership by rebalancers drops by about 3.7 bp more). We use this estimate from all common stocks since the micro elasticity estimates in the literature are derived from them too. Institutional wealth management and long-term investors hold about 20% of the aggregate stock market, i.e., $\bar{\omega} = 20\%$.[21] Because $\frac{\zeta^{\perp}}{\zeta}$ lies between 2.3 and 4.9, Eq. (23) implies that the aggregate stock market reaction due to rebalancing is between −1.7 and −3.6 (which means the aggregate stock market declines by between 17 bp and 36 bp in response to a 10 bp monetary shock).[22]

In column (0) of panel (a) in Table 4, our update of Bernanke and Kuttner (2005) shows that a 10 bp policy rate hike triggers an 89 bp drop in the aggregate stock market. From our SVAR decomposition (Table A-14), 63% of this reaction, which is about 56 bp, reflects changes in expected excess returns. The rebalancing channel contributes to changes in expected excess returns in the cross section, as our panel regression already controls for stock fundamentals. Hence the implied aggregate market reaction from rebalancing, ranging from 17 bp to 36 bp, accounts for about 30%–64% of that 56 bp response. Using alternative macro and micro elasticities in the literature (Table A-16), we show the lower bound of the explanatory power of the rebalancing channel is 26%. Therefore, the rebalancing channel can plausibly account for a substantial share of the large stock market sensitivity to monetary shocks documented by Bernanke and Kuttner (2005).

7. Conclusion

This paper introduces a rebalancing channel through which monetary policy affects stock prices. We address the puzzle posed by Bernanke and Kuttner (2005) regarding the aggregate market reaction to monetary shocks using a cross-sectional approach.

We test the cross-sectional implications of rebalancing by comparing stocks with different investor bases, both within dual-share firms and across all common stocks with similar fundamentals. We find that, *ceteris paribus,* stocks held more heavily by rebalancers react more to monetary shocks. Moreover, consistent with the rebalancing channel, the stock price reactions are stronger when FOMC announcements fall near quarter- and month-end rebalancing dates, highlighting the role of rebalancing timing. We provide further placebo tests contrasting rebalancers against other pure-equity institutions and present quantity evidence in support of rebalancing.

[20] To explain Eq. (22) technically and the need to purge $\bar{\omega}(1-\theta)$, we note that the two stocks' price reactions in Eqs. (4) and (5) in relative terms are governed by the arbitrageur's elasticities ψ^A, ψ^C. These elasticities thus also determine the ratio of the aggregate return $\bar{r} = \frac{r_1+r_2}{2}$ relative to the return difference $r_1 - r_2$, which is embedded in the cross-sectional sensitivity γ. As the micro and macro elasticities $\zeta^{\perp}, \zeta$ in Eqs. (20) and (21) are provided by both the rebalancer ($\bar{\omega}(1-\theta)$) and the arbitrageur (ψ^A, ψ^C), we deduct the rebalancer's contribution in the ratio to arrive at Eq. (22).

[21] In our calibration, we only use the FactSet estimate but not the Morningstar estimate. This is because while the estimated coefficient γ using Morningstar balanced fund ownership is one magnitude larger than our FactSet estimate, the share of the stock market (0.3%) directly held by balanced funds is two magnitudes smaller than FactSet rebalancers (20%). Since what matters for the aggregate market reaction is the estimated γ times the market share, the balanced funds' contribution is overshadowed.

[22] We use Eq. (23) instead of Eq. (22) since $\bar{\omega} = 0.2$ and $\theta = 0.8$, the latter according to Gabaix and Koijen (2022), which means $\bar{\omega}(1-\theta)$ is much lower than $\zeta^{\perp}, \zeta$. (If we overstate the rebalancer ownership from FactSet, the true $\bar{\omega}$ for Eq. (22) will be even lower.) If using Eq. (22) and $\bar{\omega} = 0.2, \theta = 0.8$, the implied aggregate stock market decline in response to a 10 bp monetary shock is between 18 bp and 45 bp.

Finally, we use our model and estimates to quantify the impact of rebalancing demand on the aggregate stock market reaction to monetary shocks. By combining our empirical estimates of the cross-sectional sensitivity and estimates in the literature of micro and macro elasticities, our calibration suggests that the rebalancing channel accounts for about one-third to two-thirds of the aggregate market reaction attributed to expected excess returns.

Although our analysis centers on institutional ownership and rebalancing, the cross-sectional approach can be applied to household portfolios as richer data become available (Gabaix et al., 2022). More generally, our empirical design using cross-sectional variation in ownership to test for demand-induced price pressure may be useful in other settings. For example, how do policy interventions (such as quantitative easing) or shocks to individual bonds propagate across financial markets? To what extent does the rebalancing behavior of international investors transmit shocks between home and foreign markets? We hope future work will address these and other related questions.

CRediT authorship contribution statement

Xu Lu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lingxuan Wu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Xu Lu's research on this project was funded by the Dixon and Carol Doll Fellowship (through a grant to Stanford Institute for Economic Policy Research). Lingxuan Wu's research on this project was funded by the Institute for Humane Studies (grant no. IHS017072).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2026.104324.

Data availability

Monetary Transmission and Portfolio Rebalancing: A Cross-Sectional Approach (Reference data) (Mendeley Data)
Online Appendix for Monetary Transmission and Portfolio Rebalancing: A Cross-Sectional Approach (pdf)

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Online Appendix for

"Monetary Transmission and Portfolio Rebalancing: A Cross-Sectional Approach"

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June 30, 2026

- Section A provides a microfoundation for the arbitrageur's demand function.
- Section B presents additional model predictions and various model extensions.
- Section C encloses all proofs.
- Section D describes data construction in detail. Section D.1 discusses FactSet holdings data, and Section D.2 discusses Morningstar holdings along with complementary data on bonds. Section D.3 details the sample construction for millisecond TAQ data. Section D.4 computes stock characteristics using variables from CRSP and Compustat. Section D.5 summarizes the construction for the dual-share sample, and Section D.6 discusses the relationship between voting rights and rebalancer ownership in depth.
- Section E includes additional empirical results. Section E.1 reports additional results and robustness checks for dual shares, compares the linear model in the main text with an alternative firm-fixed-effect linear model, and assesses the persistence of monetary shocks in dual-share price gaps. Section E.2 summarizes a variety of robustness checks for the primary pricing results. Section E.3 discusses robustness to the Fed information effect. Section E.4 reports the extensive margins of rebalancing activities. Section E.5 provides quantity evidence on rebalancing. Section E.6 presents a placebo test using other institutions' ownership at quarter and month ends. Section E.7 shows that rebalancer ownership is not spanned by the existing asset-pricing factors documented in previous literature, nesting double-selection LASSOs in transparent two-pass regressions. Finally, Section E.8 reports determinants for security-level rebalancer ownership and information on residual variations in rebalancer ownership.

- Section F updates the Bernanke-Kuttner estimate with Nakamura-Steinsson shocks in our sample period, shows the contribution of risk premia to total returns post monetary shocks using an SVAR-IV system, and documents market-wide revaluation in bond and stock markets using price changes in popular ETFs that track these markets.
- Section G summarizes calibration results using different estimates of demand elasticities in the literature and discusses the consistency of our calibration.

A Microfoundation of Arbitrageur's Demand

We provide a microfoundation of the arbitrageur's demand in the baseline static model and in the multi-period environment.

A.1 Static Model with Many Stocks

We consider N stocks in a static environment, with $N = 2$ nesting our baseline model. The stocks have stochastic payouts that are jointly normal with identical mean $\bar{D}$, variance σ^2, and pair-wise covariance $\rho\sigma^2$ with $\rho \in (0, 1)$. Hence the variance-covariance matrix is $\Sigma = (1 - \rho)\,\sigma^2 I + \rho\sigma^2 \boldsymbol{\iota}\boldsymbol{\iota}'$, with I being the identity matrix and $\boldsymbol{\iota}$ being a vector of ones.

The equity arbitrageur (E) invests in all stocks and a short-term risk-free bond with return η to maximize a mean-variance preference,

$$\max_{\boldsymbol{Q}^E} \left(\boldsymbol{Q}^E\right)' \boldsymbol{\mu} - \frac{\Gamma}{2} \left(\boldsymbol{Q}^E\right)' \Sigma \boldsymbol{Q}^E$$

and thus demands

$$\boldsymbol{Q}^E = \Gamma^{-1} \Sigma^{-1} \boldsymbol{\mu}$$

where $\mu = \left(D + \Delta D - (1 + \eta + \Delta\eta) P_i\right)_i$ is the vector of expected returns, and $\Delta D, \Delta\eta$ are the changes in expected dividends (which are the same across all the stocks) and the risk-free rate.

Using the Sherman-Morrison formula $(A+uv')^{-1} = A^{-1} - \frac{A^{-1}uv'A^{-1}}{1+v'A^{-1}u}$, we get

$$\Sigma^{-1} = \frac{1}{1-\rho}\sigma^{-2}I - \frac{\rho}{(1-\rho)\left[1+(N-1)\rho\right]}\sigma^{-2}\boldsymbol{\iota\iota}'$$

Thus the demand is

$$Q_i^E = \frac{\left[1+(N-2)\rho\right]\left(\bar{D}+\Delta D-(1+\eta+\Delta\eta)P_i\right) - \rho\sum_{j\neq i}\left(\bar{D}+\Delta D-(1+\eta+\Delta\eta)P_j\right)}{\Gamma(1-\rho)\left[1+(N-1)\rho\right]\sigma^2}$$

As prices change by $P_i = \bar{P}(1+r_i)$, the changes in demand to the first order are

$$\Delta Q_i^E = -\psi^A(r_i - \check{r}) - \sum_{j\neq i}\psi^C(r_i - r_j) \tag{1}$$

with $\psi^A \equiv \frac{(1+\eta)\bar{P}}{\Gamma[1+(N-1)\rho]\sigma^2}, \psi^C \equiv \frac{(1+\eta)\rho\bar{P}}{\Gamma(1-\rho)[1+(N-1)\rho]\sigma^2}, \check{r} \equiv \frac{\Delta D-\bar{P}\Delta\eta}{(1+\eta)\bar{P}}$. The levels of ψ^A, ψ^C are controlled by $\Gamma\sigma^2$, with the relative magnitude $\frac{\psi^A}{\psi^C} = \frac{1}{\rho} - 1$ tuned by ρ. When ρ is higher, the two stocks are more substitutable.

In our model of the rebalancing channel, we treat ψ^A and ψ^C as primitive parameters, acknowledging they are sufficient statistics in our model and can be micro-founded in other ways.[1] ψ^C parameterizes the substitutability between two stocks, while ψ^A determines the arbitrageur's demand of the total stock market. The short-term rate η is subsumed by ψ^A, ψ^C here, but plays an independent role as a *discount rate* in the multi-period environment.

A.2 Multi-Period Environment

Here we consider the multi-period environment in Section 2.2, with $T+1$ periods, indexed by $t = 0, \ldots, T$, the last of which is like the static model. There are two stocks $i = 1, 2$ paying dividends $D_{i,t}$ that are jointly normal with mean $\bar{D}$ in the first T periods and mean $\bar{D} + \bar{P}$ in the last period. The latter assumption ensures a stationary environment but is otherwise innocuous. Two stocks' dividends have identical variance σ^2 and covariance $\rho\sigma^2$

[1]Technically, dual shares we analyze in Section 4 have the same dividends ($\rho = 1$) which would imply perfect substitutability of two stocks ($\psi^C \to \infty$) in our microfoundation. One can resort to a constraint on the arbitrageur's position due to contracting frictions as a common alternative modeling device to generate limits to arbitrage. In practice, dual shares are imperfectly substitutable since one has superior voting rights. We directly assume a finite ψ^C, the empirically relevant case.

in each period. Thus we have the same variance-covariance matrix Σ as in the static model.

The equity arbitrageur (E) invests in both stocks to maximize a period-by-period mean-variance preference

$$\max_{\boldsymbol{Q}_t^E} (\boldsymbol{Q}_t^E)'\mu_t - \frac{\Gamma}{2}(\boldsymbol{Q}_t^E)'\Sigma\boldsymbol{Q}_t^E,$$

with $\boldsymbol{Q}_t^E = \left(Q_{1t}^E, Q_{2t}^E\right)'$, $\mu_t = \left(\bar{D} + \Delta D_t + P_{i,t+1} - (1+\eta+\Delta\eta_t)P_{it}\right)'_{i=1,2}$ denoting share and expected return per share, solved by

$$\boldsymbol{Q}_t^E = \Gamma^{-1}\Sigma^{-1}\mu_t$$

Thus the arbitrageur's demand (in shares) for stock i is

$$Q_{it}^E = \frac{\bar{D} + \Delta D_t + P_{i,t+1} - (1+\eta+\Delta\eta_t)P_{it} - \rho\left[\bar{D} + \Delta D_t + P_{-i,t+1} - (1+\eta+\Delta\eta_t)P_{-i,t}\right]}{\Gamma(1-\rho^2)\sigma^2},$$

in which P_{-i} denotes the other stock's price. In response to small price changes $r_{it} = \frac{P_{it}-\bar{P}}{\bar{P}}$, the change in their demanded share is

$$\Delta Q_{it}^E = -\psi^A\left(r_{it} - \check{r}_t - \frac{r_{i,t+1} - \check{r}_{t+1}}{1+\eta}\right) - \psi^C\left[r_{it} - \check{r}_t - \frac{r_{i,t+1} - \check{r}_{t+1}}{1+\eta} - \left(r_{-i,t} - \check{r}_t - \frac{r_{-i,t+1} - \check{r}_{t+1}}{1+\eta}\right)\right], \tag{2}$$

with $\psi^A \equiv \frac{(1+\eta)\bar{P}}{\Gamma(1+\rho)\sigma^2}$, $\psi^C \equiv \frac{(1+\eta)\rho\bar{P}}{\Gamma(1-\rho^2)\sigma^2}$, $\check{r}_t = \sum_{\tau=t}^{T} \frac{\Delta D_\tau - \Delta\eta_\tau\bar{P}}{(1+\eta)^{\tau-t+1}\bar{P}}$. Compared to the arbitrageur's demand eq. (1) in the static model, in this multi-period environment, they take into account the future prices of both stocks with a discount rate η.

B Additional Theory Results and Extensions

B.1 Rebalancing Quantity and Relative Revaluation

Proposition 4 (Rebalancing quantity and relative revaluation)**.** *In the baseline model of Section 2.1, the changes in quantities and prices satisfy the following*

(a) *The change in the rebalancer's stock 1 holding is*

$$\frac{\mathrm{d}\Delta Q_1^R}{\mathrm{d}MS} = \psi^A(\psi^A + 2\psi^C)R\omega\frac{\mathrm{d}[(1+\chi)r_B - \check{r}]}{\mathrm{d}MS} < 0 \tag{3}$$

with $R = \frac{1-\theta}{\psi^A(\psi^A+2\psi^C)+(\psi^A+\psi^C)\omega(1-\theta)}$. *Further, such a change in quantity is reflected in the change in equity share as*

$$\Delta Q_1^R = \omega\theta^{-1}(\vartheta - \check{\vartheta}) \tag{4}$$

where $\vartheta = \frac{W_1^R}{W^R}$ *is the* actual equity share *of the rebalancer, which valuates their* post-shock *holdings at equilibrium prices, and* $\check{\vartheta} = \frac{\bar{W}_1^R(1+r_1)}{\bar{W}^R(1+\theta r_1+(1-\theta)r_B)}$ *is the* counterfactual equity share*, which valuates their* pre-shock *holdings at equilibrium prices.*

(b) *The difference in aggregate stock and bond revaluation is*

$$\frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} - \frac{\mathrm{d}r_B}{\mathrm{d}MS} = C\left[\bar{\omega}\chi(1-\theta)\underbrace{\frac{\mathrm{d}r_B}{\mathrm{d}MS}}_{<0} - \left(\psi^A + \frac{\psi^A}{\psi^A+2\psi^C}\bar{\omega}(1-\theta)\right)\underbrace{\left(\frac{\mathrm{d}r_B}{\mathrm{d}MS} - \frac{\mathrm{d}\check{r}}{\mathrm{d}MS}\right)}_{<0}\right] \tag{5}$$

which is positive when $\chi = 0$ *and decreasing in* χ*, with* $C = \frac{\psi^A+2\psi^C}{\psi^A(\psi^A+2\psi^C)+(\psi^A+\psi^C)\omega(1-\theta)}$*. That is, the aggregate stock market revaluates less than the long-term bond when* $\chi = 0$ *and revaluates more when* χ *is sufficiently high.*

In the case with no reaching-for-yield incentive $\chi = 0$, the aggregate stock market reaction $\bar{r}$ will be smaller than the bond market revaluation r_B according to eq. (5). That occurs because, if the rebalancer targets a fixed equity share, a downward bond revaluation triggers the rebalancer to sell stock 1 only if the equilibrium price reaction of stock 1 is smaller in magnitude than the bond revaluation r_B.

With a reaching-for-yield incentive $\chi > 0$, the rebalancer wants to lower the equity share when the bond revalues downward and hence provides a higher return going forward. This incentivizes the rebalancer to sell stock 1 and may result in an equilibrium stock price reaction that is larger than r_B.

B.2 Consequences of Overstating Rebalancer Ownership

To test the rebalancing channel, we need to measure each stock's rebalancer ownership. As discussed in Section 3, data limitations force us to use coarse proxies that may overstate true ownership. Below we demonstrate that this overstatement neither undermines our cross-sectional findings nor alters the implied aggregate stock market response.

Proposition 5 (Consequences of overstating rebalancer ownership)**.** *In the baseline model, suppose the true ownership share of stock 1 is* ω *but we overstate it by a factor of* $S \geq 1$ *as* $\hat{\omega} = S\omega$ *in our measurement.*

(a) The measured cross-sectional sensitivity $\hat{\gamma} \equiv \hat{\omega}^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right)$ *is biased downward by a factor of* S *relative to the true sensitivity* $\gamma \equiv \omega^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right)$

$$\hat{\gamma} = S^{-1}\gamma \tag{6}$$

(b) The implied aggregate stock market reaction $\mathrm{d}(\hat{\bar{r}} - \check{r})/\mathrm{d}MS = \frac{\zeta^{\perp} - \hat{\bar{\omega}}(1-\theta)}{\zeta - \hat{\bar{\omega}}(1-\theta)}\hat{\gamma}\hat{\bar{\omega}}$ *beyond fundamental changes* $\check{r}$ *differs from the true reaction* $\mathrm{d}(\bar{r} - \check{r})/\mathrm{d}MS$ *by a correction that is small when* $\hat{\bar{\omega}}(1-\theta)$ *is small*

$$\frac{\mathrm{d}(\hat{\bar{r}} - \check{r})/\mathrm{d}MS}{\mathrm{d}(\bar{r} - \check{r})/\mathrm{d}MS} = 1 + \underbrace{\frac{\left(1 - S^{-1}\right)\left(\zeta^{\perp} - \zeta\right)\hat{\bar{\omega}}\left(1-\theta\right)}{\left[\zeta^{\perp} - S^{-1}\hat{\bar{\omega}}\left(1-\theta\right)\right]\left[\zeta - \hat{\bar{\omega}}\left(1-\theta\right)\right]}}_{\textit{correction}} \tag{7}$$

Equation (6) is intuitive: overstating rebalancer ownership in the denominator leads to under-estimation of the cross-sectional sensitivity γ, which is the difference in price reaction divided by difference in ownership. Yet the implied aggregate market reaction in (22) remains essentially unchanged, because the downward bias in γ is offset by the upward bias in $\bar{\omega}$. The only remaining correction enters through the term $\bar{\omega}(1-\theta)$, which is quantitatively unimportant. Indeed, under the approximation in (23), the aggregate response is invariant to this overstatement.

B.3 Heterogeneous Rebalancers and More Flexible Demand

Here we extend our model to a general setup with heterogeneous rebalancers, indexed by $n \in \mathcal{R}$, who each own both stocks, and allow for more flexible demand. We illustrate that the cross-sectional sensitivity reflects rebalancing flows which consist of multiple margins of demand and informs the aggregate stock market reaction. For simplicity, we assume no changes in the stock dividends and the risk-free rate so $\check{r} = 0$, to focus on the effects of monetary shocks on stock prices through portfolio rebalancing.

To determine the rebalancers' demand for individual stocks, we proceed in three steps.

1. Rebalancer's allocation across two stocks. At the steady state, in their stock portfolio, each rebalancer holds ω_1^n share of stock 1 and ω_2^n share of stock 2. Let $\rho_1^n = \frac{\omega_1^n \bar{P}}{\omega_1^n \bar{P} + \omega_2^n \bar{P}} = \frac{\omega_1^n}{\omega_1^n + \omega_2^n}$ denote the steady state share of stock 1 in stock holdings and $\rho_2^n = 1 - \rho_1^n$ denote the share of stock 2. As the prices of these two stocks change, suppose that the rebalancer tilts their stock holdings towards the stock that has a lower price (hence a higher return going forward) with elasticity ϕ^n, i.e.,

$$\frac{W_1^n}{W_1^n + W_2^n} = \frac{\omega_1^n \bar{P}\left(1 + r_1\right)}{\omega_1^n \bar{P}\left(1 + r_1\right) + \omega_2^n \bar{P}\left(1 + r_2\right)} - \underbrace{\phi^n}_{\text{within-class elasticity}} \left(r_1 - r_2\right) \tag{8}$$

   With $\phi^n = 0$, rebalancer n always holds two stocks in proportion to their market values.

2. Rebalancer's equity share. Given the allocation across two stocks, the weighted average return of stocks is $\sum_{i=1,2} \frac{W_i^n}{W_1^n + W_2^n} \frac{\bar{D}}{\bar{P}(1+r_i)} = \delta\left(1 - \rho_1^n r_1 - \rho_2^n r_2\right)$ and the bond return is $\frac{\bar{D}_B}{\bar{P}_B(1+r_B)} = \delta_B\left(1 - r_B\right)$. Thus the change in equity premium π is $\pi^n - \bar{\pi} = \delta\left(1 - \rho_1^n r_1 - \rho_2^n r_2\right) - \delta_B\left(1 - r_B\right) - \left(\delta - \delta_B\right) = -\delta \rho_1^n r_1 - \delta \rho_2^n r_2 + \delta_B r_B$. Suppose rebalancer n raises their equity share when the equity premium is high by flexibility κ^n, and when the bond return is low by intensity χ^n as

$$\frac{W_1^n + W_2^n}{W^n} = \theta^n \exp\left\{ \underbrace{\kappa^n}_{\text{mandate flexibility}} \left(1 - \theta^n\right)\left(\pi^n - \bar{\pi}\right) - \underbrace{\chi^n}_{\text{reaching for yield}} \left(1 - \theta^n\right)\left(\delta_B\left(1 - r_B\right) - \delta_B\right) \right\} \tag{9}$$

3. Rebalancer's wealth. As prices change, each rebalancer's wealth is revaluated at

$$W^n = \bar{W}^n \left[1 + \theta^n \rho_1^n r_1 + \theta^n \rho_2^n r_2 + (1 - \theta^n)\, r_B\right] \tag{10}$$

Combining these three equations, the rebalancer's demand for each stock $\Delta Q_i^n = \frac{\frac{W_i^n}{W_1^n + W_2^n} \frac{W_1^n + W_2^n}{W^n} W^n}{\bar{P}(1+r_i)} - \omega_i^n$ is

$$\Delta Q_i^n = -\underbrace{\omega_i^n (1 - \theta^n)(1 + \kappa^n \delta)}_{\text{own elasticity due to rebalancer}} r_i - \underbrace{\left[\phi^n - \rho_1^n \rho_2^n (1 - \theta^n)(1 + \kappa^n \delta)\right] (\omega_1^n + \omega_2^n)}_{\text{cross elasticity due to rebalancer}} (r_i - r_{-i})$$
$$\underbrace{\omega_i^n (1 - \theta^n)\left[1 + (\kappa^n + \chi^n)\,\delta_B\right] r_B}_{\text{rebalancing flow}} \tag{11}$$

In addition to the equity share θ^n and the reaching-for-yield incentive χ^n, this demand function incorporates additional margins such as the within-class elasticity ϕ^n, the holding of both stocks $\rho_1^n, \rho_2^n > 0$, and the mandate flexibility κ^n. Most of these margins are only measurable with data on rebalancers' portfolios of both stocks and bonds, which we do not have, except the within-class elasticity ϕ^n. However, our cross-sectional approach works without measuring them, as demonstrated next.

The arbitrageur's demand is, same as (3),

$$\Delta Q_i^E = -\psi^A r_i - \psi^C (r_i - r_{-i}) \tag{12}$$

Thus the total demand is $\Delta Q_i = \sum_{n \in \mathcal{R}} \Delta Q_i^n + \Delta Q_i^E$, which satisfies

$$\Delta Q_i = \Psi_i^B r_B - \Psi_i^A r_i - \Psi^C (r_i - r_{-i}) \tag{13}$$

with

$$\Psi_i^B = \sum_{n \in \mathcal{R}} \omega_i^n (1 - \theta^n)[1 + (\kappa^n + \chi^n)\delta_B] \tag{14}$$

$$\Psi_i^A = \psi^A + \sum_{n \in \mathcal{R}} \omega_i^n (1 - \theta^n)(1 + \kappa^n \delta) \tag{15}$$

$$\Psi^C = \psi^C + \sum_{n\in\mathcal{R}} \left[\phi^n - \rho_1^n \rho_2^n \left(1-\theta^n\right)\left(1+\kappa^n \delta\right)\right]\left(\omega_1^n + \omega_2^n\right) \tag{16}$$

and the market clearing condition is

$$\Delta Q_i = 0,\ i = 1,2$$

Proposition 6 (Price reactions with heterogeneous rebalancers and more flexible demand)**.** *In this general model with heterogeneous rebalancers, the price reactions satisfy the following.*

(a) the cross-sectional sensitivity $\gamma \equiv \frac{\frac{dr_1}{dMS}-\frac{dr_2}{dMS}}{\omega_1-\omega_2}$, *with* $\omega_i = \sum_{n\in\mathcal{R}} \omega_i^n$, *is*

$$\gamma = \frac{\Psi_2^A\Psi_1^B - \Psi_1^A\Psi_2^B}{\omega_1 - \omega_2} \frac{\frac{dr_B}{dMS}}{\Psi_1^A\Psi_2^A + \Psi^C\left(\Psi_1^A + \Psi_2^A\right)} \tag{17}$$

(b) the aggregate stock market reaction $\bar{r} \equiv \frac{r_1+r_2}{2}$ *is*

$$\frac{d\bar{r}}{dMS} = \left[\frac{\Psi_2^A\Psi_1^B + \Psi_1^A\Psi_2^B}{2} + \Psi^C(\Psi_1^B + \Psi_2^B)\right] \frac{\frac{dr_B}{dMS}}{\Psi_1^A\Psi_2^A + \Psi^C\left(\Psi_1^A + \Psi_2^A\right)} \tag{18}$$

In this general case, we note that both the cross-sectional sensitivity and the aggregate stock market reaction reflect the same term $\frac{\frac{dr_B}{dMS}}{\Psi_1^A\Psi_2^A+\Psi^C\left(\Psi_1^A+\Psi_2^A\right)}$ but with different coefficients. According to eqs. (14) to (17), the cross-sectional sensitivity γ not only reflects the ownership shares ω_1^n, ω_2^n but also embeds the various margins of demand. While we cannot measure these parameters without data on rebalancers' bond holdings, the idea that the cross-sectional sensitivity can inform the aggregate stock market reaction via the micro-to-macro-elasticity ratio holds precisely in a special case with proportional holdings, i.e., $\frac{\omega_1^n}{\omega_1} = \frac{\omega_2^n}{\omega_2}$ for all n, with $\omega_i = \sum_{n\in\mathcal{R}} \omega_i^n$.

To see the connection between $\bar{r}$ and γ, note that in this model with heterogeneous rebalancers and more flexible demand, generalizing Equations (20) and (21), the macro elasticity corresponds to

$$\zeta = \frac{\Psi_1^A + \Psi_2^A}{2} \tag{19}$$

and the micro elasticity equals

$$\zeta^{\perp} = \frac{\Psi_1^A + \Psi_2^A}{2} + 2\Psi^C \tag{20}$$

Proposition 7 (The aggregate market reaction under proportional holdings)**.** *In this general model with heterogeneous rebalancers, under proportional holdings, i.e.,* $\frac{\omega_1^n}{\omega_1} = \frac{\omega_2^n}{\omega_2}$ *for all* n*,*

$$\frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} = \frac{\zeta^{\perp} - \bar{\omega}K\frac{\mathrm{var}(\omega_i)}{(\bar{\omega})^2}}{\zeta - \bar{\omega}K}\bar{\omega}\gamma = \frac{\zeta^{\perp}}{\zeta}\bar{\omega}\gamma + O\left(\frac{\bar{\omega}K}{\zeta^{\perp}}\frac{\mathrm{var}\left(\omega_i\right)}{\left(\bar{\omega}\right)^2}\bar{\omega}\gamma\right) + O\left(\frac{\bar{\omega}K}{\zeta}\bar{\omega}\gamma\right) \tag{21}$$

with $K = \sum_{n\in\mathcal{R}} \frac{\omega_1^n}{\omega_1}(1-\theta^n)(1+\kappa^n\delta)$*.*

This proposition illustrates that, to the leading order, the aggregate stock market reaction relates to the cross-sectional sensitivity in the same manner as Proposition 3.

B.4 Many Stocks

In the baseline model, we consider two stocks, which is the minimum environment to establish the distinction of and connection between the aggregate stock market reaction and the cross-sectional sensitivity. Here we demonstrate that, our insight readily carries through to an environment with a generic N number of stocks. For simplicity, we assume no changes in the stock dividends and the risk-free rate so $\check{r} = 0$, to focus on the effects of monetary shocks on stock prices through portfolio rebalancing.

Suppose each stock i is held by one rebalancer and the share held is ω_i . Each rebalancer has equity share θ so that the demand in quantity of stock i is

$$\Delta Q_i^R = -\omega_i(1-\theta)r_i + \omega_i(1-\theta)(1+\chi)r_B \tag{22}$$

exactly as in (2). We make these assumptions to keep the message focused on the dimension of many stocks and abstract away from the within-class elasticity in allocation and other heterogeneity of rebalancers, which we discussed in Section B.3.

The equity arbitrageur trades all N stocks and demands, following the microfoundation in Section A.1

$$\Delta Q_i^E = -\psi^A r_i - \sum_{j \neq i} \psi^C (r_i - r_j) \tag{23}$$

The stock price reactions are determined by the market clearing conditions

$$\Delta Q_i = \Delta Q_i^R + \Delta Q_i^E = 0, \; i = 1, \dots, N$$

Parallel to the two-stock setting, we map our model parameters to the measured macro and micro elasticities of the stock market, so that we can determine the aggregate stock market reaction using the measured cross-sectional sensitivity.

1. For the macro elasticity, consider a price change of all stocks by r, the aggregate stock demand is $\Delta \bar{Q} = -\bar{\omega}(1-\theta)r - \psi^A r + \bar{\omega}(1-\theta)(1+\chi)r_B$ and thus the macro elasticity

$$\zeta \equiv -\frac{\partial \Delta \bar{Q}}{\partial r} = \underbrace{\bar{\omega}(1-\theta)}_{\text{rebalancer contribution}} + \underbrace{\psi^A}_{\text{arbitrageur contribution}} \tag{24}$$

2. For the micro elasticity, consider the relative demand of a randomly selected stock pair (i, j), $\Delta Q_i - \Delta Q_j = -\omega_i(1-\theta)r_i + \omega_j(1-\theta)r_j - (\psi^A + N\psi^C)(r_i - r_j) + (\omega_i - \omega_j)(1-\theta)(1+\chi)r_B$. We define the micro elasticity in a symmetric way, averaging over all stock pairs, as

$$\zeta^{\perp} \equiv \overline{\frac{1}{2}\left[-\frac{\partial (\Delta Q_i - \Delta Q_j)}{\partial r_i} + \frac{\partial (\Delta Q_i - \Delta Q_j)}{\partial r_j}\right]} = \underbrace{\bar{\omega}(1-\theta)}_{\text{rebalancer contribution}} + \underbrace{\psi^A + N\psi^C}_{\text{arbitrageur contribution}} \tag{25}$$

with $\bar{\omega} = \frac{\sum_{i=1}^N \omega_i}{N}$ representing the ownership share of the aggregate stock market.

Proposition 8 (Many stocks)**.** *In the model with N stocks, in response to a monetary shock MS, the stock price reactions are as follows.*

(a) The cross-sectional sensitivity, defined as the coefficient γ of a regression $r_i = \gamma \omega_i MS +$

const, is

$$\gamma = \psi^A R_N \frac{\mathrm{d}r_B}{\mathrm{d}MS} + O\left(\mathrm{var}(\omega_i)\frac{\mathrm{d}r_B}{\mathrm{d}MS}\right) \tag{26}$$

with $R_N = \frac{(1-\theta)(1+\chi)}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}\frac{1}{\bar{\omega}(1-\theta)+\psi^A}$. γ *is negative to the leading order, suggesting that stocks with higher rebalancer ownership revalue more in response to monetary shocks*

(b) The aggregate stock market reaction $\bar{r}$ *satisfies*

$$\begin{aligned}\frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} &= \frac{\psi^A + N\psi^C + \bar{\omega}(1-\theta)}{\psi^A}\gamma\bar{\omega} + O\left(\mathrm{var}(\omega_i)\right) \\ &= \frac{\zeta^\perp}{\zeta - \bar{\omega}(1-\theta)}\gamma\bar{\omega} + O\left(\mathrm{var}(\omega_i)\right) = \frac{\zeta^\perp}{\zeta}\gamma\bar{\omega} + O\left(\mathrm{var}(\omega_i)\right) + O\left(\frac{\bar{\omega}(1-\theta)}{\zeta}\gamma\bar{\omega}\right)\end{aligned} \tag{27}$$

This proposition extends the baseline 2-stock results and suggests that the dependence of the aggregate stock market reaction on the cross-sectional sensitivity carries through. Notably, the factor of 2 in Proposition 1(c) becomes N here. However, as we recognize that the measured macro and micro elasticities $\zeta, \zeta^\perp$ of stock demand map differently into the model parameters ψ^A, ψ^C too, we arrive at the same final expression in terms of $\zeta, \zeta^\perp$ as in Proposition 3.

C Proofs

Proof of Proposition 1. Using Equations (2) and (3), the market clearing conditions are

$$\begin{pmatrix} \psi^A + \omega(1-\theta) + \psi^C & -\psi^C \\ -\psi^C & \psi^A + \psi^C \end{pmatrix} \begin{pmatrix} r_1 - \check{r} \\ r_2 - \check{r} \end{pmatrix} = \begin{pmatrix} \omega(1-\theta)(1+\chi)r_B - \omega(1-\theta)\check{r} \\ 0 \end{pmatrix}$$

which yields

$$r_1 - \check{r} = \frac{(\psi^A + \psi^C)\omega(1-\theta)\left[(1+\chi)r_B - \check{r}\right]}{\psi^A(\psi^A + \omega(1-\theta)) + \psi^C(2\psi^A + \omega(1-\theta))} \tag{28}$$

$$r_2 - \check{r} = \frac{\psi^C}{\psi^A + \psi^C}(r_1 - \check{r}) \tag{29}$$

The cross-sectional sensitivity is

$$\gamma \equiv \omega^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right) = \psi^A \frac{(1-\theta)\left[(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} - \frac{\mathrm{d}\check{r}}{\mathrm{d}MS}\right]}{\psi^A(\psi^A + \omega(1-\theta)) + \psi^C(2\psi^A + \omega(1-\theta))} \tag{30}$$

□

Proof of Proposition 2. In period T, the prices of two stocks are the same as in Proposition 1. For $t = 0, \dots, T-1$, the rebalancer does not trade. Through the market clearing conditions, the arbitrageur's demand (9) ensures that

$$r_{i,t} = \frac{1}{1+\eta} r_{i,t+1} = \frac{1}{(1+\eta)^{T-t}} r_{i,T} \tag{31}$$

Hence we have $\frac{\partial |\mathrm{d}\bar{r}_0/\mathrm{d}MS|}{\partial T} < 0$ and $\frac{\partial|\gamma|}{\partial T} < 0$. The relation between the aggregate stock market reaction $\bar{r}_0$ and the cross-sectional sensitivity γ_0 holds as in the baseline static model with $\check{r} = 0$. □

Proof of Proposition 3. The aggregate stock market reaction $\bar{r} = \frac{r_1 + r_2}{2}$ satisfies

$$\frac{\mathrm{d}(\bar{r} - \check{r})}{\mathrm{d}MS} = \frac{\psi^A + 2\psi^C}{\psi^A}\gamma\bar{\omega} = \frac{\zeta^\perp - \bar{\omega}(1-\theta)}{\zeta - \bar{\omega}(1-\theta)}\gamma\bar{\omega} \tag{32}$$

□

Proof of Proposition 4. Proposition 1 and (2) imply that the change in the rebalancer's stock 1 holding is

$$\Delta Q_1^R = \psi^A(\psi^A + 2\psi^C)R\omega[(1+\chi)r_B - \check{r}]$$

with $R = \frac{1-\theta}{\psi^A(\psi^A + 2\psi^C) + (\psi^A + \psi^C)\omega(1-\theta)}$.

To establish $\Delta Q_1^R = \omega\theta^{-1}(\vartheta - \check{\vartheta})$ (which holds under any prices), simply note that the actual equity share is, using (1),

$$\vartheta = \theta(1 + \chi(1-\theta)r_B)$$

and the counterfactual equity share is

$$\check{\vartheta} = \theta[1 + (1-\theta)(r_1 - r_B)]$$

Thus the change in the rebalancer's stock 1 holding according to (2) is

$$\Delta Q_1^R = -\omega(1-\theta)r_1 + \omega(1-\theta)(1+\chi)r_B = \omega\theta^{-1}(\vartheta - \check{\vartheta})$$

Using Proposition 1, the difference in stock and bond revaluation is

$$\begin{aligned}\bar{r} - r_B &= \left(\frac{\psi^A}{2} + \psi^C\right) R\omega[(1+\chi)r_B - \check{r}] + \check{r} - r_B \\ &= \frac{\psi^A + 2\psi^C}{\psi^A(\psi^A + 2\psi^C) + (\psi^A + \psi^C)\omega(1-\theta)} \left[\bar{\omega}\chi(1-\theta)r_B - \left(\psi^A + \frac{\psi^A}{\psi^A + 2\psi^C}\bar{\omega}(1-\theta)\right)(r_B - \check{r})\right]\end{aligned}$$

□

Proof of Proposition 5. When we overstate ω by S times as $\hat{\omega} = S\omega$, the measured cross-sectional sensitivity is

$$\hat{\gamma} \equiv \hat{\omega}^{-1}\left(\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}\right) = S^{-1}\gamma \tag{33}$$

The implied aggregate market reaction using the mismeasured ownership share is thus

$$\mathrm{d}(\hat{\bar{r}} - \check{r})/\mathrm{d}MS = \frac{\zeta^\perp - \hat{\bar{\omega}}\,(1-\theta)}{\zeta - \hat{\bar{\omega}}\,(1-\theta)}\hat{\bar{\omega}}\hat{\gamma} = \frac{\zeta^\perp - \hat{\bar{\omega}}\,(1-\theta)}{\zeta - \hat{\bar{\omega}}\,(1-\theta)}\bar{\omega}\gamma$$

As the true aggregate market reaction satisfies

$$\mathrm{d}(\bar{r} - \check{r})/\mathrm{d}MS = \frac{\zeta^\perp - \bar{\omega}(1-\theta)}{\zeta - \bar{\omega}(1-\theta)}\bar{\omega}\gamma = \frac{\zeta^\perp - S^{-1}\hat{\bar{\omega}}(1-\theta)}{\zeta - S^{-1}\hat{\bar{\omega}}(1-\theta)}\bar{\omega}\gamma$$

we have

$$\frac{\mathrm{d}(\hat{\bar{r}} - \check{r})/\mathrm{d}MS}{\mathrm{d}(\bar{r} - \check{r})/\mathrm{d}MS} = \frac{\zeta^\perp - \hat{\bar{\omega}}\,(1-\theta)}{\zeta^\perp - S^{-1}\hat{\bar{\omega}}\,(1-\theta)}\,\frac{\zeta - S^{-1}\hat{\bar{\omega}}\,(1-\theta)}{\zeta - \hat{\bar{\omega}}\,(1-\theta)}$$

$$= 1 + \frac{\left(1 - S^{-1}\right)\left(\zeta^{\perp} - \zeta\right)\hat{\hat{\omega}}\left(1-\theta\right)}{\left[\zeta^{\perp} - S^{-1}\hat{\hat{\omega}}\left(1-\theta\right)\right]\left[\zeta - \hat{\hat{\omega}}\left(1-\theta\right)\right]} \tag{34}$$

□

Proof of Proposition 6. Rebalancer n's allocation across two stocks is

$$\begin{aligned}\frac{W_1^n}{W_1^n + W_2^n} &= \frac{\omega_1^n \bar{P}\left(1+r_1\right)}{\omega_1^n \bar{P}\left(1+r_1\right) + \omega_2^n \bar{P}\left(1+r_2\right)} - \underbrace{\phi^n}_{\text{within-class elasticity}}\left(r_1 - r_2\right) \\ &= \rho_1^n + \left(\rho_1^n \rho_2^n - \phi^n\right)\left(r_1 - r_2\right)\end{aligned} \tag{35}$$

Rebalancer n's equity share is

$$\begin{aligned}\frac{W_1^n + W_2^n}{W^n} &= \theta^n \exp\left\{\underbrace{\kappa^n}_{\text{mandate flexibility}}\left(1-\theta^n\right)\left(\pi^n - \bar{\pi}\right) - \underbrace{\chi^n}_{\text{reaching-for-yield incentive}}\left(1-\theta^n\right)\left(\delta_B\left(1-r_B\right) - \delta_B\right)\right\} \\ &= \theta^n\left[1 + \left(\chi^n + \kappa^n\right)\left(1-\theta^n\right)\delta_B r_B - \kappa^n(1-\theta^n)\delta\rho_1^n r_1 - \kappa^n(1-\theta)\delta\rho_2^n r_2\right]\end{aligned} \tag{36}$$

As prices change, rebalancer n's total wealth is

$$W^n = \bar{W}^n\left[1 + \theta^n \rho_1^n r_1 + \theta^n \rho_2^n r_2 + \left(1-\theta^n\right) r_B\right] \tag{37}$$

$\frac{W_1^n + W_2^n}{W^n}$ share of the total wealth should be invested in stock, among which $\frac{W_1^R}{W_1^R + W_2^R}$ share is in stock 1.

Hence their demand for stock 1 in quantity is

$$\begin{aligned}\Delta Q_1^n &= \frac{\frac{W_1^n}{W_1^n + W_2^n}\frac{W_1^n + W_2^n}{W^n} W^n}{\bar{P}\left(1+r_1\right)} - \omega_1^n \\ &= \left[\rho_1^n + \left(\rho_1^n \rho_2^n - \phi^n\right)\left(r_1 - r_2\right)\right]\theta^n\left[1 + \left(\chi^n + \kappa^n\right)\left(1-\theta^n\right)\delta_B r_B - \kappa^n(1-\theta^n)\delta\rho_1^n r_1 - \kappa^n(1-\theta^n)\delta\rho_2^n r_2\right] \\ &\quad \cdot \frac{\bar{W}^n\left[1 + \theta^n \rho_1^n r_1 + \theta^n \rho_2^n r_2 + \left(1-\theta^n\right) r_B\right]}{\bar{P}\left(1+r_1\right)} - \omega_1^n \\ &= - \underbrace{\omega_1^n\left(1-\theta^n\right)\left(1+\kappa^n\delta\right)}_{\text{own elasticity due to rebalancer}} r_1 - \underbrace{\left[\phi^n - \rho_1^n \rho_2^n\left(1-\theta^n\right)\left(1+\kappa^n\delta\right)\right]\left(\omega_1^n + \omega_2^n\right)}_{\text{cross elasticity due to rebalancer}}\left(r_1 - r_2\right) \\ &\quad + \underbrace{\omega_1^n\left(1-\theta^n\right)\left[1 + \left(\kappa^n + \chi^n\right)\delta_B\right] r_B}_{\text{rebalancing flow}}\end{aligned} \tag{38}$$

and their demand for stock 2 is symmetric.

Note that the arbitrageur's demand is $\Delta Q_i^E = -\psi^A r_i - \psi^C (r_i - r_{-i})$. We can write the total demand $\Delta Q_i = \sum_{n\in\mathcal{R}} \Delta Q_i^n + \Delta Q_i^E$ as

$$\Delta Q_i = \Psi_i^B r_B - \Psi_i^A r_i - \Psi^C (r_i - r_{-i}) \tag{39}$$

with

$$\begin{aligned}
\Psi_i^B &= \sum_{n\in\mathcal{R}} \omega_i^n (1-\theta^n)[1+(\kappa^n+\chi^n)\delta_B] \\
\Psi_i^A &= \psi^A + \sum_{n\in\mathcal{R}} \omega_i^n (1-\theta^n)(1+\kappa^n\delta) \\
\Psi^C &= \psi^C + \sum_{n\in\mathcal{R}} [\phi^n - \rho_1^n\rho_2^n (1-\theta^n)(1+\kappa^n\delta)](\omega_1^n+\omega_2^n)
\end{aligned}$$

The market clearing conditions are

$$\begin{pmatrix} \Psi_1^A + \Psi^C & -\Psi^C \\ -\Psi^C & \Psi_2^A + \Psi^C \end{pmatrix} \begin{pmatrix} r_1 \\ r_2 \end{pmatrix} = \begin{pmatrix} \Psi_1^B r_B \\ \Psi_2^B r_B \end{pmatrix}$$

Thus the equilibrium price responses are

$$\begin{aligned}
r_1 &= \frac{\Psi_2^A\Psi_1^B + \Psi^C(\Psi_1^B+\Psi_2^B)}{\Psi_1^A\Psi_2^A + \Psi^C(\Psi_1^A+\Psi_2^A)} r_B \\
r_2 &= \frac{\Psi_1^A\Psi_2^B + \Psi^C(\Psi_1^B+\Psi_2^B)}{\Psi_1^A\Psi_2^A + \Psi^C(\Psi_1^A+\Psi_2^A)} r_B
\end{aligned}$$

and their price gap and the aggregate stock market reaction are

$$r_1 - r_2 = \frac{\Psi_2^A\Psi_1^B - \Psi_1^A\Psi_2^B}{\Psi_1^A\Psi_2^A + \Psi^C(\Psi_1^A+\Psi_2^A)} r_B \tag{40}$$

$$\bar{r} = \frac{\frac{\Psi_2^A\Psi_1^B + \Psi_1^A\Psi_2^B}{2} + \Psi^C(\Psi_1^B+\Psi_2^B)}{\Psi_1^A\Psi_2^A + \Psi^C(\Psi_1^A+\Psi_2^A)} r_B \tag{41}$$

The cross-sectional sensitivity $\gamma = \frac{\frac{\mathrm{d}r_1}{\mathrm{d}MS} - \frac{\mathrm{d}r_2}{\mathrm{d}MS}}{\omega_1 - \omega_2}$ is thus

$$\gamma = \frac{\Psi_2^A \Psi_1^B - \Psi_1^A \Psi_2^B}{\omega_1 - \omega_2} \frac{\frac{\mathrm{d}r_B}{\mathrm{d}MS}}{\Psi_1^A \Psi_2^A + \Psi^C \left(\Psi_1^A + \Psi_2^A\right)} \tag{42}$$

□

Proof of Proposition 7. Define $\omega_i \equiv \sum_{n \in \mathcal{R}} \omega_i^n$. In the case of proportional holdings, i.e. $\frac{\omega_1^n}{\omega_1} = \frac{\omega_2^n}{\omega_2}, \forall n \in \mathcal{R}$, define

$$X = \sum_{n \in \mathcal{R}} \frac{\omega_1^n}{\omega_1} (1 - \theta^n)[1 + (\kappa^n + \chi^n)\delta_B] \tag{43}$$

$$K = \sum_{n \in \mathcal{R}} \frac{\omega_1^n}{\omega_1} (1 - \theta^n)(1 + \kappa^n \delta) \tag{44}$$

and we have $\Psi_i^B = \omega_i X, \Psi_i^A = \psi^A + \omega_i K$.

Thus the cross-sectional sensitivity is

$$\gamma = \psi^A X \frac{\mathrm{d}r_B / \mathrm{d}MS}{\Psi_1^A \Psi_2^A + \Psi^C \left(\Psi_1^A + \Psi_2^A\right)}$$

and the aggregate stock market reaction is

$$\mathrm{d}\bar{r} / \mathrm{d}MS = \left[(\psi^A + 2\Psi^C) X \bar{\omega} + K X \omega_1 \omega_2 \right] \frac{\mathrm{d}r_B / \mathrm{d}MS}{\Psi_1^A \Psi_2^A + \Psi^C \left(\Psi_1^A + \Psi_2^A\right)}$$

In relative terms, we have

$$\mathrm{d}\bar{r} / \mathrm{d}MS = \frac{\psi^A + 2\Psi^C + K \bar{\omega} \frac{\omega_1 \omega_2}{(\bar{\omega})^2}}{\psi^A} \bar{\omega} \gamma$$

Using eqs. (19) and (20), we have

$$\zeta = \psi^A + \bar{\omega} K, \quad \zeta^{\perp} = \psi^A + \bar{\omega} K + 2\Psi^C$$

and thus

$$\mathrm{d}\bar{r}/\mathrm{d}MS = \frac{\zeta^{\perp} - \bar{\omega}K\left(1 - \frac{\omega_1\omega_2}{(\bar{\omega})^2}\right)}{\zeta - \bar{\omega}K}\bar{\omega}\gamma = \frac{\zeta^{\perp} - \bar{\omega}K\frac{\mathrm{var}(\omega_i)}{(\bar{\omega})^2}}{\zeta - \bar{\omega}K}\bar{\omega}\gamma \tag{45}$$

If we set $\omega_2 = 0$ (thus $\bar{\omega} = \frac{\omega_1}{2}$ and $\mathrm{var}(\omega_i) = (\bar{\omega})^2$) and assume away mandate flexibility ($\kappa^n = 0$), this nests Proposition 3. □

Proof of Proposition 8. The N market clearing conditions in matrix form are

$$\left(D^{\omega}(1-\theta) + \left[\psi^A + N\psi^C\right] I - \psi^C \boldsymbol{\iota}\boldsymbol{\iota}'\right)\mathbf{r} = (1-\theta)(1+\chi)r_B\boldsymbol{\omega}$$

where D^{ω} is a diagonal matrix with entries ω_i, I is the identity matrix, $\boldsymbol{\iota}$ is the (column) vector of ones, $\boldsymbol{r}$ is the vector of r_i and $\boldsymbol{\omega}$ is the vector of ω_i.

Let $D = D^{\omega}(1-\theta) + \left[\psi^A + N\psi^C\right] I$ be a diagonal matrix and $\Lambda = D - \psi^C\boldsymbol{\iota}\boldsymbol{\iota}'$, we use the Sherman-Morrison formula $(A + uv')^{-1} = A^{-1} - \frac{A^{-1}uv'A^{-1}}{1+v'A^{-1}u}$ to arrive at

$$\Lambda^{-1} = D^{-1} + \frac{\psi^C D^{-1}\boldsymbol{\iota}\boldsymbol{\iota}' D^{-1}}{1 - \psi^C\boldsymbol{\iota}' D^{-1}\boldsymbol{\iota}}$$

with $D^{-1} = \mathrm{diag}\left\{\frac{1}{\omega_i(1-\theta)+\psi^A+N\psi^C}\right\}_i$

Hence the stock price reactions are given by

$$\mathbf{r} = (1-\theta)(1+\chi)r_B\Lambda^{-1}\boldsymbol{\omega} \tag{46}$$

Here we note that if Λ were proportional to an identity matrix, $\boldsymbol{r}$ would be proportional to $\boldsymbol{\omega}$, motivating our cross-sectional regression. Next we show that the regression coefficient of r_i on ω_i is indeed an informative moment, under a first-order approximation of dispersion in rebalancer ownership ω_i.

Let $\alpha = \frac{(1-\theta)}{[\bar{\omega}(1-\theta)+\psi^A+N\psi^C]^2}$, and to the first order

$$D^{-1} = \bar{D}^{-1} - \alpha D^{\tilde{\omega}} + O\left(\left(D^{\tilde{\omega}}\right)^2\right)$$

where $\tilde{\omega}_i = \omega_i - \bar{\omega}$, $\bar{D}^{-1} = \frac{1}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}I$, and $O\left(\left(D^{\tilde{\omega}}\right)^2\right)$ is the second-order term in ownership dispersion. Thus

$$
\begin{aligned}
\Lambda^{-1} &= \bar{D}^{-1} - \alpha D^{\tilde{\omega}} + O\left(\left(D^{\tilde{\omega}}\right)^2\right) + \frac{\psi^C\left(\bar{D}^{-1} - \alpha D^{\tilde{\omega}} + O\left(\left(D^{\tilde{\omega}}\right)^2\right)\right)\boldsymbol{\iota}\boldsymbol{\iota}'\left(\bar{D}^{-1} - \alpha D^{\tilde{\omega}} + O\left(\left(D^{\tilde{\omega}}\right)^2\right)\right)}{1 - \psi^C\boldsymbol{\iota}'\left(\bar{D}^{-1} - \alpha D^{\tilde{\omega}} + O\left(\left(D^{\tilde{\omega}}\right)^2\right)\right)\boldsymbol{\iota}} \\
&= \bar{D}^{-1} - \alpha D^{\tilde{\omega}} + \frac{\psi^C\left(\bar{D}^{-1}\boldsymbol{\iota} - \alpha\tilde{\boldsymbol{\omega}}\right)\left(\boldsymbol{\iota}'\bar{D}^{-1} - \alpha\tilde{\boldsymbol{\omega}}'\right)}{1 - \psi^C\boldsymbol{\iota}'\bar{D}^{-1}\boldsymbol{\iota}} + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right) \\
&= \bar{D}^{-1} - \alpha D^{\tilde{\omega}} + \frac{\psi^C\left(\frac{1}{[\bar{\omega}(1-\theta)+\psi^A+N\psi^C]^2}\boldsymbol{\iota}\boldsymbol{\iota}' - \alpha\frac{1}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}\tilde{\boldsymbol{\omega}}\boldsymbol{\iota}' - \alpha\frac{1}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}\boldsymbol{\iota}\tilde{\boldsymbol{\omega}}'\right)}{1 - \psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}} + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right) \\
&= \bar{D}^{-1} - \alpha D^{\tilde{\omega}} + \alpha_0\boldsymbol{\iota}\boldsymbol{\iota}' - \alpha_1\tilde{\boldsymbol{\omega}}\boldsymbol{\iota}' - \alpha_1\boldsymbol{\iota}\tilde{\boldsymbol{\omega}}' + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right)
\end{aligned}
$$

with $\alpha_0 = \frac{\frac{\psi^C}{[\bar{\omega}(1-\theta)+\psi^A+N\psi^C]^2}}{1-\psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}, \alpha_1 = \frac{\alpha\frac{\psi^C}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}{1-\psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}$

Plugging that into eq. (46) gives

$$
\begin{aligned}
\frac{\mathbf{r}}{(1-\theta)(1+\chi)r_B} &= \Lambda^{-1}\boldsymbol{\omega} = \Lambda^{-1}\left(\bar{\omega}\boldsymbol{\iota} + \tilde{\boldsymbol{\omega}}\right) \\
&= \left[\bar{D}^{-1} - \alpha D^{\tilde{\omega}} + \alpha_0\boldsymbol{\iota}\boldsymbol{\iota}' - \alpha_1\tilde{\boldsymbol{\omega}}\boldsymbol{\iota}' - \alpha_1\boldsymbol{\iota}\tilde{\boldsymbol{\omega}}' + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right)\right]\left(\bar{\omega}\boldsymbol{\iota} + \tilde{\boldsymbol{\omega}}\right) \\
&= \frac{\bar{\omega}\boldsymbol{\iota} + \tilde{\boldsymbol{\omega}}}{\bar{\omega}(1-\theta) + \psi^A + N\psi^C} - \alpha\bar{\omega}\tilde{\boldsymbol{\omega}} + \alpha_0 N\bar{\omega}\boldsymbol{\iota} - \alpha_1 N\bar{\omega}\tilde{\boldsymbol{\omega}} + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right)
\end{aligned}
$$

We collect terms and arrive at

$$
\mathbf{r} = \left[\beta_0\boldsymbol{\iota} + \beta_1\tilde{\boldsymbol{\omega}} + O\left(\tilde{\boldsymbol{\omega}}\tilde{\boldsymbol{\omega}}'\right)\right](1-\theta)(1+\chi)r_B \tag{47}
$$

with coefficients

$$
\begin{aligned}
\beta_0 &= \frac{\bar{\omega}}{\bar{\omega}(1-\theta) + \psi^A + N\psi^C} + \alpha_0 N\bar{\omega} \\
&= \frac{\bar{\omega}}{\bar{\omega}(1-\theta) + \psi^A + N\psi^C}\left[1 + \frac{\frac{N\psi^C}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}{1 - \psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}\right] \\
&= \frac{\bar{\omega}}{\bar{\omega}(1-\theta) + \psi^A + N\psi^C}\frac{1}{1 - \psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}} \\
&= \frac{\bar{\omega}}{\bar{\omega}(1-\theta) + \psi^A}
\end{aligned}
$$

and

$$\begin{aligned}
\beta_1 =& \frac{1}{\bar{\omega}\,(1-\theta)+\psi^A+N\psi^C} - \alpha\bar{\omega} - \alpha_1 N\bar{\omega} \\
=& \frac{1}{\bar{\omega}\,(1-\theta)+\psi^A+N\psi^C} - \frac{\frac{\bar{\omega}(1-\theta)}{[\bar{\omega}(1-\theta)+\psi^A+N\psi^C]^2}}{1-\psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}} \\
=& \frac{1}{\bar{\omega}\,(1-\theta)+\psi^A+N\psi^C}\left[1-\frac{\frac{\bar{\omega}(1-\theta)}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}{1-\psi^C\frac{N}{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}}\right] \\
=& \frac{1}{\bar{\omega}\,(1-\theta)+\psi^A+N\psi^C}\frac{\psi^A}{\bar{\omega}\,(1-\theta)+\psi^A}
\end{aligned}$$

Therefore, we arrive at the aggregate stock market reaction $\bar{r}$ and the regression coefficient γ of $\boldsymbol{r}$ on $\boldsymbol{\omega}\cdot MS$, using $\boldsymbol{\omega}=\bar{\omega}\boldsymbol{\iota}+\tilde{\boldsymbol{\omega}}$ with $\boldsymbol{\iota}'\tilde{\boldsymbol{\omega}}=0$

$$\frac{\mathrm{d}\bar{r}}{\mathrm{d}MS} = \frac{1}{N}\boldsymbol{\iota}'\boldsymbol{r} = \beta_0\,(1-\theta)\,(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} + O\left(\mathrm{var}\,(\boldsymbol{\omega})\,\frac{\mathrm{d}r_B}{\mathrm{d}MS}\right) \tag{48}$$

$$\gamma = \frac{\mathrm{cov}\left(\boldsymbol{\omega},\frac{\mathrm{d}\mathbf{r}}{\mathrm{d}MS}\right)}{\mathrm{var}\,(\boldsymbol{\omega})} = \beta_1\,(1-\theta)\,(1+\chi)\frac{\mathrm{d}r_B}{\mathrm{d}MS} + O\left(\mathrm{var}\,(\boldsymbol{\omega})\,\frac{\mathrm{d}r_B}{\mathrm{d}MS}\right) \tag{49}$$

Last, we connect the aggregate stock market reaction $\bar{r}$ to the cross-sectional sensitivity, under a first-order approximation

$$\frac{\mathrm{d}\bar{r}/\mathrm{d}MS}{\gamma} = \frac{\bar{\omega}(1-\theta)+\psi^A+N\psi^C}{\psi^A}\bar{\omega} + O(\mathrm{var}(\boldsymbol{\omega})) = \frac{\zeta^{\perp}}{\zeta-\bar{\omega}(1-\theta)}\bar{\omega} + O(\mathrm{var}(\boldsymbol{\omega})) \tag{50}$$

When there are only two stocks, this result is nested by Proposition 7 since $\frac{\mathrm{var}(\omega_i)}{(\bar{\omega})^2}$ is a second-order term. □

D Data Appendix

D.1 FactSet Holdings

Our main empirical analysis uses institutional investors and holdings data from FactSet Ownership, accessed through WRDS. FactSet collects holdings data from various sources, including:

- 13F filings: 13F filings are quarterly reported to SEC on US-traded equities held by institutions managing more than $100 million in US-traded securities. In FactSet, these filings are stored in Table *own_ inst_ 13f_ detail_ eq* on WRDS server.

- Institutional stakes: FactSet collects institutional stakes from public firms' annual reports filed to SEC (10K), beneficial ownership (13D, and 13G), and insider filings. We access this data from Table *own_ inst_ stakes_ detail_ eq* on WRDS server.

- Sum of fund level reports: Table *own_ fund_ detail_ eq* on WRDS server.

We follow the recommendation from FactSet User Guide to link and construct holdings at the institutional level. That is, for 13F-mandated institutions and 13F securities, we use the latest 13F positions unless there is a more recent stake position filing; for non-13F securities and non-13F institutions, we use the stake positions; if both stakes and 13F positions are not available, we use the sum of fund level reports. We aggregate the filer level information using the linking tables *own_ ent_ 13f_ combined_ inst* and *own_ ent_ funds*.

We follow (Koijen, Richmond, and Yogo, 2022) to aggregate institutions into six groups using table *entity_ sub_ type_ map*: a Hedge Fund group, which contains five FactSet *subtype*s, including AR (Arbitrage), FH (Fund of Hedge Funds Manager), FF (Fund of Funds Manager), FU (Fund), and FS (Fund Distributor); a Broker group that includes BM (Bank Investment Division), IB (Investment Banking), ST (Stock Borrowing/Lending), and MM (Market Maker); an Institutional Wealth Management group, which includes CP (Corporate), FY (Family Office), and VC (Venture Capital/Pvt Equity); an Investment Advisor group that maps to IC (Investment Company), RE (Research Firm), PP (Real Estate Manager), and SB (Subsidiary Branch); a Long-Term Investor group which refers to FO (Foundation/Endowment Manager), SV(Sovereign Wealth Manager), and IN (Insurance Company); and finally, a Mutual Fund group that maps to FactSet type MF (Mutual Fund Manager). However, this mapping left many institutions unclassified due to missing *subtype*s. We supplement this classification with another mapping file from FactSet (table *entity_ type_ map*), where we further classify the Institutional Wealth Management group with *entity_ type* ESP (Emp Stk Ownership Plan), *entity_ sub_ type* PB (Private Banking/Wealth Mgmt), the Long-Term Investor group with *entity_ sub_ type* PF (Pension Fund Manager), *entity_ type*

PEF (Pension Fund), and *entity_type* COL (College/University), the Hedge Fund group with *entity_type* HED (Hedge Fund), and the Mutual Fund group with *entity_type* MUC (Mutual Fd-Closed End), MUE (Mutual Fd-ETF), MUT (Mutual Fd-Open End), and UMB (Umbrella Fund). Finally, we manually correct some unclassified institutions.[2]

Examples of rebalancers. Table A-1 summarizes the five largest investors in each category by market value at the beginning of the sample period.

D.2 Morningstar Holdings

Previous papers have used CRSP Mutual Fund Database, Thomson Mutual Fund Holdings, and Morningstar for mutual funds' holdings. However, (Schwarz and Potter, 2016) finds that CRSP Mutual Fund Database is mostly reported at quarter end, Thomson Mutual Fund Holdings at semi-annual frequency. For coverage of mutual fund holdings at monthly frequency, we use Morningstar's mutual fund holdings data.

Our primary data set consists of long positions in equity and corporate bonds held by mutual funds that invest primarily in equity and corporate bonds. We merge the equity holdings of each fund with CRSP to double-check prices and stock status; we use the values from CRSP when there is a disparity. We consider a collection of bond categories available on Morningstar for bond holdings, including municipal bonds, corporate bonds, and Treasurys. We obtain yield-to-maturity, coupon, and maturity information from GovPX through CRSP, WRDS Corporate Bond Database, and TRACE through WRDS. Following (Chernenko and Sunderam, 2020), we compute implied bond prices from our holdings data: for each month, the implied price is given by dividing the market value of each fund's holdings of a given bond by its par value and average across all funds holding the bond at the end of the month. We compute the weighted modified duration for each fund in each month by weighting the security level duration information based on the bond holdings' yield-to-maturity, coupon, and maturity. Finally, following (Choi and Kronlund, 2018), we exclude two funds (with Morningstar Fund ID "FSUSA001ZG" and "FSUSA001ZF") from our sample because of their extreme cash ratios, probably due to data errors.

[2] For example, Adage Capital, which operates as a hedge fund but was classified as unknown.

Table A-1: Top 5 institutions by type and assets under management, 2004Q4

Name	Type	Active Share (%)	Within-type Share (%)	AuM ($bn)
Blackrock Institutional Trust Co Na	**Institutional Wealth Mngmt**	**17.03**	**23.51**	**551.38**
State Street Corp	**Institutional Wealth Mngmt**	**20.13**	**17.61**	**413.00**
Northern Trust Corp	**Institutional Wealth Mngmt**	**17.73**	**7.05**	**165.26**
American Century Cos Inc	**Institutional Wealth Mngmt**	**37.30**	**2.56**	**59.95**
Invesco Management Group Inc	**Institutional Wealth Mngmt**	**46.39**	**2.56**	**59.91**
California Public Employees Retirement System	**Long Term Investor**	**7.49**	**9.57**	**57.61**
New York State Common Retirement Fund	**Long Term Investor**	**11.26**	**8.96**	**53.93**
California State Teachers Retirement System	**Long Term Investor**	**11.93**	**8.06**	**48.54**
Teacher Retirement System Of Texas	**Long Term Investor**	**16.03**	**7.51**	**45.21**
New York State Teachers Retirement System	**Long Term Investor**	**14.96**	**7.46**	**44.90**
Vanguard Group Inc	Mutual Fund	8.73	14.51	279.98
Wellington Management Co Llp	Mutual Fund	38.54	11.59	223.58
Alliancebernstein Lp	Mutual Fund	48.20	10.09	194.77
T Rowe Price Associates Inc	Mutual Fund	45.42	6.75	130.29
Putnam Investment Management Llc	Mutual Fund	40.89	5.38	103.82
Fidelity Management & Research Co Llc	Advisor	32.62	11.74	485.91
Capital Research & Management Co	Advisor	35.88	8.46	350.03
Smith Barney Asset Management	Advisor	39.04	3.32	137.21
Deutsche Bank Ag	Advisor	26.68	2.90	120.02
Tiaa Cref Investment Management Llc	Advisor	14.02	2.62	108.56
Morgan Stanley & Co Llc	Broker	30.11	18.62	33.29
Credit Suisse Securities Usa Llc	Broker	22.82	16.38	29.28
Goldman Sachs & Co Llc	Broker	42.20	12.61	22.55
Ubs Securities Llc	Broker	26.87	10.64	19.02
Blair William & Co Llc	Broker	69.77	7.66	13.70
Maverick Capital Ltd	Hedge Fund	48.00	3.31	10.40
Adage Capital Partners Gp Llc	Hedge Fund	29.19	3.12	9.81
Renaissance Technologies Llc	Hedge Fund	44.23	2.63	8.27
Perry Corp (New York)	Hedge Fund	71.62	2.13	6.70
Nationwide Fund Advisors	Hedge Fund	39.02	2.10	6.62

This table reports the snapshot of the five largest institutions by assets under management for each institution type at the end of the year 2004. The active share is one-half times the sum of the absolute value of active weights, which are portfolio weights minus market weights within the set of stocks held for each manager (Koijen, Richmond, and Yogo, 2022). The within-type share stands for the market share within each institutional type.

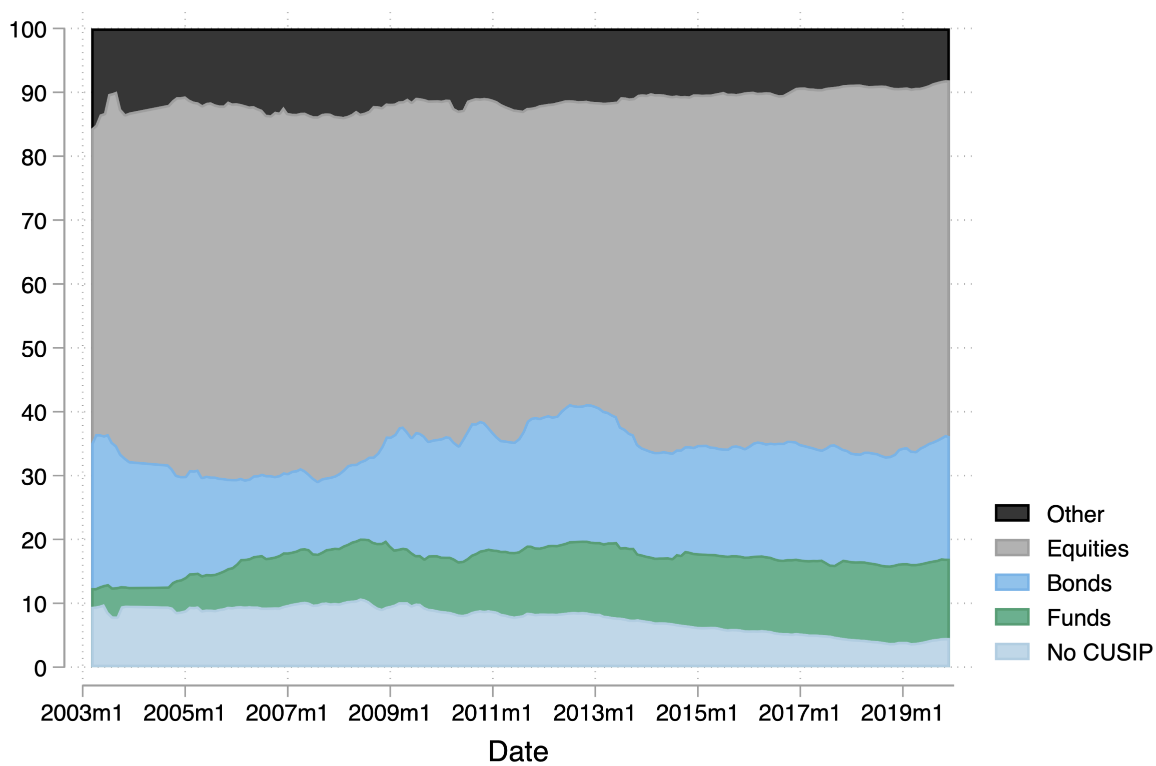
We link the securities in Morningstar's holdings data to the CUSIP Master File to decipher the flows of balanced funds by asset classes. Specifically, we use the first two digits of the Classification of Financial Instruments (CFI; also known as ISO 10962) code in CUSIP Master File. When a financial instrument is issued, CUSIP records a CFI code, which allows us to classify each security in the holdings data. Specifically, we group the Mutual Funds (CFI code starting with CI), Hedge Funds (CFI code starting with CH), ETFs (CFI code starting with CE), and Money Market Instruments (CFI code starting with DY) as the *Funds* category, the Common Shares (CFI code starting with ES), Preferred Shares (CFI code starting with EP), Convertible Shares (CFI code starting with EC), Preferred Convertible Equity (CFI code starting with EF), and Preference Shares (CFI code starting with ER) as the *Equities* category, and Bonds (CFI code starting with DB), Convertible Bonds (CFI code starting with DC), Bonds with Warrants Attached (CFI code starting with DW), Medium-term Notes (CFI code starting with DT), and Municipal Bonds (CFI code starting with DN) as the *Bonds* category. The three categories cover around 80% of holdings in market value during the sample period (Figure A-1).

Additionally, to understand the risk profile of the bond holdings for balanced funds, we merge the bond holdings in Morningstar with Mergent Fixed Income Securities Database (FISD) to obtain monthly bond ratings. Figure A-2 summarizes the bond holdings for balanced funds during the sample period. For balanced funds, most corporate bond holdings are concentrated in the investment-grade universe.

The sample of balanced and pure-equity funds. Balanced funds are mutual funds with diverse asset-allocation strategies that divide investment into a mix of equity, fixed income, and other asset classes. Despite many balanced funds having rebalancing needs based on their target mandates, some balanced-fund managers have been delegated discretionary authority with considerable flexibility regarding rebalancing. To accurately pinpoint the rebalancing mutual funds, we use both fund names and investment styles provided by Morningstar to discriminate between funds with and without mandates.

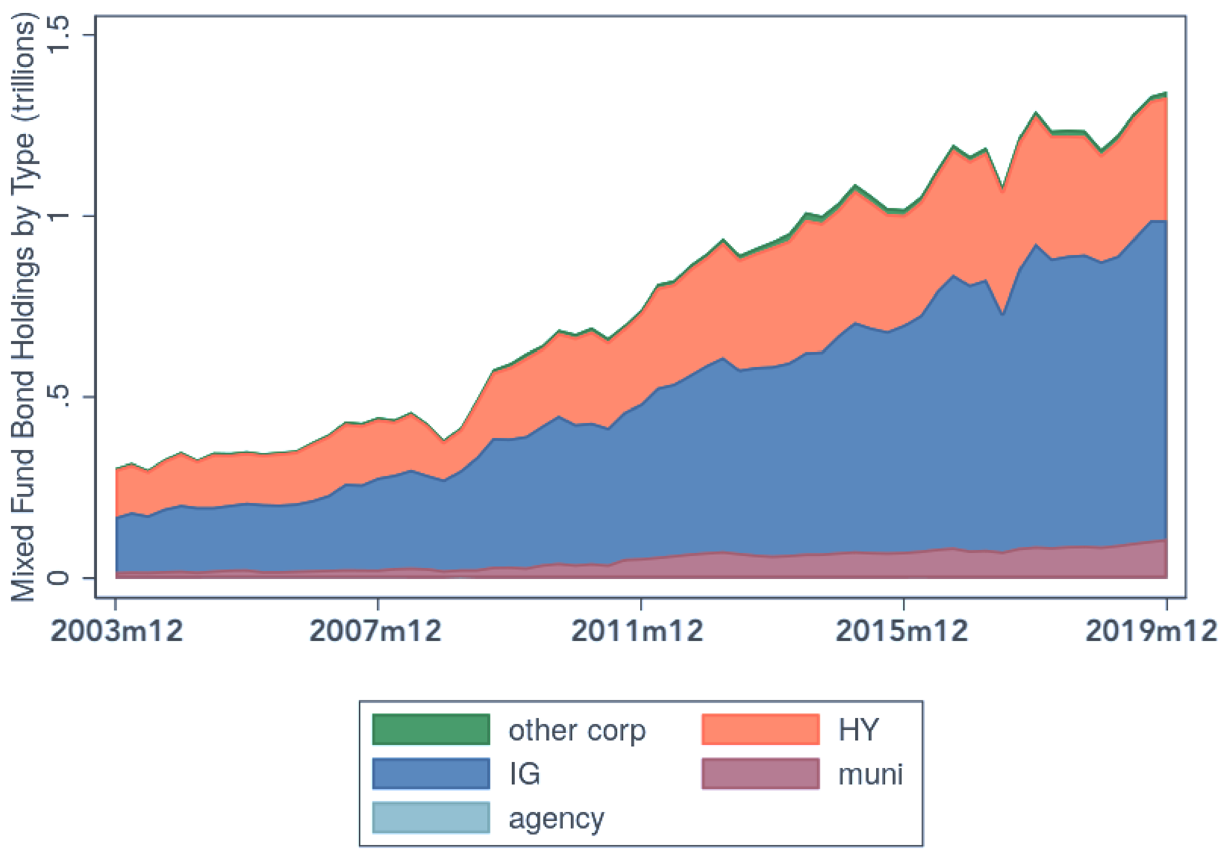
First, we collect a list of candidate TDFs and balanced funds (the mutual fund rebalancers) from fund names associated with the portfolios. Fund names with *retirement, bal-*

Figure A-1: CUSIP coverage of Morningstar holdings



This graph plots the CUSIP information of securities held by mutual funds between 2003 and 2019, in percentages of total market value. CFI codes are from CUSIP Master File, and fund holdings data is from Morningstar. We group the Mutual Funds (CFI code starting with CI), Hedge Funds (CFI code starting with CH), ETFs (CFI code starting with CE), and Money Market Instruments (CFI code starting with DY) as the *Funds* category, the Common Shares (CFI code starting with ES), Preferred Shares (CFI code starting with EP), Convertible Shares (CFI code starting with EC), Preferred Convertible Equity (CFI code starting with EF), and Preference Shares (CFI code starting with ER) as the *Equities* category, and Bonds (CFI code starting with DB), Convertible Bonds (CFI code starting with DC), Bonds with Warrants Attached (CFI code starting with DW), Medium-term Notes (CFI code starting with DT), and Municipal Bonds (CFI code starting with DN) as the *Bonds* category.

Figure A-2: Bond holdings of Morningstar balanced funds



This graph plots bonds held by mutual funds between 2003 and 2019. Bonds are classified by categories and ratings. Bond ratings are from Mergent Fixed Income Securities Database (FISD) accessed through WRDS, and list of balanced funds are as described in Section D.2.

ance, target date or years in numbers (for the majority of target-date funds; e.g., *Goldman Sachs Target Date 2035 Inv*) are considered candidate rebalancers. TDFs are mutual funds with a glide path designed to reduce investment risk over time. The portfolio shares among asset classes change over the years until the target date. TDFs are also candidate rebalancers because they actively rebalance after differential asset-class returns according to their mandates (Parker, Schoar, and Sun, 2022).

Second, we zoom into the spectrum of balanced fund candidates, leveraging the detailed institutional categories from Morningstar. Within the broad universe of balanced funds, Morningstar classifies them based on their investment strategies. We merge the candidate rebalancing portfolios with the Morningstar institutional categories and exclude the portfolios that likely use a discretionary strategy without any return targets or mandates, classified as *Tactical Asset Allocation* or *Flexible Allocation*, along with a few outliers that are pure bond and pure-equity funds. Tactical asset-allocation strategies allow managers to rebalance the asset mix based on their perception of the most vital market segments or to take advantage of temporary price anomalies; hence, these portfolios are not generally subject to the mechanical rebalancing pressure. Similarly, flexible allocation portfolios hold a mix of assets across asset classes, but these funds do not commit to a preset target share; our results are robust to either including or excluding these tactical allocation funds with similar results. We hereby report the results excluding the tactical allocation funds.

Table A-2 is a snapshot of our balanced funds by Morningstar fund category at the first year of the sample period. Most balanced funds at the time were within the category of *Moderate Allocation*, but TDFs have become more important over the sample period: since the Pension Protection Act of 2006, TDFs have been used as a default option in retirement saving plans, and at the end of 2018, more than half of 401(k) participants held TDFs (Holden, VanDerhei, and Bass, 2021).

D.3 TAQ Data Filters

We filter the stock transaction data following (Aït-Sahalia and Xiu, 2019, Aït-Sahalia, Kalnina, and Xiu, 2020) and (Da and Xiu, 2021).

We exclude transactions with condition codes Z (Sold Out of Sequence), B (Average

Table A-2: Snapshot of balanced funds by category, 2004Q4

Fund Category	Market Value (mil $)	N
Aggressive Allocation	13.24	1
Conservative Allocation	258.71	4
Global Allocation	92.56	2
Moderate Allocation	101,252.11	81
Moderately Aggressive Allocation	95.62	3
Moderately Conservative Allocation	1,873.15	6
Target Date 2000-2010 Aggressive	943.21	2
Target Date 2000-2010 Moderate	1,193.08	5
Target Date 2011-2015 Aggressive	344.46	1
Target Date 2011-2015 Moderate	344.23	2
Target Date 2016-2020 Aggressive	1,179.48	3
Target Date 2016-2020 Conservative	31.47	1
Target Date 2016-2020 Moderate	6,930.87	6
Target Date 2021-2025 Aggressive	273.33	2
Target Date 2021-2025 Moderate	773.52	4
Target Date 2026-2030 Aggressive	707.73	3
Target Date 2026-2030 Conservative	18.32	1
Target Date 2026-2030 Moderate	5,529.55	6
Target Date 2031-2035 Aggressive	91.85	2
Target Date 2031-2035 Moderate	426.77	4
Target Date 2036-2040 Aggressive	319.42	3
Target Date 2036-2040 Conservative	17.19	1
Target Date 2036-2040 Moderate	2,353.22	6
Target Date 2041-2045 Moderate	81.22	2
Target Date Retirement Income Moderate	379.25	4
Target Risk	4,456.31	9

This table reports the snapshot of the balanced funds by category at the end of year 2004. Market value sums up the funds' direct stock and bond holdings within each category.

Price Trade), U (Extended Hours Sold Out of Sequence), T (Extended Hours Trade), L (Sold Last), G (Bunched Sold Trade), W (Average Price Trade), and K (Rule 155 Trade); we only consider trades with correction code 00. (Aït-Sahalia and Xiu, 2019) suggest that during our sample period, about half of the publicly traded stocks are subject to market microstructure noises at 30-minute frequencies; we use the realized bid-ask spread to select the top 50% most liquid stocks. In line with the convention in high-frequency asset-pricing literature, we exclude penny stocks (stocks with trade prices lower than 5 dollars) from the sample.

D.4 Stock Characteristics

This section complements Section 3.4 with additional details on stock characteristics construction.

Duration. The most commonly adopted equity duration measure by academics and practitioners is the implied equity duration proposed by (Dechow, Sloan, and Soliman, 2004). Similar to the notion of Macaulay duration for fixed income, (Dechow, Sloan, and Soliman, 2004) constructs the sensitivity of the equity prices to changes in the discount rate, using an analytical model for stock prices based on discounted cash flows. We implement the stock estimation procedure in our sample period, using the linked Compustat-CRSP data available on WRDS and two sets of parameters (Dechow, Sloan, and Soliman, 2004, Weber, 2018). We name the duration estimates with the parameters from (Dechow, Sloan, and Soliman, 2004) Dur^{DSS} and the duration estimates with the parameters from (Weber, 2018) Dur^{W}. The average duration (in years) is 19 following (Dechow, Sloan, and Soliman, 2004), and 18 using parameters from (Weber, 2018), yielding results similar to each other. We report the primary analysis results using Dur^{DSS}. The details for constructing duration measures are available in Section D.4.

More recently, (Gormsen and Lazarus, 2022) proposes a new growth/duration factor by sorting firms on expected growth rates, specifically, the long-term cash-flow growth forecast (LTG) from the IBES database. Because the (median) LTG variable is available annually for a limited subset of firms, the authors instead use four characteristics to predict the expected long-term growth rate. The cross-sectional ranks of the predicted expected long-term growth rate is then used to measure growth/duration. We replicate the procedure in (Gormsen and Lazarus, 2022) and call the predicted duration factor $Duration^{GL}$ for stocks in the sample.

MPE. We replicate the monetary policy exposure (MPE) index developed by (Ozdagli and Velikov, 2020). The MPE index is a function of the Whited-Wu financial friction index, cash, equity duration, cash-flow volatility, and operating profitability. We estimate the Whited-Wu financial constraints index (Whited and Wu, 2006) for all firms during the sample period as

$$\begin{aligned} \textit{Whited-Wu} = & -0.091 \times CF/ATQ - 0.062 \times DIVPOS + 0.021 \times DLTTQ/ATQ \\ & -0.044 \times ln(ATQ) + 0.102 \times ISG - 0.035 \times SG + 0.65, \end{aligned}$$

where CF is cash flow (computed as NIQ-DPQ in Compustat), ATQ stands for total assets, DIVPOS is the cash dividend indicator variable, DLTTQ is the long-term debt, ISG is the average growth rate for the firm's three-digit industry, and SG is sales growth, all from quarterly Compustat data. Since the Whited–Wu index is an estimated variable, potentially prone to measurement error as a proxy, the literature usually discretely separates firms into financially constrained and unconstrained groups every period. We take this approach to the limit by using the percentile rank within each monthly cross-section.

We estimate the cash flow duration measure as per (Dechow, Sloan, and Soliman, 2004), where cash flows are measured and forecasted following (Nissim and Penman, 2001), assuming that return on equity follows a first-order autoregressive process with an autocorrelation coefficient equal to the long-run average rate of mean reversion in ROE and a long-run mean equal to the cost of equity; following the two papers we use the auto-correlation coefficients for returns on equity and sales growth at 0.57 and 0.24, with the long-run cost of equity set at 12% and long-run GDP growth assumed at 6%; the terminal period is set at ten years.

We compute cash flow volatility and operating profitability following (Ozdagli and Velikov, 2020). Cash flow volatility is the standard deviation over the last 20 quarters of cash flows, measured by operating cash flow (SALEQ-COGSQ-XSGQ-WCAPQ+lagged WCAPQ in Compustat) divided by total assets (ATQ in Compustat). A minimum of eight consecutive quarters is required. Operating profitability is estimated as sales (SALEQ in Compustat) minus cost of goods sold (COGSQ in Compustat), divided by the market value of assets, which equals total assets minus shareholder equity (SEQQ in Compustat) plus market capitalization (PRCCQ times CSHO in Compustat).

The MPE index is then given as

$$MPE = -1.60 \times \textit{Rank(Whited-Wu)} - 0.87 \times \textit{Cash} + 0.63 \times \textit{CF Duration}$$
$$+4.36 \times \textit{CF Volatility} - 5.74 \times \textit{Operating Profitability}.$$

Rank(Whited-Wu) is the percentile rank of the Whited-Wu financial constraints index within each monthly cross-section. Cash is the cash and short-term investments (item CHEQ in quarterly Compustat) scaled by market capitalization (computed as the product of PRCCQ and CSHO in Compustat). CF Duration stands for the cash-flow duration.

Other characteristics. We compute the market beta factor following (Frazzini and Pedersen, 2014). We use the CRSP 4-week nominal risk-free rate for excess returns. We compute the rolling 5-year correlations with a minimum of 750 non-missing trading days and estimate rolling standard deviations with 1-year horizon with a minimum of 120 non-missing trading days.

We obtain the monthly S&P500 historical index constituents and Fama-French 4 factors data from WRDS.

In addition to the conventional accounting measure of cash-flow duration above, we estimate two alternative measures of cash-flow duration. The first alternative duration measure uses the same procedure and different parameters from (Weber, 2018), and the second alternative follows (Gormsen and Lazarus, 2022) to focus on the cross-sectional differences in duration.

D.5 Dual-Share Sample

First, we identify dual-share firms with more than one publicly traded share class by checking their trading symbol roots in TAQ. We look for companies with one symbol root but multiple symbol suffixes in the sample period and limit the sample to companies with two share classes of common stocks. We also cross-check the candidate list from TAQ by comparing it with the dual-share firm list, *DUALCLASS*, from the corporate governance dataset in Institutional Shareholder Services. Then we manually collect the voting and cash-flow rights by share class for the candidate companies in the sample period from SEC regulatory filings (form S-1, S-3, S-4, 13-D, 10-K, and 10-Q). This procedure identifies about 100 firms with dual shares and information on cash-flow rights and voting rights during the sample period.

One natural concern is that some of the superior-voting-right share classes might be less liquid; for example, share classes with superior voting rights are sometimes controlled by founding families (Anderson, Ottolenghi, and Reeb, 2017) who are less likely to trade frequently. However, although the share class with superior voting rights tends to respond less quickly to information, surprisingly, they are also less likely to be mispriced (Schultz and Shive, 2010). We address the liquidity concern by first filtering out the share classes with large intraday bid-ask spreads: the sample used for this analysis is limited to the firms with both share classes traded with dollar-value-weighted percent realized spread (calculated with the Lee-Ready algorithm from WRDS) less than 5%. This step leaves us with a sample of 68 dual-share companies during the sample period.

To further check intraday liquidity for the stocks in the sample, we compute price discrepancies between dual shares of the same firm and test if they converge to zero at high frequency. Since equity prices behave differently around important scheduled macroeconomic news announcements from average days (Savor and Wilson, 2014, Lucca and Moench, 2015, Andersen, Thyrsgaard, and Todorov, 2021), we focus on the FOMC announcement days. For each FOMC announcement day, between 9:35 AM EST and 3:45 PM EST,[3] we obtain 5-minute prices for all the dual shares from TAQ, following the data cleaning procedure in Section 3, and test how fast the price gap for dual shares reverts to mean. We define the

[3]The market opens at 9:30 AM EST with an opening auction, and NYSE starts its closing imbalance period at 3:50 PM EST.

percentage price differences between the two share classes of firm f at minute t for date d as $g_{f,d,t} \equiv \frac{P_{f,d,t}^{low\ voting\ right\ share} - P_{f,d,t}^{high\ voting\ right\ share}}{P_{f,d,t}^{low\ voting\ right\ share}}$, and test the null hypothesis of a unit root using firm-by-FOMC-day pairs. Since we have a short panel with a fixed number of intervals (around 1,700 firm-day pairs and 75 5-minute prices for each pair), we employ a unit root test for short panels proposed by (Harris and Tzavalis, 1999). Suppose the price gap for dual shares $p_{f,d,t}$ follows

$$g_{f,d,t} = c_f + \rho_f g_{f,d,t-1} + \varepsilon_{f,d,t}, \tag{51}$$

where c_f is the time-invariant firm fixed effect. If $|\rho_f| < 1$ then the steady-state level of $p_{f,d,t}$ is $\frac{c_f}{1-\rho_f}$, i.e., the limit of the sample mean of $g_{f,d,t}$ conditional on the fixed effect c_f. If $c_f = 0$, the two share classes' prices converge; but generally, c_f can deviate from zero to reflect the voting right premium and liquidity premium at the share-class level.

The (Harris and Tzavalis, 1999) test statistic is the least squares dummy variable estimator of ρ, and with a large cross-sectional dimension and fixed time dimension, ρ converges to standard normal distribution under the null of a unit root. Table A-3 summarizes the test results by significance levels. All dual-share firms in this sample during the sample period reject the null hypothesis of a unit root (column (1)). About 5% of the firms in the sample do not have a statistically non-zero price gap for dual shares at 1% significance level. The median ρ_f is around 0.8 (with interquartile range around 0.2), suggesting a median half-life of around $\frac{\log(0.5)}{\log(0.8)} \times 5min \approx 15.5min$.

To sum up, these dual shares have the same economic fundamentals for a given firm f, and they are highly liquid in that a typical innovation in their price gap is halved within about 15 minutes during our sample period.

D.6 Voting Rights and Rebalancer Ownership

Dual shares have different rebalancer ownership: on average, there is a 13-percentage-point difference in rebalancer ownership for the two share classes within each firm. It is also interesting to investigate these rebalancers' preferences for one share class over the other, behind which one factor relates to voting rights.

Table A-3: H_0 rejection rate, tests for price gaps of dual shares

Significance Levels	Unit Root Test ($H_0 : \|\rho_f\| = 1$) (1)	No Price Gap ($H_0 : c_f = 0$) (2)
10%	100.00%	12.20%
5%	100.00%	9.76%
1%	100.00%	4.88%

This table reports, by significance levels, the unit root tests and coefficient tests for the price gap for dual shares $g_{f,d,t}$ of any given dual-share firm f, using 5-minute trade prices at FOMC days:

$$g_{f,d,t} = c_f + \rho_f g_{f,d,t-1} + \epsilon_{f,d,t},$$

Column (1) reports the proportion of dual-share firms for which the null hypothesis of a unit root is rejected (in percentage), using the LSDV estimator from (Harris and Tzavalis, 1999). Column (2) tests if c_f is significantly different from zero for each firm f using OLS with robust standard errors and reports the proportion of dual-share firms for which the null hypothesis of $c_f = 0$ is rejected (in percentage).

Many rebalancing institutions are conventionally considered passive shareholders (Bebchuk, Cohen, and Hirst, 2017) and prefer the share class with fewer voting rights. Using data from Institutional Shareholder Services, (Larcker and Tayan, 2015) finds institutional investors vote in support of the management 95% of the time when the management is seeking a vote "for" a proposal, and 56% of the time when they seek a vote "against" a proposal. One reason for such preference could be the cost of engaging in corporate governance. Given the complex shareholder composition, any effort exerted to vote and improve corporate performance will be enjoyed by all shareholders, creating a free-rider problem. Table A-4 summarizes the average holdings of FactSet institutions by share class. Institutional wealth management and long-term investors hold more of the share class with lower voting rights in the number of stocks and percentages of shares outstanding.[4]

[4] This is in contrast to some other types of institutions that actively seek it (Clifford, 2008, Lewellen and Lewellen, 2022). For example, hedge funds are sometimes incentivized to direct financial resources to corporate governance for the stocks in their portfolio.

Table A-4: Summary statistics for dual-share holdings

	Share Class with High Voting Rights						Share Class with Low Voting Rights					
	N	Mean	SD	p10	Median	p90	N	Mean	SD	p10	Median	p90
Advisor %	64	20.40	15.40	0.61	19.10	39.10	68	34.30	11.90	17.10	35.50	48.50
Broker %	62	1.27	1.78	0.05	0.71	3.06	67	1.53	1.09	0.59	1.31	2.65
Hedge Fund %	60	9.05	11.70	0.08	3.89	27.40	67	9.39	9.18	1.85	6.50	19.20
Long Term %	46	0.70	0.90	0.02	0.42	1.60	62	0.93	1.12	0.11	0.71	1.59
Mutual Funds %	57	7.39	7.16	0.12	6.17	22.00	68	12.80	7.67	3.14	11.40	24.20
Institutional Wealth Mngmt %	64	8.17	7.40	0.17	6.65	18.20	68	19.60	7.19	10.40	20.00	27.80

This table shows summary statistics for dual shares holdings of FactSet institutions. Dual shares are publicly traded companies on NYSE, NYSE MKT, and NASDAQ sharing one symbol root but different symbol suffixes in millisecond TAQ data. Voting rights for each share class are collected from SEC regulatory filings (form S-1, S-3, S-4, 13-D, 10-K, and 10-Q). Due to intraday liquidity concerns, the sample of dual shares is restricted to 68 companies.

E Additional Empirical Results

E.1 Additional Results for Dual Shares

Within-firm variation. We empirically verify that rebalancer ownership varies within a firm over time.

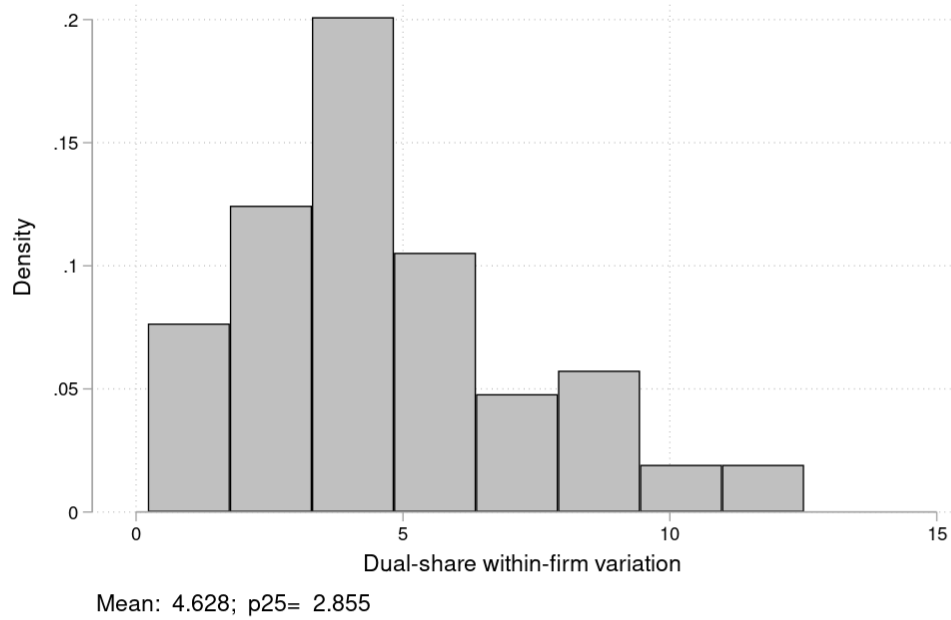
Recall that for dual shares, we exploit within-firm variations with the model below:

$$r_{sft} = \gamma^{dual}\omega_{sft} \cdot MS_t + \nu\omega_{sft} + \delta_{ft} + \epsilon^2_{sft},$$

where δ_{ft} controls for firm-meeting fixed effects.

To verify that such variation exists after controlling for δ_{ft}, for every dual-share firm, we compute the standard deviation of $|\omega_{1ft} - \omega_{2ft}|$ for the same firm f across time and plot the distribution in Figure A-3 across firms. The histogram shows substantial dispersion: the average within-firm standard deviation is 4.6% and fewer than 25% of firms have a standard deviation of less than 2.9%.

Figure A-3: Variations across firms in within-firm dual-share rebalancer ownership



This figure plots the distribution of rebalancer ownership variation: for each dual-share firm, we compute the standard deviation of $|\omega_{1ft} - \omega_{2ft}|$ and show the distribution of the standard deviations by firm.

Fully saturated vs. restricted fixed-effect models. We explain why a *fully saturated* specification with firm-meeting fixed effects, as used in our main text, is preferred to a *restricted fixed-effect* specification with firm fixed effect interacted with monetary shocks.

Consider a linear specification for dual shares with firm fixed effects time monetary shocks, henceforth the *restricted fixed-effect model*

$$r_{sft} = \gamma_2^{dual} \omega_{sft} MS_t + \nu_2 \omega_{sft} + \delta_f + \delta_t + \sum_{f' \in \mathcal{F}} \kappa_f \mathbb{I}[f' = f] MS_t + u_{sft}, \tag{52}$$

where r_{sft} denotes the 30-minute return of share class s of firm f around FOMC announcement t, MS_t represents monetary shock, and $\sum_{f' \in \mathcal{F}} \kappa_f \mathbb{I}[f' = f] MS_t$ collects firm dummies interacted with monetary shocks for all dual-share firms collected in $\mathcal{F}$. We are interested in the cross-sectional sensitivity γ_2^{dual} regarding the rebalancer ownership ω_{sft} on announcement day t for share class s of firm f.

This restricted fixed-effect model may produce a biased estimate of γ^{dual}, when firms' price responses to monetary shocks are time-varying due to reasons correlated with rebalancer ownership across firms. This bias may arise from firms' incentive to change characteristics to cater to investor preferences (Baker and Wurgler, 2004, Polk and Sapienza, 2008). In the dual-share setting, for example, rebalancers may have preferences for (or against) stocks with longer duration or other firm characteristics X_{it}. If X_{it} change over time and affect firm i's stock price reactions in the absence of rebalancing, then the estimated γ^{dual} from the restricted fixed-effect model may pick up such correlation. This concern can be addressed by a *fully saturated* specification in which we control for firm-meeting fixed effects δ_{ft},[5]

$$r_{sft} = \gamma_1^{dual}\omega_{sft} \cdot MS_t + \nu_1\omega_{sft} + \delta_{ft} + \epsilon_{sft}, \tag{53}$$

the cross-sectional sensitivity estimate γ_1^{dual} exploits the within-firm-meeting variation, and any firm-specific drift over time is completely swept out by the fixed effects δ_{ft}.

We illustrate the bias with a toy example in Table A-5, with 2 firms, 2 share classes, and 2 dates. Suppose the true structural model is

$$r_{sft} = -2\omega_{sft}MS_t - X_{ft}MS_t \tag{54}$$

in which a higher rebalancer ownership ω_{sft} leads to a more negative stock price reaction by sensitivity $\gamma^{dual} = -2$ and a larger value of certain characteristic (e.g., duration) X_{ft} also leads to a more negative stock price reaction. Suppose between time 1 and 2, firm 1's rebalancer ownership ω_{sft} increases for both shares, and the firm 1's duration decreases. For firm 2, the rebalancer ownership and the duration are the same over time. The fully saturated model with firm-meeting fixed effects δ_{ft} recovers $\gamma_1^{dual} = -2$ whereas the restricted fixed-effect model with $\delta_f MS_t$ yields a biased estimate $\gamma_2^{dual} = -1.4$.

[5] (Wing, Freedman, and Hollingsworth, 2024) have a more formal and thorough discussion to show that, in a staggered-adoption difference-in-differences design that is comparable to our setting, the fully saturated empirical model with firm-meeting fixed effects yields an unbiased average treatment effect, while restricted fixed-effect models using firm fixed effects are generally biased.

Table A-5: Toy dataset

f	s	t	r_{sft}	MS_t	ω_{sft}	X_{ft}
1	1	1	-4	1	2	0
1	1	2	-2	1	3	-4
1	2	1	-2	1	1	0
1	2	2	0	1	2	-4
2	1	1	-3	1	1.5	0
2	1	2	-3	1	1.5	0
2	2	1	-1	1	0.5	0
2	2	2	-1	1	0.5	0

Suppose the true data generating process for how rebalancing affects monetary transmission between dual shares is given by:

$$r_{sft} = -2\omega_{sft} MS_t - X_{ft} MS_t,$$

where r_{sft} is the price change of share s of firm f at time t, ω_{sft} is its rebalancer ownership, MS_t is a monetary shock, and X_{ft} is a firm characteristic.

Dual-share regressions with intraday liquidity controls. Table A-6 introduces additional liquidity controls to the dual-share results.

Table A-6: An additional liquidity control for dual shares

	OLS	1st Stage		2SLS	OLS
	(1)	(2)	(3)	(4)	(5)
	Ownership$_{Rebalancer}$	Ownership$_{Rebalancer}$	MS× Ownership$_{Rebalancer}$	Returns	Returns
$I_{High\ Voting\ Rights}$	-0.0561***	-0.0559***	0.000171*		
	(0.00357)	(0.0210)	(0.0000935)		
MS×$I_{High\ Voting\ Rights}$		0.117*	-0.0739***		
		(0.0675)	(0.0214)		
Ownership$_{Rebalancer}$ ×MS				-37.87***	-17.17***
				(12.27)	(5.549)
Ownership$_{Rebalancer}$				-0.475	-0.0419
				(0.380)	(0.122)
MS× % Realized Spread		×	×		×
% Realized Spread		×	×		×
Firm-Meeting FE	N	Y	Y	Y	Y
N	4,162	4,162	4,162	4,162	4,162
Adj. R^2	0.109	0.634	0.869		0.840

This table summarizes the instrumented regressions for dual shares and compares the results with OLS regressions, controlling for intraday liquidity, computed as the dollar value-weighted percent realized spread ("% Realized Spread") at daily frequency (Lee and Ready, 1991, Holden and Jacobsen, 2014) from WRDS millisecond TAQ data. ω_{sft} is the rebalancer ownership for share class s of firm f before announcement day t. $I_{High\ Voting\ Rights}$ is an indicator function that equals one when the share class s of firm f before announcement day t has higher voting rights in $t-1$ than the other share class $-s$ of firm f, and zero otherwise. Columns (1)–(3) show the relevance of instruments. Columns (4) and (5) report the 2SLS estimate of returns on instrumented ownership variables ($\widehat{\omega_{sft}}$ and $\widehat{\omega_{sft} \cdot MS}$), and the OLS estimate of returns on raw ownership variables (ω_{sft} and $\omega_{sft} \cdot MS$).
Standard errors are clustered at the firm by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Dual-share IRF from OLS. Figure A-6 reports additional empirical results from the raw ownership $I_{High\ Rebalancer\ Ownership} \cdot MS$ and the results are consistently significant from the 5-minute on to 60-minute estimation window.

Price gaps between dual shares caused by monetary shocks vs. other shocks. We contrast the decay path of dual-share price gaps due to monetary shocks with the decay path implied by firms' own AR(1) dynamics outside announcement windows, estimated in Section D.5.

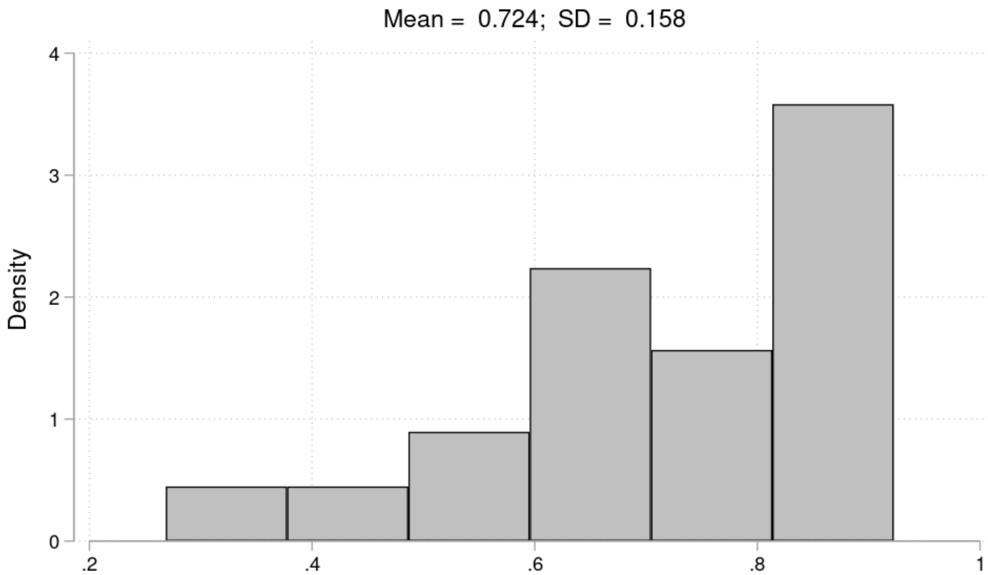
Figure 2 reports the sensitivity of dual-share cumulative returns after the FOMC announcement to a monetary shock, estimated from

$$r_{sft}^{h} = \gamma_{2SLS}^{dual,h}\widehat{\omega_{sft} \cdot MS_t} + \nu_{2SLS}^{h}\widehat{\omega_{sft}} + \delta_{ft}^{h} + \epsilon_{sft}^{2SLS,h},$$

where r_{sft}^{h} are the cumulative returns from 30 minutes before the FOMC announcement to $(h \times 5)$-minute after for share class s of firm f at FOMC announcement t. $\widehat{\omega_{sft}}$ is the rebalancer ownership for share class s of firm f before announcement day t, instrumented by whether this share class has more voting rights.

We benchmark this policy decay against firm-specific AR(1) persistence outside announcement windows. Figure A-4 shows that dual-share firms have considerable cross-sectional heterogeneity in the persistence of their price gaps, ρ_f. We generate the average and interquartile decay paths of a unit shock using the cross-sectional distribution of 500 Monte Carlo decay paths based on firm-specific AR(1) parameters for each dual-share firm.

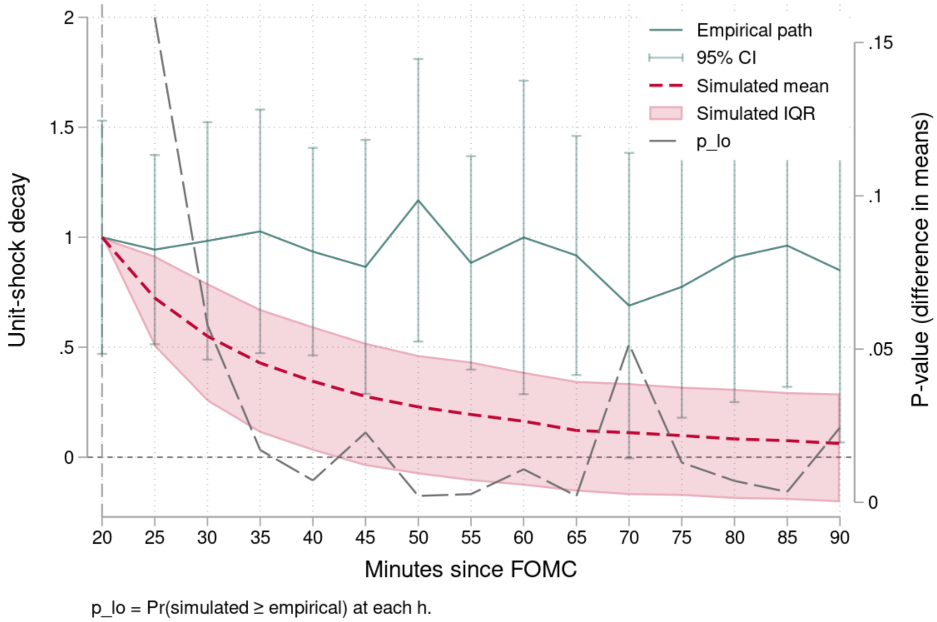
Figure A-4: Persistence in dual-share price gaps



This figure plots the distribution of persistence parameter for each dual-share firm for the price gap estimated from a unit root test for short panels ((Harris and Tzavalis, 1999)). Suppose the price gap for dual shares $p_{f,d,t}$, defined as percentage price differences between the two share classes of firm f at minute t for date d, follows $g_{f,d,t} = c_f + \rho_f g_{f,d,t-1} + \varepsilon_{f,d,t}$, where c_f is the time-invariant firm fixed effect. If $|\rho_f| < 1$ then the steady-state level of $p_{f,d,t}$ is $\frac{c_f}{1-\rho_f}$, i.e., the limit of the sample mean of $g_{f,d,t}$ conditional on the fixed effect c_f. If $c_f = 0$, the two share classes' prices converge; but generally, c_f can deviate from zero to reflect the voting right premium and liquidity premium at the share-class level.

Figure A-5 overlays the two decay paths and reports one-sided p-values; monetary-shock-induced gaps revert significantly more slowly for horizons from the peak (20-minute after the FOMC announcement) to up to 90 minutes. We also include the one-sided p-values of difference-in-means tests between $\gamma^{dual,h}$ and the average ρ_f^h on the right axis. The monetary-shock-induced gaps revert more slowly than other-shock-induced gaps. Pinpointing the exact cause is interesting but beyond the scope of this paper.

Figure A-5: Decay in price deviations between dual shares



This graph plots the cumulative decay of dual-share price deviations per unit monetary shock over successive five-minute intervals. The solid blue line shows the average summed coefficients $\{\gamma^h\}$ from

$$r^h_{sft} = \gamma^{dual,h}_{2SLS}\widehat{\omega_{sft} \cdot MS_t} + \nu^h_{2SLS}\widehat{\omega_{sft}} + \delta^h_{ft} + \epsilon^{2SLS,h}_{sft},$$

where r^h_{sft} are the cumulative returns from 30 minutes before the FOMC announcements to $(h \times 5)$-minute after for share class s of firm f at FOMC announcement t. ω_{sft} is the rebalancer ownership for share class s of firm f at FOMC announcement t; $\widehat{\omega_{sft}}$ is the rebalancer ownership for share class s of firm f before announcement day t from the first stage. δ^h_{ft} collects firm-meeting fixed effects. The standard errors are two-way clustered at the firm-meeting level, and the 95% confidence intervals are displayed. The solid green line plots the empirical impulse response of $\log R_t$ to a unit shock. Thin vertical bars show the corresponding 95% confidence interval. The dashed red line is the cross-sectional mean of 500 Monte Carlo survival fraction paths based on firm-specific AR(1) parameters, while the light red band encloses their interquartile range (25th to 75th percentile). The grey long-dashed line (right axis) shows the one-tailed difference-in-means test's p-value for each h, $\mathrm{p}_l o = \Pr[\text{simulated mean} \geq \text{empirical}]$, at each horizon $h = 20, 25, \ldots, 90$ minutes.

Dual-share quarter-end vs. full sample.

Table A-7: Dual shares: rebalancer ownership and returns

	All			Quarter-End		
	First-Stage			First-Stage		
	(1)	(2)	(3) Returns	(4)	(5)	(6) Returns
$I_{High\ Voting\ Rights}$	−0.0641 * **	−0.0619 * **		−0.0660 * **	−0.0636 * **	
	(0.00344)	(0.0203)		(0.00480)	(0.0202)	
MS×$I_{High\ Voting\ Rights}$		0.117*			0.0828	
		(0.0675)			(0.0984)	
ω_{sft}×MS			−37.83 * **			−41.98 * **
			(12.23)			(11.76)
ω_{sft}			−0.454			−0.0468
			(0.366)			(0.443)
Firm-Meeting FE	Y	Y	Y	Y	Y	Y
N	4250	4164	4164	2144	2100	2100

This table summarizes the instrumented regressions for dual shares for the full sample and the quarter-end subsample. ω_{sft} is the rebalancer ownership for share class s of firm f on announcement day t. Columns (1)–(3) show the first stage and the second stage for the full sample. Columns (4)-(6) show the first stage and the second stage for the quarter-end subsample.
Standard errors are clustered at the firm by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

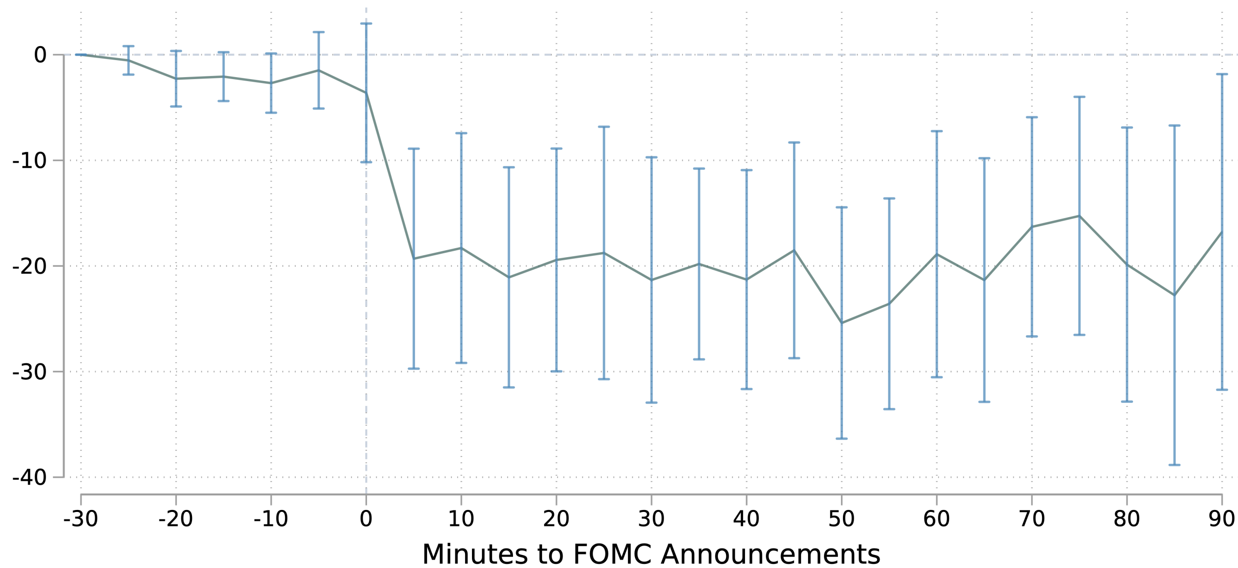
E.2 Robustness Tests for the Main Analysis

Table A-8 summarizes additional robustness checks on the main results in Section 5.1 using alternative measures, different subsamples, and weighted observations.

Column (1) introduces stock fixed effects into the fully controlled panel in column (5), panel (a) of Table 4; Columns (2) and (3) consider alternative duration measures using the equal-weighted cross-sectional duration ranks developed by (Gormsen and Lazarus, 2022), and duration using parameters from (Weber, 2018). Column (4) considers an alternative measure of rebalancer ownership using cross-sectional ownership ranks. The next three columns report results for the index inclusion effect: column (5) introduces the interaction between monetary shocks and SP500 index membership as a dummy (I_{SP500}, included in SP500 $=$ 1), and column (6) uses the subsample of SP500 stocks only, and column (7) reports the results using the subsample excluding SP500 stocks. We report a separate set of summary statistics for SP500 stock holdings in Table A-9. Column (8) completes the beta factor with the Fama-French 4 factors. The last two columns weigh the observations with market capitalization for each observation, with the last column excluding the top 5% firms. Overall, across the specifications, the coefficient for the interaction between rebalancer ownership and monetary shocks is consistent with previous estimates.

There are two exceptions regarding statistical power: when we restrict firms to SP500 constituents (column (6)) or weigh the observations with market caps while including the largest 5% firms (column (9)). In these cases, the statistical power is very limited due to a lack of variation in rebalancer ownership among the largest firms. For example, among the top 5% firms, the average rebalancer ownership for these firms is higher than for the whole sample, but its standard deviation of rebalancer ownership across stocks is halved. When weighing all firms by market cap, these top 5% firms essentially drive the estimate, in which case a lack of variation in rebalancer ownership leads to a large standard error.

Figure A-6: Returns for dual shares around FOMC announcements under OLS



This figure plots the cross-sectional sensitivity $\gamma^{dual,h}$ of dual shares around FOMC announcements from the empirical model

$$r^h_{sft} = \gamma^h \omega_{sft} \cdot MS_t + \nu^h \omega_{sft}$$

$$+\check{\beta}^{1h} I_{high\ voting\ right,sft} \cdot MS_t + \check{\beta}^{2h} I_{high\ voting\ right,sft} + \delta^h_{ft} + \epsilon^h_{sft}.$$

r^h_{sft} are the cumulative returns from 30-minute before the FOMC announcements to $(h \times 5)$-minute after for share class s of firm f at FOMC announcement t. ω_{sft} is the rebalancer ownership for share class s of firm f before announcement day t; δ^h_{ft} collects firm-meeting fixed effects. $I_{high\ voting\ right,sft}$ is an indicator function that equals one when the share class s of firm f before announcement day t has higher voting rights than the other share class $-s$ of firm f, and zero otherwise. The standard errors are two-way clustered at the firm-meeting level, and the 95% confidence intervals are displayed.

An additional concern is that many pensions' in-house asset management is not marked to market, but rather uses the prevailing corridor approach for accounting (Burke, Chen, and Eaton, 2017). If that is the case, we should not anticipate pension managers to rebalance based on market value fluctuations. since many pensions' in-house managed holdings are not marked to market. Our results are robust to excluding the in-house managed pension

Table A-8: Robustness tests

	Stock FE	Duration Measure		Ownership Measure	SP500 Index			FF4 Factors	Weighted OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\text{Ownership}_{Rebalancers}\times$MS	-3.365**	-3.507**	-3.626**		-3.011*	-2.236	-3.942*	-3.937**	-1.157	-3.379*
	(1.542)	(1.550)	(1.570)		(1.588)	(2.107)	(2.057)	(1.564)	(2.253)	(1.874)
$\text{Ownership}_{Rebalancers}$	×	×	×		×	×	×	×	×	×
DSS Duration×MS	×			×	×	×	×	×	×	×
DSS Duration	×			×	×	×	×	×	×	×
MPE	×	×	×	×	×	×	×	×	×	×
MPE×MS	×	×	×	×	×	×	×	×	×	×
Size×MS	×	×	×	×	×	×	×	×	×	×
Size	×	×	×	×	×	×	×	×	×	×
Dividend×MS	×	×	×	×	×	×	×	×	×	×
Dividend	×	×	×	×	×	×	×	×	×	×
$\beta\times$MS	×	×	×	×	×	×	×			
β	×	×	×	×	×	×	×			
GL Duration×MS		×								
GL Duration		×								
Weber Duration×MS			×							
Weber Duration			×							
$\text{Rank}_{Rebalancers}\times$MS				-0.709*						
				(0.374)						
$\text{Rank}_{Rebalancers}$				×						
FF4 Factors×MS								×	×	×
FF4 Factors								×	×	×
Stock FE	Y	N	N	N	N	N	N	N	N	N
$I_{SP500}\times$ MS	N	N	N	N	Y	N	N	N	N	N
Meeting FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$I_{ind.}\times$ MS	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	55730	55766	58489	58497	58497	20837	37657	58497	58497	55514
Adj. R^2	0.601	0.599	0.595	0.594	0.595	0.678	0.579	0.596	0.696	0.659

This table supplements Table 4 with robustness checks using different measures, subsamples, and observation weights. Column (1) introduces stock fixed effects into the fully controlled panel in Table 4 (column (5), panel (a)). Columns (2) and (3) consider alternative duration measures using the equal-weighted cross-sectional duration ranks developed by (Gormsen and Lazarus, 2022) (column (2)), and duration using parameters from (Weber, 2018). Column (4) considers an alternative measure of rebalancer ownership using cross-sectional ownership ranks. The next three columns report results for the index inclusion effect: column (5) introduces SP500 index membership as a dummy (included in SP500 = 1), column (6) uses the subsample of SP500 stocks only, and column (7) reports the results using the subsample excluding SP500 stocks. In column (8) we use the Fama-French 4 factors instead of the beta factor in (Frazzini and Pedersen, 2014). The last two columns report results for weighted OLS: column (9) reports results for the full sample, and column (10) excludes the largest 5% of listed firms sorted by market cap.

Table A-9: Summary statistics for common stocks in FactSet holdings, SP500 only

		N	Mean	Median	SD	p10	p90
2004	Advisor %	477	31.60	31.30	10.10	18.60	44.60
	Broker %	475	1.36	1.12	0.824	0.771	2.07
	Hedge Fund %	475	2.39	1.34	2.94	0.44	5.18
	Long-Term Investor %	475	4.48	4.42	0.91	3.60	5.43
	Mutual Fund %	477	15.20	14.20	6.67	7.11	24.20
	Institutional Wealth Mgmt %	476	18.40	17.40	5.24	13.00	25.70
	Market Value ($ million)	475	17,110	9,762	20,080	2,777	44,500
	β	451	1.013	0.886	0.588	0.391	1.884
	DSS Duration (year)	197	17.41	17.57	3.834	15.67	18.66
	Weber Duration (year)	202	19.96	21.70	7.518	16.74	23.27
2009	Advisor %	469	36.20	36.50	9.64	23.30	48.90
	Broker %	468	1.69	1.54	0.79	1.02	2.55
	Hedge Fund %	468	4.13	2.79	4.10	0.98	9.18
	Long-Term Investor %	468	4.81	4.74	1.14	3.53	6.10
	Mutual Fund %	469	16.30	15.50	6.20	8.74	24.90
	Institutional Wealth Mgmt %	469	16.90	16.20	4.75	12.70	21.50
	Market Value ($ million)	468	16,460	8,504	20,060	2,695	39,850
	β	444	1.032	0.935	0.494	0.486	1.695
	DSS Duration (year)	237	16.67	16.73	2.286	14.61	18.59
	Weber Duration (year)	240	19.67	20.41	4.385	16.25	23.07
2014	Advisor %	466	36.00	35.50	8.40	25.30	46.50
	Broker %	466	2.55	2.31	1.09	1.43	3.88
	Hedge Fund %	466	4.97	3.28	5.06	1.07	11.40
	Long-Term Investor %	466	5.21	5.05	1.29	3.79	6.79
	Mutual Fund %	466	17.20	16.00	6.01	10.30	25.90
	Institutional Wealth Mgmt %	466	17.90	17.20	4.02	13.90	22.80
	Market Value ($ million)	466	28,300	17,330	25,480	6,323	84,370
	β	422	1.235	1.223	0.323	0.831	1.637
	DSS Duration (year)	263	17.25	17.48	1.575	15.87	18.66
	Weber Duration (year)	263	20.98	21.49	2.800	18.28	23.35
2019	Advisor %	466	36.50	36.00	8.80	25.90	48.10
	Broker %	463	2.58	2.38	1.08	1.46	3.96
	Hedge Fund %	465	4.44	3.17	4.02	1.14	9.72
	Long-Term Investor %	463	5.02	4.82	1.48	3.45	7.05
	Mutual Fund %	466	18.10	17.40	5.66	11.90	25.80
	Institutional Wealth Mgmt %	463	17.20	16.70	4.11	13.50	21.60
	Market Value ($ million)	463	35,400	24,120	27,160	8,338	84,370
	β	422	0.983	1.007	0.314	0.544	1.345
	DSS Duration (year)	303	17.20	17.55	1.547	15.17	18.65
	Weber Duration (year)	304	20.77	21.61	3.366	17.21	23.38

This table shows summary statistics for stocks that are listed as constituents of the SP500 index at the reporting time. At each year end of 2004, 2009, 2014, and 2019, we summarise the number of securities, statistics on their market value, estimated equity durations (DSS duration and Weber duration; based on parameter values from (Dechow, Sloan, and Soliman, 2004) and (Weber, 2018) respectively), and average institutional holdings by type. Percentage of market value owned by institutions are from SEC regulatory filings accessed via FactSet, and reported by category in percentage points. Market values are computed from the end-of-year adjusted prices and shares outstanding from CRSP. Stocks with SIC codes between 4900 and 5000 or between 6000 and 7000 are excluded from duration computation. Variables are winsorized at 1% and 99% cutoffs. The sample only includes common stocks listed on NYSE, NYSE MKT, and NASDAQ.

holdings from rebalancer ownership computations.

E.3 The Fed Information Effect

To address additional concerns on the Fed information effect (Section 5.1), we replicate the asset-pricing results in Table 4 with a limited sample following (Jarociński and Karadi, 2020) and (Kekre, Lenel, and Mainardi, 2022). If the central bank has superior information than the private market, positive monetary shock may convey unexpected good news about the market, moving the market returns positively. To address this concern, we exclude the subset of monetary shocks where stock market returns move in the same direction as monetary shocks. Table A-10 summarizes the findings.

E.4 Extensive Margins

In principle, to rebalance after monetary shocks towards their target allocation, rebalancers can either adjust positions of stocks *within* their current portfolios (the intensive margin) or add (/subtract) new (/existing) stocks to (/from) their portfolios (the extensive margin). Our theory prediction is based on the assumption that rebalancers rebalance through the intensive margin.

To quantify the importance of the extensive margin, we introduce two measures:

- Proportion of new securities added to rebalancer j's holdings during quarter t:

$$Added_{j,t} = \frac{\#\text{ of securities added to } j\text{'s portfolio in quarter } t}{\#\text{ of securities in } j\text{'s portfolio in quarter } t-1}.$$

- Proportion of old securities dropped from rebalancer j's holdings during quarter t:

$$Dropped_{j,t} = \frac{\#\text{ of securities dropped from } j\text{'s portfolio in quarter } t}{\#\text{ of securities in } j\text{'s portfolio in quarter } t-1}.$$

We run local projections of the average extensive-margin adjustment across institutions j on monetary shock on announcement day t with four-quarter lags. We project $\overline{Added_{t+h}}$ (/$\overline{Dropped_{t+h}}$), averaged across rebalancers j winsorized at 1%, on negative (/positive) monetary shocks at t with 4 lags, for quarters $h = 0, 1, ..., 6$ ahead. Figure A-7 plots the coefficients. We do not find any statistically significant coefficient, indicating that the exten-

Table A-10: Robustness check on the Fed information effect

	Aggregate	Rebalancers					
	(0)	(1)	(2)	(3)	(4)	(5)	(6)
MS	-11.00***	×	×	×	×	×	×
	(1.171)						
$\text{Ownership}_{Rebalancers} \times$MS		-2.704*	-3.379**	-3.492**	-3.842**	-3.932**	-4.182***
		(1.628)	(1.649)	(1.649)	(1.600)	(1.610)	(1.608)
$\text{Ownership}_{Rebalancers}$		×	×	×	×	×	×
MPE			×	×	×	×	×
MPE×MS			×	×	×	×	×
Dividend			×	×	×	×	×
Dividend×MS			×	×	×	×	×
DSS Duration×MS				×	×	×	×
DSS Duration				×	×	×	×
β×MS					×	×	
β					×	×	
Size×MS						×	×
Size						×	×
FF4 Factors ×MS							×
FF4 Factors							×
Meeting FE	N	Y	Y	Y	Y	Y	Y
$I\_ind.\times$ MS	N	Y	Y	Y	Y	Y	Y
N	70	36,672	36,672	36,672	36,672	36,672	36,672
Adj. R^2	0.552	0.604	0.605	0.605	0.609	0.609	0.612

(a) Stocks with higher rebalancer ownership are more responsive to monetary shocks

	Non-Rebalancers					
	(1)	(2)	(3)	(4)	(5)	(6)
MS	×	×	×	×	×	×
$\text{Ownership}_{NonRebalancers} \times$MS	-0.257	-0.0469	-0.0292	0.570	0.719	0.305
	(0.800)	(0.805)	(0.804)	(0.791)	(0.808)	(0.813)
$\text{Ownership}_{NonRebalancers}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
Dividend			×	×	×	×
Dividend×MS			×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
Size×MS					×	×
Size					×	×
FF4 Factors ×MS						×
FF4 Factors						×
Meeting FE	Y	Y	Y	Y	Y	Y
$I\_ind.\times$ MS	Y	Y	Y	Y	Y	Y
N	36,672	36,672	36,672	36,672	36,672	36,672
Adj. R^2	0.604	0.605	0.605	0.609	0.609	0.611

(b) Non-rebalancer ownership does not affect monetary sensitivities

This table reports the results of the regressions of 30-minute equity returns around FOMC announcements on institutional ownership interacted with high-frequency monetary shocks (Nakamura and Steinsson, 2018):

$$r_{it} = \gamma Ownership_{ijt} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + \nu Ownership_{ijt} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it},$$

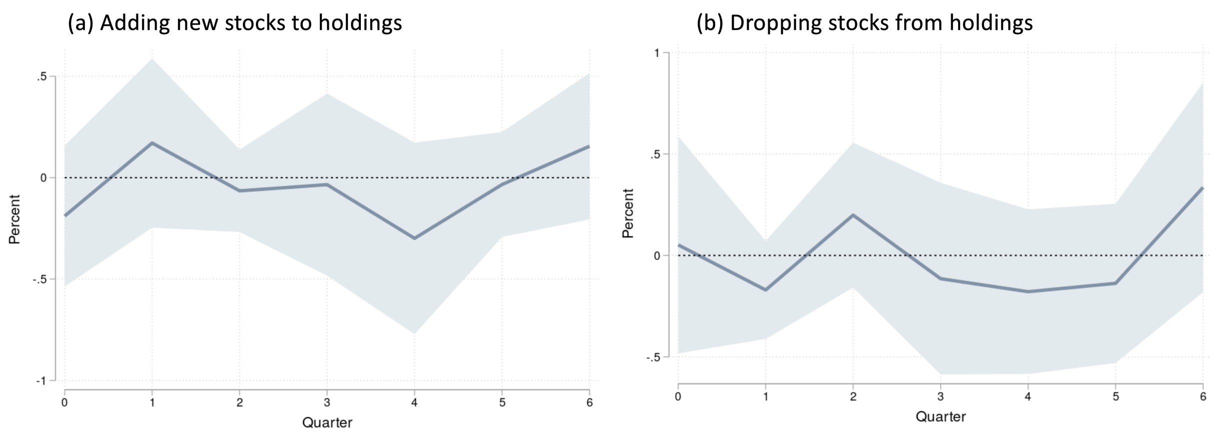
where i indexes stocks, j indexes types of institutions, and t indexes the date in quarters. Equity returns around FOMC announcements are the log returns between the beginning price, as the last valid trade price 10 minutes before the FOMC announcement (and no more than 90 minutes before that time), and the end price, the first valid trade 20 minutes after the FOMC announcement (and no more than 90 minutes after that time). Monetary shocks are estimated as the principal component of five fed funds futures and Eurodollar futures using 30-minute windows around FOMC announcements; these shocks are normalized based on the daily treasury yield around FOMC dates (Nakamura and Steinsson, 2018). Institutional ownership is collected from FactSet; $Ownership_{ijt}$ in Panel (a) sums up the quarterly ownership of institution categories *institutional wealth management* and *long-term investors* for security i in quarter t, and $Ownership_{ijt}$ in Panel (b) sums up the quarterly ownership of the rest of the institution categories for security i.

The sample period runs from 2004Q4 to 2019Q3, excluding meetings where the monetary shock and stock market returns move in the same direction (Jarociński and Karadi, 2020, Kekre, Lenel, and Mainardi, 2022).

Standard errors are clustered at the industry by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

sive margin is not detectable. In other words, the investment universe for institutions does not change significantly after monetary shocks, echoing the unconditional persistence of the investment universe in (Koijen and Yogo, 2019).

Figure A-7: Extensive margin of rebalancing



These two panels plot the extensive margins of rebalancing in response to monetary shocks. The plotted coefficients in panels (a) and (b) are from local projections of $\overline{Added_t}$ and $\overline{Dropped_t}$: we run local projections of $\overline{Added_{t+h}}$ ($/\overline{Dropped_{t+h}}$), averaged across rebalancers j winsorized at 1%, on negative (/positive) monetary shocks at t with four lags, for quarters $h = 0, 1, ..., 6$ ahead. We define $Added_{j,t}$ and $Dropped_{j,t}$ below:
Proportion of new securities added to rebalancer j's holdings during quarter t:

$$Added_{j,t} = \frac{\#\text{ of securities added to } j\text{'s portfolio in quarter } t}{\#\text{ of securities in } j\text{'s portfolio in quarter } t-1}.$$

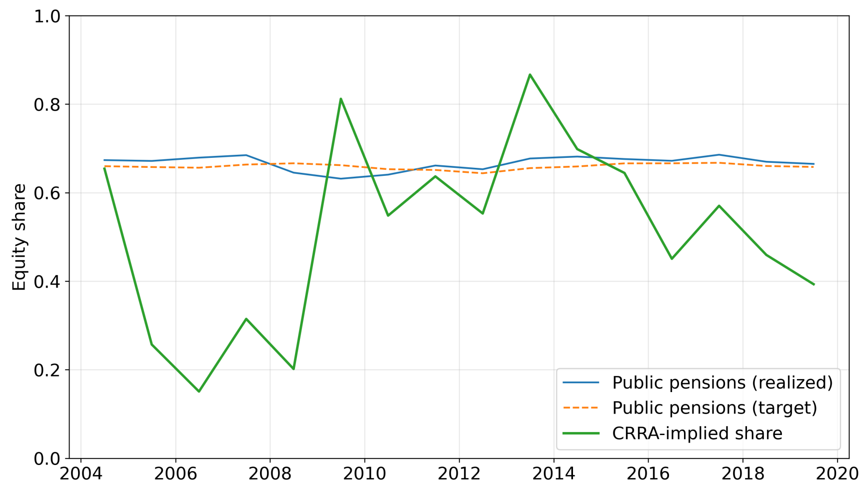
Proportion of old securities dropped from rebalancer j's holdings during quarter t:

$$Dropped_{j,t} = \frac{\#\text{ of securities dropped from } j\text{'s portfolio in quarter } t}{\#\text{ of securities in } j\text{'s portfolio in quarter } t-1}.$$

The quarterly monetary shocks are aggregated from Nakamura-Steinsson high-frequency monetary shocks following the method in (Gertler and Karadi, 2015). The sample period is from 2004 to 2019. 95% confidence intervals are displayed, using robust standard errors.

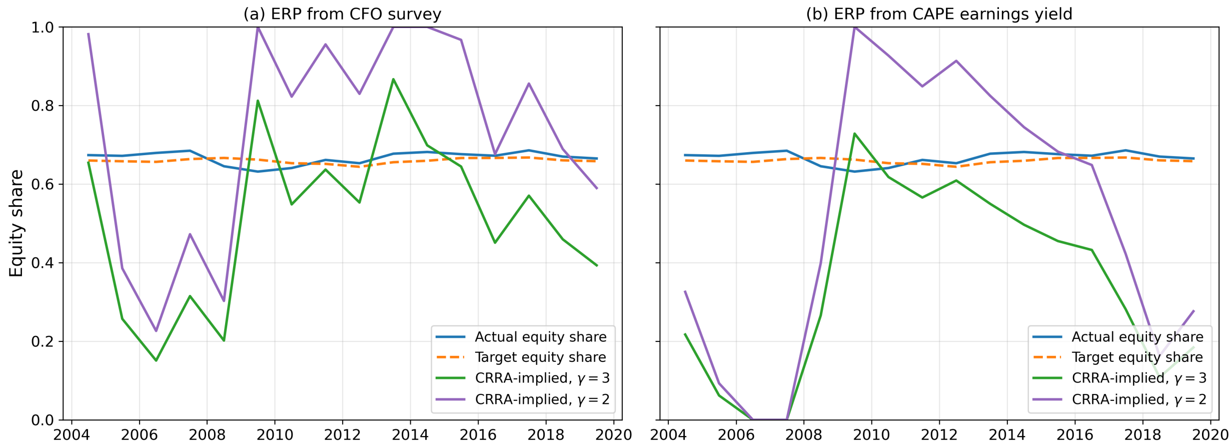
E.5 Quantity Evidence of Rebalancing

Figure A-8: Public pensions' equity shares and CRRA-implied equity shares



This figure plots annual public-pension equity shares and a CRRA-implied equity-share benchmark for 2004–2019. The blue line is the cross-plan average actual equity share, computed for each fiscal year as EQTotal_Actl/(EQTotal_Actl + FITotal_Actl) from the Public Plans Database (PPD); the dashed orange line is the analogous cross-plan average target share constructed from EQTotal_Trgt and FITotal_Trgt. Each annual observation is aligned to July 1 of the corresponding year. The green line is the CRRA-implied equity share $\theta_t = \pi_t/(\gamma\sigma^2)$, where π_t is the one-year expected excess return from the Duke CFO survey (Q2 expected 12-month return) net of the one-year risk-free rate (GS1, FRED). We set $\gamma = 3$ as a conventional CRRA value; θ_t is clipped to $[0, 1]$ to match the no-short, no-leverage constraint facing public pensions, and we use an annual equity return variance $\sigma^2 = 0.0256$. Robustness to $\gamma = 2$ and to a CAPE-based ERP proxy is reported in Figure A-9. Our finding is in line with (Dahlquist and Ibert, 2024) which show that the sensitivity of portfolios to expectations is smaller than predicted by a standard portfolio choice theory and seems to be muted by investment mandates.

Figure A-9: CRRA-implied equity share under alternative γ and ERP proxies



This figure replicates Figure A-8 for $\gamma \in \{2, 3\}$ under two ERP proxies. Panel (a) uses the Duke CFO survey expected one-year S&P 500 return net of the one-year Treasury yield (GS1). Panel (b) uses the Shiller CAPE-implied earnings yield (1/CAPE) net of GS1. The CRRA-implied share $\theta_t = \pi_t/(\gamma\sigma^2)$ is clipped to $[0, 1]$ to match the no-short, no-leverage constraint facing public pensions; the unconstrained Merton solution would lie further from the realized share. The sample-period means (2004–2019) are: actual 0.67, target 0.66; $\theta^{\text{CFO}}_{\gamma=3} = 0.51$, $\theta^{\text{CFO}}_{\gamma=2} = 0.74$, $\theta^{\text{CAPE}}_{\gamma=3} = 0.35$, $\theta^{\text{CAPE}}_{\gamma=2} = 0.52$. The qualitative contrast—near-flat realized shares versus highly volatile CRRA-implied shares—is robust across all four specifications.

Table A-11: Weekly rebalancing and arbitrage activities following monetary policy shocks

	Cross-asset net position changes					
	Rebalancers			Arbitrageurs		
	All weeks (1)	Month-end (2)	Quarter-end (3)	All weeks (4)	Month-end (5)	Quarter-end (6)
MS	-0.4189^{*}	-0.7641^{***}	-0.5995^{***}	0.4935	0.9838^{***}	0.6237^{*}
	(0.2263)	(0.2284)	(0.2166)	(0.3454)	(0.1842)	(0.3381)
Observations	108	58	52	108	58	52

Each column reports a weekly Newey–West/HAC regression of the cross-asset net trading position changes $Q_{g,t}$ on monetary shocks, where $g \in \{\text{rebal}, \text{arb}\}$ indexes trader groups; rebalancers refer to the asset managers, and arbitrageurs are the leveraged funds reported in weekly CFTC Traders-in-Financial-Futures (TFF) futures-only reports, available from 2010 to 2025. Constants are included but not tabulated. We define cross-asset net trading $Q_{g,t}$ for trader group g in week t as the Tuesday-to-Tuesday change in that group's net long-minus-short positions in E-mini S&P 500 (ES) minus the analogous change in 10-year U.S. Treasury note futures (TY), with each leg scaled by that contract's total open interest. More negative $Q_{g,t}$ corresponds to rotation out of equities and into Treasuries. MS is the monetary policy shock aligned to the CFTC reporting week. Results are robust to adding lagged $Q_{g,t}$. Month-end weeks and quarter-end weeks restrict the sample to the corresponding calendar weeks as defined in the main text. Standard errors are Newey-West with 5 lags; *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

We provide evidence that balanced funds actively adjust their portfolios in the direction predicted by Proposition 4(a). We test this prediction using Morningstar mutual fund data. Empirically, we use panel local projection (Jordà, 2005) with a shift-share design (Chodorow-Reich, Nenov, and Simsek, 2021) to test their rebalancing. Since the notion of target equity shares is at the asset class level for all security holdings, we unpack the fund holdings of mutual funds by linking the holding security's CUSIPs with the mutual funds in Morningstar and constructing fund-level equity shares. Section D.2 details the construction of equity shares and reports additional summary statistics of the funds included. We construct an *actual* equity share for each fund j as

$$\vartheta_{jt} = \frac{\Sigma_i P_{it} Q_{ijt}}{\Sigma_i P_{it} Q_{ijt} + \Sigma_{i'} P^B_{i't} Q^B_{i'jt}},$$

where P_{it}, Q_{ijt} are the price and quantity of stock i in fund j's portfolio in quarter t, and $P^B_{i't}, Q_{i'jt}$ is the price and quantity of bond i' held by j in quarter t. Changes in actual equity shares of funds could be caused by either price movements after monetary shocks or active rebalancing in quantities by fund managers. To isolate active rebalancing, after time-t

shocks, we compare the actual time-$(t+h)$ actual equity share $\vartheta_{j,t+h}$ against a *counterfactual* equity share, assuming that funds keep their time-$(t-1)$ holdings fixed. The counterfactual share is calculated based on time-$t-1$ quantities evaluated at time-$t+h$ prices as

$$\check{\vartheta}_{j,t-1\to t+h} = \frac{\Sigma_i P_{i,t+h} Q_{ij,t-1}}{\Sigma_i P_{i,t+h} Q_{ij,t-1} + \Sigma_{i'} P^B_{i',t+h} Q^B_{i'j,t-1}}.$$

We use the following specification to test if there is a difference between the actual equity share $\vartheta_{j,t+h}$ and the counterfactual equity share $\check{\vartheta}_{j,t-1\to t+h}$

$$\vartheta_{j,t+h} - \check{\vartheta}_{j,t-1\to t+h} = \beta_h \vartheta_{j,t-1}(1-\vartheta_{j,t-1}) MS_t + \boldsymbol{\varphi}' \boldsymbol{X}_{j,t+h} + \epsilon_{j,t-1\to t+h}, \tag{55}$$

where MS_t denotes the monetary shocks averaged to monthly frequency, and $\vartheta_{j,t-1}(1-\vartheta_{j,t-1})$ reflects rebalancing needs. As discussed when setting up the rebalancer's equity share in (1), a pure-equity or pure-bond fund ($\vartheta_{j,t-1} = 1, 0$) does not rebalance across asset classes. $\boldsymbol{X}_{j,t+h}$ collects fund fixed effects, along with four lags of the main variables. The unmodeled determinants of equity share remain in $\epsilon_{j,t-1\to t+h}$. β_h is the coefficient of interest, which is predicted to be negative from the rebalancing channel as balanced funds sell stocks upon monetary tightening. (Borusyak, Hull, and Jaravel, 2022) shows that a consistent estimation of β_h requires the exogeneity of the shifter (monetary shocks) and $\mathrm{E}[MS_t \, \mathrm{E}_t(\vartheta_{j,t-1}(1-\vartheta_{j,t-1})\epsilon_{j,t-1\to t+h})] = 0$. That is, we assume that the market-wide monetary shocks are exogenous, and funds with equity mandates closer to one-half (i.e., higher $\vartheta_{j,t-1}(1-\vartheta_{j,t-1})$) do not have systematically larger or smaller unexplained residuals ($\epsilon_{j,t-1,t+h}$) when there is a monetary shock.

Additionally, we use CFTC Traders-in-Financial-Futures data on E-mini S&P 500 (ES) and 10-year Treasury (TY) futures and measure cross-asset net trading as the change in a group's net ES position minus the change in its net TY position (each scaled by open interest), where negative values indicate rotation out of equities and into Treasuries. **?** find that futures positions held by institutional investors, such as asset managers, tend to reflect portfolio rebalancing, whereas leveraged funds' positions are indicative of arbitrage activities. In the context of monetary transmission, we show in Table A-11 that monetary tightening induces negative net trading for rebalancer-type institutions (asset managers), while leveraged funds (often relative-value/arbitrage-oriented) move in the opposite direction. Columns (2)-(3) and (5)-(6) confirm that these effects are stronger at month- and quarter-ends, consistent with our mechanism.

Table A-12: Weekly rebalancing and arbitrage activities following monetary policy shocks

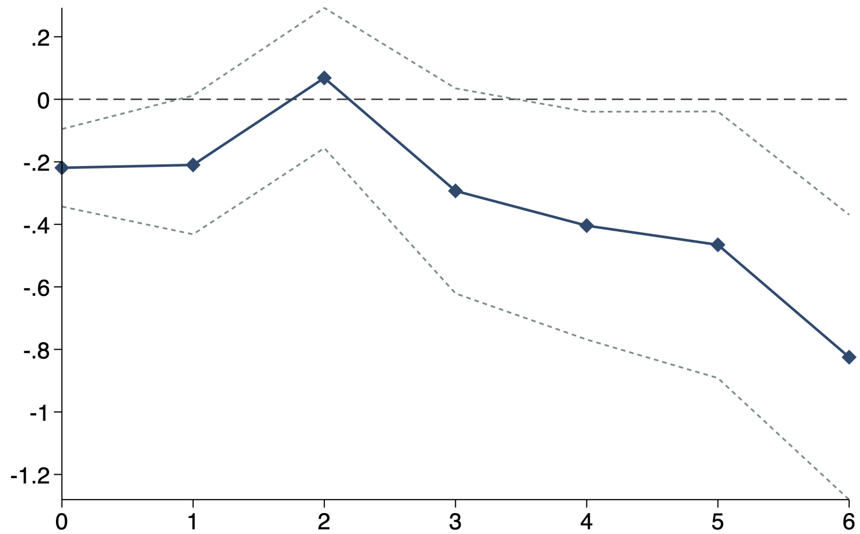
	Cross-asset net position changes					
	Rebalancers			Arbitrageurs		
	All weeks (1)	Month-end (2)	Quarter-end (3)	All weeks (4)	Month-end (5)	Quarter-end (6)
MS	-0.4189^{*}	-0.7641^{***}	-0.5995^{***}	0.4935	0.9838^{***}	0.6237^{*}
	(0.2263)	(0.2284)	(0.2166)	(0.3454)	(0.1842)	(0.3381)
Observations	108	58	52	108	58	52

Each column reports a weekly Newey–West/HAC regression of the cross-asset net trading position changes $Q_{g,t}$ on monetary shocks, where $g \in \{\text{rebalancers}, \text{arbitrageurs}\}$ indexes trader groups; rebalancers refer to the asset managers, and arbitrageurs refer to the leveraged funds (often relative-value/arbitrage-oriented) reported in weekly CFTC Traders-in-Financial-Futures (TFF) futures-only reports, available from 2010 to 2025. We define cross-asset net trading $Q_{g,t}$ for trader group g in week t as the Tuesday-to-Tuesday change in that group's net long-minus-short positions in E-mini S&P 500 (ES) minus the analogous change in 10-year U.S. Treasury note futures (TY), with each leg scaled by that contract's total open interest. More negative $Q_{g,t}$ corresponds to rotation out of equities and into Treasuries. MS is the monetary policy shock aligned to the CFTC reporting week. Results are robust to adding lagged $Q_{g,t}$. Month-end weeks and quarter-end weeks restrict the sample to the corresponding calendar weeks as defined in the main text. Constants are included but not tabulated. Standard errors are Newey-West with 5 lags; *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Figure A-10 displays the estimated β_h coefficients, which are negative as predicted with high significance. Notably, the on-impact β_0 is negative and statistically significant at the 0.1% level, suggesting that some balanced funds may adjust to monetary shocks within a month. Over time, the estimate gets larger in magnitude, and reflects larger cumulative adjustment, consistent with the idea that many funds rebalance periodically. In conclusion, we find significant differences in the actual and counterfactual equity shares, indicating active rebalancing in a direction consistent with the theory prediction.

Figure A-11 shows that the actual equity share is not significantly affected by monetary shocks, and we find significant differences in the actual equity shares and the counterfactual equity shares, consistent with the rebalancing channel.

Figure A-10: Rebalancing activities of balanced funds



This graph plots the panel local projection $\vartheta_{j,t+h} - \check{\vartheta}_{j,t-1\to t+h} = \beta_h\left[\vartheta_{j,t-1}(1-\vartheta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, where $\vartheta_{j,t+h}$ is the actual equity share of fund j at month $t+h$, $\check{\vartheta}_{j,t-1\to t+h}$ is the counterfactual fund equity share, holding quantities constant from $t-1$ to $t+h$. The difference $\vartheta_{j,t+h} - \check{\vartheta}_{j,t+h}$ captures the active rebalancing quantity. MS_t is the (Nakamura and Steinsson, 2018) shocks aggregated to monthly frequency following (Gertler and Karadi, 2015). $\boldsymbol{X}_{j,t+h}$ contains fund fixed effects along with four lags of the main variables. The unmodeled determinants of equity share remain in $\epsilon_{j,t-1\to t+h}$. Morningstar funds included have at least 80% of holdings identified through CUSIP master file, and the sample period spans from 2004Q4 to 2019Q3. Standard errors are clustered at the fund level, and we plot the 95% confidence intervals.

E.6 Placebo Tests for Quarter-Ends and Month-Ends

In Table A-13, we report the placebo regressions using other institutions' ownership instead of rebalancer ownership. The interaction coefficient is insignificant across specifications, suggesting that this alternative ownership does not affect returns' sensitivities in monetary shocks in the quarter-end and month-end subsamples.

E.7 A Spanning Test of Rebalancing Demand

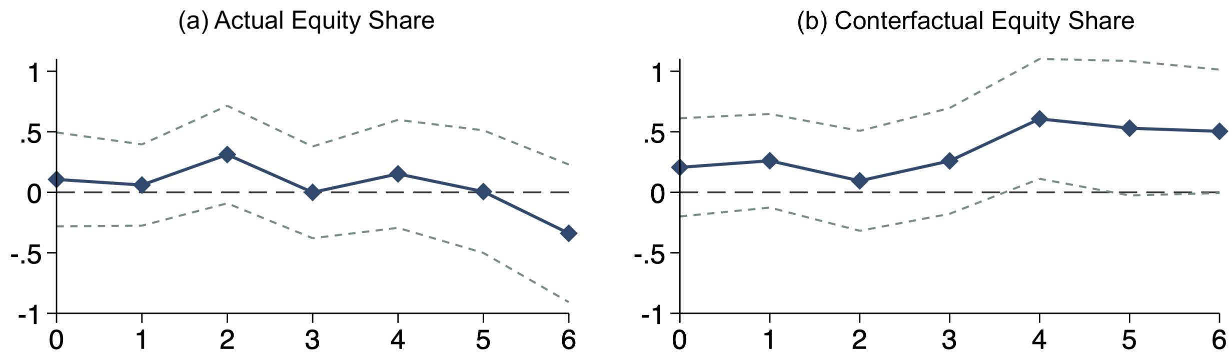
We have shown that the rebalancer's ownership consistently predicts cross-sectional price reactions to monetary shocks across specifications. In Figure A-13, we further demonstrate that there are sizeable ownership variations in the cross section even after residualizing ownership with the relevant covariates and fixed effects. However, suppose these rebalancing institutions choose their holdings based on security-level characteristics that are not controlled for,

Table A-13: Other institutions' ownership does not lead to larger price reactions at month/quarter ends

	Quarter-End			Month-End		
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership of Other Institutions×MS	-0.223	0.245	0.271	-0.00393	0.539	0.627
	(0.946)	(0.937)	(0.956)	(0.869)	(0.858)	(0.877)
Ownership of Other Institutions	×	×	×	×	×	×
Duration×MS		×	×		×	×
DSS Duration		×	×		×	×
MPE×MS		×	×		×	×
MPE		×	×		×	×
β×MS		×	×		×	×
β		×	×		×	×
Dividend×MS		×	×		×	×
Dividend		×	×		×	×
Size×MS			×			×
Size			×			×
Meeting FE	Y	Y	Y	Y	Y	Y
$I\_ind.\times$ MS	Y	Y	Y	Y	Y	Y
N	29,329	29,329	29,329	37,270	37,270	37,270
Adj. R^2	0.626	0.631	0.631	0.584	0.588	0.588

This table reports the results of the regressions of 30-minute equity returns around FOMC announcements on institutional ownership interacted with high-frequency monetary shocks (Nakamura and Steinsson, 2018): $r_{it} = \gamma Ownership_{it} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + \nu Ownership_{it} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, where i indexes stocks, j indexes types of institutions, and t indexes date. Equity returns around FOMC announcements are the log returns between the beginning price, as the last valid trade price 10 minutes before the FOMC announcement (and no more than 90min before that), and the end price, the first valid trade 20 minutes after the FOMC announcement (and no more than 90min after that). The monetary shocks are estimated as the principal component of five fed funds futures and Eurodollar futures using 30-minute windows around FOMC announcements; these shocks are normalized based on the daily treasury yield around FOMC dates (Nakamura and Steinsson, 2018). Institutional ownership is collected from FactSet; $Ownership_{it}$ sums up the quarterly ownership of institution other than the rebalancer categories (*institutional wealth management* and *long-term investors*) for security i before announcement day t.
The sample period runs from 2004Q4 to 2019Q3; the quarter-end subsample includes only the FOMC announcements that occur in the last month of a quarter, and the month-end subsample includes only the FOMC announcements that occur in the second half of each month.
Standard errors are clustered at the industry by meeting level and are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

Figure A-11: Actual and counterfactual equity shares



Graph (a) plots the panel local projection of $\vartheta_{j,t+h} = \beta_h \left[\vartheta_{j,t-1}(1-\vartheta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, and graph (b) plots the panel local projection of $\check{\vartheta}_{j,t-1\to t+h} = \beta_h \left[\vartheta_{j,t-1}(1-\vartheta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, where $\vartheta_{j,t+h}$ is the actual equity share of fund j at month $t+h$, $\check{\vartheta}_{j,t-1\to t+h}$ is the counterfactual fund equity share, holding quantities constant from $t-1$ to $t+h$. The difference $\vartheta_{j,t+h} - \check{\vartheta}_{j,t+h}$ captures the active rebalancing quantity absent revaluation of stocks and bonds. MS_t is the monthly Nakamura-Steinsson shocks aggregated following (Gertler and Karadi, 2015). $\boldsymbol{X}_{j,t+h}$ contains fund fixed effects along with four lags of the main variables. The unmodeled determinants of equity share remain in $\epsilon_{j,t-1\to t+h}$. Morningstar funds included have at least 80% of holdings identified through the CUSIP master file, and the sample period spans from 2004Q4 to 2019Q3. Standard errors are clustered at the fund level, and we plot the 95% confidence intervals.

which also affect return sensitivities to monetary shocks. In that case, our analysis is subject to an omitted-variable bias. To address this concern, we resort to recent asset pricing developments that leverage machine learning techniques to guard against the omitted-variable bias (Jensen, Kelly, and Pedersen, 2021, Belloni, Chernozhukov, and Hansen, 2014). This method allows us to test the marginal contribution of additional factors using a transparent two-pass framework, which is similar to the (Fama and MacBeth, 1973) regressions. We find that the rebalancer ownership is not spanned by the asset-pricing factors identified in previous literature.

We test the marginal contribution of the rebalancer ownership factor against a high-dimensional benchmark model with the 153 pre-existing asset-pricing factors constructed by (Jensen, Kelly, and Pedersen, 2021), following the double-selection LASSO method developed by (Belloni, Chernozhukov, and Hansen, 2014), and (Feng, Giglio, and Xiu, 2020). To begin with, we obtain the rebalancer ownership factor $F_{ownership,t}$ from a long-short value-weighted tercile portfolio sorted by the last quarter's ownership for the stocks listed on NYSE with a market cap above the 20-th NYSE percentile.[6] Following the literature, we construct long-short portfolios using the breakpoints from (Haddad, Kozak, and Santosh, 2020) and industry portfolios. We compute covariances between returns and factors for each portfolio instead of betas from time-series regression to circumvent potential non-invertibility. Using covariances between each portfolio's returns and factors, we estimate the following model:

$$\mathrm{E}\, r_i = \mathrm{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right) \cdot \lambda_O + \mathrm{Cov}_{i,X} \cdot \lambda_X + const, \tag{56}$$

where $\mathrm{E}\, r_i$ is a $N \times 1$ vector of average 30-minute returns around FOMC announcements for each portfolio i, $\mathrm{Cov}(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t])$ is a $N \times 3$ matrix that captures the covariances between stock returns and the three factors (ownership, monetary shock, and their interaction), and $\mathrm{Cov}_{i,X}$ is a $N \times 306$ matrix that captures the covariances between stock returns and the 153 pre-existing asset-pricing factors, along with their interactions with monetary shocks. We run the double-selection LASSO procedure, where we first use one factor selection on the expected returns $\mathrm{E}r_i$, and then run another LASSO on $\mathrm{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right)$ to identify the unselected factors potentially causing omitted variable bias. We then fit the OLS in eq. (56) using the union of selected factors from the two LASSOs.[7]

Table A-14 summarizes the post-selection estimation. Because asset-pricing factors such as turnover and market betas are potentially equilibrium outcomes that can be attributed to institutional ownership, we report an estimate using fundamental factors only in column (1), in addition to an estimate involving all factors in column (2). The fundamental factors refer to factors in clusters *Accruals, Investment, Debt Issuance, Quality, Profit Growth, Profitability* from (Jensen, Kelly, and Pedersen, 2021). Column (1) shows that only 11 factors are selected from the universe of 169 variables (84 factors related to fundamentals, along with their interactions with monetary shocks and one stand-alone monetary shock factor). The

[6] Using NYSE breakpoints and value-weighted portfolios avoids the problem of large excess cross-sectional dispersion driven by microcap stocks (Fama and French, 2008, Hou, Xue, and Zhang, 2020).

[7] This is justified under the assumption that there is a linear treatment-effect model with time-invariant covariances and λ that capture risk premia and risk exposures respectively. When this assumption is violated, (Giglio and Xiu, 2021) shows that for tradable factors, the OLS estimator of λ is a consistent estimator for the time-series averages of the SDF loadings, which are still informative.

low number of nonzero-coefficient factors is in line with previous asset-pricing literature, where sparsity for the factor structure is commonly assumed. Column (2) analyzes all 153 asset-pricing factors documented in previous literature and their interactions with monetary shocks. Note that many of the asset-pricing factors related to liquidity (Datar, Y. Naik, and Radcliffe, 1998) and intermediaries (He and Krishnamurthy, 2013, Adrian, Etula, and Muir, 2014, He, Kelly, and Manela, 2017) may be related to institutional ownership. Hence, this exercise may err on the side of over-controlling.

Given a positive (/negative) monetary shock, $F_{Ownership}$ is expected to be negative (/positive) as the portfolio longs high-rebalancer-ownership shocks. If a portfolio i earns negative returns upon monetary tightening, a positive correlation between its returns and $F_{Ownership} \cdot MS$ suggests the portfolio is more exposed to rebalancing risk following monetary shocks and consequently requires a positive risk premium. Table A-14 demonstrates that the coefficient of $\text{Cov}\left(r_{it}, F_{ownership,t} \cdot MS_t\right)$ is positive at 5% level, which indicates that securities' monetary sensitivities due to variations in rebalancer ownership are *not* spanned by the 153 existing asset-pricing factors.

Table A-14: Testing rebalancing demand against the factor zoo

	Fundamental Factors Only	All Asset Pricing Factors
	(1)	(2)
$\text{Cov}\left(r_{it}, F_{ownership,t} \cdot MS_t\right) \cdot T^{-1}$	160.2**	162.0**
	(62.25)	(63.54)
N	103	103
# of Selected Controls	11	15
# of Controls	169	307
Adj. R^2	0.575	0.625

This table summarizes the post-selection OLS regression

$$\mathrm{E}\, r_i = \text{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right) \cdot \lambda_O + \text{Cov}_{i,X} \cdot \lambda_X + const.,$$

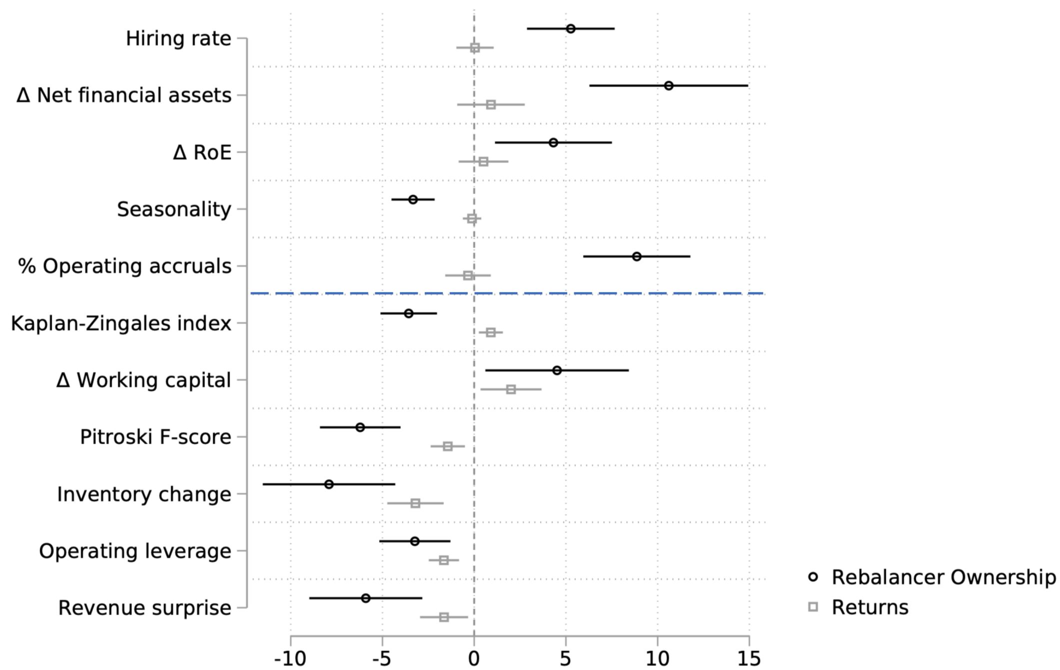
where $\mathrm{E}\, r_i$ is a $N \times 1$ vector that summarizes the average returns for each portfolio i in the sample, $\text{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right)$ is a $N \times 3$ matrix that captures the covariances between stock returns and the three factors (ownership, monetary shock, and their interaction), and $\text{Cov}_{i,X}$ is a $N \times 306$ matrix that captures the covariances between stock returns and the 153 pre-existing asset-pricing factors, along with their interactions with monetary shocks. The first column controls for factors that reflect the fundamentals of the firm; fundamental factors refer to the factors in clusters *Accruals, Investment, Debt Issuance, Quality, Profit Growth, Profitability* defined in (Jensen, Kelly, and Pedersen, 2021); the second column controls for the 153 pre-existing asset-pricing factors, along with their interactions with monetary shocks. Reported numbers should be interpreted as SDF loadings instead of risk premia (Feng, Giglio, and Xiu, 2020). The estimation period for $\mathrm{E}\, r_i$, $\text{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right)$, and $\text{Cov}_{i,X}$ is 2004Q4 to 2019Q3. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%.

E.8 Determinants and Residual Variations in Rebalancer Ownership

In this appendix, we describe the potential determinants of rebalancer ownership. Similar to Section E.7, we first obtain the rebalancer ownership factor $F_{ownership,t}$ from a long-short value-weighted tercile portfolio sorted by the last quarter's ownership for the stocks listed on NYSE with a market cap above the 20-th NYSE percentile. Following the literature, we construct long-short portfolios using the breakpoints from (Haddad, Kozak, and Santosh, 2020) and industry portfolios. We compute covariances between returns and factors for each portfolio instead of betas from time-series regression to circumvent potential non-invertibility. Using these covariances between each portfolio's returns and factors, we estimate a double-selection model as detailed in Section E.7 for unconditional returns and lagged ownership at the monthly frequency to select the fundamental factors that pin down rebalancer ownership. Figure A-12 summarizes the results. The five factors at the top, *Hiring rate* (Belo, Lin, and Bazdresch, 2014), Δ *net financial assets* (Richardson, Sloan, Soliman, and Tuna, 2005), Δ *RoE* (Hou, Xue, and Zhang, 2015), *Seasonality* (Heston and Sadka, 2010) (computed as the nonannual lagged returns from years 2 to 5), and *% Operating accruals* (Hafzalla, Lundholm, and Matthew Van Winkle, 2011) explain around 32% of the cross-sectional variations in the rebalancer ownership factor, while all of them have coefficients not significantly away from zero, suggesting these factors are likely affecting ownership only while not directly affecting the unconditional returns during the sample period.

Additionally, one might be concerned about the residual variations the cross-sectional asset pricing regressions hinge on. Figure A-13 reports the residual variations in rebalancer ownership for both dual shares and the common stock sample. The top two panels capture the average share-class level ownership variations; the top left graph shows that the predicted ownership using voting rights and firm-meeting fixed effects have standard deviations similar to the raw share-class level rebalancer ownership for dual shares on the top right panel. The bottom panels show all common stocks' residual and raw ownership. The bottom left graph suggests that after residualizing with duration, MPE index, beta, log(book equity), and meeting and industry fixed effects, there are still considerable variations in rebalancer ownership, with a standard deviation similar to the raw rebalancer ownership (bottom right panel).

Figure A-12: Ownership determinants



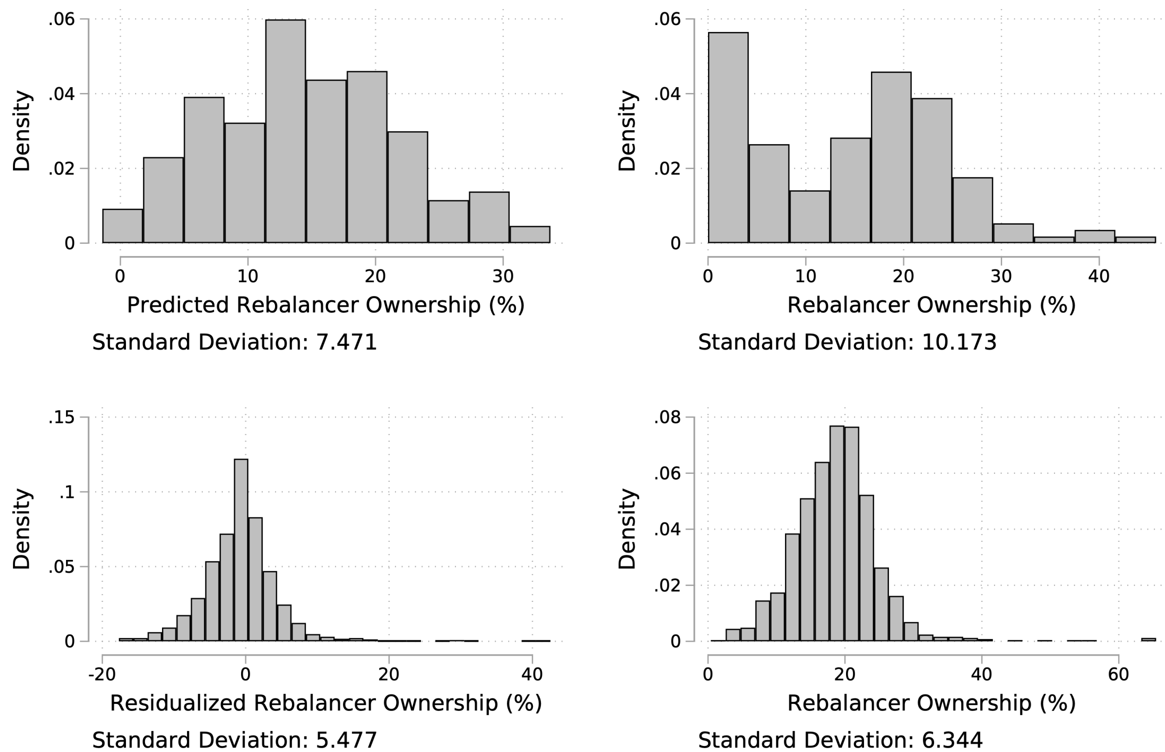
This graph summarizes results from post-selection OLS regressions

$$\mathrm{E}\, r_i = \mathrm{Cov}\left(r_{it}, F_{ownership,t}\right) \cdot \lambda_O + \mathrm{Cov}_{i,X} \cdot \lambda_X + const.,$$

$$\mathrm{Cov}\left(r_{it}, F_{ownership,t}\right) = \mathrm{Cov}_{i,X} \cdot \lambda_X + const.,$$

where $\mathrm{E}\, r_i$ is a $N \times 1$ vector that summarizes the average returns for each portfolio i in the sample, $\mathrm{Cov}\left(r_{it}, F_{ownership,t}\right)$ is a $N \times 1$ matrix that captures the covariances between stock returns and the ownership factor, and $\mathrm{Cov}_{i,X}$ are the LASSO selected factors from a $N \times 153$ matrix that captures the covariances between stock returns and the 153 pre-existing asset-pricing factors. Fundamental asset pricing factors are the factors in clusters *Accruals, Investment, Debt Issuance, Quality, Profit Growth, Profitability* defined in (Jensen, Kelly, and Pedersen, 2021). Reported numbers should be interpreted as SDF loadings instead of risk premia (Feng, Giglio, and Xiu, 2020). The estimation period for $\mathrm{E}\, r_i$, $\mathrm{Cov}\left(r_{it}, F_{ownership,t}\right)$, and $\mathrm{Cov}_{i,X}$ is 2004Q4 to 2019Q3. 95% confidence intervals are displayed.

Figure A-13: Residual variations in ownership



This graph summarizes the cross-sectional variations of rebalancer ownership at the security level. The top two panels capture the average share-class level ownership variations; the top left graph shows that the predicted ownership using voting rights and firm-meeting fixed effects have standard deviations similar to the raw share-class level rebalancer ownership for dual shares on the top right panel. The bottom panels show all common stocks' residual and raw ownership. The bottom left graph suggests that after residualized with duration, MPE index, beta, log(book equity), and meeting and industry fixed effects, there are still considerable variations in rebalancer ownership, with a standard deviation similar to the raw rebalancer ownership (bottom right panel).

F Aggregate Market Reactions and Decomposition

F.1 Decomposition of the Aggregate Market Reaction

We update the decomposition result in (Bernanke and Kuttner, 2005) using (Nakamura and Steinsson, 2018) shocks and decompose the aggregate market returns following monetary shocks to expected changes in cash flows, risk-free rate, and excess returns with an SVAR-IV approach (Mertens and Ravn, 2013, Gertler and Karadi, 2015, Kekre and Lenel, 2022).

We estimate the first-stage VAR from October 1979 to September 2019 with six variables and six lags, including one-year Treasury yield, CPI, industrial production, real S&P 500 index excess returns, real one-month Treasury-bill rate, and smoothed dividend price ratio from S&P500 index. The estimated residuals are then instrumented by the monthly monetary shocks of (Nakamura and Steinsson, 2018) from October 1995 to September 2019.[8] The underlying assumption for the SVAR-IV method is that these shocks are correlated with the structural shocks to the interest rate in the SVAR but not with other structural shocks. The first-stage F statistic is 4.67; we show the impulse responses to a one-standard-deviation positive monetary shock in Figure A-14.

We find that a one-standard-deviation positive monthly Nakamura-Steinsson shock causes the one-year Treasury yield to increase by around 0.17%. This number is similar to (Kekre and Lenel, 2022) estimates using (Gertler and Karadi, 2015) shocks. On impact, the real excess returns decrease by 1.63%, consistent with the estimates in (Kekre and Lenel, 2022) (1.62% excess returns) and (Bernanke and Kuttner, 2005) (1.87% excess returns).

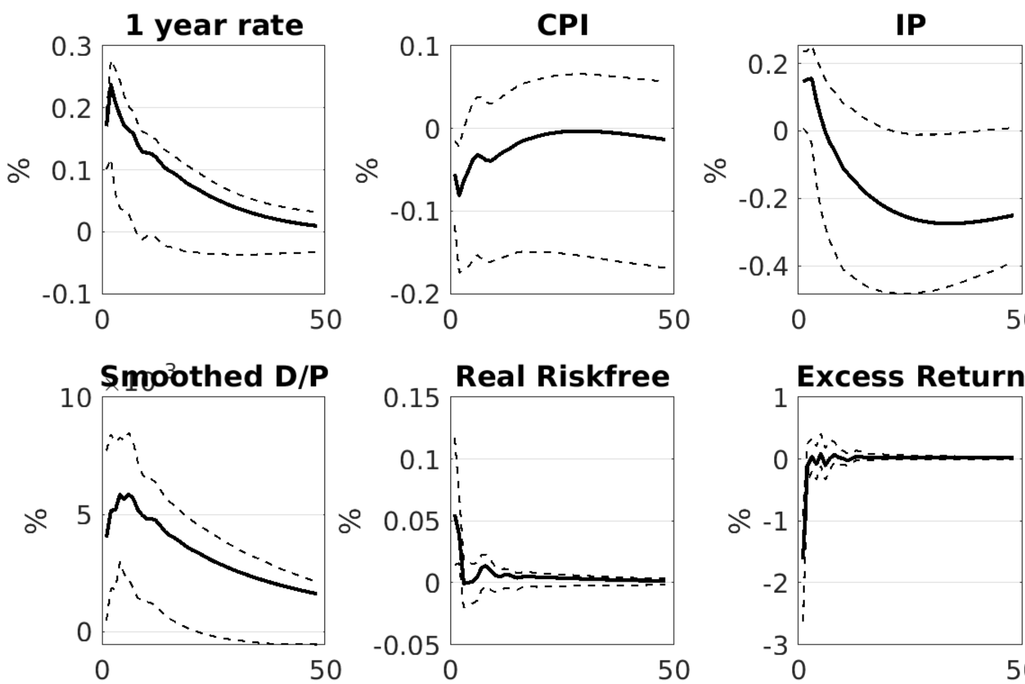
Same as in (Bernanke and Kuttner, 2005) and (Kekre and Lenel, 2022), we use the Campbell-Shiller decomposition to relate the real excess returns to revisions in expectations about future cash flows, real rates, or excess returns:

$$r_t - \mathbb{E}_{t-1}[r_t] = (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=0}^{\infty}\rho^j \Delta d_{t+j} - (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=1}^{\infty}\rho^j r_{t+j}^f - (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=1}^{\infty}\rho^j er_{t+j}, \tag{57}$$

where r_t is the real equity return, Δd_{t+j} is dividend growth, r_{t+j}^f is the real risk-free rate, and er_{t+j} is the future excess return where the discount factor ρ comes out of the linearization (Campbell and Shiller, 1988) and is set to 0.9962 following (Campbell and Ammer, 1993) and (Kekre and Lenel, 2022). Table A-15 reports the on-impact return decomposition and sums up the relative contributions of the three sources. On average, news about future dividends explains 19%–22% of the excess return following monetary shocks, whereas expected excess returns news explains 63%–78% of the instantaneous excess returns, with the remaining

[8]The monthly monetary shocks are averaged from high-frequency monetary shocks following (Gertler and Karadi, 2015). To confirm the relevance of the smoothed Nakamura-Steinsson shocks to the treasury yield and excess bond premium (Gilchrist and Zakrajšek, 2012), we use both SVAR and local projection with Nakamura-Steinsson shocks to replicate (Gertler and Karadi, 2015) and find results of a similar magnitude but different significance.

Figure A-14: Impulse responses to a one-standard-deviation monetary shock



This figure plots the impulse responses to one-standard-deviation Nakamura-Steinsson monetary shock. The first-stage VAR model is estimated from October 1979 to September 2019 with six variables: one-year Treasury yield, CPI, industrial production, real S&P 500 index excess returns, real one-month Treasury-bill rate, and smoothed dividend price ratio from S&P500 index. The estimated residuals are then instrumented with the policy news shocks (Nakamura and Steinsson, 2018), following (Kekre and Lenel, 2022, Gertler and Karadi, 2015, Mertens and Ravn, 2013), from October 1995 to September 2019. The 90% confidence intervals are computed at each horizon using the wild bootstrap with 10,000 iterations.

share attributed to real rate news.[9] The predominant role of expected excess returns in explaining monetary transmission to the equity market has attracted considerable attention in the literature, on which we hope to shed light.

Table A-15: Conditional Campbell-Shiller decomposition

	Policy News Shock		Fed Fund Futures Shock	
	Values (pp)	Shares of Effect	Values (pp)	Shares of Effect
Current Excess Return	1.630		2.725	
	(0.922, 2.630)		(2.065,3.34)	
- Cash Flow News	0.357	22%	0.505	19%
	(-0.316, 1.253)	(-21%, 75%)	(-0.342, 1.588)	(-84%, 89%)
- Real Rate News	0.240	15%	0.093	3%
	(0.045, 0.379)	(2.3%, 29%)	(-0.364, 0.218)	(-7.8%, 14%)
- Future Excess Returns	**1.032**	**63%**	**2.128**	**78%**
	(0.071, 2.192)	**(7.5%, 113%)**	**(0.885, 3.189)**	**(36%, 112%)**

This table reports the Campbell-Shiller decomposition after a one-standard-deviation monetary shock. A one-standard-deviation policy-news shock (fed funds futures shock) translates into 0.17% (0.13%) of a one-year Treasury yield change. The three revisions in expectations come from the sum of 50-year impulse responses estimated using the six variables and the six-lag SVAR-IV model. The estimation period for the first stage is October 1979 to September 2019; the monetary-shock instruments are available from October 1995 to September 2019. Policy news shocks are the updated Nakamura-Steinsson shocks, and fed funds futures shocks are aggregated following (Gertler and Karadi, 2015) using the current month's fed funds futures. Both underlying high-frequency shocks are obtained from (Acosta and Saia, 2020) and cross-checked using the CME Datamine data we have for a subperiod. The 90% confidence intervals are computed at each horizon using the wild bootstrap with 10,000 iterations.

F.2 The aggregate Market Reaction at High Frequency

We replicate (Bernanke and Kuttner, 2005) using the cumulative returns with 5-minute incremental estimation periods:

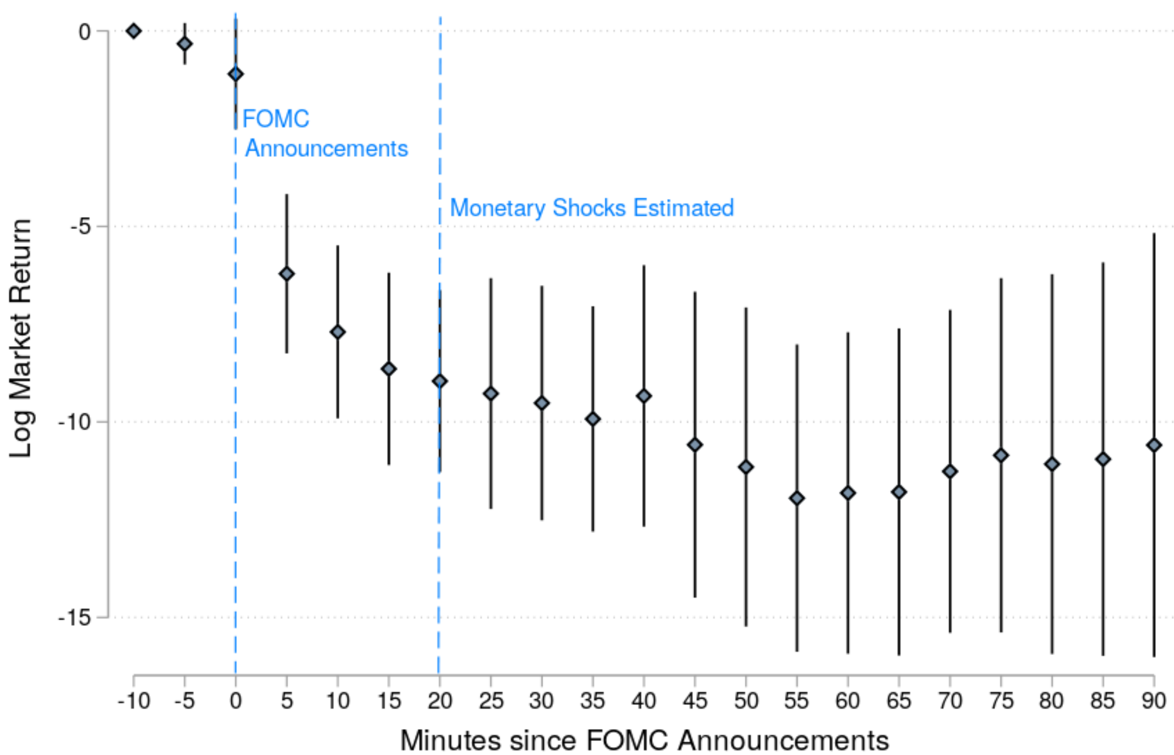
$$r_{m,t-10+h\times 5} = \alpha_h + \beta_h MS_t + \epsilon_{t-10+h\times 5}, \tag{58}$$

where t is the minute of an FOMC statement release and $r_{m,t-10+h\times 5}$ is the $(h \times 5)$-minute cumulative market return from 10 minutes before the release, measured by the returns of SPY (the most liquid index ETF for S&P 500). Figure A-15 plots the coefficients β_h. Monetary

[9] The large confidence intervals reflect the lack of power, well-known in the macro literature using the SVAR-IV approach. In theory, SVAR and local projection should be equivalent (Plagborg-Møller and Wolf, 2021), but in practice, they may deliver different results due to limited lags and data. However, recent papers using alternative approaches, such as local projections, cannot reject the point estimates obtained from the SVAR-IV system (Ramey, 2016, Stock and Watson, 2018).

shocks significantly affect equity prices at high frequency. At the end of the 30-minute window, in response to a 10 bp surprise short rate hike, the market drops about 90 bp. The price decline persists until the end of the day, closing at around 1.06%. Over our sample period from 2004 to 2019, the estimated multiplier of daily return reaction to monetary shocks is about 2.5 times larger than the (Bernanke and Kuttner, 2005) estimate of about four from 1989 to 2002.

Figure A-15: Bernanke-Kuttner at high frequency



This figure shows the OLS regression coefficients of returns on Nakamura-Steinsson monetary shocks. The cumulative returns are computed in 5-minute increments for SP500 ETF (ticker: SPY) from 10 minutes before the FOMC announcements. The high-frequency shocks we use are estimated from a 30-minute window starting from 10 minutes before the announcements to 20 minutes after it (blue dash line at $t = 20$). The sample period is from 2004 to 2019. 95% confidence intervals are displayed, using robust standard errors.

F.3 Relative Revaluation of Bond and Equity Markets

As discussed in Section 2.4 and formalized in Proposition 4(a), if there is no reaching-for-yield incentive ($\chi = 0$), then the model predicts that, the bond market reaction should be larger than the stock market reaction. If there is a strong reaching-for-yield incentive χ, the stock market may revalue more than the bond market. Thus, examining the relative size of stock and bond market reactions will inform the reaching-for-yield incentive χ.

We empirically measure the stock and bond market reactions to monetary shocks here. Ideally, we would like to check the revaluation of the bonds held by rebalancers and compare them with the stock revaluations. Unfortunately, the FactSet institutions do not report their bond holdings. For balanced funds in Morningstar, the bonds they hold are traded too sporadically to properly reflect their revaluations at 30-min or daily frequency. We instead proxy by comparing cumulative returns on various liquid bond-market index-tracking ETFs to those of the S&P 500 index-tracking ETF. Specifically, we estimate the following long-difference local projection:

$$\frac{P_{i,t+h} - P_{i,t}^{before}}{P_{i,t}^{before}} = \beta^h MS_t + \epsilon_{i,t,h},$$

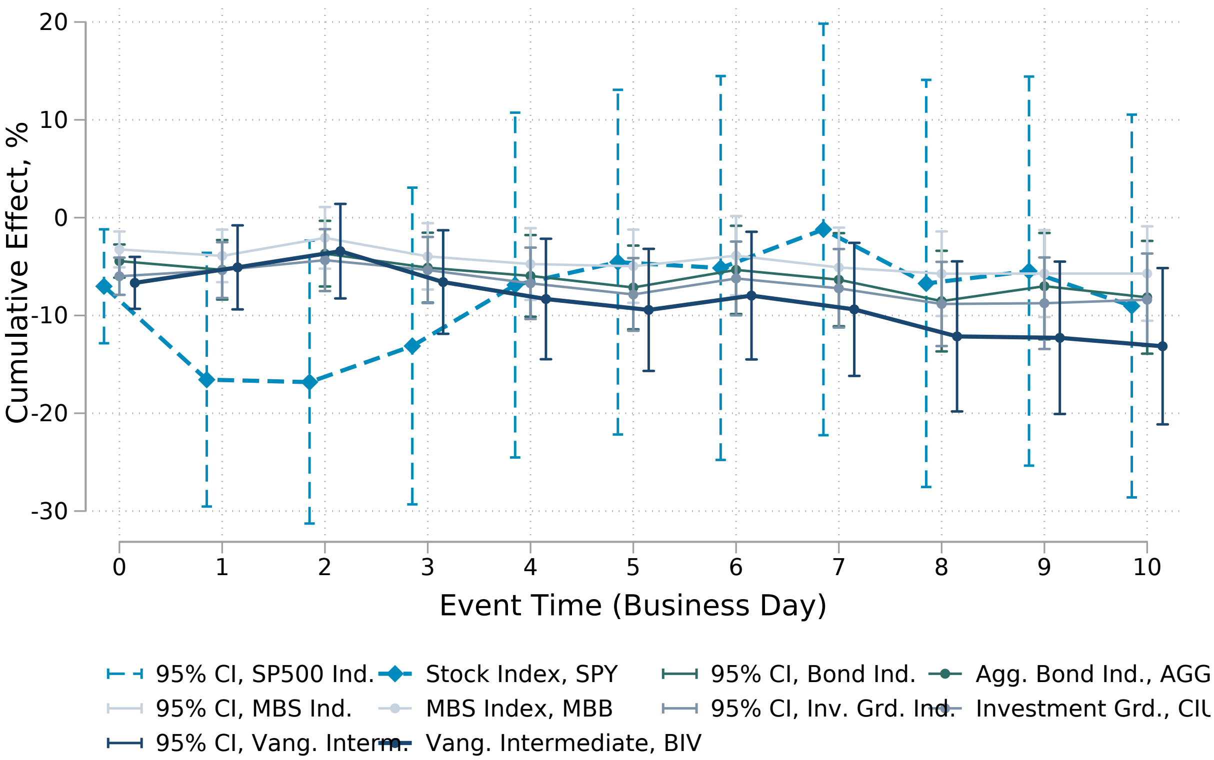
where $P_{i,t+h}$ is the price of security i h days after the FOMC announcement on day t, $P_{i,t}^{before}$ is i's price 10 minutes before the FOMC announcement on day t, and MS_t is the monetary shock on announcement day t.

Figure A-16 then plots cumulative returns for the S&P 500 ETF (ticker: SPY) alongside those of MBB (iShares MBS index-tracking ETF), CIU (iShares investment-grade corporate bond ETF), AGG (iShares aggregate bond-market ETF), and BIV (Vanguard intermediate-term bond ETF). The immediate reaction of SPY is comparable to BIV and exceeds the rest. However, in around five days post announcement, BIV price response overtakes SPY, and other bond ETF price reactions are fairly comparable to SPY. We cannot reject that the stock market revalues less than the bond market, especially in a few days after the FOMC announcements.

G Alternative Calibration

Demand elasticities in the literature. Table A-16 summarizes recent micro and macro elasticity estimates from the literature. We categorize the elasticity estimates by estimation

Figure A-16: Local projections of bond and stock market index ETFs



This graph plots cumulative effect of monetary shocks on returns by security β^h from the following long-difference local projection:

$$\frac{P_{i,t+h} - P_{i,t}^{before}}{P_{i,t}^{before}} = \beta^h MS_t + \epsilon_{i,t,h},$$

where $P_{i,t+h}$ is the price of security i h-day after the FOMC announcement on day t, $P_{i,t}^{before}$ is i's price 10 minutes before the FOMC announcement on day t, and MS_t is the monetary shock on announcement day t. The results are robust to controlling for the pre-shock day daily returns. Securities plotted are: S&P 500 ETF (ticker: SPY) alongside those of MBB (iShares MBS index-tracking ETF), CIU (iShares investment-grade corporate bond ETF), AGG (iShares aggregate bond-market ETF), and BIV (Vanguard intermediate-term bond ETF). Different from the main sample period starting from 2004, we restrict the sample to post May 9, 2007 because bond ETF prices were unavailable before then.

periods for reduced-form estimates from event studies (Column *Estimation Type*). There are two types of event windows: the *announcement date* (e.g., FOMC announcements, dividend payout announcements, QE announcements, and index inclusion/deletion announcements) and the *action date* (e.g., rebalancing events, dividend payments, passive funds' flows to new index additions, and central bank purchases). The difference can be seen through the lens of our multi-period model in Section 2.2: in period 0, as investors anticipate a future flow in period T, stock prices react immediately by r_0 and then continue to drift at a rate of $1+\eta$ to

r_T when the flow realizes at time T. The measured return reactions around announcement dates can thus be seen as r_0, whereas the ones measured around action dates are $r_T - r_{T-1}$.[10]

Calibration using alternative elasticity estimates. For robustness, we present calibration results using two different estimates from the literature in this section and provide a summary of different calibration results in Table A-17.

Quarter-end calibration. The model extension with delayed rebalancing suggests that the rebalancing channel is stronger for monetary shocks during quarter ends when rebalancing is imminent. Empirically, at quarter ends, our estimate of the aggregate stock market reaction to a 10 bp rate hike is 1.01%. Moreover, the cross-sectional sensitivity associated with a 10% ownership difference is 5.8 bp (columns 1 and 4, Table 5). Following similar calculations as in Section 6, the implied aggregate price reaction to a 10 bp rate hike is around 27 bp ($= 2.3 \times 20\% \times 5.8 \times 10$) bp to 57 bp ($= 4.9 \times 20\% \times 5.8 \times 10$) bp. Therefore, the percentage of aggregate returns due to changes in expected excess returns that our rebalancing channel can explain is about 42% ($= \frac{27 \text{ bp}}{1.01\% \times 63\%}$) to 90% ($= \frac{57 \text{ bp}}{1.01\% \times 63\%}$). Unsurprisingly, when rebalancing is more potent during the quarter-ends, the share attributed to rebalancing demand in the aggregate price reaction gets larger.

Remarks on consistency. Last, to shed light on the internal consistency of our estimates, we note an additional theoretical prediction from our delayed rebalancing model: if we take the difference between aggregate stock market reactions at two different dates in time, it should relate to the difference between cross-sectional sensitivities via the micro-to-macro-elasticity ratio,

$$\frac{\mathrm{d}\bar{r}_{t_1}}{\mathrm{d}MS} - \frac{\mathrm{d}\bar{r}_{t_2}}{\mathrm{d}MS} \approx \frac{\zeta^{\perp}}{\zeta}(\gamma_{t_1} - \gamma_{t_2})\bar{\omega}$$

This formula remains valid even if stock prices change due to shifts in fundamentals (such as dividends or the risk-free rate), since those changes do not depend on the time gap between FOMC announcements and rebalancing events and cancel off when taking the difference.

[10] A special case is one where flows are unanticipated ($T = 0$), as analyzed by (Gabaix and Koijen, 2022). Then, the measured return reaction reflects the full effect r_T.

Our estimates are internally consistent. From Table 5, on the subsample of quarter-end FOMC announcements, the aggregate stock market reaction to monetary shocks is -10.1, and the cross-sectional sensitivity is -5.8. On the full sample, the aggregate stock market reaction is -8.9, and the cross-sectional sensitivity is -3.7. With $\gamma_{t_1} - \gamma_{t_2} = -3.7 - (-5.8) = 2.1, \bar{\omega} = 20\%$ and $\zeta^{\perp}/\zeta$ between 2.3 and 4.9, the implied difference $\frac{\mathrm{d}\bar{r}_{t_1}}{\mathrm{d}MS} - \frac{\mathrm{d}\bar{r}_{t_2}}{\mathrm{d}MS}$ is between 0.97 and 2.1. The actual difference, $-8.9 - (-10.1) = 1.2$, lies within the predicted range. A parallel month-end versus full-sample check suggests the same consistency.

Table A-16: Micro and macro elasticity estimates in literature

micro elasticity $\zeta^{\perp}$ (in absolute value)					
	Estimate Type	Market	Event Type	Sample Period	Elasticity
(Schmickler and Tremacoldi-Rossi, 2022)	Drift	US	Dividend payouts	1980-2017	1.25
(Greenwood, Laarits, and Wurgler, 2023)	Drift	Hong Kong	Fiscal stimuli	2020-2021	0.25-0.5
(Lou, 2012)	Drift	US	Idiosyncratic demand shocks	1980-2006	0.83
(Pavlova and Sikorskaya, 2023)	Announcement/Full	US	Index inclusion/deletion	1998-2018	1-3.3
(Chang, Hong, and Liskovich, 2015)	Announcement/Full	US	Index inclusion/deletion	1996-2012	0.37-1.43
(Barbon and Gianinazzi, 2019)	Announcement	Japan	Equity QE	2013-2017	1
(Haddad, Huebner, and Loualiche, 2021)	Structural	US	-	2001-2020	0.5
(Koijen and Yogo, 2019)	Structural	US	-	2017	0.38 [a]
macro elasticity ζ (in absolute value)					
(Gabaix and Koijen, 2022)	Full/GIV	US	Idiosyncratic demand shocks	1993-2019	0.17
(Hartzmark and Solomon, 2022)	Drift	US	Dividend payouts	1926-2018	0.43-0.67
(Li, Pearson, and Zhang, 2021)	Drift	China	Locked up funds for IPO subscriptions	2006-2018	0.21-0.33
(Da, Larrain, Sialm, and Tessada, 2018)	Announcement/Full	Chile	Pension funds' reallocations	2011-2014	0.45

For elasticity measures from event studies, the estimation type reports the estimation period for the elasticity estimates: each identified event has an announcement date and an action date. Estimates of the "Announcement" type are from reduced-form analysis using price and quantity data around announcement dates. Announcement dates are typically informational; hence, the elasticity estimates are likely biased on the fundamental news. "Drift" estimates are based on analysis using data after the announcement and around action dates. Some analyses are low frequency, and announcement/action dates are poorly defined. We call these "Announcement/Full" estimates. "Structural" estimates are derived from structural models of asset demand instead of event studies.

This table summarizes recent estimates on micro and macro elasticities; (Wurgler and Zhuravskaya, 2002) provides a comprehensive review of earlier elasticity estimates. The trade-by-trade elasticity estimate from (Frazzini, Israel, and Moskowitz, 2018) is not reported because their price-impact measure may be subject to an order-splitting multiplier, which varies over time and ranges between 2.3 and 16 (Kim and Murphy, 2013, Bouchaud, Bonart, Donier, and Gould, 2018, Gabaix and Koijen, 2022).

[a] This is the point estimate for a median stock in 2017; (Koijen and Yogo, 2019) reports a time series of micro elasticity estimates from 1980 to 2017 (Figure 6 in their paper).

Table A-17: Calibration using alternative elasticity estimates in literature

	(Gabaix and Koijen, 2022)		(Hartzmark and Solomon, 2022)		(Li, Pearson, and Zhang, 2021)		(Da, Larrain, Sialm, and Tessada, 2018)	
	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}
(Schmickler and Tremacoldi-Rossi, 2022)	7.35	6.03	**2.38**	**1.95**	**4.88**	**4.00**	2.78	2.28
(Greenwood, Laarits, and Wurgler, 2023)	2.21	1.81	0.71	0.58	**1.46**	**1.20**	0.83	0.68
(Lou, 2012)	**4.90**	**4.02**	1.58	1.30	**3.26**	**2.67**	1.85	1.52
(Pavlova and Sikorskaya, 2023)	**12.65**	**10.37**	4.09	3.35	8.40	6.89	**4.78**	**3.92**
(Chang, Hong, and Liskovich, 2015)	**5.29**	**4.34**	1.71	1.40	3.52	2.88	**2.00**	**1.64**
(Barbon and Gianinazzi, 2019)	5.88	4.82	1.90	1.56	3.91	3.20	**2.22**	**1.82**
(Haddad, Huebner, and Loualiche, 2021)	2.94	2.41	0.95	0.78	1.95	1.60	1.11	0.91
(Koijen and Yogo, 2019)	2.24	1.83	0.72	0.59	1.48	1.22	0.84	0.69

This table summarizes calibration results using alternative elasticity estimates (for papers reporting ranges of elasticities, we take the mean of the estimates). Text in **bold** highlights the results using macro and micro elasticities estimated with the same estimation windows or events, as detailed in Table A-16.

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