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Preface

This dissertation centers on the asset pricing and macro-finance implications of intermediation. In particular, I examine how demand and supply frictions affect asset prices, with well-identified empirical support from granular data and insights from applied theory.

The first chapter, *Monetary Transmission and Portfolio Rebalancing: A Cross-sectional Approach*, joint with Lingxuan Wu, addresses the puzzlingly significant stock market reactions to monetary shocks through a novel demand-based mechanism. This chapter unveils the crucial role of intermediaries' demand in monetary transmission through their preferences for a target share between equities and bonds. For example, given a one percent monetary shock, bond prices devaluate ten percent if the duration is ten. Institutions sell their equity holdings to maintain the pre-shock equity-bond ratios, creating downward price pressure. Such institutions serve as an amplifying mechanism for aggregate market returns. The rebalancing channel provides rich cross-sectional implications, and the chapter identifies empirical evidence in the cross-section unique to the mechanism.

The second chapter, *The Political Economy of Chinas Housing Boom,* joint with Jiwei Zhang, uses transaction-level land sales data to understand how the Chinese Communist Partys cadre promotion system contributed to Chinas real estate boom. Promotions of Chinas city-level communist officials to higher ranks were largely based on local GDP performances. In turn, local officials were incentivized to sell more land to firms with higher GDP contributions instead of developing the local housing market, pushing up the housing prices locally. Analyzing a large dataset of Chinese Communist Party members biographies, we identify exogenous variations in promotion chances caused by social connections between the local officials and their bosses and find that the shortage in land supply induced by promotion incentives played an important role in the Chinese housing boom.

Acknowledgments

I am deeply grateful to my primary and co-advisors, Arvind Krishnamurthy and Hanno Lustig.

I owe much of my progress in grad school to Arvind's patient guidance and kind encouragement. Over the past six years, Arvind has taught me an incredible amount about finance, teaching, mentorship, and even myself. Arvind understands everything exceptionally fast, yet he remains extremely patient with his students. He is an amazing teacher who can simplify complex ideas and communicate abstract concepts in the most intuitive manner. After all this time, I still can't comprehend how he does it. Arvind also possesses a remarkable ability to see through people. He is always willing to point out my flaws to help me improve and takes the time to help me see my strengths when I feel down. Shortly after my practice job market talk last year, fatigue consumed me, and doubt took hold of my mind completely. That night, I couldn't help but email Arvind at midnight, sharing all my doubts. Even though he was struggling with a terrible Covid infection at home, the following morning, Arvind uplifted me with an hour-long phone call at 8 am. The warm encouragement from Arvind filled me with the strength and confidence I desperately needed throughout the job market.

Hanno is the guru of finding value in even the most rudimentary projects. I vividly remember our conversation at Coupa, right by the green library, during the chaotic pandemic. Back then my job market paper was just a modest three-page proposal among my gazillion ideas, but Hanno's excitement sparked my curiosity to delve deeper. Hanno is also an incredibly supportive advisor. Hanno attended four of my job talks in the last year. Each time, he came with new invaluable insights and fresh perspectives that helped me improve. There is also no limit to the knowledge I can learn from him, in asset pricing, about presentation skills, and even cycling.

I am also very thankful for all the help from my other committee members, Jonathan Berk, Charles Lee, and Matteo Maggiori. Jonathan's thought-provoking questions never fail to take me by surprise and challenge me to see things from a fresh perspective. Matteo's thorough inquiries helped me navigate the complicated mutual fund data. Charles' curiosity is contagious. Every conversation with him leaves me thrilled about the new things I've learned. I am genuinely amazed by how well-versed he is in market microstructure, behavioral finance, asset pricing, and even institutional details. Coming straight from college to grad school, I didn't have much institutional knowledge about the wealth management industry; Charles provided invaluable input for my job market paper, adding realistic elements that practitioners can relate to.

I want to express my heartfelt gratitude to my amazing coauthors. Jiwei Zhang and I are both from Zibo, China. Our shared hometown and research interests created a strong bond between us. Whenever we chat, fresh ideas emerge. We even turned a conversation about home into a paper exploring social connections in China. Lingxuan Wu and I met in college in 2017. His remarkable clarity of logic and positive attitude were evident right from the start. But he is not just an amazingly reliable and intelligent colleague I have learned a lot from; he is also a compassionate friend who's always willing to lend an ear and offer suggestions.

I am also overflowing with gratitude for the kindness and generosity of individuals outside of Stanford on this journey. Sam Hanson and Adi Sunderam placed their faith in our fledgling concept and provided us with the key data that propelled our project forward. The detailed handwritten notes and extensive email conversations from Sam Hanson and Xavier Gabaix on my job market paper were a testament to the selfless mentorship within our field. I strive to be a generous mentor like them, always ready to assist aspiring young researchers in our community.

I owe a great amount of debt to my friends at Stanford: Nicole Gorton Caratelli, my trusty running buddy and confidante, greets me at 7 am in the morning, filling me with bursts of endorphins and uplifting spirits; Huizi Mao and Fei Xia, my companions on two wheels, whisk me away on countless adventures across California; the insightful faculty group at Stanford, particularly Chenzi Xu, Markus Pelger, Steven Grenadier, Darrell Duffie, Anat Admati, Jeff Zwiebel, and Antonio Coppola; and my wonderful colleagues, Shawn Shi, Zefeng Chen, Yang Song, Abhi Mukerji, Ulysses Valasquez, Yiming Ma, David Yang, Zhengyang Jiang, Ido Spector, Zihan Lin, Hala Moussawi, Becky Zhang, Daniele Caratelli, Jacob Conway, Ana Ribeiro, and Frederic Martenet; and my amazing friends from Tsinghua here, Wenhao Li, Dan Luo, Yue Wang, Shuo Wang, and Di Pei; this list is just the beginning...

Finally, I owe my survival on this roller coaster to my incredible boyfriend, Lorenzo Rigon. He has been my rock, accompanying me through every twist and turn. I also thank my loving furry companion Dodo, who ran by my side every step of the way during the academic and SF marathon. I am most grateful to my parents, who have supported me in pursuing my dreams without hesitation. It's hard to believe it's been fifteen whole years since I bid them farewell and ventured off to junior high school alone. The past three years of Covid have kept us apart, and I miss them more with each passing day. I dedicate this dissertation to my beloved parents.

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Chapter 1

Monetary Transmission and Portfolio Rebalancing

1.1 Introduction

A central question in macro-finance is how monetary policy transmits to financial markets. Standard macro models suggest that monetary shocks only have transitory effects (44, 165). Under this conventional view, prices of long-dated financial assets should not react to unexpected monetary news with a large magnitude. However, extensive research documents substantial price reactions to monetary shocks. As a prominent example, (22) finds that a 10-basis-point contractionary monetary shock leads to a 40-basis-point decline in daily aggregate stock market returns. Importantly, the price reactions are mainly attributed to movements in expected excess returns rather than changes in expected future cash flows or the risk-free rate.

This chapter proposes a portfolio rebalancing channel that contributes to the puzzlingly large stock market reaction. It is based on the friction and inelasticity present in financial markets, which complements recent works that consider changes in risk-bearing capacity (113, 148) and investor beliefs (23). The biggest challenge in assessing theories about such an aggregate puzzle has been the limited power of aggregate time-series data. To address this, we adopt a cross-sectional approach to test the unique predictions of the demand-based mechanism and gain insights into the aggregate implications.

Our contribution is two-fold. Thematically, we unveil the crucial role of investor demand in monetary transmission. Previous works have documented the excessive sensitivity of long-term bond yields to monetary shocks, attributing it to demand forces (95, 26, 94). In this chapter, we propose that institutional rebalancing transmits bond market fluctuations into stock prices. We provide cross-sectional evidence unique to our mechanism, showing that stock prices of companies more exposed to rebalancing demand react more to high-frequency monetary shocks of (138) around FOMC announcements, even if these companies share the same fundamentals. To corroborate our mechanism, we conduct a set of exercises: (1) a quasi-experimental setting exploiting within-firm variations using dual-class shares, (2) stronger price reactions after quarter/month-end FOMC meetings when rebalancing is more imminent, and (3) placebo tests discriminating between rebalancing and pure-equity institutions.

Methodologically, contributing to the demand-based asset pricing literature, the cross-sectional approach in conjunction with high-frequency identification we adopt complements the structural approach (118) and the granular instrumental variable (GIV) approach (73).[1,2] Our theory links the implied aggregate stock market reaction due to rebalancing to our cross-sectional estimates through a ratio of the *micro elasticity* to the *macro elasticity* of the stock market à la (73). In aggregate, our calibration results suggest that this rebalancing channel accounts for about one-third to two-thirds of the stock market reactions to monetary shocks unexplained by changes in future cash flows and the risk-free rate.

Our channel results from the institutional rebalancing demand across various asset classes, which is a widely observed phenomenon. As of the end of 2019, institutional investors prone to rebalancing held more than 20% of the US equity market, according to our calculations based on FactSet holdings data. These institutions, which we call "rebalancers," include pensions, sovereign wealth funds, and target date funds. Their portfolio managers need to periodically adjust and report their market exposures across asset classes to comply with allocation mandates set by beneficiaries. These mandates specify target portfolio shares for each asset class, such as bonds and equities. For instance, Norges Bank Investment Management (overseeing the "Oil Fund", one of the largest sovereign wealth funds; henceforth *NBIM*), wrote to the Ministry of Finance highlighting the significance of target allocation mandates in managing the Oil Fund. They stated that "the choice of equity proportion will probably constitute the single most important decision regarding the return on the Petroleum Fund over time" (139). The Oil Fund's most recent benchmark portfolio was set at a 70% equity proportion (140). Additionally, pension funds in the US are subject to similar asset-allocation targets set by pension trustees per state and local laws and regulations (111). These ex-ante allocation restrictions prompt asset managers to rebalance across asset classes after market-wide revaluations.

Based on these observations, we build a model in Section 2.3 to study the asset pricing implications of rebalancing demand. Our model features two investors: a rebalancer that invests in a stock with a fixed portfolio share and a risk-averse equity market arbitrageur that trades the cross-section of two stocks. A positive interest rate shock revaluates the bond market downward, triggering a

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[1] The theory-guided cross-sectional approach has been widely used in the macroeconomics literature to estimate the fiscal multiplier and housing and stock wealth effect, among other things. See (40) and (88) for reviews.

[2] It could be promising to use the cross-sectional approach to corroborate the GIV and structural approaches too, by tracing out the cross-sectional impacts of demand shocks extracted from these approaches.

deviation from the rebalancer's target-allocation rule. In turn, the rebalancer increases its bond holdings and sells its equity holdings. This selling pressure pushes down the price of the stock held by the rebalancer and spills over into the other stock, to an extent that depends on the arbitrageur's demand elasticity between the two stocks. With limited substitutability, the stock directly exposed to the rebalancing demand reacts more than the other stock. We show that the aggregate stock market reaction relates to cross-sectional return differences via a ratio of two demand elasticities.

There are two identification challenges in testing the rebalancing mechanism in the cross-section. First, a classic challenge in monetary economics is that monetary policy announcements are primarily expected and endogenous to changes in economic fundamentals. Following (138), we isolate unexpected changes in the policy rate from 30-min estimation windows surrounding FOMC announcements to minimize the concern of spurious variation. The limitation is that the estimated shocks are small. Similar to (138), we use high-frequency changes in asset prices over the same window for our analysis.

Second, monetary policy announcements affect stock prices in myriad ways. Our empirical design is modeled on an ideal experiment, in which one would compare stocks with different exposure to rebalancing demand but identical otherwise. Any return difference would only pick up the rebalancing channel in this case. In Section 1.4 we exploit a quasi-experimental setting using dual-listed firms with highly liquid shares. The dual-class shares of dual-listed firms have the same fundamentals but different investor bases, allowing us to identify the *within-firm* variation due to rebalancing. We measure rebalancing demand using the share-class-level rebalancer ownership in the last quarter constructed from FactSet. We find that rebalancers hold more class shares with lower voting rights, likely due to their preference to not involve in corporate decisions. Regardless if we proxy rebalancing demand with raw rebalancer ownership or ownership instrumented by voting rights, we show that after a positive short rate shock, the share class with higher rebalancer ownership loses significantly more than the other share class.

While our quasi-experimental design minimizes the concern of omitted variable bias, it is restricted to a limited set of stocks. In Section 1.5, we show that our finding generalizes to the cross-section of all common stocks, controlling for characteristics. We aggregate institution-level ownership of rebalancing institutions to security levels from FactSet and Morningstar holdings data to measure exposure to rebalancing demand. The result in Section 1.5.1 suggests that in response to a 10bp rate hike, a stock with 10% (/1-standard-deviation) higher rebalancer ownership drops by about 3.7bp (/2.6bp) more in price. Under comparable specifications, the point estimates on all common stocks are not statistically different from our estimates from dual-class shares, supporting the external validity of our findings.

By adopting a high-frequency identification scheme, we obtain our empirical results from tight estimation windows around monetary shocks rather than rebalancing dates. Anecdotally, instead of continuously rebalancing to their target allocation, pensions and mutual funds mainly rebalance at the end of each quarter or month. Though rebalancing may not happen immediately after monetary shocks, the arbitrageurs incorporate anticipated future rebalancing demand into immediate price reactions. As the arbitrageurs trade more aggressively to front-run more imminent rebalancing flows, monetary shocks closer to quarter and month ends should lead to wider cross-sectional return differences and larger aggregate market reactions. We formalize this intuition in our model in Section 1.2.2, and test the implications of delayed rebalancing in Section 1.5.2. In support of this mechanism, the cross-sectional price differences are statistically different for monetary shocks derived from quarter-end FOMC meetings and about 1.54 times larger than full-sample estimates.

We present placebo tests contrasting rebalancing and pure-equity institutions to illustrate the mechanism further. In addition to using the universe of institutional investors from FactSet, in Section 1.5.3, we propose a cleaner measure of rebalancer ownership using fund-level holdings from Morningstar mutual fund data. We identify the mutual funds with target mandates through their names and observe the complete holdings of each fund. We find that stocks held more by balanced funds with target mandates respond more to monetary shocks, whereas pure equity funds' ownership does not predict stock price reactions in the cross-section. Since we observe the complete portfolios from Morningstar, we also provide evidence of rebalancing quantities in Appendix A.4.5, suggesting that balanced funds sell equities in response to monetary tightening.

Finally, we quantify the contribution of rebalancing demand to the aggregate market returns following monetary shocks. In line with the literature, we find that 63% of the aggregate market reaction is attributed to expected excess returns (Appendix A.5). In Section 1.6, we use various demand elasticity estimates from the literature to calibrate the implied aggregate returns driven by the rebalancing channel based on the model. Intuitively, our model suggests that the cross-sectional return differences multiplied by the *micro elasticity* equal the rebalancing flow. We then use this implied rebalancing flow and the *macro elasticity* to back out the implied aggregate market returns. In conclusion, our rebalancing channel accounts for about one- to two-thirds of the expected excess returns.

Related literature. Our rebalancing mechanism addresses the longstanding puzzle whereby monetary surprises move the equity price by a large magnitude. (22) finds that a $10bp$ surprise hike in the short rate leads to a $40bp$ decline in daily stock index returns. Moreover, changes in future excess returns contribute to around 50%–80% of the price reactions, dwarfing the contribution of changes in future cash flows or the risk-free rate. Instead of variable risk intolerance (28, 113, 148), we take a complementary view grounded in financial market inelasticity and frictions à la (38, 39), and (73).[3]

Our quantity-based model connects the equity market reactions to the vast literature on monetary

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[3] Related facts and frictions, such as reaching for yield, have also been highlighted in the literature (18, 95, 56).

transmission in bond markets (50, 90, 86, 77, 95, 46, 138, 26, 94, 171). These papers document and explain the excessive sensitivity of long-term bond yields to short-rate shocks. Our rebalancing channel transmits this excess movement in bond markets into the stock market, contributing to the excess return component behind the aggregate stock market reaction. This result is in line with findings in (170), which show that unconditionally, risk premia for stocks are no larger than duration-matched bonds. Our findings that stocks with comparable fundamentals but different investor bases react differently to monetary shocks stress the importance of understanding financial frictions for monetary transmission. There is no single risk premium or risk appetite that governs all assets. Rather, the price of each asset depends on its specific demand. In this regard, we concur with (163), which documents a weak unconditional correlation between arbitrage spreads and proposes a model of segmented arbitrage with funding frictions and balance sheet constraints of financial intermediaries.

More broadly, this chapter contributes to the intermediary asset pricing literature (100), in which the demands of financial intermediaries take center stage. Our model draws from (38, 39) and (73), which emphasize demand inelasticity.[4] In the presence of limits to arbitrage (162, 171), we uncover the cross-sectional implications of this demand-based mechanism for monetary transmission to equity prices. This chapter adds to the growing body of work on demand-based asset pricing by quantifying the aggregate impact of institutional rebalancing demand on market returns. We show that the aggregate market reaction connects to the estimated cross-sectional demand-driven return differences through the micro and macro elasticities of the stock market estimated in the literature (70, 132, 32, 21, 55, 107, 73, 98, 146).

This chapter specifically highlights the asset pricing implications of the rebalancing feature of delegated investment. A longstanding strand of the literature suggests that asset allocations for a long-term investor involve constantly rebalancing to an asset-allocation mix, which also affects asset price dynamics (for example, see **(author?)** 154, 136, 38, 39). Our findings are related to studies on target-date funds (TDFs), a rapidly growing class of rebalancers (137, 144, 145). (145) shows that TDFs actively rebalance at the quarterly frequency based on differential returns across asset classes and argues that stocks with greater TDF ownership have lower returns when equities outperform bonds. While we share the emphasis on rebalancing demand, we make three contributions in particular. First, we examine the transmission of shocks from the bond market to the stock market instead of the contrarian flows due to stock market fluctuation. Second, we leverage monetary shocks for causal inference instead of generic market fluctuations. Finally, we show that the rebalancing effect manifests through many other institutions, including wealth management and pension funds, which own a much larger market share than TDFs.

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[4] See (14, 15) for earlier work.

Last, previous papers also find various *firm-level fundamentals* that affect stocks' return sensitivities to monetary shocks, such as different price stickiness (84), financial frictions (142, 33, 89), and investors' expectations of future cash flows through the Fed information effect (5).[5] (143) proposes a parsimonious monetary policy exposure (MPE) index based on firm characteristics. Unlike these papers, our channel contributes to the excess returns not explained by cash flow channels. We replicate the MPE index and control for it in our regressions. We further control for industry-level stock return sensitivities and a host of other relevant factors.[6]

1.2 The Rebalancing Channel

We present a model of the rebalancing channel to guide the cross-sectional empirical tests. The model formalizes the intuition that the cross-sectional return difference we will measure is dampened relative to the aggregate market's reaction to the rebalancing flows. We present the simplest models and discuss intuition in the main text. Appendix A.1 collects the proofs and Appendix A.2 contains theory extensions.

1.2.1 A Two-Period Model

Here we assume that there are two periods indexed by $t = 0, 1$. There are two stocks in the market ($i = 1, 2$), each in a fixed supply of one share. The stocks have stochastic payouts in period 1 that are jointly normal with mean $\bar{D}$, and variance-covariance matrix $\Sigma = \begin{pmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{pmatrix}$. We assume $\rho \in (0, 1)$ so that the two stocks are imperfectly substitutable. The two stocks have the same pre-shock prices $\bar{P}$, but differ in their investor bases, as we specify below. After a monetary policy shock, we study prices and demand in period 0 and suppress the time index. We take first-order approximations of changes in demand and prices, as monetary shocks are small. To highlight the role of demand forces in determining prices, here we assume the dividends remain unchanged in response to monetary policy shocks. Our analysis carries through without this simplifying assumption (see Appendix A.2.2).

In this economy, a bond revaluates after a monetary shock proportionally by $r_B = P_B/\bar{P}_B - 1$ from its pre-shock price $\bar{P}_B$. The two stocks endogenously revaluate proportionally by $r_1 = P_1/\bar{P} - 1$, and $r_2 = P_2/\bar{P} - 1$, respectively, which will be pinned down by demand forces in equilibrium. We use r_1, r_2, and r_B to denote instantaneous revaluations following monetary shocks, i.e., capital gains, for consistency with our notation in the empirics. The aggregate stock market revaluates by $\bar{r} = (r_1 + r_2)/2$. We describe the monetary shock in the direction of tightening (resulting in a downward bond revaluation, $r_B < 0$).

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[5] The Fed information effect states the Fed may have superior knowledge regarding the economy compared with the private sector (152, 138). Relatedly, (47) shows that non-monetary news affects stocks via the Fed information effect.

[6] In Appendix A.4.7, we adopt the double-selection LASSO procedure to show that our rebalancer ownership factor is not spanned by asset pricing factors identified previously (92, 109).

There are two investors, a rebalancer (R) and an equity arbitrageur (E), referred to as “he” and “she” respectively. Superscripts denote investors, and subscripts denote assets.

1. A rebalancer R initially holds share ω of stock 1 and some bonds.[7] He invests θ share of his wealth in stock. To the first order, the log change in wealth due to changing security prices is $\Delta w^R = \theta r_1 + (1-\theta) r_B$ and the log change in demanded quantity is $\Delta q_1^R = \Delta w^R - r_1$. As the rebalancer initially holds ω share of stock 1, the absolute change in demanded share is

$$\Delta Q_1^R = \omega \Delta q_1^R = \omega(\Delta w^R - r_1) = \omega(1-\theta)(r_B - r_1). \tag{1.1}$$

   Upon unexpected tightening news ($r_B < 0$), if there is a selling pressure of stock 1 from the rebalancer as found in our empirics, it is implied that the bond revaluates more than stock 1, that is, $|r_B| > |r_1|$. This is consistent with our findings on balanced funds’ holdings and also in line with (170). Nonetheless, we note that the model can be easily extended to generate a selling pressure of stock after monetary tightening with the bond revaluation no more than the stock if the rebalancer can deviate slightly from the mandated equity share to reach for yield (95). Crucially, no matter how much the rebalancing flow is attributed to a rigid mandate vs. a reaching-for-yield incentive, our predictions in Proposition 1 hold similarly. See Appendix A.2.1 for an extension where both margins are at play.[8]

2. An equity arbitrageur (E) invests in both stocks subject to a funding cost of $1+\eta$ per dollar with $\eta > 0$ to maximize a mean-variance preference,

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

   with share $Q^E = \left(Q_1^E, Q_2^E\right)'$ and expected return $\mu = \left(\bar{D} + \bar{P} - (1+\eta)P_1, \bar{D} + \bar{P} - (1+\eta)P_2\right)'$, resulting in demanded share $Q^E = \Gamma^{-1}\Sigma^{-1}\mu$. Her demand (in shares) of stock i is

$$Q_i^E = \frac{\bar{D} + \bar{P} - (1+\eta)P_i - \rho\left[\bar{D} + \bar{P} - (1+\eta)P_{-i}\right]}{\Gamma(1-\rho^2)\sigma^2},$$

   in which P_{-i} is the other stock’s price. In response to small price changes $P_i = \bar{P}(1+r_i)$, the change in demanded shares is

$$\Delta Q_i^E = -\psi^A r_i - \psi^C (r_i - r_{-i}), \tag{1.2}$$

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[7] The assumption that R *only* holds stock 1 is motivated by the empirical observation that the set of stocks held by institutions is sparse and sticky and that little extensive-margin adjustment occurs after monetary shocks (Appendix A.4.3).

[8] It is interesting further to disentangle the mandate-driven demand from the reaching-for-yield demand. Unfortunately, this is not feasible with our primary data from FactSet, which does not contain the bond holdings of the rebalancers. Merging bond holdings data (e.g. eMAXX data) with stock holdings in FactSet could address the problem, but that is known to be challenging (118).

with $\psi^A := \frac{(1+\eta)\bar{P}}{\Gamma(1+\rho)\sigma^2}, \psi^C := \frac{(1+\eta)\rho\bar{P}}{\Gamma(1-\rho^2)\sigma^2}$. ψ^C parameterizes the substitutability between two stocks, while ψ^A determines the arbitrageur's demand of the total stock market. 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; hence, ψ^C is higher than ψ^A. We assume $\rho < 1$ and the arbitrageur is risk-averse ($\Gamma > 0$) to generate limits to arbitrage between two stocks (finite ψ^C). Henceforth, we treat ψ^A and ψ^C as free parameters in our discussion, acknowledging they are sufficient statistics in our model and can be micro-founded in other ways.[9] The funding cost parameter η is subsumed by ψ^A, ψ^C here, but will play an independent role as a time discounting factor in the multi-period environment in Section 1.2.2.

Taking stock, the market-clearing conditions of two stocks are

$$\Delta Q_1^R + \Delta Q_1^E = 0, \tag{1.3}$$

$$\Delta Q_2^E = 0. \tag{1.4}$$

Proposition 1 (Cross-sectional and aggregate returns). *In this two-period model, when a bond revaluates by r_B due to monetary policy changes, the price changes in stocks relative to pre-shock levels denoted by r_1, r_2 are*

$$r_1 = \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)} r_B, \tag{1.5}$$

$$r_2 = \frac{\psi^C}{\psi^C + \psi^A} r_1 = \frac{\psi^C}{\psi^C + \psi^A} \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)} r_B, \tag{1.6}$$

with $\Psi := \frac{\psi^A + 2\psi^C}{\psi^A + \psi^C}\psi^A \in (\psi^A, 2\psi^A)$. The aggregate price reaction is $\bar{r} = \frac{r_1 + r_2}{2}$. Consequently,

(a) the return difference between two stocks is larger if the rebalancer owns more of stock 1's shares

$$\frac{\partial^2(r_1 - r_2)}{\partial r_B \partial \omega} = \frac{\psi^A}{\psi^C + \psi^A} \frac{(1-\theta)\Psi}{[\Psi + \omega(1-\theta)]^2} > 0, \tag{1.7}$$

(b) the aggregate stock price reaction $\bar{r}$ and the cross-sectional return difference $r_1 - r_2$ satisfy

$$\bar{r} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_1 - r_2). \tag{1.8}$$

Equation (1.6) demonstrates that the return of the stock held by the rebalancer changes more than the stock held only by the arbitrageur. $\omega(1-\theta)$ parameterizes the rebalancing price pressure

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[9] Technically, the dual-class shares we analyze in Section 1.4 have the same dividends ($\rho = 1$) which would imply perfect substitutability of two stocks ($\psi^C \to \infty$) in our micro foundation. 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. We assume a finite ψ^C, the empirically relevant case.

initiated by the rebalancer. The higher the rebalancer's bond share (higher $1-\theta$) and the higher its ownership (higher ω), the higher the exposure of the stock market to the bond market. Equation (1.7) further shows that the more stock 1 is held by the rebalancer (higher ω), the higher the cross-sectional return differences after monetary shocks.

If ψ^A is zero, we will observe $r_1 = r_2 = r_B$. This is a knife-edge case where all assets move in perfect tandem. Instead, if ψ^A is positive, the stock price reactions will depend on the strength of cross-sectional arbitrage. With extreme limits to arbitrage ($\psi^C \to 0$), to the first order, we have $\Psi = \psi^A$, $r_1 = \frac{\omega(1-\theta)}{\psi^A+\omega(1-\theta)} r_B, r_2 = 0$, and $\bar{r} = \frac{1}{2} r_1$. That is, while stock 1 moves with the bond, stock 2's price remains unchanged. Another limiting case is one without limits to arbitrage ($\psi^C \to \infty$): we will have $\Psi = 2\psi^A$, $\bar{r} = r_2 = r_1 = \frac{\omega(1-\theta)}{2\psi^A+\omega(1-\theta)} r_B$. In this case, the two stocks also comove perfectly—without limits to arbitrage, there will be no cross-sectional return differences after monetary shocks.

Remarks on model assumptions. This model assumes that dividends remain unchanged by the monetary shock, nor does the funding cost η vary. Indeed, both can affect the aggregate market price. However, any price difference between two stocks with the same fundamentals can only be attributed to our rebalancing channel since the dividend and discount rate channels cancel out. Thus, it will still be valid to calculate the implied aggregate price reaction due to rebalancing using (1.8), even with changing dividends and discount rates. In Appendix A.2.2, we formalize this intuition in an extended model with changes in dividends and varying funding costs. Regarding the aggregate stock market reaction, the rebalancing channel contributes to the component attributed to expected excess returns rather than the changes in cash flows or risk-free rate (see Appendix A.5 for the decomposition).

We build a partial equilibrium model on purpose that focuses only on the stock market to guide our empirical design, taking the bond revaluation r_B as given. This partial equilibrium model can be easily incorporated into larger models where government and corporate bond returns and investors' consumption-investment decisions are jointly determined. The rebalancing channel will still be present, and our empirical design remains valid in that case.

1.2.2 Delayed Rebalancing

The two-period model in Section 1.2.1 assumes instantaneous rebalancing between equity and bond following a monetary policy change 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.

Assume there are $T+2$ periods, indexed by $t = 0, \ldots, T+1$, the last two of which are like in the two-period model. Two stocks $i = 1, 2$ pay dividends $D_{i,t}$ that are jointly normal with mean $\bar{D}$ in the first $T+1$ periods, mean $\bar{D}+\bar{P}$ in the last period, and variance-covariance matrix $\Sigma = \begin{pmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{pmatrix}$ in each period. We assume that the expected dividend is $\bar{D}+\bar{P}$ in the last period to make the environment stationary, which is an innocuous assumption.

There are still two investors, a rebalancer R and an equity arbitrageur E. The equity arbitrageur E adjusts her portfolio in each period to maximize a period-by-period mean-variance preference. The rebalancer R holds ω share of stock 1 until he can adjust his portfolio in period T. Assume a monetary shock in period 0 triggers a predictable bond revaluation of r_B in period T.[10] We have fully characterized period-T outcomes in our 2-period model. Now we analyze the demand in previous periods $t = 0, \ldots, T-1$:

1. The rebalancer R holds his portfolio unchanged; thus, $\Delta Q_{1t}^R = 0$.

2. The equity arbitrageur E maximizes a period-by-period mean-variance preference

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

   with $Q_t^E = \left(Q_{1t}^E, Q_{2t}^E\right)'$, $\mu_t = \left(\bar{D}+P_{1,t+1}-(1+\eta)P_{1t}, \bar{D}+P_{2,t+1}-(1+\eta)P_{2t}\right)'$ denoting share and expected return per share, solved by $Q_t^E = \Gamma^{-1}\Sigma^{-1}\mu_t$. Her demand (in shares) for stock i is

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

   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 her demanded share is

   $$\Delta Q_{it}^E = -\psi^A\left(r_{it} - \frac{r_{i,t+1}}{1+\eta}\right) - \psi^C\left[r_{it} - \frac{r_{i,t+1}}{1+\eta} - \left(r_{-i,t} - \frac{r_{-i,t+1}}{1+\eta}\right)\right], \tag{1.9}$$

   with $\psi^A := \frac{(1+\eta)\bar{P}}{\Gamma(1+\rho)\sigma^2}, \psi^C := \frac{(1+\eta)\rho\bar{P}}{\Gamma(1-\rho^2)\sigma^2}$. We use r_{it} to denote price changes relative to their steady-state levels.

Using period-by-period market clearing conditions and Proposition 1, the instantaneous returns following monetary shocks due to future rebalancing flows can be characterized below.

Proposition 2 (Delayed rebalancing). *In this delayed-rebalancing model with rebalancing in period T, if a time-0 monetary shock leads to a time-T bond revaluation by r_B, the time-t price changes in*

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[10] Anecdotally, rebalancers adjust portfolios at the end of each quarter or month, represented by period T. The assumption that r_B is independent of T is justified because the effect of monetary policy shock does not vanish within a quarter or month. A weaker assumption that r_B declines in T will only strengthen our prediction in Proposition 2(a) that $\bar{r}_0$ decreases in T.

stocks relative to pre-shock levels denoted by r_{1t}, r_{2t} *are*

$$r_{1t} = \frac{1}{(1+\eta)^{T-t}} \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)} r_B, \tag{1.10}$$

$$r_{2t} = \frac{\psi^C}{\psi^C + \psi^A} r_{1t} = \frac{1}{(1+\eta)^{T-t}} \frac{\psi^C}{\psi^C + \psi^A} \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)} r_B, \tag{1.11}$$

with $\Psi := \frac{\psi^A + 2\psi^C}{\psi^A + \psi^C} \psi^A \in (\psi^A, 2\psi^A)$*. The aggregate price reaction is* $\bar{r}_t = \frac{r_{1t} + r_{2t}}{2}$*. Consequently,*

(a) both the cross-sectional return difference and the aggregate price reaction decrease in the time gap T *between the monetary shock and the rebalancing event,*

$$\frac{\partial^2 (r_{10} - r_{20})}{\partial r_B \partial T} < 0, \tag{1.12}$$

$$\frac{\partial^2 \bar{r}_0}{\partial r_B \partial T} < 0, \tag{1.13}$$

(b) the time-0 *aggregate stock price reaction* $\bar{r}_0$ *and the time-*0 *price differential between two stocks* $r_{10} - r_{20}$ *satisfy*

$$\bar{r}_0 = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_{10} - r_{20}). \tag{1.14}$$

Proposition 2 suggests that when rebalancing is delayed, the time-0 prices partially incorporate future rebalancing. The longer the delay, the more dampening (1.12 and 1.13). The funding cost η here acts as a discount factor, which can also be micro-founded by other frictions, such as inattention (72). It is straightforward to see that Proposition 1(a), which predicts all returns increase in the rebalancer's ownership ω extends here naturally. Further, the relation of time-0 aggregate reaction to time-0 cross-sectional price gap (1.14) remains the same as in our 2-period model. Indeed, this relation holds for any time t.

1.2.3 Empirical Implications

We take stock of our theoretical predictions and motivate our empirical design.

A cross-sectional test. Proposition 1(a) presents a cross-sectional test of the model. In the model, the instantaneous bond return r_B represents the monetary shock (with an opposite sign), and Proposition 1(a) states that the cross-partial of return differences concerning rebalancer ownership and the instantaneous bond return is positive. Empirically, for each FOMC meeting t, we use the cross-section of equities to test if the cross-partial $\gamma := \frac{\partial^2 r_{it}}{\partial MS_t \partial \omega_{it}} < 0$, where MS_t is the unexpected monetary shock at time t, r_{it} is the instantaneous return for stock i at time t, and ω_{it} is rebalancer ownership for stock i at time t. Note that a *negative* cross-partial γ is consistent with a *positive* cross-partial in Proposition 1(a), because a positive MS_t triggers a downward bond revaluation (i.e., $\frac{\mathrm{d}r_{Bt}}{\mathrm{d}MS_t} < 0$).

A quasi-experiment. In the model, the two stocks have the same dividend responses to monetary shocks but differ in rebalancer ownership.[11] The ideal test of the model should hence use two stocks with the same fundamentals but different investor bases. In Section 1.4, we use a sample of dual-listed firms similar to this set-up: dual shares $i = 1, 2$ of a given firm f have the same fundamentals but differ in investor bases. Assuming that share class 1 is held more by the rebalancers at monetary policy announcement t than share class 2, i.e. $\omega_{1ft} > \omega_{2ft}$, we test Proposition 1(a) with the following empirical specification:

$$r_{ift} = \gamma I_{high\ rebalancer\ ownership,ift} \cdot MS_t + \vartheta I_{high\ rebalancer\ ownership,ift} + \delta_{ft} + \epsilon_{ift},$$

where $I_{high\ rebalancer\ ownership,ift}$ is an indicator function that equals one for share class 1 and zero otherwise. δ_{ft} is a firm-by-time fixed effect. Proposition 1(a) implies $\gamma < 0$.

Controls for the cross-section of stocks. When we generalize our empirical findings to the cross-section of all common stocks, as cash flows respond to monetary policy, monetary shocks can affect the cross-section of returns differently, even absent rebalancing. Therefore, for the generalized empirical specification using all common stocks (Section 1.5.1), we test if the cross-partial $\gamma = \frac{\partial^2 r_{it}}{\partial MS_t \partial \omega_{it}}$ is negative, controlling for stock characteristics that capture alternative channels.

The timing of shocks. Proposition 2(a) shows that when the rebalancing period T is further away from the monetary policy announcement date ($t = 0$), the cross-sectional return difference and the aggregate return are both smaller. The market is more responsive to monetary shocks announced closer to the rebalancing dates. To test this prediction, in Section 1.5.2, we split the sample based on the proximity of the monetary policy announcement periods to rebalancing periods. Using subsamples when routine rebalancing events are more imminent, we test if the aggregate and the cross-sectional price reactions after monetary shocks are more pronounced. This test exploits a unique institutional feature associated with our rebalancing channel.

The connection between cross-sectional and aggregate price reactions. Proposition 1(b) and Proposition 2(b) demonstrate that the cross-sectional return difference we measure is dampened compared with the aggregate market's reaction under the condition that $\frac{\psi^C}{\psi^A} > \frac{1}{2}$. Section 1.6 relates ψ^A and ψ^C to the *macro* and *micro* stock demand elasticities estimated in the literature (73), which

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[11] In the baseline model we assume no dividend responses. In the extended model in Appendix A.2.2, as long as the dividend responses are the same, their price difference can only be attributed to different exposure to rebalancing demand.

allows us to calibrate the aggregate market reactions based on cross-sectional estimates. The derived aggregate implication due to rebalancing speaks to the expected excess return component in the decomposition of aggregate market reaction, as we control for fundamentals in our cross-sectional estimates.

1.3 Holdings and Prices Data

This section describes the price and quantity data we use for the empirical analysis. We use intraday equity prices obtained from the Trade and Quote Database (TAQ) to construct high-frequency returns aligned with the estimation window of (138). We collect quarterly equity holdings from FactSet, which maintains comprehensive coverage of institutional ownership across large institutions in the US equity market. We use monthly Morningstar holdings data for US mutual funds to compare the pricing implications between balanced funds' ownership and pure equity funds' ownership. To identify the asset classes of securities in Morningstar, we use the CUSIP master files. Morningstar holdings data also allows us to provide fund-level evidence of rebalancing quantities. In addition, we collect daily stock prices and fundamentals, bond prices, and issuance information from CRSP, Compustat, Mergent, TRACE, and CRSP Treasuries (GovPX).

1.3.1 Institutional Equity Holdings

FactSet provides comprehensive coverage of the equity holdings by large institutional investors who jointly hold more than 70% of the US equity market by the end of 2019. We use this dataset to construct measures of stock ownership by certain institutions.

We group institutional investors into five types: institutional wealth management, long-term investors, investment advisors, hedge funds, and brokers. Closely following (117), by and large, we use FactSet's entity types (*subtype*) for classification. We supplement the classification strategy in (117) with another mapping file provided by FactSet (*entity_type*), along with manual corrections for unclassified institutions. Appendix A.2.4 details the steps to clean the FactSet data and construct the institution categories. Figure 1 breaks down institutional equity holdings by institution type during the sample period (2004 to 2019).

The rebalancing mechanism relies on the mandate friction in financial intermediaries, commonly observed in sovereign wealth, pension, and balanced funds.[12] In FactSet, sovereign wealth funds are within the *long-term investor* category; pension holdings are absorbed into three categories: the

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[12] The target equity allocation (mandate) is a defining characteristic of balanced funds. For pension and sovereign wealth funds, we searched for annual reports and investment-board-meeting minutes online and found many of them specify target-asset-allocation rules by asset classes. See, for example, *Investing with a Mandate: The 30-Year History*, a report from NBIM: https://www.nbim.no/en/organisation/governancemodel/executiveboard-documents/investmentmandategovernmentpensionfundglobal/; investment minutes from Teachers Retirement System of the State of Illinois: https://www.trsil.org/sites/default/files/documents/2013MayInvest.pdf; and annual report from Tennessee Consolidated Retirement System: https://www.tn.gov/content/dam/tn/finance/acfr/acfr_fy11.pdf. Last retrieved: March 18, 2022.

long-term investor category, which reports the in-house managed holdings, the *institutional wealth management* category when asset management is delegated to external asset managers (64), and in addition, some balanced funds such as TDFs in the *mutual fund* category (145). Hence, this defining feature of our rebalancers directly points to *long-term investor*, *institutional wealth management*, and *mutual fund* in our classification of FactSet institutions. In Appendix A.2.4, we summarize the largest investors in *institutional wealth management* and *long-term investor*. The former are prominently wealth management subsidiaries and firms, and the latter are mostly in-house pension management and endowment funds. However, as we discuss below, we include *long-term investor* and *institutional wealth management* but not the *mutual fund* category as our measure of rebalancer.

The *mutual fund* category in FactSet is a mix of balanced mutual funds and pure equity funds, which are not subject to mandates. We exclude the *mutual fund* category and focus on the other two categories in the main empirical results on FactSet institutions and the calibration. Still, we report additional results in the appendix and show that the exclusion is quantitatively inconsequential.

In addition to the omission of balanced funds, another source of omission suggests that our estimate of the strength of the rebalancing channel is likely a lower bound. The 13F filings underlying our FactSet data are mostly reported at the company level, and we hence miss some investment management subsidiaries that are in fact rebalancers. For instance, Barclays Global Investors (BGI) was the most prominent institutional wealth management company, before BlackRock acquired it. As the investment management subsidiary of Barclays Bank, instead of filing 13F themselves, BGI reported their holdings through the 13F filings of Barclays Bank (categorized as *investment advisor* in FactSet) until December 2005.

The recent decade has seen a high growth rate for index-like investing, particularly the growth of exchange-traded products (ETPs). One concern is that the institutions may hold many ETPs besides the common stocks in our analysis. We show that ETP holdings make up only less than 10% of the market value of rebalancers (Appendix A.2.4).

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 by institutions of the same type. We measure active portfolio management for each type of institution 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 for each manager (117).[13] 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.

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[13] Conventionally, practitioners use tracking-error volatility to measure active management. (53) shows active share is a better measure than tracking-error volatility regarding stock selection.

1.3.2 Mutual Fund Holdings Across Asset Classes

In addition to the FactSet dataset, which has only equity holdings, we use the Morningstar holdings database that provides monthly security-level holdings for all asset classes held by open-end mutual funds in the US. The majority of the securities in Morningstar have CUSIPs that can be linked to the CUSIP Master File. We identify balanced funds with target mandates based on their names and holdings. We take the sample period from the last quarter of 2004 to the third quarter of 2019 to align with our primary analysis using FactSet. We construct ownership shares by balanced funds and pure equity funds for the cross-section of common stocks and also use security-level holdings of balanced funds to provide quantity evidence of rebalancing. The details about the data-cleaning procedures and coverage of Morningstar holdings are Appendix A.2.5.

1.3.3 High-Frequency Shocks and Prices

To separate the exogenous changes in monetary policy from the endogenous responses of monetary policy to the economy, we use the high-frequency monetary shock following (138). They compute the unexpected monetary shocks as the principal component of five fed funds futures and Eurodollar futures, using the 30-minute windows around FOMC meetings; these shocks are normalized based on the daily treasury yield around FOMC dates.[14] We use the updated monetary shocks in (138) from (3), which spans from 1994 to 2019.[15]

We align stock returns to the same estimation window using data from the Millisecond Trade and Quote (TAQ) database, accessed through WRDS. The TAQ database consolidates intraday transaction data for all securities listed across exchanges, including the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), Nasdaq National Market System (NMS), as well as stocks traded on Arca, from which we extract common stock prices from 2004Q4 to 2019Q3. We restrict stocks not subject to market microstructure noises at 30-minute frequencies (Appendix A.2.6 details the data-cleaning procedure). The final sample contains about half of the listed tickers (about 532 firms on average), accounting for more than 90% of the total market capitalization. For each FOMC announcement, following (143), we define the beginning price for a stock as the last valid trade price 10 minutes before the FOMC announcement (and no more than 90 minutes before that), and the end price is from the first valid trade 20 minutes after the FOMC announcement (and no more than 90 minutes after that).

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[14] Specifically, the authors use the 30-minute windows from 10 minutes before scheduled FOMC announcements to 20 minutes after it 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.

[15] We have access to tick-level futures data from the CME group until mid-2018, which is outdated by the publicly available series from (3). Within the overlapping period, our replication of monetary shocks from (138) is mostly consistent with (3).

1.3.4 Stock Characteristics

We construct a variety of security characteristics, such as equity duration (58, 174, 83), monetary policy exposure (MPE) index (143), firm size (118), and market beta (71) from CRSP and IBES database, accessed through WRDS.

We construct the MPE for securities in the sample following (143). (143) surveys the literature that studies cross-sectional stock price reactions to monetary shocks and proposes 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 (58, 174, 83). We detail the construction of duration, MPE, and other stock characteristics in Appendix A.3.

1.4 A Quasi-Experiment: Dual-Class Shares

Monetary shocks affect stock prices in myriad ways. Ideally, one would identify the rebalancing channel with stocks with the same fundamentals. Then the only channel through which monetary shocks can differentially affect stock prices is the stocks' different exposure to rebalancing demand. In this section, we exploit *within-firm* variation for dual-class common stocks. We show that stocks with higher exposure to rebalancing demand are more sensitive to monetary shocks, controlling for the firm-by-time fixed effect.

1.4.1 The Sample of Dual-Class Shares

Dual-listed firms are companies with more than one class of common stock; we look into the dual-listed firms with two share classes publicly traded. For the dual-class shares, each share class typically has proportional economic interests but disproportionate voting rights that induce price differences between share classes (122, 52). Most dual-class firms chose their capital structure before the IPOs (81), including many large market-capitalization stocks (such as Alphabet Inc., Meta Platforms Inc., and Berkshire Hathaway Inc.). To our knowledge, no existing panel for dual-class firms has information on share-class-level voting and dividend rights for our sample period. We detail the construction of our dual share sample and the share-class level liquidity checks in Appendix A.3.1. The final sample has 68 dual-listed companies during the sample period. These dual-class shares have the same economic fundamentals for a given firm f, constituting the ideal quasi-experiment for us. They are also highly liquid in that a typical innovation in their price gap is halved within 15 minutes during our sample period.

1.4.2 Empirical Design and Results

Proposition 1(a) predicts that rebalancers hold the more a stock (higher ω), the larger its price reaction. We construct institutional ownership at time t for share class i of firm f by aggregating institution-level holdings of share class i of firm f across all rebalancers:

$$\omega_{ift} = \Sigma_{j=1}^{N} \omega_{ijft},$$

where ω_{ijft} is the holding of share class i for firm f by rebalancer j at time $t-1$ (we use the last filing period to mitigate endogeneity concerns about holding choices made in response to monetary shocks), computed as the ratio between shares of share class i for firm f held by rebalancer j and shares outstanding for share class i for firm f at time $t-1$. N is the total number of rebalancers in the FactSet dataset at period $t-1$.

Our baseline specification to identify the *within-firm* price reactions to a monetary shock caused by differences in rebalancer ownership is

$$r_{ift} = \gamma I_{high\ rebalancer\ ownership,ift} \cdot MS_t + \vartheta I_{high\ rebalancer\ ownership,ift} + \delta_{ft} + \epsilon_{ift}, \tag{1.15}$$

where r_{ift} is the 30-minute return of share class i of firm f around FOMC announcement t and MS_t is the high-frequency monetary surprises from (138). $I_{high\ rebalancer\ ownership,ift}$ is an indicator function that equals one when the share class i of firm f at time t has higher rebalancer ownership in $t-1$ than the other share class $-i$ of firm f (i.e., $\omega_{ift} > \omega_{-i,ft}$), and zero otherwise. ϵ_{ift} is the residual. δ_{ft} is a set of firm-by-FOMC-meeting fixed effects. Including these fixed effects addresses concerns that monetary shocks can affect stock returns via changes in firm-specific fundamentals (such as changes in cash flows), date-specific news (such as time-varying risk aversion), or even interactions between the two (such as time-varying firm-specific investor beliefs). γ is the coefficient of interest: if γ is negative, higher rebalancer ownership leads to more price reactions to monetary shocks compared to the other share class *within the same firm*.

The identifying assumption is that monetary shocks are exogenous to market fundamentals, and different share classes of the same firm react to monetary shocks differently only due to their differential exposure to rebalancing demand.

Voting rights and rebalancer ownership. Variations in rebalancer ownership across two share classes can be idiosyncratic or due to systematic reasons unknown to us. In addition to the ordinary least-squares (OLS) specification (1.15), we identify a specific source of variations in ownership at the share-class level from voting right differences and present two-stage least-squares (2SLS) estimates. Many rebalancing institutions are conventionally considered passive shareholders (17) and prefer the share class with fewer voting rights. We provide the first-stage estimates that show a strong negative relationship between voting rights and rebalancer ownership (see Appendix A.3.2 for more discussion).

Given the small magnitude of unexpected monetary shocks ((with a standard deviation of a few basis points), monetary shocks are unlikely to trigger important corporate governance events that alter the premium of voting rights.[16] We use $I_{high\ voting\ rights,ift}$, an indicator function that equals 1 for the share class i of firm f at time $t-1$ with higher rebalancer ownership and 0 otherwise, as an instrument for our ownership indicator $I_{high\ rebalancer\ ownership,ift}$. The exclusion restriction states that dual shares' return gaps are unaffected by voting rights in response to monetary shocks, except through rebalancer ownership. We find that the partial R^2 of adding $I_{high\ voting\ rights,ift}$ to the panel regression of $I_{high\ rebalancer\ ownership,ift}$ with firm-by-meeting fixed effects is 10.2%, suggesting that voting right is a strong instrument for rebalancer ownership.

We estimate the following first-stage regression:

$$\begin{pmatrix} I_{high\ rebalancer\ ownership,ift} \cdot MS_t \\ I_{high\ rebalancer\ ownership,ift} \end{pmatrix} = \mathbf{\Phi} \begin{pmatrix} I_{high\ voting\ rights,ift} \cdot MS_t \\ I_{high\ voting\ rights,ift} \end{pmatrix} + \delta_{ft} + \epsilon^1_{ift}, \tag{1.16}$$

where $I_{high\ voting\ rights,ift} \cdot MS_t$ and $I_{high\ voting\ rights,ift}$ are the instrumental variables. The second stage estimates returns as a function of predicted $\widehat{I_{high\ rebalancer\ ownership,ift} \cdot MS_t}$ and $\widehat{I_{high\ rebalancer\ ownership,ift}}$ from the first stage, along with the aforementioned controls:

$$r_{ift} = \gamma^{2SLS} \widehat{I_{high\ rebalancer\ ownership,ift} \cdot MS_t} + \vartheta^{2SLS} \widehat{I_{high\ rebalancer\ ownership,ift}} + \delta_{ft} + \epsilon^2_{ift}. \tag{1.17}$$

Empirical results. Table 3 summarizes the instrumented regressions for dual-class shares and compares the results with OLS regressions. Column (1) reports the unconditional regression of the high rebalancer ownership dummy on the high voting rights dummy, and Columns (2)–(3) present the first-stage results. In Columns (1) and (2), the dependent variable equals one if a dual-class share has higher rebalancer ownership than the other. Columns (1) and (2) show that the coefficient of the indicator variable, $I_{high\ voting\ rights,ift}$, which equals one if a dual-class share has higher voting rights than the other, is significantly negative at the 5% level. The estimates suggest that a dual share class with superior voting rights is around 30% less likely to have higher rebalancer ownership. Similarly, Column (3) shows the interaction between $MS_t \cdot I_{high\ rebalancer\ ownership,ift}$ is negatively predicted by interaction $MS_t \cdot I_{high\ voting\ rights,ift}$ at the 1% level. Columns (4)–(5) show the second stage and

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[16] Previous research suggests that individual firms' voting right premium varies significantly during episodes of control threats and special shareholder meetings (112). We are unaware of any evidence that small monetary shocks lead to these major events. In our analysis, when including an indicator function for high voting rights and its interaction with monetary shocks in our OLS regression (1.15) as controls, the rebalancer ownership interaction coefficient γ is unchanged.

OLS estimates for the 30-minute share return around FOMC announcements, controlling for firm-by-meeting fixed effects.[17] For the 2SLS specification, the F-statistic is well above the thresholds for weak identification test (168) (column 4). The interaction coefficient from 2SLS (/OLS) suggests that the share class with higher rebalancer ownership reacts about 73*bp* (/28*bp*) more than the other share class for a 10*bp* short rate shock, statistically significant at the 1% (/5%) level.

The estimated coefficient from 2SLS for dual-class 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 is also likely because this instrumented ownership estimates the local average treatment effect rather than population (12): the instrumented $\widehat{I_{high\ rebalancer\ ownership,ift} \cdot MS_t}$ estimates 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 difference in return reactions after monetary shocks for an increment of rebalancer ownership for the entire population of rebalancers. The entire population may have considerably more heterogeneity than the rebalancer ownership pinned down by the voting right instrument. In our theory, the stock price reaction increases in ownership ω, holding the rebalancer's mandate θ and bond revaluation r_B fixed. If different sets of rebalancers selected by OLS and 2SLS have different portfolio shares θ or bond revaluation r_B if they hold different bonds, the slope of price reaction to ownership generically differs across these specifications.

Figure 2 plots the coefficient for the instrumented interaction term $\widehat{I_{High\ Rebalancer\ Ownership} \cdot MS}$ across different return-estimation windows. The difference in return sensitivities to monetary shocks due to rebalancer ownership is incorporated into prices within five minutes after the FOMC announcements. It persists throughout the rest of the day. In Appendix A.4, we report additional empirical results using the raw ownership $I_{High\ Rebalancer\ Ownership} \cdot MS$, which feature persistent price gaps too. This contrasts with the quick convergence after a typical innovation in our unit root test, suggesting that our finding is not due to short-lived liquidity differences.[18]

1.5 Empirical Design and Results on All Common Stocks

This section generalizes the empirical results from the quasi-experiment to the cross-section of all common stocks and provides additional evidence of rebalancing flows. Section 1.5.1 demonstrates the main empirical result that stocks held more by rebalancers respond more strongly to monetary shocks. In contrast, the ownership by pure-equity investors is not predictive of stock price reaction. Section 1.5.2 tests the theory prediction on delayed rebalancing that monetary shocks from FOMC meetings closer to routine rebalancing time trigger larger price reactions. Section 1.5.3 uses

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[17] Column (5) reports the OLS estimates without controlling for voting rights. Adding voting rights as a control does not change the point estimate significantly.

[18] (121) argue that liquidity plays a role in asset price response to monetary shocks, which should not be a concern in our sample of highly liquid dual shares. Still, for robustness, we show that adding liquidity controls does not change the magnitude or significance of our estimates (Appendix A.4).

Morningstar data to provide another placebo test, discriminating between balanced and pure equity funds.

1.5.1 Cross-Sectional Tests and Results

Motivated by the result in Proposition 1, we empirically test if the instantaneous cross-sectional returns following monetary shocks differ based on rebalancers' holdings. The returns are measured from 30-minute windows around FOMC meetings, aligned with the (138) monetary shocks we use.

We construct security-level institutional ownership for stock i at announcement time 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 time $t-1$ (we use the last filing period to mitigate endogeneity concerns about holding choices made in response to monetary shocks), and N is the total number of rebalancers in the FactSet dataset at period $t-1$. We also calculate the ownership share of stock i by other types of institutions for our placebo tests.

The main empirical model for the intraday stock prices around FOMC meetings is:

$$r_{it} = \gamma \omega_{it} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + \vartheta \omega_{it} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it}, \tag{1.18}$$

where r_{it} is the 30-minute return of stock i around FOMC announcements and MS_t is the high-frequency monetary surprises from (138). δ_t is a set of meeting fixed effects that absorb monetary shock as a stand-alone term. ω_{it} is the security-level institutional ownership. $\boldsymbol{X}_{i,t}$ collects the controls discussed below, and ϵ_{it} is the residual.

The model in Section 2.3 highlights the role of rebalancing using two stocks with the same fundamentals. Across all common stocks, alternative channels related to fundamentals may affect the cross-section of stock prices differently. The identifying assumption embedded in the empirical model is that monetary shocks are exogenous and, before the monetary policy announcements, institutions did not choose equities based on fundamentals that affect their return sensitivities to monetary shocks, except for the controls.

We introduce a collection of covariates to control alternative transmission channels. First, rebalancers may actively manage the cash-flow duration of their equity holdings, which affects equities' sensitivities to monetary shocks. Hence we compute security-level cash-flow duration following (58, 174) and (83) and control for cash-flow duration along with their interactions with monetary shocks. Second, high-beta stocks may respond more to monetary shocks, and institutional investors may actively manage their exposure to systematic risk. We compute betas based on (71) and control for both equity betas and their interaction with monetary shocks to account for the monetary-sensitivity changes induced by betas. Similarly, institutional investors may actively manage their exposures to other important asset-pricing factors, such as momentum, and we address these concerns with additional asset-pricing controls. In addition, previous research finds different stock price sensitivities to monetary shocks due to fundamentals such as profitability, financial constraints, and informational frictions (33, 143, 142). We replicate the monetary policy exposure (MPE) index proposed by (143) that considers many known channels. We control for both MPE and its interaction with monetary shocks. Finally, we control for log(market equity) (118) and its interaction with monetary shocks. Across specifications, we also control for industry fixed effects and the interaction with monetary shocks using 3-digit SIC codes—(22) finds disparities in return sensitivities to monetary shocks across different industry portfolios,[19] and high-frequency risk factors are also closely related to industry factors (147).

Results using rebalancer ownership. Table 4 shows the main pricing results from (1.18). A 10*bp* positive monetary shock decreases the aggregate market return by approximately 89*bp* (column 0, panel a). Column (1) shows the regression of returns on monetary shocks, institutional ownership, and their interactions, controlling for meeting and industry fixed effects that interacted with monetary shocks. Columns (1) to (6) gradually saturate the main empirical model with the controls above, including equity duration, beta, MPE index, log(size), and the Fama-French and Carhart asset pricing factors, along with their interaction with monetary shocks. The fully saturated model in column (5) shows an additional 10% ownership (one-standard-deviation) by rebalancers is associated with an additional 3.7-basis-point (2.5-basis-point) decrease in equity returns, in response to a 10*bp* hike in the short rate. Without controlling for meeting fixed effects and industry fixed effects interacted with monetary shocks, the coefficient for the stand-alone monetary shock becomes insignificant (column 7, panel a), and the R^2 is substantial. This attests to the quantitative importance of our rebalancing channel.

Besides cash-flow duration and other channels mentioned above, Appendix A.4.1 shows that our result is robust to alternative duration measures (83, 174), an alternative proxy of rebalancer ownership using cross-sectional ranks, weighted OLS, and SP500 index inclusion. Our estimate is also robust to include firm fixed effects.

Placebo test using other institutions' ownership. In contrast, when one replaces the rebalancer ownership in the regression with the ownership of other institutions, its interaction with monetary shocks becomes insignificant across all specifications (panel b). That is, other institutions' ownership is not predictive of cross-sectional price reactions. While we are relatively certain that the

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[19] Moreover, (84) shows heterogeneous price stickiness across sectors affects monetary transmission to the equity market.

types of institutions we select from FactSet as "rebalancers" indeed invest in both equity and bond markets, there may be other rebalancers among the other institutions we do not select, which might contaminate this placebo test. Nonetheless, panel (b) suggests that the overlooked rebalancers are overwhelmed by pure-equity institutional investors. In Section 1.5.3, we provide another placebo test using Morningstar data that differentiate between balanced and pure-equity funds. There, it continues to hold that the balanced funds' ownership share is predictive of cross-sectional price reactions, while the pure-equity funds' ownership is not.

Discussion of other channels. Previous works suggest the Fed may have superior knowledge regarding the economy compared with the private sector (152, 138, 47, 108). Hence, actions from the monetary authority may reveal new information that private agents did not know ex-ante. This Fed information effect implies that monetary tightening reveals the good news about the economy and thus dampens the equity-return decrease. Applying this insight to our cross-sectional setting, if institutions process information better than retail investors, the information effect suggests that stocks held more by institutions—irrespective of the institution type—are *less* sensitive to monetary surprises. It is opposite to our prediction, and its presence would imply that we underestimate the strength of the rebalancing channel. Appendix A.4.2 provides additional robustness checks using a subsample with meetings less prone to the information effect (108). Indeed, estimates of aggregate stock market reaction and cross-sectional return differences are larger in magnitudes on this subsample than on the full sample.

It is also possible that because institutions incorporate macroeconomic news faster than retail shareholders, stocks with higher institutional ownership are more responsive to monetary shocks at high frequency. Our placebo test between the rebalancers and other institutions in FactSet works against this hypothesis unless different institutions differ significantly in their reaction speed to the news. Section 1.5.3 provides another placebo test between balanced and pure equity funds to show that, even within the same class of institutional investors likely to have similar information and traits, only the balanced funds' ownership is predictive of cross-sectional price reaction. Further, our results in Section 1.5.2 on the timing of the shocks support that rebalancers move only periodically. Still, their rebalancing demand is incorporated into the price through other investors' front-running.

Comparison with results from dual-class shares. We remark that the magnitude of γ from the sample of all common stocks is not directly comparable with the estimate from the dual-class share sample. In the dual-class share exercise, we use as the predictor an indicator function, which is equal to one for the share classes with higher rebalancer ownership due to the limited sample size of dual-class shares. For a fair comparison with our exercise on all common stocks, we force the effect to be linear in ownership and share the same coefficient across pairs of dual-class shares, as we do in the analysis on common stocks. Accordingly, we control for interactions between firm fixed effects and monetary shocks. In this case, we find that the point estimate of $\gamma_{dual\ share}$, the coefficient of the interaction between monetary shock and rebalancer ownership *in percentage terms*, is around -8.36, with two-way clustered standard error of about 6.58. That is comparable to the point estimate we obtain from the common stock panel. Their difference is not statistically significant (i.e., $H_0 : \gamma_{dual\ share} = \gamma_{common\ stock}$ cannot be rejected, with a p-value equal to 0.27).

Margins of rebalancing. We interpret our findings in the context of certain institutional features of rebalancers. First, rebalancers tend to hold a small subset of stocks listed in the major exchanges. For example, within the institutional wealth management type, which constitutes the majority of rebalancers, in terms of the number of stocks held, a median institution holds about 60–70 stocks only, while an institution at the 90-th percentile holds about 300–400 stocks only. These numbers are one to two orders of magnitude smaller than the total number of stocks traded in the US. Second, rebalancers' investment universe appears unresponsive to monetary shocks. Appendix A.4.3 provides evidence that rebalancers do not adjust via the extensive margin—adding (/subtracting) new (/existing) stocks to (/from) their portfolios. Additionally, Appendix A.4.5 shows evidence for active rebalancing in a direction consistent with the theory prediction, using a sample of balanced funds from Morningstar for which we see the comprehensive holdings.

1.5.2 The Timing of Shocks

The empirical estimates are from high-frequency windows, assuming prices instantly incorporate rebalancing demand following monetary policy announcements. From our conversations with practitioners, many large pension funds rebalance at the end of quarters and months.[20] Moreover, as our delayed rebalancing model suggests, prices can adjust before realizing these flows as long as other market participants anticipate these rebalancing flows. In that case, as these active arbitrageurs are only imperfectly forward-looking, instantaneous price actions will be larger when the rebalancing events are more imminent, as in Proposition 2(b). Therefore, a further unique prediction of the rebalancing channel is that the timing of shocks matters. We find support for this prediction, exploiting the dates' proximity between FOMC announcements and quarter-end/month-end rebalancing events.

The premise of this prediction is that market participants anticipate impending trades that take a favorable position in the market in advance. Evidence of such front-running strategies has been well documented in the literature. (13) find empirical evidence that hedge funds engage in arbitrage

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[20] 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/;
- ZeroHedge, last retrieved on November 18, 2020: https://www.zerohedge.com/markets/goldman-warns-massive-36bn-month-end-pension-selling-4th-largest-record.

activities that exploit the equity flows from mutual funds. (129) shows that arbitrageurs potentially have significant gains by buying and selling securities before scheduled rebalancing events.

Figure 3 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 front-running more quickly. We expect the arbitrageur to be more active and cause larger price movements in the latter case.

In Table 5, we split the FOMC meetings by their dates' proximity to quarter-ends and month-ends and adopt the same empirical specifications on these subsamples. When an FOMC announcement is released in the last month of a quarter, we label the announcement a *quarter-end* announcement. Similarly, we label announcements that happened in the last two weeks in each month *month-end* announcements. Comparing column 1 (/column 5) with column 9 of Table 5, the aggregate market reaction for the quarter-end (/month-end) subsample is about 1.14 (/1.1) times larger than on the whole sample. Column 4 (/column 8) shows that the estimated interaction coefficient γ at quarter-end (/month-end) is about 1.54 (/1.28) times larger than its full-sample counterpart (column 10). We test the differences in coefficients under the null $H_0 : \gamma_{quarter-end} = \gamma_{full-sample}$ and $H_0 : \gamma_{month-end} = \gamma_{full-sample}$, and reject the hypotheses that the quarter-end (/month-end) interaction coefficient is the same as the full-sample one, with $\chi^2 = 3.12$ (p-value $= 0.08$) for the quarter-end sample and $\chi^2 = 3.17$ (p-value $= 0.07$) for the month-end sample respectively. These results suggest closer proximity between FOMC announcements and routine rebalancing times leads to larger instantaneous price reactions, consistent with the model prediction from Section 1.2.2.

In Appendix A.4.6, we report additional placebo regressions using other institutions' ownership instead of rebalancer ownership. The interaction coefficient is insignificant across specifications. These placebo tests lend further support to our mechanism in that the stronger price reactions closer to quarter- and month-ends are not driven by market-wide conditions but rather uniquely associated with our delayed rebalancing mechanism.

1.5.3 Evidence from Mutual Funds

So far in our analysis, we use FactSet classification and SEC filings to *infer* if an institution is a rebalancing institution, in that we do not actually see their bond holdings. To recover a more accurate measure of rebalancer ownership, we consider a second proxy for rebalancer ownership using mutual funds, for which we have detailed holdings data and can identify the type of funds from names and mutual fund categories. We use the following specification to compare the role of balanced funds with other (pure equity) mutual funds:

$$r_{it} = \gamma\omega_{it}^{F} \cdot MS_t + \boldsymbol{\phi}'\boldsymbol{X}_{it} \cdot MS_t + \vartheta\omega_{it}^{F} + \boldsymbol{\varphi}'\boldsymbol{X}_{it} + \delta_t + \epsilon_{it}, \tag{1.19}$$

where ω_{it}^{F} is the share of stock i held by balanced funds. We also calculate the ownership share of stock i by pure equity mutual funds for our placebo tests. As in the previous section, r_{it} is the 30-minute return of stock i around FOMC announcements, MS_t is the high-frequency monetary surprises from (138), $\boldsymbol{X}_{it}$ contains controls, δ_t is a time fixed effect, and ϵ_{it} collects residuals.

To provide a clean supplementary exercise to our main analysis based on FactSet ownership, we construct ω_{it}^{F} using only direct stock holdings of balanced funds from Morningstar. We exclude indirect stock holdings through balanced funds' holdings of tactical-allocation funds. These tactical-allocation funds may actively adjust to monetary shocks via the extensive margin (adding/deleting stocks), which may contaminate ownership as a measure of exposure to rebalancing demand.[21]

Table 6 summarizes the results from mutual funds. In the panel for balanced funds (columns 1–4), returns load negatively on the monetary shocks due to balanced fund ownership (the interaction between ω_{it}^{F} and monetary shocks). Column (3) presents the fully saturated specification where we control for the interactions with monetary shocks of stock duration, monetary-policy-exposure index, market equity, beta, and industry fixed effects. In this specification, for a 10*bp* surprise rate hike, 10% more balanced fund ownership is associated with an additional 59*bp* decline in returns. Columns (5) and (6) in Table 6 report the placebo tests using equity fund ownership; these regressions fail to reject a null effect of equity fund ownership on return sensitivity to monetary shocks.

Discussion of FactSet and Morningstar results. We have shown that both proxies from FactSet and Morningstar are valid predictors of cross-sectional stock price sensitivities to monetary shocks, supporting our rebalancing channel. However, the interaction coefficient is much smaller in the FactSet analysis compared to Morningstar, behind which there may lie two reasons.

First, one factor implicitly omitted from this comparison is each rebalancer's bond share $(1-\theta)$, which is unobserved in the FactSet data. Holding fixed the share of stocks held by the rebalancer, the more bonds it holds, the larger its need to sell stocks after monetary tightening due to larger investment loss from the bond holdings. Indeed, Proposition 1 implies that the cross-sectional price gap is increasing in rebalancer ownership ω and its bond share $1-\theta$. Any difference in the unobserved bond shares across these two exercises can lead to different coefficients. The same logic applies to unobserved heterogeneity in the revaluation of bond holdings r_B.

A less obvious reason has to do with our imperfect ownership measures. Our FactSet measure of

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[21] (145) shows that about 21% of total TDFs' holdings of funds are in index funds, and 25% are in active funds, while the rest are likely hybrid.

rebalancer ownership is based on broad FactSet categories, which may include non-rebalancing institutions and exclude true rebalancers. Nonetheless, it is our preferred measure because it considers all institutional investors and the selected rebalancers collectively hold about 20% of the market. In contrast, our Morningstar measure of balanced mutual funds is cleaner. Still, it only filters mutual funds.[22] If one has an ideal measure of rebalancer ownership, it would contain the balanced funds we identify and correlate with our FactSet measure. In that case, as the Morningstar balanced fund ownership measure is lower than but likely correlated with the true measure, its coefficient will be enlarged. A more sensible comparison is on the coefficients in units of the cross-sectional standard deviation of ownership. Indeed, they are comparable across two measures: in response to a 10bp surprise short rate hike, a one-standard-deviation increase in FactSet (/Morningstar) rebalancer ownership is associated with a $2.5bp$ ($/2.6bp$) drop in stock price. As there might be additional variations in rebalancer ownership not captured by FactSet or Morningstar measures, the estimated coefficients in both cases may understate the strength of the rebalancing channel.

1.6 Implied Aggregate Stock Market Reaction

In Section 1.5, we have estimated the cross-sectional return differences to monetary shocks due to rebalancer ownership, corresponding to $r_1 - r_2$ in the model. We now connect the aggregate market price reaction to the cross-sectional return differences via calibration of the model, using estimates of stock demand elasticity at different levels from the literature.

The intuition of this calibration can be illustrated via a simple limiting case where the two stocks are not substitutable ($\psi^C \to 0$). In this case, stock 1's price changes in response to the rebalancing demand, but stock 2 is unaffected, i.e., $r_2 = 0$. The aggregate market reaction is thus simply equal to r_1 scaled by one-half, the ratio of stock 1's market capitalization in the total market capitalization. Outside of this limiting case, the rebalancing demand of stock 1 spills into stock 2 through the equity arbitrageur's trading. As a result, r_2 moves in the same direction as r_1 but by a smaller magnitude. The larger the elasticity ψ^C relative to ψ^A, the smaller the return gap $r_1 - r_2$. Taking this into account, Proposition 1(b) and Proposition 2(b) predict that the aggregate market price reaction $\bar{r}$ due to rebalancing is equal to the cross-sectional return difference $r_1 - r_2$ times one-half plus $\frac{\psi^C}{\psi^A}$.

In our model, we show that ψ^A and ψ^C capture the macro and micro stock demand elasticities à la (73). Using the literature estimates thus allows us to quantify the implied aggregate market reaction due to rebalancing. We analyze the impact of period-0 demand shocks in the delayed rebalancing model and suppress the time subscript. It is a realistic characterization since rebalancers adjust only periodically.

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[22] Apart from the empirical choice of focusing on direct holdings discussed above, using balanced funds' ownership may also underestimate rebalancing demand as many other institutions, such as collective investment vehicles, hold similar stocks as balanced funds. See (145) for an extensive discussion.

Macro and micro stock demand elasticities $\zeta, \zeta^{\perp}$. Following (73), we describe the macro and micro stock demand elasticities $\zeta, \zeta^{\perp}$ in their inverse form—the macro and micro price multipliers. These multipliers characterize the sensitivity of stock prices to demand shocks.

The macro multiplier ζ^{-1} is defined in terms of *aggregate* price reaction $\bar{r}$ to a demand shock of ε percentage of the *aggregate* stock market, or equivalently the sensitivity of total market capitalization to a \$1 demand shock. We show that ζ exactly maps into ψ^A in our model. Adding up the equity arbitrageur's demand (1.9) across two stocks gives her demand of the aggregate stock market in percentage term $\Delta\bar{Q} = \frac{\Delta Q_1 + \Delta Q_2}{2} = -\frac{\psi^A}{2}(r_1 + r_2) = -\psi^A \bar{r}$. In response to a ε percentage demand shock, the market-clearing condition $\varepsilon + \Delta\bar{Q} = 0$ determines the aggregate price reaction. The implied macro multiplier is $\zeta^{-1} := \frac{\bar{r}}{\varepsilon} = (\psi^A)^{-1}$.

The micro multiplier $(\zeta^{\perp})^{-1}$ derives from individual stock price reaction to individual stock demand, controlling for price changes in comparable stocks, which we show relates to both ψ^A and ψ^C in our model. We consider two offsetting demand shocks of dollar value $\varepsilon^{\$}$ into stock 1 and out of stock 2 (i.e., a long-short strategy).[23] The micro multiplier is defined as the sensitivity of the difference in their market capitalization to dollar demand shock $\varepsilon^{\$}$ as $(\zeta^{\perp})^{-1} := \frac{P_1 r_1 - P_2 r_2}{2\varepsilon^{\$}}$. In our model with two stocks having identical pre-shock prices, the relative demand of two stocks by the equity arbitrageur from (1.9) is $\Delta Q_1 - \Delta Q_2 = -(\psi^A + 2\psi^C)(r_1 - r_2)$. Combined with market clearing conditions $\bar{P}\Delta Q_1 + \varepsilon^{\$} = 0, \bar{P}\Delta Q_2 - \varepsilon^{\$} = 0$, we get $r_1 - r_2 = \frac{2\varepsilon^{\$}/\bar{P}}{\psi^A + 2\psi^C}$, indicating a micro multiplier of $(\zeta^{\perp})^{-1} := \frac{r_1 - r_2}{2\varepsilon^{\$}/\bar{P}} = (\psi^A + 2\psi^C)^{-1}$.

Therefore, we can rewrite our theory predictions (1.8, 1.14) that link the aggregate price reaction to the cross-sectional return difference, using macro and micro elasticities $\zeta, \zeta^{\perp}$,

$$\bar{r} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_1 - r_2) = \frac{\zeta^{\perp}}{2\zeta}(r_1 - r_2)\,. \tag{1.20}$$

Intuitively, in terms of flows, the return difference $(r_1 - r_2)$ multiplied by the micro elasticity $\zeta^{\perp}$ gives the magnitude of rebalancing flows to stock 1, the stock in the rebalancer's portfolio. The implied aggregate flow to the stock market is halved in this two-stock world. We then use this aggregate flow and the macro elasticity to back out the implied aggregate market returns, as shown in (1.20).

Calibration. The cross-sectional empirical estimates in this chapter focus on the price reactions around announcement dates; hence, the natural elasticity estimates are those from announcement dates. However, teasing out demand forces from other forces around macro announcement dates is generically challenging. For example, FOMC announcements may be associated with the information

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[23] For example, (32, 146) estimate the micro elasticity exactly using such offsetting demand shocks from index inclusion/deletion. They improve on the previous literature (161, 96) with better benchmarks for the added/dropped stocks from the indices to identify the effect of demand.

effect (138). Firms' dividend announcements may also convey information about their future profits. To address this, we resort to the elasticity estimates from the literature using information-free events. These empirical estimates are reasonable for our calibration as Proposition 2 suggests that the ratio of the aggregate price reaction $\bar{r}_t$ to the cross-sectional return difference $r_{1t} - r_{2t}$ is the same in all periods. We use estimates of $\zeta^{\perp}$ and ζ over the same horizon for consistency. For robustness, we use two groups of estimates from the literature.

First, we use the elasticities estimated around dividend *payment* dates. Since the dividend payouts are typically announced weeks before, the news effect is separated from the price pressure due to reinvestment. (156) studies the prices of connected stocks on the payment day to recover the micro demand elasticity. Using a sample of US common stocks from 1980 to 2017, they find a micro elasticity of approximately 1.25. Using the dividend payout dates, (98) finds a macro elasticity of between 0.43 and 0.66 for US common stocks between 1926 and 2018. Using the mid-point of this range, the ratio between micro and macro elasticity $\frac{\zeta^{\perp}}{\zeta}$ is around 2.3.

Second, we use the elasticities from (132), and (73), both of which use idiosyncratic demand shocks from institutional investors' flows for estimation. (132) aggregate flow-induced trading across all mutual funds for each stock to construct a measure of demand shocks. Using quarterly fund holdings from 1980 to 2006, he finds a micro elasticity of around 0.83. (73) leverages a collection of equity holdings data from 1993 to 2019 and estimates a macro elasticity of around 0.17 with a GIV approach. These numbers imply a micro-to-macro-elasticity ratio $\frac{\zeta^{\perp}}{\zeta}$ of around 4.9.

Our estimate suggests that in response to a $10bp$ surprise short rate hike, a stock with 10 percent higher ownership by rebalancers drops about 3.7 basis-point more (column 5, panel (a) in Table 4). Because institutional wealth management and long-term investors hold about 20% of the aggregate stock market, we set $\omega = 40\%$ in our two-stock model. The estimate suggests $r_1 - r_2 = -\frac{3.7bp}{10\%} \times 40\% = -14.8bp$. Because $\frac{\zeta^{\perp}}{\zeta}$ is between 2.3 and 4.9, the implied aggregate price reaction $\bar{r}$ from the rebalancing channel is between $17bp$ and $36bp$.[24]

Our updated estimation of (22) (column 1, panel (a) in Table 4) finds the aggregate stock market drops by $89bp$ in response to a $10bp$ rate hike on our sample. This reaction also reflects other channels, such as changes in future cash flows and risk-free rates. Our decomposition (Table 24) suggests that about 63% (i.e., $63\% \times 89bp = 56bp$) of the overall price reaction is attributed to expected excess returns. We consider the impact of the rebalancing demand on aggregate price as one channel that contributes to changes in expected excess returns since we control for cash-flow sensitivity in our panel regression, and the change in the risk-free rate is common to all stocks. Therefore, the implied aggregate market reaction from rebalancing accounts for about 30%–64% of the measured

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[24] 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, as we have discussed, 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.

aggregate price reaction attributed to expected excess returns.[25] We conclude that the quantity-based rebalancing channel we uncover is promising in explaining the puzzlingly large stock market sensitivity to monetary shocks, as noted by (22).

In our sample period post-2004, we also observe that the stock market reaction to monetary shocks is roughly twice as large as the previous estimate over an earlier sample in (22). This coincides with a rise in passive investing over the past decades. According to our theory, the more rebalancers there are in the market, the greater the stock market response, holding all else equal. The rebalancing channel hence provides a consistent account for these two observations. We concur with (145) that the growth of passive investing may have important implications for market dynamics.

Remarks on calibration. Our calibration exercise builds on a few premises. First, the implied aggregate price reaction is based on the cross-sectional price differentials attributed to differential rebalancing flows into different stocks proxied by rebalancer's ownership. Suppose there are common flows by all investors into the stock market. In that case, these flows will change the aggregate stock market valuation without any cross-sectional implications, thus not included in our calculation. If these common flows share the same direction as the differential flows, the aggregate stock market reaction due to all demand changes will be larger than our calibration result. Second, the model suggests a nonlinear relation between return sensitivity to monetary shocks and rebalancer ownership ω. The empirical specification imposes a linear relation. It is a reasonable approximation if the rebalancing demand is small relative to the market's ability to absorb it (i.e., $\omega(1-\theta)$ small relative to Ψ in our model). This condition is met under our calibration.[26] Moreover, we calibrate our model with two stocks having the same market values. This simplification is without loss of generality under the linear approximation.

1.7 Conclusion

This chapter contributes to the macro-finance literature with a new rebalancing channel for the impact of monetary policy on stock prices. We address the (22) puzzle about the aggregate market reaction with a cross-sectional approach. We test the cross-sectional implications of our rebalancing channel and calibrate its aggregate implications based on our cross-sectional estimates. By comparing stocks with similar fundamentals, we provide direct evidence that the investor base affects the equity price reactions to monetary shocks on samples of stocks with dual-class shares and all common stocks. The quasi-experiment using dual-class shares minimizes the concern that the

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[25] For robustness, we provide a summary of calibration results using different estimates in the literature in Table 26: using macro and micro elasticities estimated with the *same* estimation windows or events, the lower bound of the explanatory power of the rebalancing channel is 26%.

[26] We can express $\Psi = \frac{2\zeta}{1+\zeta/\zeta^{\perp}}$, which is between 0.28 and 0.76 using the estimates from the literature. (73) show that the value-weighted average equity share of rebalancing institutions is about 0.8 over our sample period. As we set $\omega = 40\%$, we get $\omega(1-\theta) = 0.08$. Given these numbers, the linear approximation appears reasonable.

different price reactions are due to omitted factors in our full-sample analysis. This effect is more potent at FOMC meetings closer to quarter-end and month-end rebalancing events, consistent with our theoretical prediction that the timing of monetary shocks matters.

Our model further allows us to quantify the impact of rebalancer demand on stock prices. We calibrate the aggregate implications of rebalancing demand using (i) empirical estimates of cross-sectional returns due to rebalancing and (ii) literature estimates of stock demand 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.

This chapter establishes that rebalancing institutions are crucial to understanding equity price reactions to unexpected monetary shocks. While we focus on ownership and rebalancing by institutions, the cross-sectional approach can also be used to examine household rebalancing with the advent of household portfolio data (74). More broadly, the demand-based mechanism, and the cross-sectional approach that traces the cross-sectional impact of demand forces to deduce the aggregate implications, are also valuable in other asset pricing and macro-finance contexts. For instance, how do market-wide disturbances in the credit market or idiosyncratic shocks to specific bonds propagate across financial markets? How does the rebalancing demand of international investors move home and foreign markets? We hope our methodology can help answer these questions in the future.

Chapter 2

The Political Economy of China's Housing Boom

2.1 Introduction

China's housing prices and residential land prices skyrocketed by almost 400% in 35 major Chinese cities in the ten years between 2004 and 2014 (Figure 4).[1] The spectacular growth of China's housing market has attracted the attention of economists and policymakers.

In this chapter, we propose China's political structure plays an important role in driving China's housing boom. In particular, we demonstrate and identify a *career incentive channel* whereby CCP's GDP-based promotion impacts China's land and housing markets. Our findings reveal that CCP's promotion system induces a suppressed supply of residential land and increased land allocation for industrial use, leading to a rise in house prices. CCP's promotion evaluation favors city leaders who foster higher economic growth (126). To achieve this, city governments, as the sole suppliers of urban land in China, allocate a significant amount of land for industrial production. However, since the annual total land supply in a city is subject to a fixed quota, allocating more land for industrial purposes reduces the land supply for residential projects. Consequently, as wages increase and the population grows with economic advancement, the limited supply of residential land fails to keep up with the demand, resulting in a surge in house prices. The career incentive channel is causally identified through exogenous shocks to local politicians' career incentives, namely, city-level communist leaders' connections with the provincial-level leaders via *hometown ties.* Social ties, particularly hometown favoritism, play a significant role in Chinese society. To empirically test the strength of this form of nepotism, we collect biographical data on prefectural and provincial communist leaders.

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[1] The National Bureau of Statistics of China collects data on 35 largest and economically significant cities since 1998; the cities included in the list can be found in (62).

Higher-level officials in the same province make decisions regarding the promotion, demotion, and re-appointment of prefectural leaders. Contrarily, owing to China's hierarchical promotion system, the central communist committee is responsible for appointing new provincial leaders, and the promotion or lateral transfers of provincial leaders remain unaffected by prefectural leaders. Hence the appointment of provincial leaders serves as a potential exogenous shock to the career motivations of prefectural leaders. We hypothesize that sharing a hometown with a provincial leader alters a prefectural leader's career perspectives and shifts their promotion probabilities. By identifying prefectural leaders who share hometowns with their corresponding provincial communist leaders in our data, we found empirical evidence that sharing a hometown with a provincial leader almost eliminates the importance of GDP on promotion. When a prefectural leader shares the same hometown as at least one of the newly appointed provincial leaders, *ceteris paribus*, their chances of promotion increase by 15%. Leveraging this novel instrument, we identify the impact of political career perspectives on city leaders' land allocation decisions and, all else being equal, their influence on local housing prices. Our findings indicate that all else equal, cities with leaders who share the same birthplace as provincial leaders have 10% higher supplies of residential land, 23% lower industrial land supplies, and 5% lower house price growth rates.

The chapter makes three main contributions. Firstly, it adds to the expanding research that examines how political connections impact asset prices. Previous research has established that political connections can affect firm values, as evidenced by studies on both developing countries (115, 48, 1) and the developed economies (59, 80, 51, 9, 8, 2, 157). In China, previous studies have demonstrated the significant role of political connections, particularly in the form of hometown ties, in gaining access to government loans, trade credit, and promotions to high-level government positions. For example, (153) find that the hometown tie is a crucial factor in obtaining government loans, while (119) show that firms with hometown connections are more likely to receive trade credit. (87) demonstrate that anticorruption investigations in China disproportionately target officials without hometown ties, while (128) show that corporate fraud is more prevalent in firms without political connections. Hometown ties play an important part when it comes to promotions. (66) reveal that hometown ties have a considerable impact in determining promotion to China's Politburo, and (67) find that they also impact fellow selection in the Chinese Academies of Sciences and Engineering. Finally, (45) document that political connections affect the quality of government audits in China.

Secondly, this chapter contributes to the literature addressing what demand and supply factors shaped China's housing boom. Previous studies have scrutinized demand factors extensively, such as speculative investment, status competition, credit expansion, and urbanization, as well as fundamental factors such as population, wages, income, and construction costs (172, 43, 62, 177, 34, 175, 180). Some research suggests that supply-side factors may have been overlooked in explaining China's housing boom (79, 101).

However, although the Chinese Communist Party has a monopoly on the country's urban land supply, the impact of China's political institutions on its housing market is not fully understood. (29, 35) document that corruption is an important consideration in primary market land auctions. Additionally, previous studies also highlight the significance of land financing in local government, and it is proposed that local governments' fiscal pressure is the most prominent political economy factor of residential land supply (82; 130; 131). This chapter is based on an alternative hypothesis where city leaders' career incentive drives land supply decisions. The career incentive channel builds upon the literature regarding the political tournament in China. Politicians are constantly ranked by their relative performance among their peers using the principle of *yardstick competition* in China (160, 134), and we show that evaluating city leaders based on relative economic performance within provinces has important implications for land supplies and housing price growth.

Thirdly, the study reveals the intricate competition dynamics among local governments and its potential effect on economic growth and local welfare. This supplements current research on state subsidies used to lure businesses. In our hypothesis, low industrial land price is a natural result of local governments' GDP competition; city governments essentially subsidize the price of land to the production sector. Interestingly, a parallel phenomenon is also drawing attention in the U.S. at the state level. (164) show that in the U.S., state governments use subsidies to attract large firms, which increases local welfare in the form of indirect job creation; however, the welfare gain is captured entirely by the firm. In the same vein, this chapter finds that the production sector compromises residents' welfare induced by housing. The welfare transfer from residents to firms could be higher than our simple model suggested since the government interventions also boost the impact of positive productivity shocks on housing price appreciation (181).

This chapter has important policy implications for China's housing market, particularly in light of the Chinese government's efforts to address the problem of an overheated market. The implementation of the Supply-side Structural Reform Policy in 2016 aimed to improve the efficiency of the housing market by increasing the supply of high-quality housing while reducing the supply of low-quality housing. Our study highlights the need for policymakers to consider the impact of the promotion system on the housing market and devise appropriate strategies to ensure a balanced allocation of land resources.

2.2 Institutional Background

2.2.1 The Chinese Communist Party's Hierarchical Structure and Leadership Roles

The CCP's political structure is organized into four different levels of administration, as depicted in the *political pyramid* in Figure 9. At the top of the pyramid is the central party committee. The CCP's central party committee is responsible for making major policy decisions and overseeing the work of the lower levels of administration. The committee comprises 25 Politburo members, the highest-ranking officials in the CCP. Among the Politburo members, seven hold the top leadership positions in the party, including the General Secretary, the most powerful figure in the CCP.

The provincial party committees are responsible for implementing the policies set by the central committee in their respective provinces. Each of the 34 provincial-level administrative units has a corresponding provincial CCP committee, which the provincial party secretary leads. The provincial party secretaries are among the most powerful officials in the CCP, and they play a critical role in implementing national policies at the local level.

The prefectural-level cities are the third level of administration in the CCP's political structure. Each province comprises 4 to 21 prefectural-level cities, and each city has a corresponding CCP committee responsible for local policies, including land allocation decisions. The city party secretaries lead their respective city governments and are responsible for implementing the policies set by the provincial party committee. Our paper focuses on the land allocation decisions made by the city-level party secretaries (henceforth *city leaders*) given their career incentives.

While the personnel of each party committee is de jure elected by a party Congress, the decision-making process is heavily influenced by the CCP leadership one level of administration above. The provincial party committees, for example, have significant control over the appointment, promotion, and demotion of city leaders within their jurisdiction.

In addition to GDP performance and demographics, social ties and personal relationships play a critical role in the CCP's promotion decision-making process. Party officials with close personal relationships to higher-ranking officials are often favored for promotion over those with stronger professional qualifications.

2.2.2 The Chinese Land Market

Overview

After gaining control in 1949, the Communist Party of China nationalized land ownership in mainland China and started to provide highly subsidized housing to Chinese citizens. The socialist policies led to both under-investment and shortage in housing supply and were eventually torn down during waves of large-scale property privatization since 1978. The central government of China embraced and pushed a series of housing reforms from the 1980s and finally established a market-based housing provision system in 1998. The land supply, in turn, has been a major component in developing the Chinese real estate market. Indeed, alongside the spectacular housing boom, China's land market also experienced striking growth in price ever since the start of land and housing privatization in 1998 (Figure 6). The total land sales revenue grew by 1,597% in the ten years following the 1998 reform (around 160% annually) and amounted to 1.7 trillion RMB in 2014.

Land Quota System and Land Supply

Starting in 1998, China adopted a land quota system regarding urban land supply.[2] On the national level, the Ministry of Land Resource Management drafts long-term plans for urban land development and arable land protection. In this long-term plan, each province is then allowed a certain amount of rural-to-urban land conversion for a period of time. The department of land resource management of each provincial government, following guidelines set by the Ministry of Land Resource Management, then divides this land conversion quota among cities in its jurisdiction. One example of such a guideline set by the Ministry of Land Resource Management is that land quota allocation should be proportional to a city's GDP and projected population growth (173). Within this assigned land quota, the city land development committee, headed by the communist leader of the city government, decide on the type of use (industrial, residential, commercial, and others), price, size, etc., of land parcels for lease. The city government then posts land parcel information online, looking for land renters. In a case where multiple renters have expressed interest in purchasing the usufruct right for a land parcel, the land is then sold through a public auction (29). In summary, from the standpoint of city leaders, he (she) decides on the ratio of industrial land supply and residential land supply, given the fixed quota.

Different types of land parcels are leased out for varying time lengths. Residential land is rented out for 70 years, industrial land for 50 years, and commercial land for 40 years. Categorized by the kind of activities legally allowed, there are four types of land uses: industrial, residential, commercial, and others. Industrial land can only be used for industrial production purposes. Residential land is used for housing projects. Commercial land hosts businesses such as shopping malls and offices. Other land uses include government buildings, parks, etc. Figure 7 plots the composition of land supply in China between 2003 and 2016 by land use type. The omitted categories are water facilities, transportation, and special-purpose land. Throughout this period of time, industrial and residential land supply take the lion's share of the total land supplied. Commercial and public service land is a small share of the total during this sample period.

Under very restrictive conditions, land renters are permitted to resell the leasehold to a third party in the secondary land market. However, compared to the primary land market, the secondary land market is only about 3.75% of all land transactions in terms of payment from 2000 to 2015 (36).

2.2.3 The 1994 Tax Sharing Reform

In 1994, the CCP implemented a tax-sharing reform that led to fiscal decentralization. While sharing more fiscal revenue with the central government, local governments obtained financial and budgeting autonomy after the reform. By allowing local governments to make independent fiscal expenditure decisions while maintaining control of the tax code at the central level, the reform

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[2] (173) provides a detailed summary of China's land quota system.

spurred economic competition among local governments for fiscal revenue. However, it is also blamed for leaving heavier financial burdens to local governments and making the local fiscal authority more dependent on land sales revenues to make ends meet. As land is deemed a state-owned asset, local Chinese governments have grown a strong dependence on land financing over time (Figure 8). Meanwhile, following the 1994 tax reform, local governments have been increasing reliance on transfer payments from the central government to finance local fiscal expenditure. In 2003, the land market reform took place and reshaped China's land markets to public auctions and sales so as to improve market transparency; land sales revenue and land-related taxes have since been expanding at an astonishing rate in local governments' fiscal budgets. Land financing accounts for a third of local government fiscal revenue, at par with central transfers and local government in-budget revenue (taxes and fees).

Motivated by the peculiar phenomenon of land financing, many works have argued in the past a fiscal pressure channel through which the GDP-based promotion evaluation spills over into China's house prices. The argument states that local communist leaders' career incentives encourage increasing local fiscal spending on infrastructure, driving up GDP through the public sector. Depending on the perceived elasticity of local residents' housing demand, city leaders would then either increase or decrease residential land supply to raise land sales revenue or boost GDP growth, hence affecting house prices. In Section 2.3, we analyze this alternative channel using our theoretical framework. We further show in Section 2.5 that the empirical evidence is not in accordance with this channel. Our estimates for China's residential land demand are close to unit elasticity, breaking the fundamental assumption of the fiscal pressure channel.

2.3 Model

This section sets up a perfect foresight general equilibrium model of a small open economy with three agents: a representative firm, a representative household, and a city leader. **Subsection C** demonstrates this paper's newly proposed mechanism through which China's GDP-based promotion system for city leaders contributes to house price appreciation. **Subsection D** further studies, in the same framework, alternative mechanisms that previous works have conjectured. Besides showcasing the mechanisms of the political economy perspective, the model provides a theoretical framework that guides the empirical exercise detailed in later sections.

A city is a static small open economy with four agents: a representative firm that is competitive and produces a homogeneous consumption good (numeraire) using capital, labor, and industrial land; a representative household that supplies labor inelastically, and consumes numeraire good along with housing services; a city leader who decides on land allocation between residential and industrial uses subject to a quota on the total land supply; and finally a continuum of monopolistically competitive real estate developers. In equilibrium, wage, residential land price, and industrial land price adjust so that labor and land markets clear locally.

A representative firm is competitive and produces a homogeneous consumption good (numeraire) using capital, labor, and industrial land, with a constant returns to scale production technology

$$\max_{K,L,D} AK^{\alpha}L^{\beta}D^{1-\alpha-\beta} - rK - wL - p_{ind}D.$$

Firm knows productivity A, which is a constant, and maximizes profit by choosing the amount of capital K rented from the global capital market, labor L hired from the local labor market, and the amount of industrial land D purchased from the local city government that is managed by the city leader. The firm takes the rental rate of capital r, wage w, and industrial land price p_{ind} as given.

Profit maximization suggests the marginal product of capital equals rental rate of capital in equilibrium. Hence, in equilibrium

$$K = (\frac{\alpha A}{r})^{\frac{1}{1-\alpha}} D^{\frac{1-\alpha-\beta}{1-\alpha}}, \tag{2.1}$$

where equilibrium labor demand, implied by local labor market clearing conditions, equals the city population (normalized to be 1).[3] Equation (1) then implies the equilibrium production is

$$Y(D) = A^{\frac{1}{1-\alpha}} (\frac{\alpha}{r})^{\frac{\alpha}{1-\alpha}} D^{\frac{1-\alpha-\beta}{1-\alpha}} = \Gamma D^{\gamma} \tag{2.2}$$

where

$$\Gamma = A^{\frac{1}{1-\alpha}} (\frac{\alpha}{r})^{\frac{\alpha}{1-\alpha}}$$

$$\gamma = \frac{1-\alpha-\beta}{1-\alpha} \in (0, 1).$$

Equation (2) suggests that equilibrium production is increasing in the amount of industrial land in the economy.

A representative household consumes numeraire good and housing services, with Cobb-Douglas utility

$$u^h(C, H) = C^{1-\eta}H^{\eta},$$

where C is the amount of numeraire good, and H is housing services. The household supplies labor and earns post-tax labor income $(1-\tau)wL$ to finance his (her) consumption bundle. By choosing the amount of numeraire good to consume, and the amount of residential land to purchase from the city government, the household maximizes utility subject to budget constraint

$$C + pH = (1-\tau)wL.$$

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[3] By normalizing city population to be 1, the model abstracts away from inter-city migration. An argument that can be made against this abstraction is that expensive living costs of a city deter labor migration, which could impede economic growth. However, labor has been relative abundant in China in this period of time. Also, China's inter-city migration policy has been notoriously restrictive, as documented in (182).

The household problem first order conditions imply that housing demand has a constant elasticity $-\epsilon$

$$p = H^{-\frac{1}{\epsilon}},$$

and the equilibrium household welfare is obtained by substituting in equilibrium housing and numeraire consumption

$$v^h(D,H) = \frac{1}{\epsilon - 1} H^{1-\frac{1}{\epsilon}} + \beta(1-\tau)Y(D), \tag{2.3}$$

where $\beta(1-\tau)Y(D)$ is the equilibrium wage rate.

Equation (3) shows that even though in equilibrium household benefits from boosted industrial land supply through a higher wage rate, suppressed residential land supply can lead to welfare losses due to low housing consumption.

There is a continuum of monopolistically competitive real estate developers $j \in [0,1]$ offering housing within the city: $H = (\int_0^1 h_j^{\frac{\epsilon-1}{\epsilon}} dj)^{\frac{\epsilon}{\epsilon-1}}$. Real estate developers convert residential land N_j into housing services H_j via a linear technology $H_j = \xi N_j$ ($\xi > 0$).

A city leader maximizes utility by allocating ζ unit(s) of land between industrial and residential uses

$$N + D = \zeta, \tag{2.4}$$

Where N is the amount of land allocated for residential housing and D is the amount of land allocated for production.

Preferences of the city leader compose of household welfare, government consumption, as well as expected payoff from promotion.[4] The leader has rational expectations about the equilibrium outcomes; therefore, the leader's preferences can be expressed as

$$u^g(D,N) = \underbrace{v^h(D,H)}_{household\, welfare} + \Omega \underbrace{log[F(D,H)]}_{utility\, from\, fiscal\, income} + \underbrace{E[V^P]}_{expected\, promotion\, payoff}, \tag{2.5}$$

where household welfare $v^h(D,H)$ is defined in equation (3). Ω denotes the weight on government consumption, and government consumption is financed by taxes levied on capital and labor incomes plus land sales

$$F(D,H) = \underbrace{\tau(rK + wL)}_{tax\ revenue} + \underbrace{pH}_{residential\ land\ sales} + \underbrace{p_{ind}D}_{industrial\ land\ sales}. \tag{2.6}$$

Following (179), we impose the same tax rate on capital and labor incomes for simplicity. However, allowing tax rates to differ will not change conclusions of the model.

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[4] The interpretation of government consumption can be flexible. Public employee wages, infrastructure investments, or even corruption are all fair interpretation of government consumption in this model.

Promotion outcome is a Bernoulli random variable where the payoff from promotion has been normalized to 1.[5] The probability of being promoted is a function of local GDP, $Y(D)$, as defined in equation (2).[6]

$$V^P = \begin{cases} 1 & \text{w/ prob. } \mathcal{P}(Y(D)) \\ 0 & \text{otherwise} \end{cases}$$

We further assume that the promotion probability is linear in GDP

$$\mathcal{P}(Y(D)) = \chi Y(D),$$

then government preferences can be re-written as

$$u^g(D,H) = v^h(D,H) + \Omega \frac{[F(D,H)]^{1-\sigma}}{1-\sigma} + \chi Y(D), \tag{2.7}$$

where χ is called *GDP concern* since χ is the weight on local GDP performance. The city leader's utility maximization problem can be summarized by equations (3), (4), (6), and (7).

An equilibrium consists of prices (w^*, p^*_{ind}, p^*) and allocation $(K^*, L^*, D^*, H^*, C^*)$ such that:

- Given equilibrium prices, (K^*, L^*, D^*) solves firm's profit maximization problem.
- Given equilibrium prices, (H^*, C^*) maximizes household utility subject to budget constraint.
- $(p^*, p^*_{ind}, D^*, H^*)$ solves city government's monopoly problem.
- Labor and land markets clear.

Theorem 1. ***Existence and Uniqueness.*** *An equilibrium exists. When productivity A is sufficiently high, the equilibrium is unique.*

Proof. See Mathematical Appendix. □

2.3.1 GDP Concern and House Prices

China's GDP-based promotion system for local leaders amplifies concerns over local economic performance. Compared to political systems in which the leader's objective is forced to align with constituents' well-being, such as democratic election, a GDP-based promotion system is much more prone to the classic principal agent problem. One of the unintended consequences of having such a promotion system is incentivizing local leaders to pursue exceissve economic development, even when

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[5] This normalization is innocuous from a modeling perspective, because relaxing this assumption will not make any difference to the trade-off that the city leader faces.

[6] China's GDP statistics do not include land sales because governments are not economic entities. House sales. however, are included in GDP statistics. We decide to exclude GDP generated from house sales in the model for house sales are not a major component in GDP for the majority of cities. See figure...

economic advancement comes at the cost of local residents' welfare. Combined with China's unique institutional setup that local government is the sole supplier of land in an city, such an unintended consequence manifests through city leaders' distorted preferences over industrial and residential land supply, adding fuel to the already spectacular Chinese housing boom.

Proposition 1. ***GDP Concern.*** *Residential land supply is decreasing in GDP concern χ.*

$$\frac{\partial H}{\partial \chi} < 0$$

Proof. See Mathematical Appendix. □

Facing immense pressure to boost local economy, the city leader responds by suppressing residential land supply in favor of industrial land supply, in an attempt to drive up local GDP. The city leader weights between local resident welfare and promotion likelihood. As *GDP concern*, χ, increases, the leader's marginal utility from expected promotion increases relative to the marginal utility from resident welfare, causing higher land allocation to industrial uses.

Corollary 1. *House price is increasing in GDP concern χ.*

$$\frac{\partial p}{\partial \chi} > 0$$

Higher *GDP concern*, χ, leads to higher industrial land supply and lower residential land supply. A direct consequence is elevated residential land price/house price, as residential land in the economy becomes scarcer.

To summarize, China's GDP-based promotion system induces city leaders to favor industrial land supply over residential land, leading to high house prices. The main challenge for identifying the proposed channel lies in measuring *GDP concern*. Previous works have resorted to age, job tenure, etc. as proxies. This paper not only offers an alternative measurement of *GDP concern*, χ, but also a new way to causally identify its effect using exogenous movements in χ. The next section illustrates the intuition behind this paper's empirical strategy in measuring *GDP concern*, χ.

2.3.2 Alternative Mechanism: Fiscal Pressure

Previous literature has conjectured alternative mechanisms in which China's GDP-based promotion system can affect China's house prices. These alternative mechanisms argue through local governments' budget constraint. This section illustrates how the model incorporates these alternative mechanisms and derives testable implications of these alternatives.

There are two major alternatives that attempt to explain local governments' land allocation behavior. Both mechanisms argue that China's GDP-based promotion evaluation prompts local governments to invest in infrastructure so as to boost the local economy. In other words, the GDP-based promotion system creates fiscal pressure on local governments. In the model's language, $\Omega = \chi$ in local government preferences. Local government directly intervenes in the local economy rather than inducing private sector production activity through land allocation. Hence, the alternative mechanisms correspond to the following government preferences

$$u^g(D,H) = v^h(D,H) + \Omega \frac{[F(D,H)]^{1-\sigma}}{1-\sigma}, \tag{2.8}$$

However, the two alternative mechanisms disagree on how land and housing markets are affected. Alternative 1 assumes elastic residential land demand and states that local governments increase residential land supply to increase residential land sales. Local governments then use residential land sales revenue to invest in infrastructure projects. Alternative 2 assumes inelastic residential land demand. Under this assumption, local governments have incentives to suppress residential land supply to raise residential land sales revenue which can be used to finance infrastructure investments.

Alternative 1 predicts the opposite land allocation behavior to this paper's mechanism. Under alternative 1, residential land supply increases in $\Omega = \chi$. As shown in the empirical results section, this prediction is not correct, casting doubts on alternative 1.

Alternative 2 can generate the same land allocation behavior as the mechanism proposed in this paper. Residential land price increases in χ, whereas residential land supply decreases. However, a unique implication of alternative 2 that distinguishes itself from this paper's mechanism is that residential land sales are increasing in $\Omega = \chi$.

Proposition 2. ***Fiscal Pressure.*** *Assuming inelastic residential land demand, residential land sales are increasing in the weight on government consumption, Ω.*

$$\frac{\partial}{\partial \Omega} pH > 0$$

Proof. See Mathematical Appendix. □

As shown in the empirical results section, this prediction is not true, undermining the validity of the fiscal pressure channel.

2.4 Data

In this section, we first detail the data collection process of Chinese politicians' biographical data, followed by procedures we employed to construct the measure of political promotion. We then explain city-level real estate, land supply, and other macroeconomic data from various sources and present relevant descriptive statistics.

2.4.1 Political Data

We combine two sources of data to construct our sample on Chinese politicians. Our main source of political data, the Chinese Political Elite Database (CPED), contains extensive demographic information for provincial/prefectural politicians.

Politicians in CPED include all city party secretaries and mayors between 2000 and 2015, all standing committee members between 2000 and 2012, all provincial party secretaries and governors between 1995 and 2015, and all other full and alternate CCP Central Committee members between 1997 and 2012. We manually extend CPED to 2015 to include all prefectural, provincial, and national leaders of interest.[7]

CPED provides information on start and end dates, places of work, employer names, and political ranks of all job assignments during each politician's career. CPED is hand-collected from government websites, yearbooks, and other creditable online sources. We verify biographical information in CPED using a mainstream commercial and political database in China, the Provincial and City Leader Database (PCLD), maintained by China Stock Market & Accounting Research Database. To account for the misinformation in CPED, whenever there is a disparity between CPED and PCLD, we manually check and correct the underlying data with a third source, e.g., the official website of the Chinese government, and verified pages from the Chinese equivalent of Wikipedia (Baidu Baike).

In short, we observe the universe of all city and province party committee leaders who assumed office between 2001 and 2015. For each leader, we obtain his/her biographical information and the entire career path, including educational background. There are 1,636 city-term observations between 2001 and 2015, which map to 1,302 Chinese politicians.

Promotion

The Chinese government is a highly unitary institution; instead of elections, promotions of provincial and prefectural politicians are decided by government officials of higher political ranks. The power structure of Communist Party of China is best characterized as a pyramid (Figure 9). At the top are the 25 central CCP Committee members (Politburos), followed by the provincial CCP Committee members (13 members each, 34 provincial divisions in total), and then the prefecture (city) level CCP committee members (10-11 members each, 334 prefecture divisions in total). The political trajectory of these leaders are predictable in the sense that local leaders are generally promoted up the power ladder level by level. County leaders with better performance are promoted into the city committee, then provincial committee if promoted again, and eventually into the central committee. The tournament for promotion is only at the local regional level; in other words, a city

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[7] We focus on the period before 2015 because since 2016, the Party Central Committee led by Xi Jinping has designated "housing is for living, not for speculation" as a long-term national strategy, and as a result, various local policy restrictions have been implemented to curb housing prices.

leader's performance is evaluated relative to other city leaders' from the same province. We focus on city leaders in this paper and follow a simple rule of thumb to construct our promotion data, based on the explicit political hierarchy in China[8]: based on the observed career path of politicians in data, we define that a government official is promoted if he is appointed to a new position with a higher political rank within three months after the end date of term-in-office.

About 56 city leaders are fired during his/her political career. One common reason for dismissals is corruption, which could introduce biases to our estimates (29, 63). We exclude those politicians from the main analysis.

Promotion for Local Communist Leaders

There has been an extensive literature on the Chinese government's personnel control. (126) find that for the turnover of provincial leaders, annual GDP growth rate, age, education, central connections, and years in office are among the most influential factors. We impute city-level politicians' expected promotion probabilities as a linear projection using these key variables.

2.4.2 Real Estate Data

We obtain urban planning and land sales data aggregated at city level from China Real Estate Index System (CREIS) database maintained by China Index Academy. CREIS collected land transaction data from the Ministry of Land and Resources, and local Land Reserve Centers.

We restrict our sample period from 2003 since the marketization of urban land supply in China took off in that year. Information available in CREIS includes acreage, price and land use type for each parcel of land.

2.4.3 Macroeconomic Series

National Bureau of Statistics of China (NBS) maintains annual macroeconomic series on city-level. For each city, we collect population (measured by usual residence), government in-budget revenue, total city-wide deposit, average wage, GDP, residential prices, secondary industry GDP, tertiary industry GDP, fixed investment, floor area sold for residential building, residential housing prices, and real estate investment by year during 2003 and 2015. Summary statistics are reported in Table 7; all price-related variables are normalised to a base year using CPI published by NBS.

2.5 Empirical Results

In this section, we show evidence that the promotion evaluation for city level communist leaders is based on economic performance. We then test implications of our model using data introduced.

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[8] The literature on Chinese promotion system has not yet reached a consensus on the definition of promotion (169); ambiguity is largely from the ambivalent orders of precedence in China. The orders of precedence for Chinese political leaders is not formally published, and varies both by person and by the period of time. However, the Chinese government also has a regimented system of political ranks, which can serve as a rough order of precedence when dictating official protocol when multiple officials attend same events and are adopted here for our empirical exercise.

Our empirical findings confirm that the career incentive channel spills over into house prices through the land use type allocation margin. At last, we investigate the fiscal pressure channel, but we do not find supporting evidence for this alternative.

2.5.1 GDP, Promotion, and Hometown Tie

To study China's promotion system for city leaders, we regress promotion outcome at the end of the term on GDP performance, hometown tie, and their interaction

$$Y_{i,t} = \beta_0 + (\beta_1 + \beta_2 HometownTie_{i,t}) \times \text{GDP Growth}_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{2.9}$$

where $Y_{i,t}$ is a promotion dummy for leader i in year t. GDP growth is defined as the annualized GDP growth rate from when the leader took office until the term ended.

Hometown tie is an indicator variable that takes the value one if and only if the following scenario happens: during the city leader's term, the central government appoints a new provincial leader to the province in which the city leader works; and, the newly appointed provincial leader has the same city of birth as the city leader.[9] As mentioned, city-level Chinese politicians' promotion decisions are made by higher level communist officials in the same province. The appointments of new provincial leaders during the city leader's term is made confidentially by the central communist committee, and hence unexpected by the city leaders in office. To avoid the possibility that a provincial leader might have favored his hometown comrades and hence appointed city leaders endogenously, we restrict our definition of hometown tie to the city leaders who already assumed office when the tie is established (i.e., the provincial leader is appointed *after* the city leader assumed office). The hometown connection is a special bond in the Chinese culture. The Chinese term *lǎoxiāng* is a phrase to describe people who share the same hometown, regardless of whether they have known each other in the past. As the ancient saying goes, *lǎoxiāng* burst into tears when they meet, which illustrates the special bond between people who share the same birthplace. We therefore conjecture that sharing hometown with the provincial communist leaders shifts city communist leaders' promotion probabilities, and hence changes their career perspectives.

β_1 indicates the correlation between GDP growth and promotion outcome, in the absence of any hometown tie. β_2 captures the effect of hometown tie on the sensitivity of promotion to GDP growth. A positive β_2 indicates that the effect of GDP on promotion is enhanced in the presence of a hometown tie, whereas a negative estimate for β_2 means a hometown tie diminishes the effect of GDP growth on promotion.

A comprehensive set of fixed effects have been included to control for unobserved characteristics that might affect a leader's promotion probability beyond the GDP-promotion linkage. City

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[9] Unlike in the U.S., the vast majority of city leaders are not local to the cities they govern. Between 2003 and 2015, only 5% of city leaders were born in the same city they managed. Only 0.5% leaders had a hometown tie and were local.

fixed effects take out level differences among different cities in the likelihood that their leaders are promoted. With Province-Year and turnover fixed effects, our estimates compare city leaders who assumed their posts in the same year and who were evaluated by the same provincial committee and in the same year. We further include demograhic controls such as age and gender, which previous studies have argued to be important factors in promotion considerations (173). Last but not least, to address the concern that hometown tie might pick up leadership qualities that people of certain regions possess, we include birth province fixed effects. In column (2), we control for the rank of a city leader, given the possibility that leaders of different ranks have different promotion chances. In column (3), we further control for whether a city leader ever faced a disciplinary action. The estimates of interest, namely, the coefficients for GDP growth, hometown tie, and their stay precisely estimated across all specifications.

Higher GDP growth is associated with a greater likelihood of being promoted. Column (3) in Table 8 shows that growing a city's annualized GDP by 10 basis point more can lead to a 6 percent increase in the leader's promotion probability in the absence of a hometown tie.

A hometown tie tremendously reduces the importance of GDP performance in someone's evaluation for promotion. As the estimates in column (3) show, having a hometown tie cuts the sensitivity of promotion to GDP by 3.416. In fact, the sum of β_1 and β_2 are not statistically significant from 0. The null hypothesis that hometown tie completely obviates the importance of GDP growth to a leader's promotion outcome is not rejected under a Wald test at a 0.1 significance level.

Hometown tie itself boosts a city leader's promotion probability. In columns (2) and (3), the estimates for the hometown tie dummy is positive and statistically significant at a 0.01 significance level. Literature on the promotion system for Chinese communist leaders is still debating between hometown favoritism ((120) and (67)) and faction control (68). The estimates provided here support the hometown favoritism hypothesis among the city-level communist party leaders.

To summarize, Table 8 suggests that GDP growth and its interaction with hometown ties are important factors in a city communist party leader's promotion decision. Developing a city's economy greatly boosts a city leader's promotion probability. A hometown tie, however, substantially diminishes the importance of GDP growth to the leader's promotion outcome.

2.5.2 Reduced Form Analysis

This section studies the effect of career concern, χ, on housing market and land markets. We regress real estate market outcomes on hometown tie status of city i in year t.

$$Y_{i,t} = \beta_0 + \beta_1 Hometown\,Tie_{i,t} + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{2.10}$$

The outcomes studied include land allocation ratios, land prices, and house price growth rate. The key coefficient is β_1 in front of hometown tie.

A rich set of controls and fixed effects have been added to check the robustness of the estimates. The full set of controls: (log) GDP, (log) resident population, (log) government in-budget fiscal revenue, and (log) government in-budget fiscal expenditure are included cumulatively as robustness checks. The first two controls are to test whether the hometown connection are correlated with conventional factors that affect real estate markets, like GDP and population. Throughout, estimated coefficients for hometown tie remain precisely estimated and almost identical in magnitude. The fact that estimation results barely change in the process of adding in full control variables suggests that GDP, population, and government fiscal conditions are not driving the estimation results.

Reverse causality related endogeneity is not a major concern either. For a reverse causality argument to go through, a city's housing/land market conditions must prompt the politburo to appoint a candidate who shares the same hometown as the city leader. This scenario is not very likely.

The possible endogeneity concern here comes from anticipation of hometown ties. It would be a serious concern if real estate markets react in anticipation of a hometown connection. If this was true, then our estimates would be biased towards zero. Although this is an unlikely scenario given that provincial communist party committee personnel is managed by the 25 Politburo members, we address possible concerns in this regard by checking the pre-trend among cities experiencing hometown ties and the rest.

Hometown Tie and Pre-trend of House Price

To address the concern that hometown tie formation is expected by the city leader or that cities with a hometown tie might be different from the ones without, this section shows that the five year pre-trend of house price in cities with hometown tie is not different from cities without a hometown tie.

Cities experiencing a hometown tie are assigned to the treatment group. The year in which a hometown forms has been normalized to be 0. -5 to -1 corresponds to the five years before the hometown tie establishment. A city-year pair, in the same province as the treatment city is in the control group if and only if the city's leader in that year has no hometown tie throughout the entire term in office. The two groups in each province are then aggregated across provinces.

Figure 11 shows that cities that receive a hometown tie do not show a different path of house price compared to their same-province counterparts who do not have a hometown tie. In other words, hometown tie is not selectively given to cities that have already been experiencing declines in house price growth before the tie formation. Neither do city leaders who experience the hometown tie foresee the formation.

Housing Market

Table 9 summarizes the estimated effect of hometown tie on a city's house price growth rate. The effect of hometown connection is captured by establishing a shared hometown between a city leader and the corresponding province leader in the year before to capture the slow-moving nature of residential land being converted into housing supply. In columns (1) to (3), (log) GDP, (log) resident population, and government fiscal conditions are added gradually to check the robustness of the estimates. Throughout all specifications, the estimate for hometown tie remains robust and similar in magnitude.

Table 9 suggests the hometown tie channel plays a large part in China's house price boom. Column (3) suggests that establishing a hometown tie decreases the house price growth rate by 4.9 percentage points. Given that the average annual house price has been growing at 9%, column (3) estimates suggest the career incentive channel proposed in the paper is quantitatively important in understanding China's real estate boom.

Land Market

This section focuses on how a city leader's land allocation behavior changes with hometown ties. As stated in **Proposition 1**, an increase in career concern suppresses residential land supply but elevates industrial land supply. Table 10 to **??** demonstrate precise and robust estimates that validate the model's implications.

As predicted by the model, residential land supply, measured as the ratio to total land supply, increases with hometown tie, whereas industrial land supply decreases. Estimates in column (1) of Table 6 indicate that introducing a hometown connection increases the residential land supply ratio by 5.6 percentage points and reduces the industrial land supply ratio by 5.7 percentage points.

In columns (2), (3), (5), and (6), (log) GDP, (log) resident population, (log) government fiscal revenue and expenditure are added. Estimates stay precisely estimated and remain almost identical in magnitude.

?? then investigates how land prices respond when the proposed career incentive channel is shut down. Accompanying increased residential land supply and decreased industrial land supply, the unit price of residential land drops by 21.3%, whereas the unit price of industrial land increases by 12.7%. These estimates on land prices stay robust and statistically significant as the full set of baseline controls are added to our estimation. Heterogeneity in Career Concern This section further substantiates the proposed career concern channel by exploring heterogeneity in career concern. The two sources of career concern considered are ethnic minority status and above-provincial rank. As shown in column (4) of Table 4, GDP-based promotion system does not apply to ethnic minority leaders. One would expect the proposed career concern channel to have reduced effect on housing and land markets for this group of leaders. On the contrary, above-provincial ranked leaders face more heated competition for promotion. Unlike prefecture or city ranked officials, provincial or politburo ranked city leaders are competing for scarce seats in the central government or the chance to become president. The proposed hometown tie channel should be enhanced for this group of leaders.

Table 9 studies how housing and land markets in cities led by either of this two group of leaders respond to hometown tie. As conjectured, movements in hometown tie do not change housing and land market conditions for ethnic minority leaders, but above-provincial leaders respond more drastically than prefecture/city ranked leaders. In columns (1) to (3), an interaction term between hometown tie and ethnic minority status is included to investigate how ethnic minority status changes the effect of the proposed hometown tie channel. As expected, even though hometown tie increases house price growth, suppresses residential land supply, and boosts industrial land supply, this is not the case for ethnic minority leaders. Sums of the coefficients for hometown tie reveal that the hometown tie channel does not have any economically meaningful impact on a city's housing and land markets if the city leader is exempt from the GDP-based promotion system due to ethnic minority status. On the other hand, for above-provincial ranked leaders, the effects of hometown tie on housing and land markets are amplified. As estimates in columns (4) to (6) suggest, compared to prefecture/city ranked leaders, hometown tie leads to higher house price growth, represses further residential land supply, and inflates extra industrial land supply if the city leader has provincial or politburo ranks. Controls in columns (1) to (6) are kept to a minimal amount due to small sample sizes of ethnic minority leaders and of above-provincial ranked leaders who experience a hometown tie within term.

2.6 Hometown Tie and Land Quota

This section further shows hometown tie is not correlated with land quota with regression analysis. Throughout all specifications, the estimated coefficients for hometown tie are not statistically different from zero.

Column (1) of Table 12 shows that the level of land quota does not move with respect to the presence of hometown tie, while city-term and year-fixed effects are controlled for. In other words, throughout a city leader's term, a hometown tie formation does not bring more land quota. In addition, we include province-year fixed effects in the analysis. So, the estimates also have the interpretation that cities with a hometown tie do not get more land quota than other cities in the same province during the same year. Overall, our analysis shows no significant effect of hometown tie to land quota allocation.

2.7 Conclusion

In this paper, we modeled the career incentive channel on house price growth. Our findings imply that policymakers should evaluate the CCP's promotion system to relieve ongoing concerns about China's housing market conditions. Taking advantage of the unique cultural background in China (hometown tie), we propose a novel identification strategy and deliver causal evidence that the career incentive channel is a major player in China's rapid house price growth. Through a static general equilibrium model, this paper has formally analyzed how the GDP-based promotion system in the CCP suppresses residential land supply and leads to house price appreciation. Researchers and scholars have not hitherto agreed on the factors driving China's house price appreciation. The lack of formal analysis of the connection between CCP's GDP-based promotion system and house price growth has retarded the understanding of the Chinese housing boom. Continued ascension in China's housing and residential land prices will undoubtedly cause further qualms over the state of China's financial sector and the Chinese economy. Our paper sheds light on the importance of political institutions in housing markets. It is shown that the CCP promotion system is key to understanding the spectacular Chinese housing boom and finding an effective solution to ease the ever-increasing uncertainty over China's land and housing market conditions.

Appendix A

Appendix for Chapter 1

A.1 Proofs

Proof of Proposition 1. The market-clearing condition of stock 2 (1.4) ensures stock 2's price comoves with stock 1's price by a coefficient weakly less than 1,

$$r_2 = \frac{\psi^C}{\psi^C + \psi^A} r_1.$$

Taking the difference between two market-clearing conditions (1.3), we easily observe that the return difference between two stocks is

$$r_1 - r_2 = \frac{\Delta Q_1^R}{\psi^A + 2\psi^C} = \frac{\omega(1-\theta)(r_B - r_1)}{\psi^A + 2\psi^C}$$

using the rebalancer's demand (1.1) in the last equality. When the rebalancer R ($q_1^R < 0$) applies additional pressure, stock 1's price drops more than stock 2's price.

Combining these two equations above gives rise to

$$r_1 = \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)} r_B,$$

with $\Psi = \frac{\psi^A + 2\psi^C}{\psi^A + \psi^C}\psi^A$. Other results in Proposition 1 follow naturally. $\square$

Proof of Proposition 2. Taking stock, the market-clearing conditions in period $t = 0, 1, ..., T-1$

are

$$\Delta Q^E_{1t} = \Delta Q^E_{2t} = 0.$$

It is then straightforward to obtain a recursive pricing formula using (1.9)

$$r_{it} = \frac{1}{1+\eta} r_{i,t+1},$$

in which $(1+\eta)$ parameterizes the forward-looking trait of asset prices. Combined with Proposition 1, this result leads to the instantaneous market price reaction to future rebalancing flow. $\square$

A.2 Theory Extensions

A.2.1 Return-Sensitive Rebalancer

In this appendix, we outline an extension of the two-period model described in Section 2.3. We show that with more general preferences of the rebalancer, the bond market does not need to revaluate more than the equity market to induce selling pressure for the stock in rebalancer's holding.

Assume the model has two periods $(t = 0, 1)$ and two stocks $(i = 1, 2)$ with stochastic dividends D_i as specified in Section 1.2.1. Denote the pre-shock returns of stock 1 and bond as $R_1 = \frac{D_1 + \bar{P}}{\bar{P}}$, and R_B. If unexpected monetary news following period 0 that revaluates the bond and stock 1 by r_B and r_1, since the markets go back to the steady state at period 1, then after revaluation, the post-shock returns are $R_1/(1 + r_1) - R_1 \approx -R_1 r_1$ for stock 1, and $R_B/(1 + r_B) - R_B \approx -R_B r_B$ for the bond.

Instead of having a fixed target, suppose the rebalancer R is sensitive to the equity premium and has the propensity to buy riskier bonds to achieve higher yields, following the notions in (38, 39) and (73). His demand function for equity is governed by

$$\frac{P_1 Q^R_1}{W^R} = \theta \mathrm{e}^{\kappa_\pi(-R_1 r_1 + R_B r_B) + \kappa_B R_B r_B},$$

where θ represents the target share for stock 1, subject to the rebalancer's sensitivity to equity risk premium $(-\mathcal{R}_1 r_1 + \mathcal{R}_B r_B)$ and a reaching-for-yield term $\kappa_B \mathcal{R}_B r_B$. Collecting terms, we have

$$\frac{P_1 Q^R_1}{W^R} = \theta \mathrm{e}^{-K_\pi r_1 + K_B r_B}, \tag{A.1}$$

where $K_\pi = \kappa_\pi R_1$ and $K_B = (\kappa_B + \kappa_\pi) R_B$. This demand function nests the rebalancer in Section 1.2.1 where the investor has a stringent fixed share mandate θ, and does not react to the risk premium and risk-free rate. If the rebalancer reaches for yield after an interest rate shock $(\kappa_B > 0)$, the rebalancer increases his riskless holdings for a positive interest rate shock.

The rebalancers demand change is now, in log and in level, respectively,

$$\begin{aligned}\Delta q_1^R &= (1-\theta)(r_B - r_1) + K_\pi(-r_1 + r_B) + K_B r_B,\\ \Delta Q_1^R &= \omega\left[(1-\theta+K_\pi+K_B)r_B - (1-\theta+K_\pi)r_1\right]. \end{aligned} \tag{A.2}$$

Upon surprise monetary tightening, for the rebalancer to have selling pressure for stock 1, we need $(1-\theta+K_\pi+K_B)|r_B| > (1-\theta+K_\pi)|r_1|$. It is of interest for future research to estimate these return sensitivity parameters κ_π and κ_B with more granular data on bond holdings of rebalancing institutions.

Proposition 3 (Cross-sectional and aggregate returns with return-sensitive demand)**.** *In this two-period model, when a bond revaluates by r_B due to monetary policy changes, the price changes in stocks relative to pre-shock levels denoted by r_1, r_2 are*

$$r_1 = \frac{\omega(1-\theta+K_\pi)}{\Psi+\omega(1-\theta+K_\pi)} r_B + \frac{\omega K_B}{\Psi+\omega(1-\theta+K_\pi)} r_B, \tag{A.3}$$

$$r_2 = \frac{\psi^C}{\psi^C+\psi^A} r_1, \tag{A.4}$$

with $\Psi := \frac{\psi^A+2\psi^C}{\psi^A+\psi^C}\psi^A \in (\psi^A, 2\psi^A)$. The aggregate price reaction is $\bar{r} = \frac{r_1+r_2}{2}$. Consequently,

(a) the return difference between two stocks is larger if the rebalancer owns more of stock 1's shares

$$\frac{\partial^2(r_1-r_2)}{\partial r_B \partial \omega} > 0, \tag{A.5}$$

(b) the aggregate stock price reaction $\bar{r}$ and the cross-sectional return difference $r_1 - r_2$ satisfy

$$\bar{r} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_1 - r_2). \tag{A.6}$$

Proof of Proposition 3. Combining the rebalancer's demand (A.2) with the equity arbitrageur's demand (1.2) specified in Section 1.2.1, the market-clearing prices for stock 1 and 2 are given by

$$\begin{aligned} r_1 &= \frac{\omega(1-\theta+K_\pi)}{\Psi+\omega(1-\theta+K_\pi)} r_B + \frac{\omega K_B}{\Psi+\omega(1-\theta+K_\pi)} r_B,\\ r_2 &= \frac{\psi^C}{\psi^C+\psi^A} r_1. \end{aligned}$$

Note that the first term in r_1 features two forces, the rebalancing pressure and the arbitraging activities, which extends the result in Proposition 1 to include the demand sensitivity to risk premium

K_π. The second term parameterizes the rebalancing price pressure from the additional reaching-for-yield incentive.

From the equilibrium prices of stock 1 and 2, it follows that the aggregate stock price reaction is

$$\bar{r} = \frac{r_1 + r_2}{2} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_1 - r_2). \tag{A.7}$$

□

We conclude that allowing for rebalancer's demand dependent on returns going forward does not change the ratio between the aggregate price reactions and cross-sectional return differences. Intuitively, the cross-sectional return differences relate to the aggregate market reaction through the substitutability between stocks 1 and 2. The primitive rebalancing force governs the magnitude of rebalancing demand, while the strength of arbitrage pins down the cross-sectional return differences relative to the aggregate price reaction.

A.2.2 Varying Dividends and Funding Costs

Here we extend the model to accommodate responses in dividends and funding cost to monetary shocks. In addition bond revaluation r_B, assume that monetary shock changes the expected dividend in period 1 by ΔD and the funding cost by $\Delta\eta$. Now we analyze two investors' demand.

1. As the rebalancer (R) is subject to the fixed allocation rule between stock 1 and bond, his demand is the same as in the baseline model,

$$\Delta Q_1^R = \omega(1-\theta)(r_B - r_1). \tag{A.8}$$

2. The equity arbitrageur (E) has a demand of $Q^E = \Gamma^{-1}\Sigma^{-1}\mu$ from her mean-variance maximization with share $Q^E = \left(Q_1^E, Q_2^E\right)'$ and expected return per share $\mu = [\bar{D} + \Delta D + \bar{P} - (1 + \eta + \Delta\eta)P_1, \bar{D} + \Delta D + \bar{P} - (1 + \eta + \Delta\eta)P_2]'$. Her demand (in shares) of stock i is

$$Q_i^E = \frac{\bar{D} + \Delta D + \bar{P} - (1+\eta+\Delta\eta)P_i - \rho\left[\bar{D} + \Delta D + \bar{P} - (1+\eta+\Delta\eta)P_{-i}\right]}{\Gamma(1-\rho^2)\sigma^2},$$

in which P_{-i} is the other stock's price. In response to small changes in prices $P_i = \bar{P}(1 + r_i)$, dividends ΔD and the funding cost $\Delta\eta$, the change in demanded shares is

$$\begin{aligned}\Delta Q_i^E &= \frac{\Delta D - \Delta\eta\bar{P} - (1+\eta)\bar{P}r_i - \rho\Delta D + \rho(1+\eta)\bar{P}r_{-i} + \rho\Delta\eta\bar{P}}{\Gamma(1-\rho^2)\sigma^2} \\ &= -\psi^A(r_i - \check{r}) - \psi^C(r_i - r_{-i}),\end{aligned} \tag{A.9}$$

with $\psi^A := \frac{(1+\eta)\bar{P}}{\Gamma(1+\rho)\sigma^2}$, $\psi^C := \frac{(1+\eta)\rho\bar{P}}{\Gamma(1-\rho^2)\sigma^2}$, $\check{r} := \frac{\Delta D - \bar{P}\Delta\eta}{(1+\eta)\bar{P}}$. We note that $\check{r}$ is exactly the revaluation of two stocks in an economy absent rebalancers. Hence $r_i - \check{r}$ is the "excess return" compared with the benchmark economy without rebalancers. We focus on the empirically relevant case with $r_B > \check{r}$, in that the long-term bond yield is excessively sensitive to monetary shocks as previous literature documents.

Taking stock, the market-clearing conditions of two stocks are

$$\Delta Q_1^R + \Delta Q_1^E = 0, \tag{A.10}$$

$$\Delta Q_2^E = 0. \tag{A.11}$$

Proposition 4 (Cross-sectional and aggregate returns with changing dividends and funding cost)**.** *In this two-period model, when a bond revaluates by r_B, time-1 dividend changes by ΔD, and funding cost varies by $\Delta\eta$ due to monetary policy changes, the price changes in stocks relative to pre-shock levels denoted by r_1, r_2 are*

$$r_1 = \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)}\left(r_B - \check{r}\right) + \check{r}, \tag{A.12}$$

$$r_2 = \frac{\psi^C}{\psi^C + \psi^A}\frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)}\left(r_B - \check{r}\right) + \check{r}, \tag{A.13}$$

with $\Psi := \frac{\psi^A + 2\psi^C}{\psi^A + \psi^C}\psi^A$, $\check{r} := \frac{\Delta D - \bar{P}\Delta\eta}{(1+\eta)\bar{P}}$. The aggregate price reaction is $\bar{r} = \frac{r_1 + r_2}{2}$. Consequently,

(a) the return difference between two stocks is larger if the rebalancer owns more stock 1's shares

$$\frac{\partial^2(r_1 - r_2)}{\partial r_B \partial\omega} = \frac{\psi^A}{\psi^C + \psi^A}\frac{(1-\theta)\Psi}{\left[\Psi_1 + \omega(1-\theta)\right]^2} > 0, \tag{A.14}$$

(b) the excess return of the aggregate stock market $\bar{r} - \check{r}$ and the cross-sectional return difference $r_1 - r_2$ satisfy

$$\bar{r} - \check{r} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)\left(r_1 - r_2\right). \tag{A.15}$$

Proof of Proposition 4. To better illustrate the intuition, we develop the proof based on the baseline model without changes in dividends and funding costs. Observe that the arbitrageur's demand (A.9) can be rewritten as

$$\Delta Q_i^E = -\psi^A \tilde{r}_i - \psi^C(\tilde{r}_i - \tilde{r}_{-i}),$$

in which $\tilde{r}_i = r_i - \check{r}$ is the "excess return" compared with the benchmark economy without rebalancers. Similarly, when we define $\tilde{r}_B = r_B - \check{r}$, we can rewrite the rebalancer's demand (A.8) as

$$\Delta Q_1^R = \omega(1-\theta)\tilde{r}_B.$$

These two demands in terms of excess returns are isomorphic to the two demands in terms of raw returns in the baseline model with $\check{r} = 0$. Thus, a direct application of Proposition 1 yields

$$\begin{aligned}\tilde{r}_1 &= \frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)}\tilde{r}_B,\\ \tilde{r}_2 &= \frac{\psi^C}{\psi^C+\psi^A}\frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)}\tilde{r}_B.\end{aligned}$$

It then follows that

$$r_1 - r_2 = \tilde{r}_1 - \tilde{r}_2 = \frac{\psi^A}{\psi^C+\psi^A}\frac{\omega(1-\theta)}{\Psi + \omega(1-\theta)}(r_B - \check{r}),$$

and thus

$$\frac{\partial^2(r_1-r_2)}{\partial r_B \partial\omega} = \frac{\psi^A}{\psi^C+\psi^A}\frac{(1-\theta)\Psi}{\left[\Psi_1 + \omega(1-\theta)\right]^2} > 0.$$

Further, the excess return of the aggregate stock market is

$$\bar{r} - \check{r} = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(\tilde{r}_1 - \tilde{r}_2) = \left(\frac{1}{2} + \frac{\psi^C}{\psi^A}\right)(r_1 - r_2).$$

□

A.2.3 Data Appendix

A.2.4 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 (117) 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.[1]

Examples of rebalancers. Table 13 summarizes the five largest investors in each category by market value at the beginning of the sample period.

Holdings of exchange-traded products. The recent decades see a high growth rate for exchange-traded products (ETPs) (166, 124). Figure 12 demonstrates that ETP holdings make up only less than 10% of the market value held by rebalancers in the sample (i.e., institutional wealth management and long-term endowment investors). One regulatory reason for the low institutional holdings of ETPs is that the large institutions are also managers of some biggest ETFs in the business and cannot own their in-house ETPs. Anecdotally, the small fraction of ETP holdings could be for inventory or hedging purposes.

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

A.2.5 Morningstar Holdings

Previous papers have used CRSP Mutual Fund Database, Thomson Mutual Fund Holdings, and Morningstar for mutual funds' holdings. However, (159) 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 (37), we compute implied bond prices from our holdings data: for each month, the implied price is given by dividing the market value of each funds 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 (42), 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.

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 13).

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 14 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.

Coverage. Figure 15 shows the majority holdings of US-dollar-denominated mutual funds are equity and bonds, with growing shares in mutual funds (including money market mutual funds).

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, balance, 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 (145).

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 do not adhere to a predefined target share, 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 mandated 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 14 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 (104).

A.2.6 TAQ Data Filters

We filter the stock transaction data following (7, 6) and (54).

We exclude transactions with condition codes Z (Sold Out of Sequence), B (Average 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. (7) 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.

A.3 Stock Characteristics

This section complements Section 1.3.4 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 (58). Similar to the notion of Macaulay duration for fixed income, (58) 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 (58, 174). We name the duration estimates with the parameters from (58) Dur^{DSS} and the duration estimates with the parameters from (174) Dur^{W}. The average duration (in years) is 19 following (58), and 18 using parameters from (174), yielding results similar to each other. We report the primary analysis results using Dur^{DSS}. The details for constructing duration measures are available in Appendix A.3.

More recently, (83) 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 (83) and call the predicted duration factor $Duration^{GL}$ for stocks in the sample.

MPE. We replicate the monetary policy exposure (MPE) index developed by (143). 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 (176) for all firms during the sample period as

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

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 WhitedWu 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 (58), where cash flows are measured and forecasted following (141), 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 (143). 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

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

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 (71). 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 (174), and the second alternative follows (83) to focus on the cross-sectional differences in duration.

A.3.1 Dual-Class Shares Sample

First, we identify dual-class firms with more than one class of 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-listed 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 (11) 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 (158). 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-listed companies during the sample period.

To further check intraday liquidity for the stocks in the sample, we compute price discrepancies between dual classes 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 (155, 133, 10), we focus on the FOMC announcement days. For each FOMC announcement day, between 9:35 AM EST and 3:45 PM EST,[2] we obtain 5-minute prices for all

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

the dual-class shares from TAQ, following the data cleaning procedure in Section 1.3, and test how fast the price gap for dual-class shares reverts to mean. We define the percentage price differences between the two share classes of stocks for company f at minute t for date d as $g_{f,d,t} = \frac{P_{f,d,t}^{low\ voting\ right\ share} - P_{f,d,t}^{high\ voting\ right\ share}}{P_{f,d,t}^{low\ voting\ right\ share}}$, 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 (97). Suppose the price gap for dual-class shares $p_{f,d,t}$ follows

$$g_{f,d,t} = c_f + \rho_f g_{f,d,t-1} + \varepsilon_{f,d,t}, \tag{A.16}$$

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 (97) 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 15 summarizes the test results by significance levels. All dual-listed 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 the dual shares at 1% significance level. The median ρ_f is around 0.8 (with interquartile rage 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-class 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.

A.3.2 Voting Rights and Rebalancer Ownership

Dual-class shares have different rebalancer ownership: on average, there is a 13% 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.

Many rebalancing institutions are conventionally considered passive shareholders (17) and prefer the share class with fewer voting rights. Using data from Institutional Shareholder Services, (122) 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 16 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.[3]

It is worth noting that, generally, institutions are unanimously against dual share class structures.[4] Nonetheless, in our sample, we find rebalancers hold about 15% of the market value of dual-listed firms. Hence we use voting rights as an instrument for rebalancer ownership at the share-class level.

A.3.3 Additional Empirical Results

A.4 Dual-Class Share Robustness Checks

Dual-class share regressions with intraday liquidity controls. Table 17 introduces additional liquidity controls to the dual-class share results.

Dual-class share IRF without IV. Figure 16 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.

A.4.1 Robustness Tests for the Main Analysis

Table 18 summarizes additional robustness checks on the main results in Section 1.5.1 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 (83), and duration using parameters from (174). 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 19. 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.

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[3] This is in contrast to some other types of institutions that actively seek it (49, 125). For example, hedge funds are sometimes incentivized to direct financial resources to corporate governance for the stocks in their portfolio.

[4] ISS Benchmark Policy Recommendations, 2022. https://www.issgovernance.com/file/policy/active/americas/US-Voting-Guidelines.pdf, last retrieved on September 5, 2022.

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.

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 (27). 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. Table 20 addresses this concern by excluding the in-house managed pension holdings from rebalancer ownership computations, and results remain largely unchanged.

A.4.2 The Fed Information Effect

To address additional concerns on the Fed information effect (Section 1.5.1), we replicate the asset-pricing results in Table 4 with a limited sample following (108, 114). 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 21 summarizes the findings.

A.4.3 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 at time 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 17 plots the coefficients. We do not find any statistically significant coefficient, indicating that the extensive 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 (118).

A.4.4 Institutional Ownership and Intraday Beta Dispersion

(10) documents that the cross-sectional dispersion of intraday betas decreases with FOMC announcements. Following (10), we define the cross-sectional dispersion of high-frequency betas for each monetary announcement t as

$$D_t = \frac{1}{N}\Sigma_{i=1}^{N}(\beta_{t,j} - 1)^2, \tag{A.17}$$

Where N is the number of stocks, and for each equity i the high-frequency beta $\beta_{t,i}$ is

$$\beta_{t,j} = \frac{\Sigma_\tau Cov(r_{i,t,\tau}, r_{m,t,\tau})}{\Sigma_\tau Var(r_{m,t,\tau})}, \tag{A.18}$$

Where $r_{i,t,\tau}$ is the return of equity j at every 5-minute window around the 1 hour before and 1 hour after the FOMC announcement at date t, and $r_{m,t,\tau}$ is the corresponding market return. We sort the equity at each date by institutional ownership and compute the beta dispersion within each ownership quantile. Figure 18 shows that except for the first quantile (held mostly by households), the cross-sectional beta dispersion is more prominent for equity held more by institutions. This could be due to the heterogeneous rebalancing needs of institutions, suggesting a plausible economic rationale for the intraday market beta dispersion pattern documented in (10).

A.4.5 Evidence on Rebalancing Quantities

We provide evidence that balanced funds actively adjust their portfolios in the direction predicted by our theory. Proposition 1 implies that as long as $\psi^A > 0$, stocks revaluate less than the bond, and the rebalancer sells his stock holding upon monetary tightening to rebalance.[5] We test this prediction using Morningstar mutual fund data. Empirically, we use panel local projection (110) with a shift-share design (41) 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. Appendix A.2.5 details the construction of equity shares and reports additional summary statistics of the funds included.

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[5] In the knife-edge case with $\psi^A = 0$, stocks revaluate by the same amount as the bond, and the rebalancer's equity share holds without quantity adjustments.

We construct an *actual* equity share for each fund j as

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

where P_{it}, Q_{ijt} are the price and quantity of stock i in fund j's portfolio at time t, and $P^B_{i't}, Q_{i'jt}$ is the price and quantity of bond i' held by j at time 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 $\theta_{j,t+h}$ 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-$t+h$ pricess as

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

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

$$\theta_{j,t+h} - \check{\theta}_{j,t-1\to t+h} = \beta_h \theta_{j,t-1}(1-\theta_{j,t-1}) MS_t + \boldsymbol{\varphi}' \boldsymbol{X}_{j,t+h} + \epsilon_{j,t-1\to t+h}, \tag{A.19}$$

where MS_t denotes the monetary shocks averaged to monthly frequency, and $\theta_{j,t-1}(1-\theta_{j,t-1})$ reflects rebalancing needs. Intuitively, a pure-equity or pure-bond fund ($\theta_{j,t-1} = 1, 0$) does not rebalance across asset classes. Generically, similar to (145), in a balanced fund j's portfolio, if the bond revaluates by r_B and the stock held revaluates by $r_1 \in (0, r_B)$, the post-shock equity share would be $\frac{\theta_j(1+r_1)}{\theta_j(1+r_1)+(1-\theta_j)(1+r_B)} \approx \theta_j - \theta_j(1-\theta_j)(r_B - r_1)$. Thus $\theta_j(1-\theta_j)$ reflects the adjustment needed to resume a target share. $\boldsymbol{X}_{j,t+h}$ 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. (24) shows that a consistent estimation of β_h requires the exogeneity of the shifter (monetary shocks) and $\mathrm{E}[MS_t \, \mathrm{E}_t(\theta_{j,t-1}(1-\theta_{j,t-1})\epsilon_{j,t-1\to t+h})] = 0$. That is, we assume that the market-wide monetary surprises are exogenous, and funds with equity mandates closer to one-half (i.e., higher $\theta_{j,t-1}(1-\theta_{j,t-1})$) do not have systematically larger or smaller unexplained residuals ($\epsilon_{j,t-1,t+h}$) when there is a monetary shock.

Here the coefficient β is identified off the variation across balanced funds. While the simple model in Section 2.3 assumes that there is one representative rebalancer, it is straightforward to generalize that model to accommodate heterogeneous rebalancers. The predictions of Propositions 1 and 2 stay the same, with $\omega(1-\theta)$ replaced by its equity-wealth-weighted average $\overline{\omega(1-\theta)}$ across all rebalancers.

Figure 19 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 20 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.

A.4.6 Placebo Tests for Quarter-Ends and Month-Ends

In Table 22, 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.

A.4.7 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 23, 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, 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 (109, 19). This method allows us to test the marginal contribution of additional factors using a transparent two-pass framework, which is similar to the (61) 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 (109), following the double-selection LASSO method developed by (19), and (65). 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 (92) and industry portfolios. We compute covariances between returns and factors for each portfolio

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[6] Using NYSE breakpoints and value-weighted portfolios avoids the problem of large excess cross-sectional dispersion driven by microcap stocks (60, 106).

instead of betas from time-series regression to circumvent potential non-invertibility. Using these covariances between each portfolio's returns and factors, we estimate the following model:

$$\mathrm{E}\, r_i = \mathrm{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right) \cdot \lambda_O + \mathrm{Cov}_{i,X} \cdot \lambda_X + const, \tag{A.20}$$

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 an OLS of (A.20) using the union of selected factors from the two LASSOs.[7]

Table 23 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 (109). 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 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 (57) and intermediaries (100, 4, 99) 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 23 demonstrates that the coefficient of $\mathrm{Cov}\left(r_{it}, F_{ownership,t} \cdot MS_t\right)$ 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.

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[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, (76) 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.

A.4.8 Correlation Between FactSet Rebalancers' Holdings and Morningstar Balanced Funds' Holdings

The main analysis of this chapter relies on FactSet data, which has comprehensive coverage of the market but less granular holdings compared with mutual fund holdings at the portfolio level. We check the correlation between holdings of FactSet rebalancers and balanced mutual funds. For both FactSet rebalancers and balanced mutual funds, we compute the cross-sectional ownership ranks at each end-of-quarter snapshot of holdings. We then compare the correlation between the two rankings in the cross-section and find that there is more than 30% correlation between the two groups of holdings in terms of cross-sectional ranks throughout the sample period. Figure 21 visualizes the correlation between the ownership of rebalancers and balanced funds by plotting the cross-sectional ranks of ownership shares by rebalancers against ownership shares by balanced funds.

A.4.9 Determinants and Residual Variations in Rebalancer Ownership

In this appendix, we describe the potential determinants of rebalancer ownership. Similar to Appendix A.4.7, 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 (92) 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 Appendix A.4.7 for unconditional returns and lagged ownership at the monthly frequency to select the fundamental factors that pin down rebalancer ownership. Figure 22 summarizes the results. The five factors at the top, *Hiring rate* (20), Δ *net financial assets* (151), Δ *RoE* (105), *Seasonality* (102) (computed as the nonannual lagged returns from years 2 to 5), and *% Operating accruals* (93) explains 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 23 reports the residual variations in rebalancer ownership for both dual-class 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 the dual-class 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(market 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).

$$\mathrm{E}\,\omega_i^a = \mathrm{Cov}\left(r_{it}^a, F_{ownership,t}^a\right) \cdot \lambda_\omega^a + \mathrm{Cov}_{i,X}^a \cdot \lambda_{X\omega}^a + const, \tag{A.21}$$

$$\mathrm{E}\,r_i^a = \mathrm{Cov}\left(r_{it}^a, F_{ownership,t}^a\right) \cdot \lambda_r^a + \mathrm{Cov}_{i,X}^a \cdot \lambda_{Xr}^a + const, \tag{A.22}$$

where $\mathrm{E}\,\omega_i^a$ is a $N \times 1$ vector of average rebalancer ownership for each portfolio i, $\mathrm{E}\,r_i^a$ is a $N \times 1$ vector of average returns for each portfolio i, $\mathrm{Cov}(r_{it}^a, F_{ownership,t}^a)$ is a $N \times 1$ matrix that captures the covariances between stock returns and the ownership factor, and $\mathrm{Cov}_{i,X}^a$ is a $N \times 153$ matrix that captures the covariances between the stock returns and the 153 pre-existing asset-pricing factors, along with their interactions with monetary shocks.

We fit equations A.21 using the selected factors.

To be finished. For now, Figure 22 is a slide that summarizes the results.

A.5 Aggregate Market Reactions and Decomposition

Updated return decomposition following (22). We update the decomposition result in (22) using (138) 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 (135, 75, 113).

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 (138) 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 24.

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 (113) estimates using (75) shocks. On impact, the real excess returns decrease by 1.63%, consistent with the estimates in (113) (1.62% excess returns) and (22) (1.87% excess returns).

Same as in (22) and (113), we use the Campbell-Shiller decomposition to relate the real excess

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[8] The monthly monetary shocks are averaged from high-frequency monetary shocks following (75). To confirm the relevance of the smoothed Nakamura-Steinsson shocks to the treasury yield and excess bond premium (78), we use both SVAR and local projection with Nakamura-Steinsson shocks to replicate (75) and find results of a similar magnitude but different significance.

returns to revisions in expectations about future cash flows, real rates, or excess returns:

$$r_t - \mathbb{E}_{t-1}[r_t] = (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=0}^{\infty}\rho^j \Delta d_{t+j} - (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=1}^{\infty}\rho^j r_{t+j}^f - (\mathbb{E}_t - \mathbb{E}_{t-1})\Sigma_{j=1}^{\infty}\rho^j er_{t+j}, \tag{A.23}$$

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 (31) and is set to 0.9962 following (30) and (113). Table 24 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 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.

Aggregate market reactions to monetary shocks at high frequency. We replicate (22) using the cumulative returns with 5-minute incremental estimation periods:

$$r_{m,t-10+5h} = \alpha_h + \beta_h MS_t + \epsilon_{t-10+5h}, \tag{A.24}$$

where t is the minute of an FOMC statement release and $r_{m,t-10+5h}$ is the $5h$-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 25 plots the coefficients β_h. Monetary surprises 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 (22) estimate of about four from 1989 to 2002.

A.6 Alternative Calibration

Demand elasticities in the literature. Table 25 summarizes recent micro and macro elasticity estimates from the literature. We categorize the elasticity estimates by estimation 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,

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[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 (149), 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 (150, 167).

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 1.2.2: 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 26.

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 return difference associated with a 10% ownership difference is 5.6*bp* (columns 1 and 4, Table 5). Following similar calculations as before, the cross-sectional return difference is $r_1 - r_2 = -\frac{5.6bp}{10\%} \times 40\% = -22.4bp$, and thus, the implied aggregate price reaction is around $26bp$ ($= \frac{2.3}{2} \times 22.4bp$) to $55bp$ ($= \frac{4.9}{2} \times 22.4bp$). Therefore, the percentage of aggregate returns due to changes in expected excess returns that our rebalancing channel can explain is about 41% ($= \frac{26bp}{1.01\% \times 63\%}$) to 86% ($= \frac{55bp}{1.01\% \times 63\%}$). Unsurprisingly, when rebalancing is more potent during the quarter-ends, the share attributed to rebalancing demand in the aggregate price reaction gets larger.

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[10] A special case is one where flows are unanticipated ($T = 0$), as analyzed by (73). Then, the measured return reaction reflects the full effect r_T.

Appendix B

Appendix for Chapter 2

B.1 Mathematical Appendix

B.1.1 Proof to Theorem 1

Proof. Rewrite the maximization problem by substituting in fiscal budget constraint equation(6) and quota constraint equation(3) into city leader's objective function equation(5)

$$u^g(H) = \underbrace{\frac{1}{\epsilon - 1} H^{1-\frac{1}{\epsilon}}}_{u(H)} + [\beta(1-\tau) + \chi]Y(H) + \Omega \frac{[F(D,H)]^{1-\sigma}}{1-\sigma},$$

where

$$F(D,H) = \underbrace{\tau(\alpha+\beta)Y(D)}_{\text{tax revenue}} + \underbrace{H^{1-\frac{1}{\epsilon}}}_{\text{residential land sales}} + \underbrace{(1-\alpha-\beta)Y(D)}_{\text{industrial land sales}}.$$

Notice the maximization problem has a continuous objective function over a compact interval $[0,\zeta]$. Extreme value theorem guarantees existence. Inada condition suggests $H^* \in (0,\zeta)$. Hence, $\exists \eta > 0$ such that $H^* \in [\eta,\zeta]$. Without loss of generality, we restrict $H \in [\eta,\zeta]$. Now take second derivative of the objective function

$$\frac{\partial^2}{\partial H^2} u^g(H) = \underbrace{u''(H)}_{<0} + [\beta(1-\tau)+\chi] \underbrace{Y''(H)}_{<0} + \Omega \frac{F''(H)[F(H)]^{\sigma} - \sigma [F'(H)]^2 [F(H)]^{\sigma-1}}{[F(H)]^{2\sigma}}.$$

Hence, a sufficient condition that ensures $F''(H) < 0$ would imply the objective function is strictly concave, therefore, would guarantee uniqueness of the solution. Notice

$$F'''(H) = -[(\alpha+\beta)\tau + 1 - \alpha - \beta]\Gamma\gamma(\gamma-1)(\gamma-2)(\zeta-H)^{\gamma-3} + (-\frac{1}{\epsilon} - 1)\frac{1-\epsilon}{\epsilon^2} H^{-\frac{1}{\epsilon}-2} < 0.$$

Hence, a condition that ensures $F''(\eta) < 0$ would imply $F''(H) < 0$ over $[\eta, \zeta]$. Under the assumption that productivity is sufficiently high,

$$A^{\frac{1}{1-\alpha}} > \frac{\frac{1-\epsilon}{\epsilon^2}}{(\frac{\alpha}{r})^{\frac{\alpha}{1-\alpha}}[(\alpha+\beta)\tau+1-\alpha-\beta]\gamma(1-\gamma)\eta^{1+\frac{1}{\epsilon}}(\zeta-\eta)^{\gamma-2}}$$

the condition needed is satisfied

$$F''(\eta) = [(\alpha+\beta)\tau+1-\alpha-\beta]\Gamma\gamma(\gamma-1)(\zeta-\eta)^{\gamma-2} + \frac{1-\epsilon}{\epsilon^2}\eta^{-\frac{1}{\epsilon}-1} < 0.$$

□

B.1.2 Proof to Proposition 1

Proof. Take first order condition and set to 0

$$\frac{\partial}{\partial H}u^g(H) = \frac{1}{\epsilon}H^{-\frac{1}{\epsilon}} + [\beta(1-\tau)+\chi]Y'(H) + \Omega\frac{F'(H)}{[F(H)]^{\sigma}} = 0$$

Applying implicit function theorem yields

$$\frac{\partial H}{\partial \chi} = \frac{-Y'(H)}{u''(H) + [\beta(1-\tau)+\chi]Y''(H) + \Omega\frac{F''(H)[F(H)]^{\sigma}-\sigma[F'(H)]^2[F(H)]^{\sigma-1}}{[F(H)]^{2\sigma}}} < 0$$

under the assumption that productivity if sufficiently high. □

B.1.3 Proof to Proposition 2

Proof. Applying the implicit function theorem yields

$$\frac{\partial H}{\partial \Omega} = \frac{-\frac{F'(H)}{[F(H)]^{\sigma}}}{u''(H) + [\beta(1-\tau)+\chi]Y''(H) + \Omega\frac{F''(H)[F(H)]^{\sigma}-\sigma[F'(H)]^2[F(H)]^{\sigma-1}}{[F(H)]^{2\sigma}}} < 0$$

under the assumption on productivity and inelastic residential land demand. Hence,

$$\frac{\partial}{\partial \Omega}pH = (1-\frac{1}{\epsilon})H^{-\frac{1}{\epsilon}}\frac{\partial H}{\partial \Omega} > 0.$$

□

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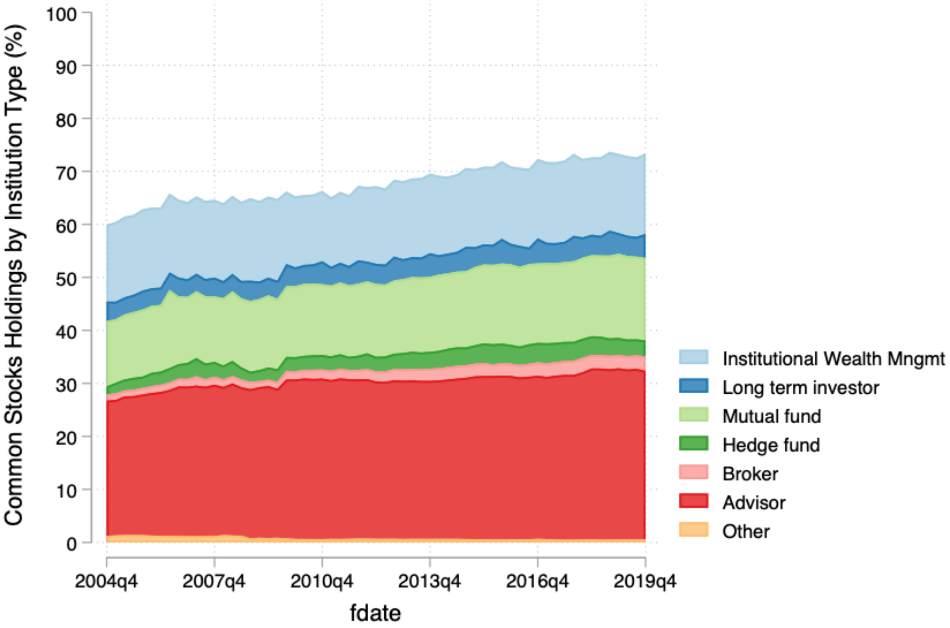
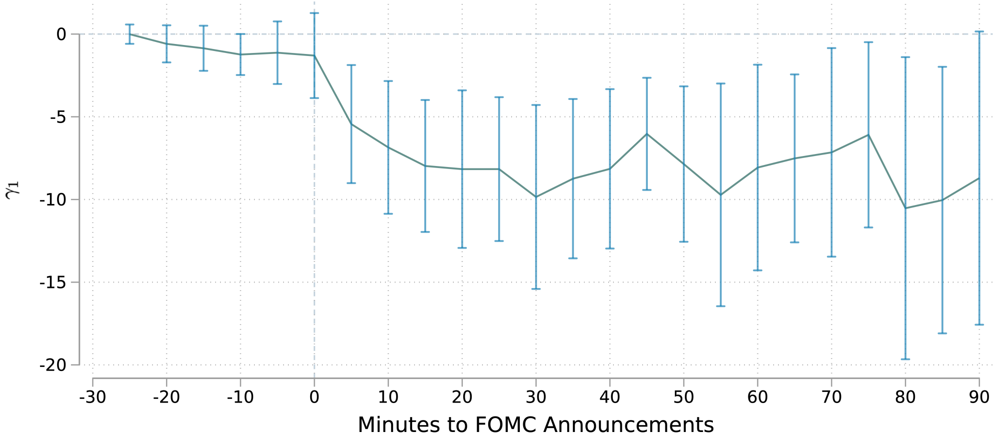
Figure 1: Equity holdings by institution types



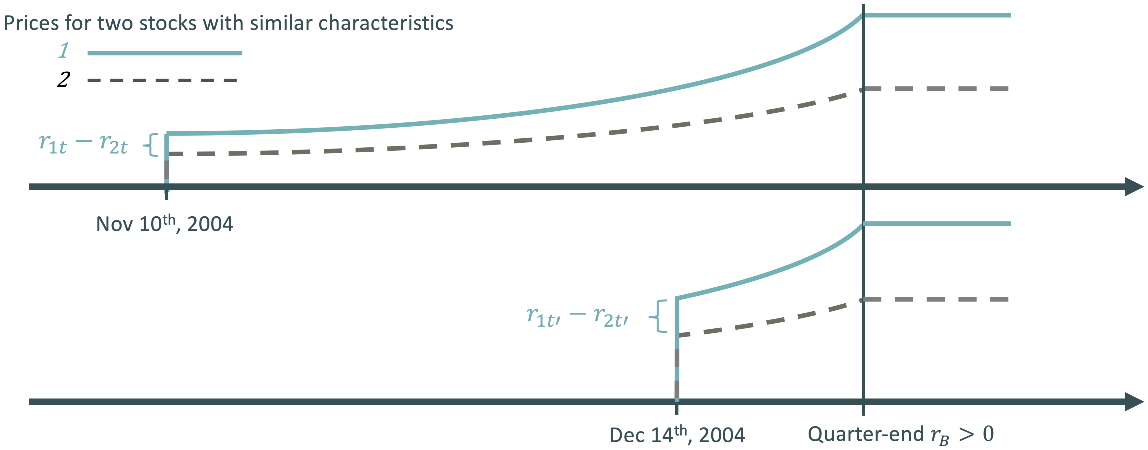
This graph plots the equity market coverage by institution types in FactSet from 2004Q4 to 2019Q4. Stocks in the sample are the common stocks (share codes 10, 11, and 12) listed on the three major exchanges (NYSE, NYSE MKT, and NASDAQ). For each institution type at any given time, we compute the equity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

Figure 2: Returns for dual-class shares around FOMC announcements under 2SLS



This figure plots the return sensitivity to monetary shocks γ^{2SLS} of dual-class shares around FOMC announcements from the second stage in the 2SLS empirical model $r_{ift} = \gamma^{2SLS}\widehat{I_{high\ rebalancer\ ownership,ift} \cdot MS_t} + \vartheta^{2SLS}\widehat{I_{high\ rebalancer\ ownership,ift}} + \delta_{ft} + \epsilon_{ift}^{2SLS}$. r_{ift} are the cumulative returns from 30-minutes before the FOMC announcements for share class i of firm f at meeting t. $I_{high\ rebalancer\ ownership,ift}$ is an indicator function that equals one when the share class i of firm f at time t has higher rebalancer ownership in $t-1$ than the other share class $-i$ of firm f, and zero otherwise; $\widehat{I_{high\ rebalancer\ ownership,ift}}$ is the predicted higher rebalancer ownership share-class from the first stage. δ_{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.

Figure 3: An illustration of the sample-split analysis

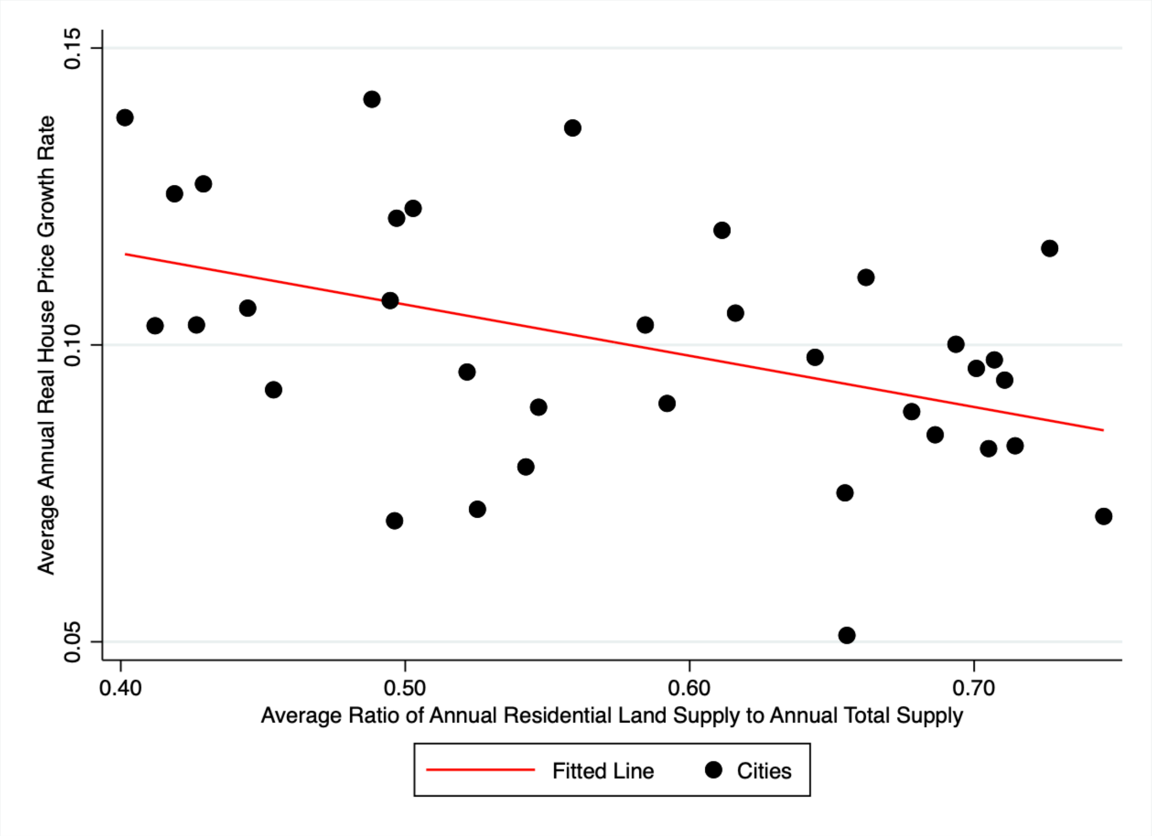


This graph demonstrates the different pricing implications for monetary shocks at the beginning and the end of a quarter, using two surprise rate cuts in the last quarter of 2004 as examples. For the surprise rate cut on November 10, 2004, to front-run the rebalancing trades at the end of the quarter, 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 more quickly, in which case we expect the arbitrageur to be more active and prices to adjust closer to its eventual levels.

Figure 4: House Price and Residential Land Price

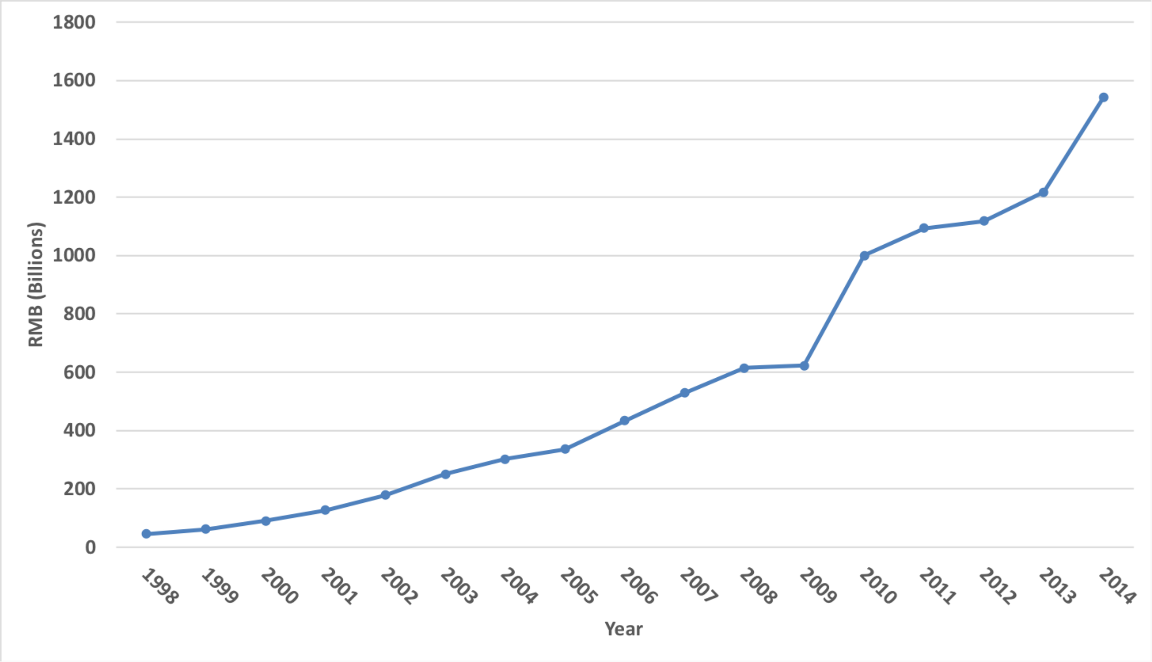
Note: This graph plots quarterly, constant quality, real housing and residential land price indices for 35 major Chinese cities between 2004 and 2013. Both indices have been normalized to 1 in the initial quarter, and the unit for both indices is price per unit floor area. House price index is from Fang et al. (2016). Residential land price comes from Wharton/Tsinghua Chinese Residential Land Price Indexes (CRLPI).

Figure 5: Land Allocation and House Price Growth Rate



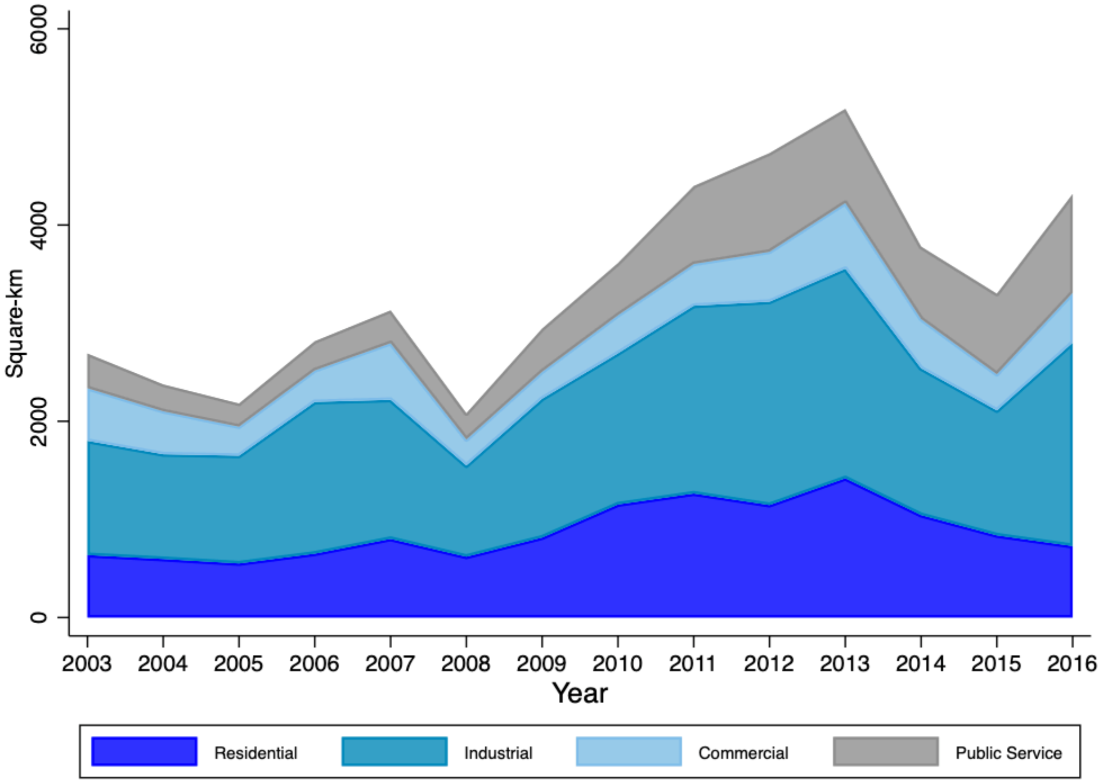
Note: This graph plots average annual house price growth rate against average annual residential land supply as a ratio of total land supply for 35 major Chinese cities between 2004 and 2013. R-squared is 20% for the regression line. Total land supply is defined as the sum of industrial, residential, commercial, and other land supplied. City level house prices come from NBS and land data comes from CREIS.

Figure 6: Total Land Sales to Real Estate Developers (RMB Billions)



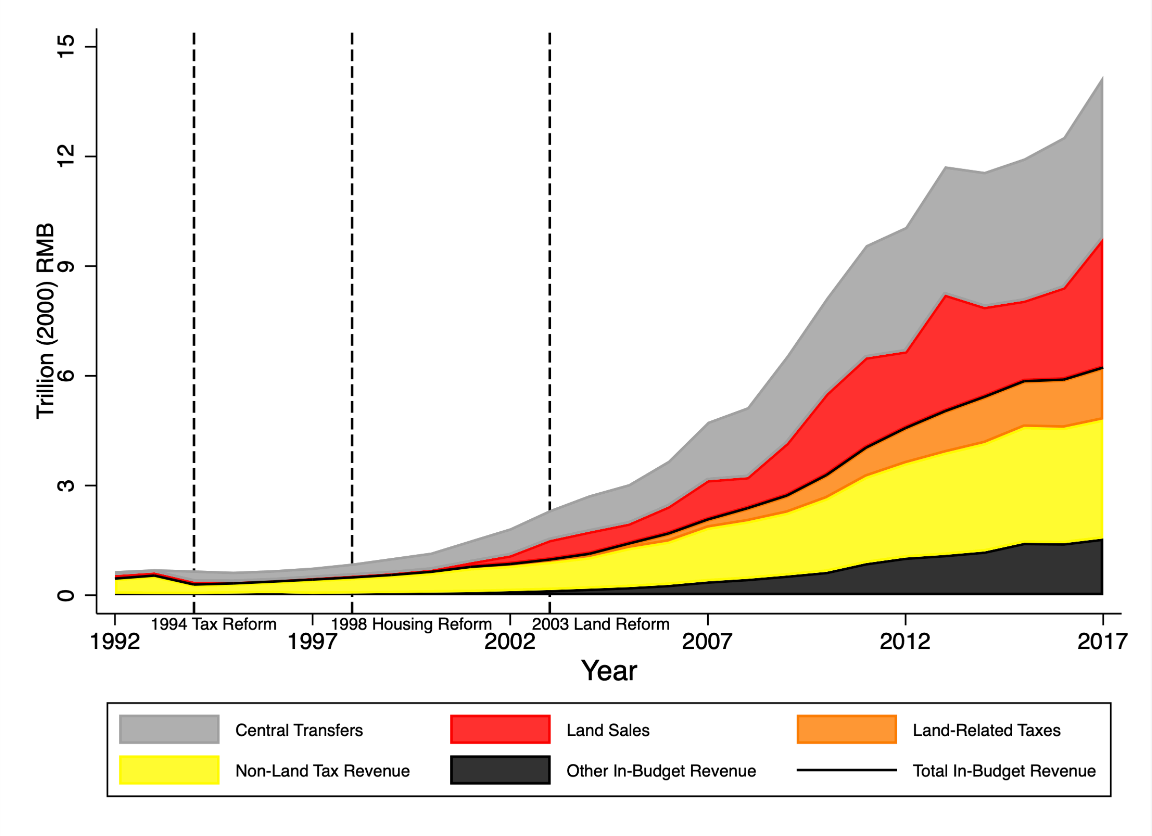
Note: This graph shows annual sales growth in the Chinese land market. We collected data from China Statistics Yearbook (1999-2016). Price are adjusted by CPI (2010=1).

Figure 7: Land Allocation by Use Type



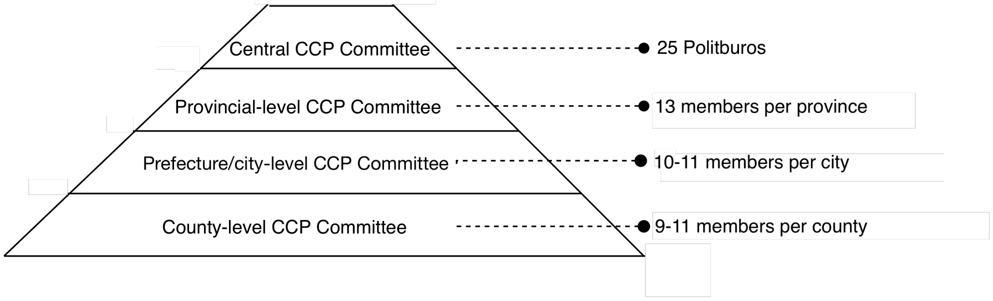
Note: This graph plots the composition of land supplied between 2003 and 2016 in China. Omitted categories are land for water facilities, transportation, and special purpose. Data is collected by China National Bureau of Statistics.

Figure 8: Local Governments' Financial Structure



Note: This graph plots local Chinese governments' financial structure between 1992 and 2017. Land sales data is from Zhang (2009) for 1992-1999 and from Finance Yearbook of China for 2000-2017. Government budget data comes from China National Bureau of Statistics.

Figure 9: The Political Pyramid of the Communist Party of China



Note: This graph plots the organizational structure of the Communist Party of China.

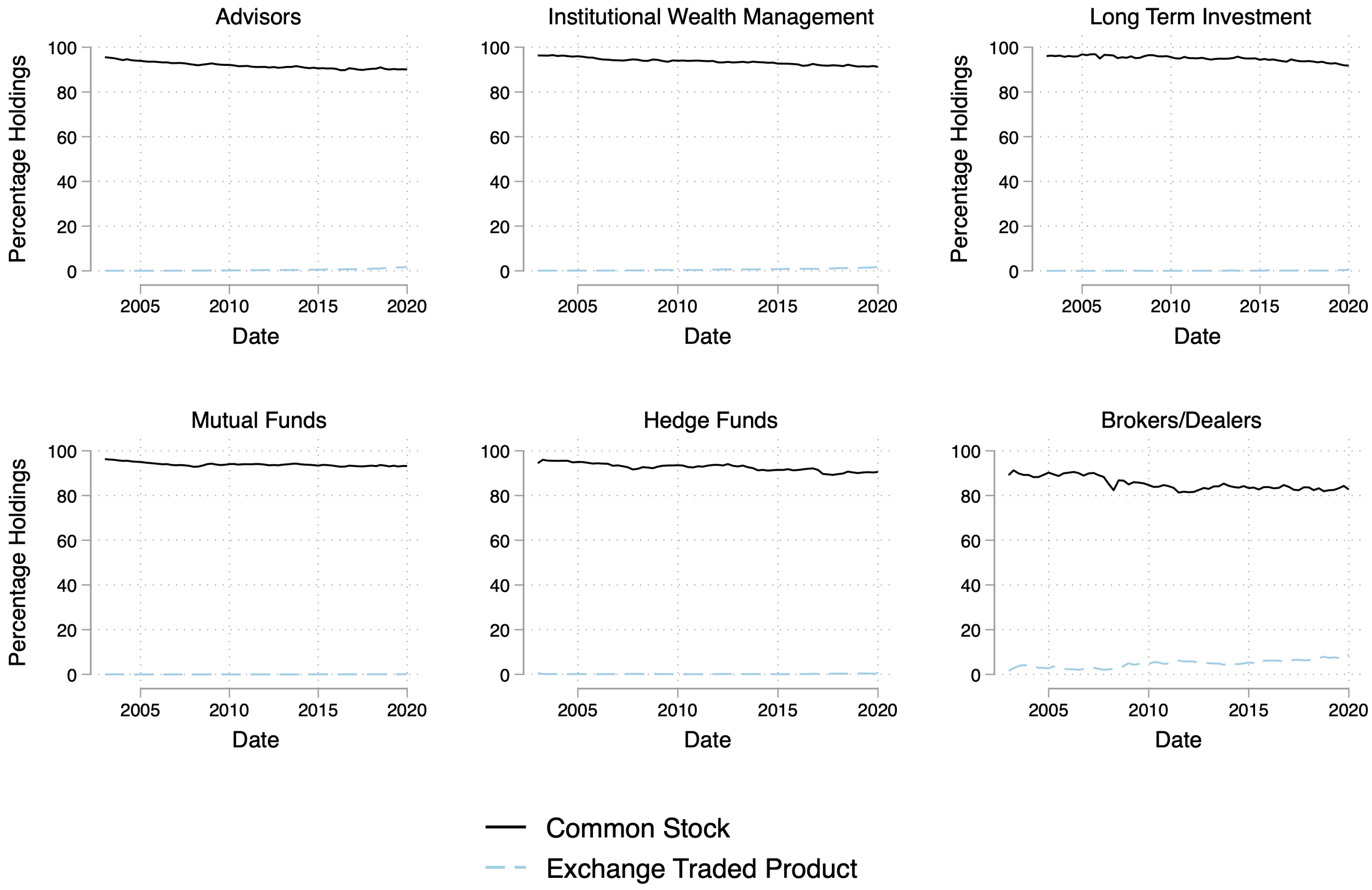
Figure 10: Housing Price Growth and Social Ties

Note: This graph plots the five-year pretrend of house prices for cities with and without a hometown tie. The time in which a city experiences a hometown tie has been normalized to 0. A city-year pair in the control group if and only if the leader of that city in that year has no hometown tie within the entire term. The comparison is drawn for cities in the same province, and the graph then aggregates across all provinces. House price data comes from China National Bureau of Statistics. Political data is from Chine Political Elite Dataset.

Figure 11: Housing Price Growth and Social Ties

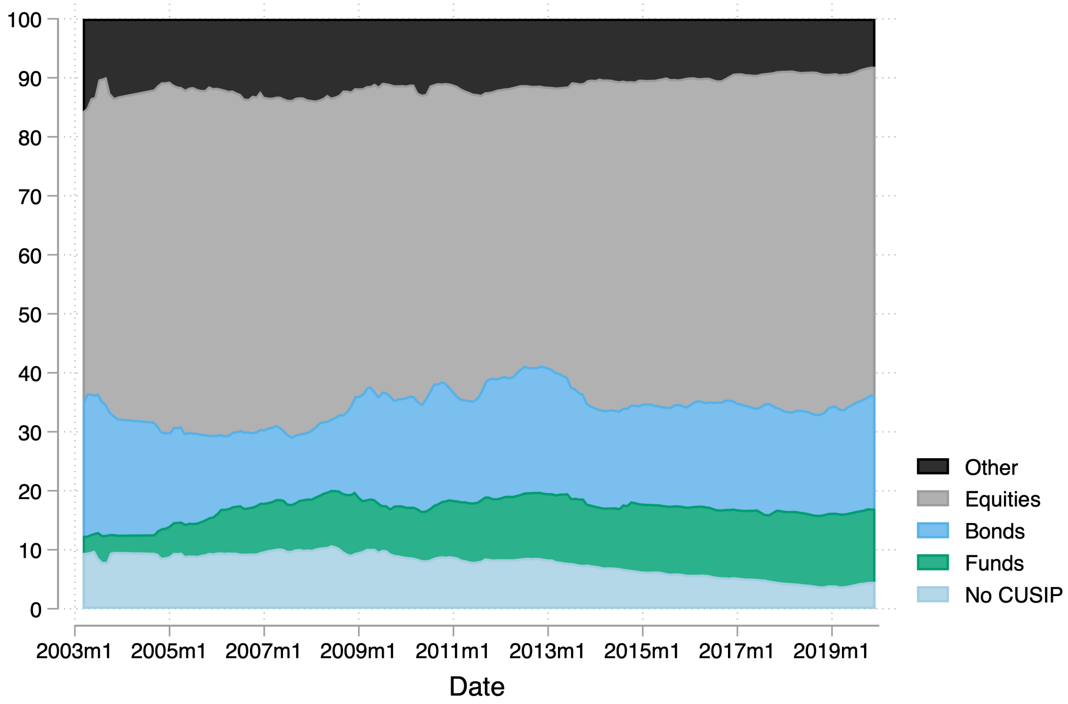
Note: This graph plots the five year pretrend of house prices for cities with and without a hometown tie. The time in which a city experiences a hometown tie has been normalized to 0. A city-year pair in the control group if and only if the leader of that city in that year has no hometown tie within the entire term. The comparison is drawn for cities in the same province, and the graph then aggregates across all provinces. House price data comes from China National Bureau of Statistics. Political data is from Chine Political Elite Dataset.

Figure 12: Institutional holdings of exchange-traded products



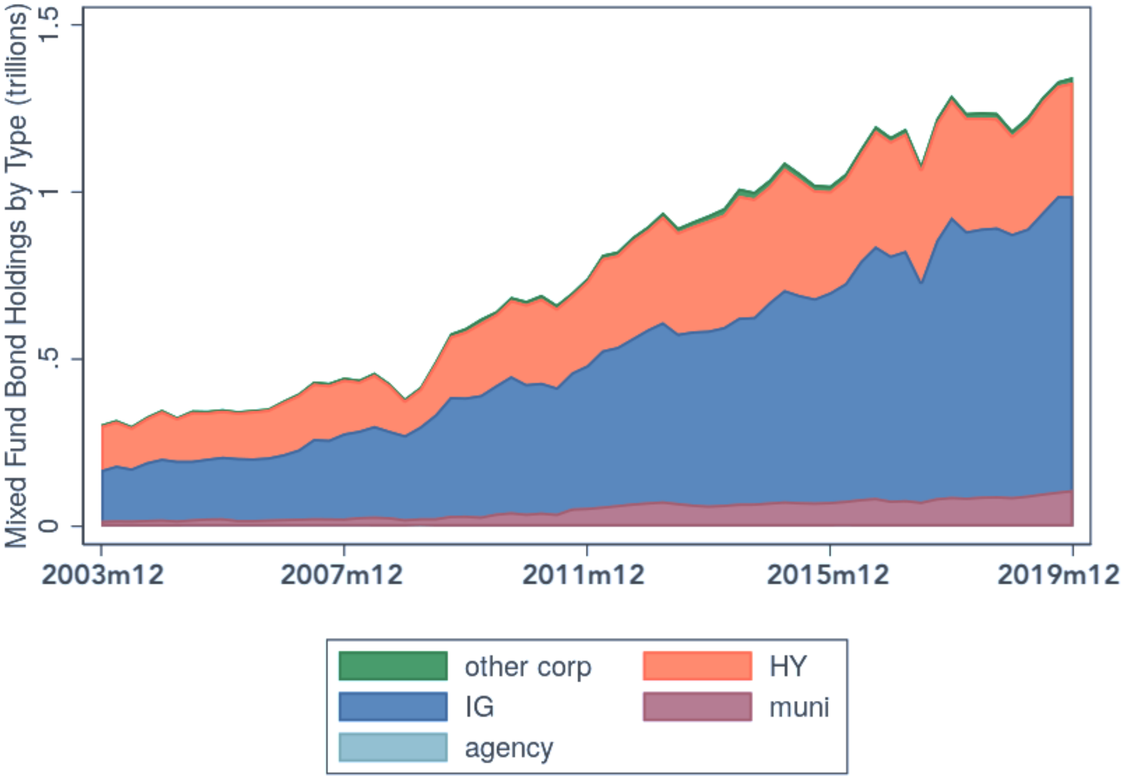
This graph reports institutional holdings of exchange-traded products (ETPs) by institution type. ETPs are publicly traded equities with share code 73 in CRSP; common stocks are equities with share code 10, 11 and 12. We sum up the market value (in dollars) of ETP and common stock holdings by institution category and quarter and report the percentage holdings.

Figure 13: CUSIP Coverage for Morningstar Holdings



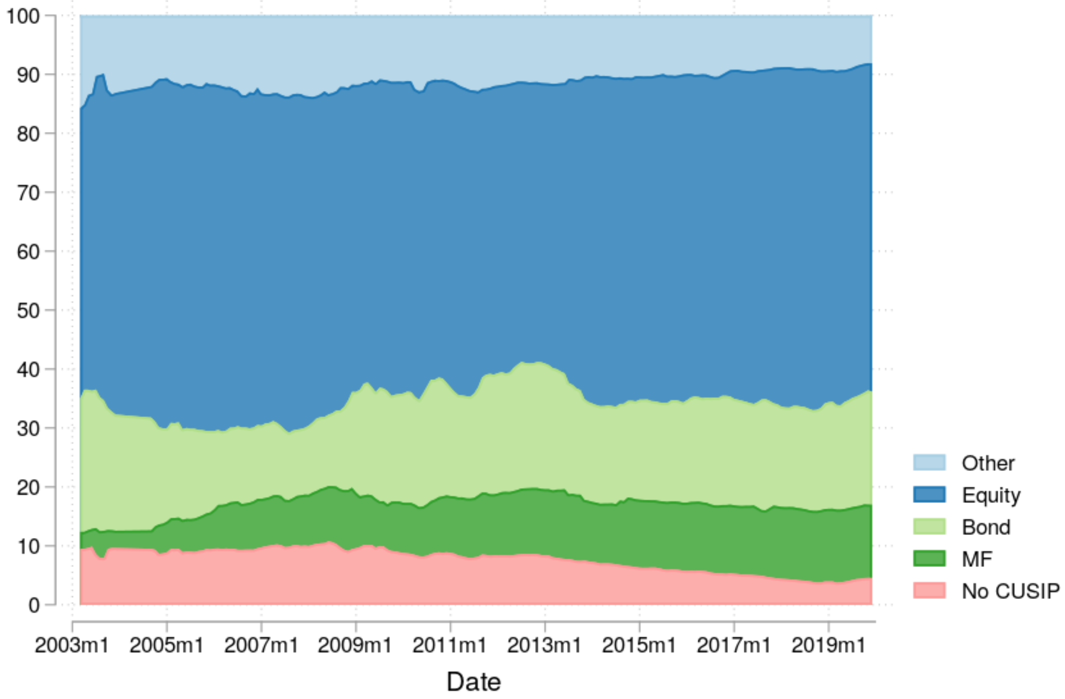
This graph plots the CUSIP information of securities held by mutual funds between 2003 and 2019, in percentages of total market value. CFI codes are from CUSIP Master File, and fund holdings data is from Morningstar. We group the Mutual Funds (CFI code starting with CI), Hedge Funds (CFI code starting 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 14: Bond Holdings for Morningstar Balanced Funds



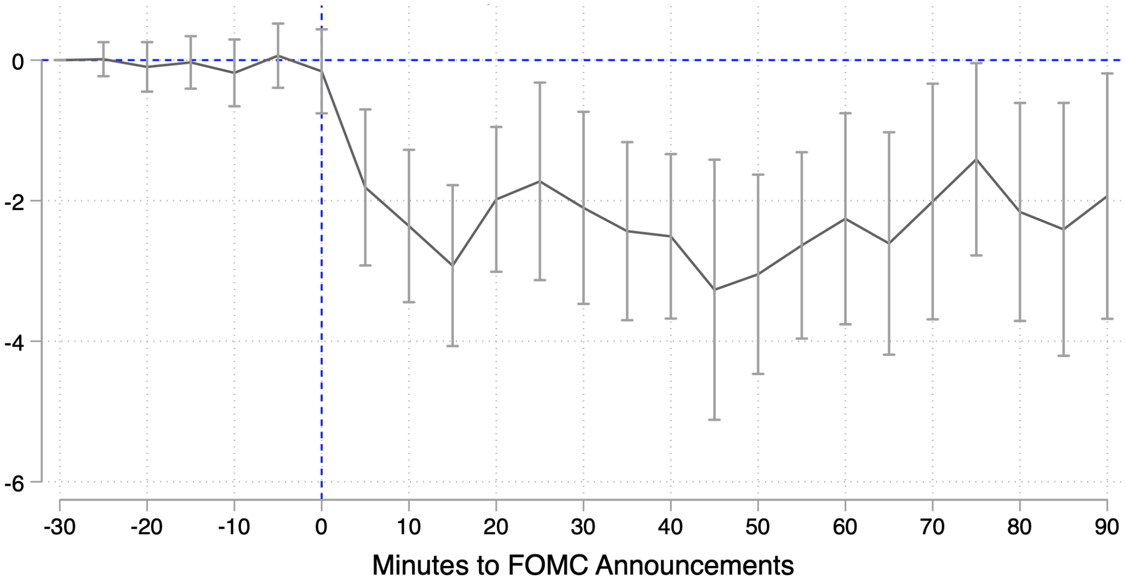
This graph plots bonds held by mutual funds between 2003 and 2019. Bonds are classified by categories and ratings. Bond ratings are from Mergent Fixed Income Securities Database (FISD) accessed through WRDS, and list of balanced funds are as described in Appendix A.4.5.

Figure 15: Morningstar holdings (percent), by security type



This graph summarizes the holdings by asset class for mutual funds in Morningstar Mutual Fund Holdings. We link the securities in Morningstar Holdings to CUSIP Master File, from which we obtain the Classification of Financial Instruments code (henceforth CFI, also called ISO 10962) for each CUSIP. We compute *Equity* holdings using CUSIPs with CFI starting with “ES”, *Bond* holdings using CUSIPs with CFI starting with “DB”, and mutual funds (*MF*) holdings with CFI starting with “CI”. The *Other* category includes REITs, private equity funds, money market instruments, and other derivatives. Some holdings in Morningstar do not have CUSIP, and are shown as “No CUSIP” in the plot. The graph is plotted with the moving average of holdings for the last quarter at each time point.

Figure 16: Returns for dual-class shares around FOMC announcements under OLS

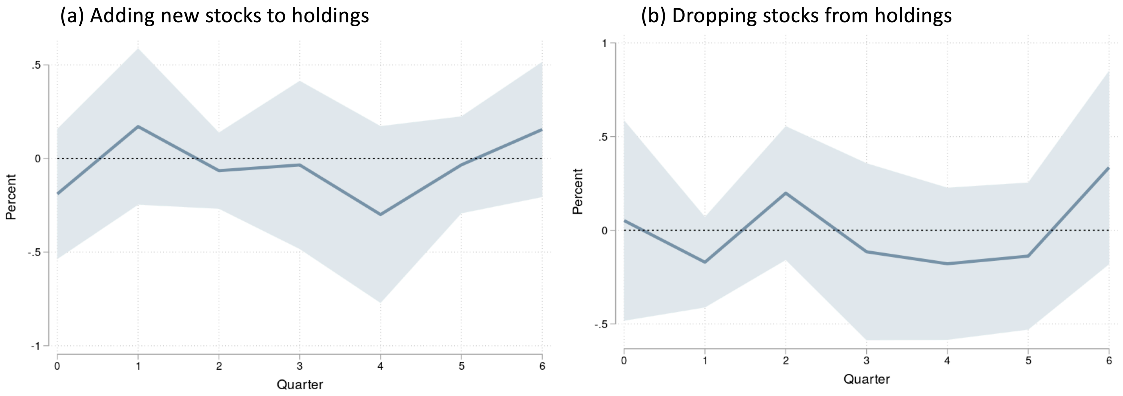


This figure plots the return sensitivity to monetary shocks γ of dual-class shares around FOMC announcements from the empirical model

$$
\begin{aligned}
r_{ift} = \gamma I_{high\ rebalancer\ ownership,ift} \cdot MS_t + \vartheta I_{high\ rebalancer\ ownership,ift} \\
+ \breve{\beta}^1 I_{high\ voting\ right,ift} \cdot MS_t + \breve{\beta}^2 I_{high\ voting\ right,ift} + \delta_{ft} + \epsilon_{ift}.
\end{aligned}
$$

r_{ift} are the cumulative returns from 30-minutes before the FOMC announcements for share class i of firm f at meeting t. $I_{high\ rebalancer\ ownership,ift}$ is an indicator function that equals one when the share class i of firm f at time t has higher rebalancer ownership than the other share class $-i$ of firm f, and zero otherwise; δ_{ft} collects firm-meeting fixed effects. $I_{high\ voting\ right,ift}$ is an indicator function that equals one when the share class i of firm f at time t has higher voting rights than the other share class $-i$ 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.

Figure 17: 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:

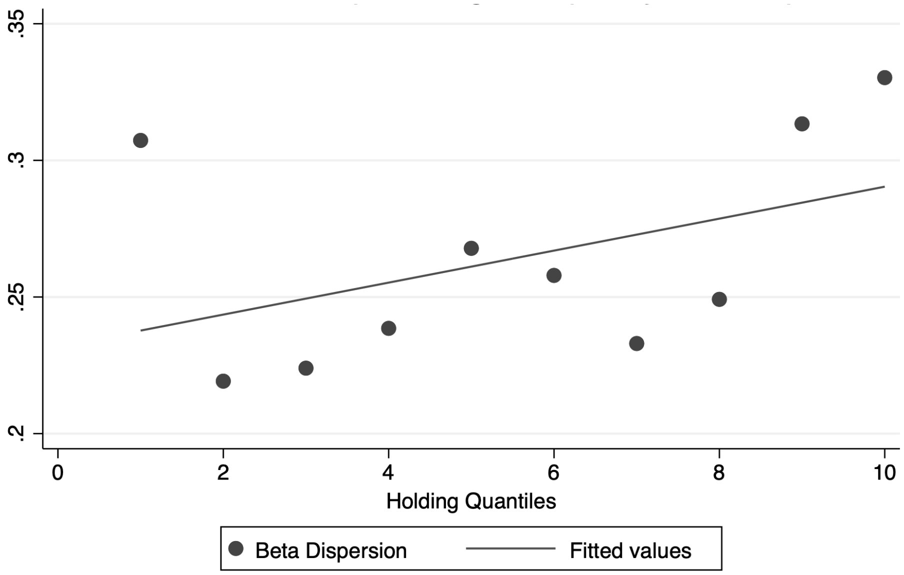
$$Added_{j,t} = \frac{\#\text{ of securities added to } j\text{'s portfolio in quarter } t}{\#\text{ of securities in } j\text{'s portfolio in quarter } t-1}.$$

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 (75). The sample period is from 2004 to 2019. 95% confidence intervals are displayed, using robust standard errors.

Figure 18: Institutional Ownership and Intraday Beta Dispersion



Following (10), we define the cross-sectional dispersion of high-frequency betas for each monetary announcement t as

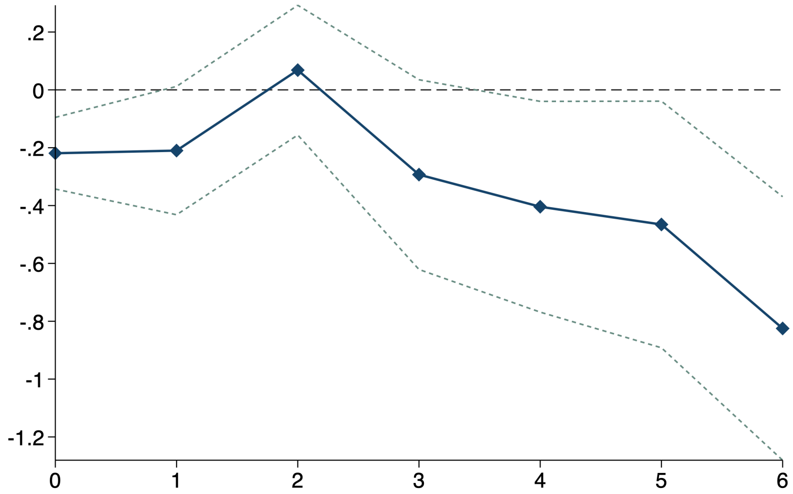
$$D_t = \frac{1}{N}\Sigma_{j=1}^{N}(\beta_{t,j} - 1)^2,$$

Where N is the number of stocks, and for each equity j the high frequency beta $\beta_{t,j}$ is

$$\beta_{t,j} = \frac{\Sigma_\tau Cov(r_{j,t,\tau}, r_{m,t,\tau})}{\Sigma_\tau Var(r_{m,t,\tau})},$$

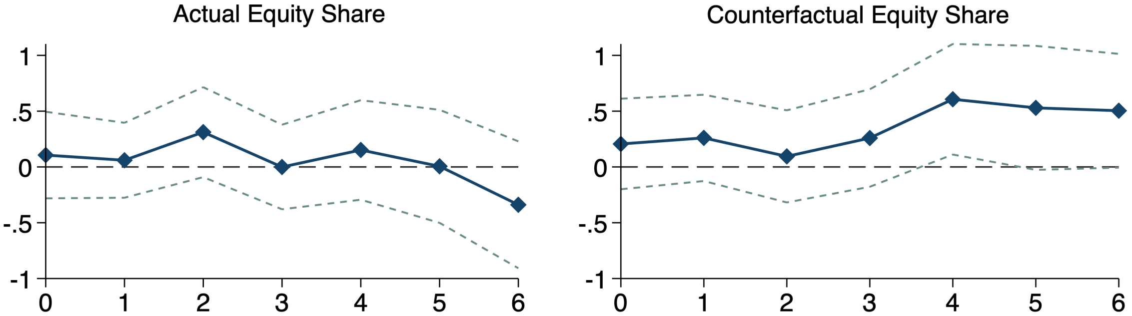
Where $r_{j,t,\tau}$ is the return of equity j at every 5-minute window around the 1 hour before and 1 hour after the FOMC announcement at date t, and $r_{m,t,\tau}$ is the corresponding market return. We sort the equity at each date by institutional ownership and compute the beta dispersion within each ownership quantile.

Figure 19: Rebalancing activities of balanced funds



This graph plots the panel local projection $\theta_{j,t+h} - \check{\theta}_{j,t-1\to t+h} = \beta_h \left[\theta_{j,t-1}(1-\theta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, where $\theta_{j,t+h}$ is the actual equity share of fund j at month $t+h$, $\check{\theta}_{j,t-1\to t+h}$ is the counterfactual fund equity share, holding quantities constant from $t-1$ to $t+h$. The difference $\theta_{j,t+h} - \check{\theta}_{j,t+h}$ captures the active rebalancing quantity. MS_t is the (138) shocks aggregated to monthly frequency following (75). $\boldsymbol{X}_{j,t+h}$ 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.

Figure 20: Actual and counterfactual equity shares

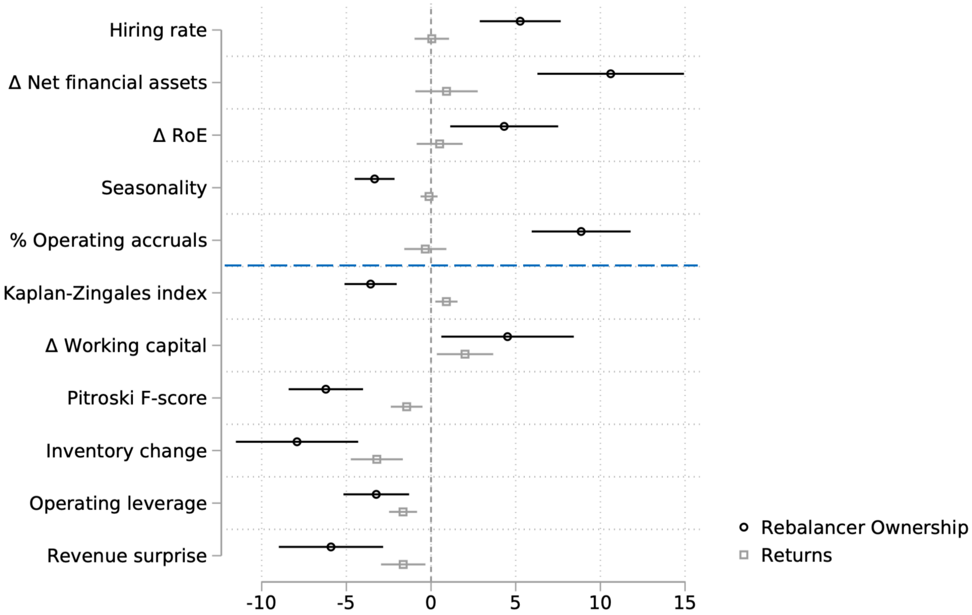


Graph (a) plots the panel local projection of $\theta_{j,t+h} = \beta_h \left[\theta_{j,t-1}(1-\theta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, and graph (b) plots the panel local projection of $\check{\theta}_{j,t-1\to t+h} = \beta_h \left[\theta_{j,t-1}(1-\theta_{j,t-1})MS_t\right] + \boldsymbol{\varphi}'\boldsymbol{X}_{j,t+h} + \epsilon_{j,t+h}$, where $\theta_{j,t+h}$ is the actual equity share of fund j at month $t+h$, $\check{\theta}_{j,t-1\to t+h}$ is the counterfactual fund equity share, holding quantities constant from $t-1$ to $t+h$. The difference $\theta_{j,t+h} - \check{\theta}_{j,t+h}$ captures the active rebalancing quantity absent revaluation of stocks and bonds. MS_t is the monthly Nakamura-Steinsson shocks aggregated following (75). $\boldsymbol{X}_{j,t+h}$ contains fund fixed effects along with four lags of the main variables. The unmodeled determinants of equity share remain in $\epsilon_{j,t-1\to t+h}$. 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.

Figure 21: Binned scatterplot of balanced funds' holdings against rebalancers' holdings in ranks

This figure plots the cross-sectional ranks of FactSet rebalancers' holdings against balanced funds' holdings. For each time point (end of the year 2004, 2009, 2014, 2019), we compute the cross-sectional ranks of ownership shares for all stocks within either rebalancers' or balanced funds' holdings and plot the average ranks grouped into bins of 1% width.

Figure 22: Ownership determinants



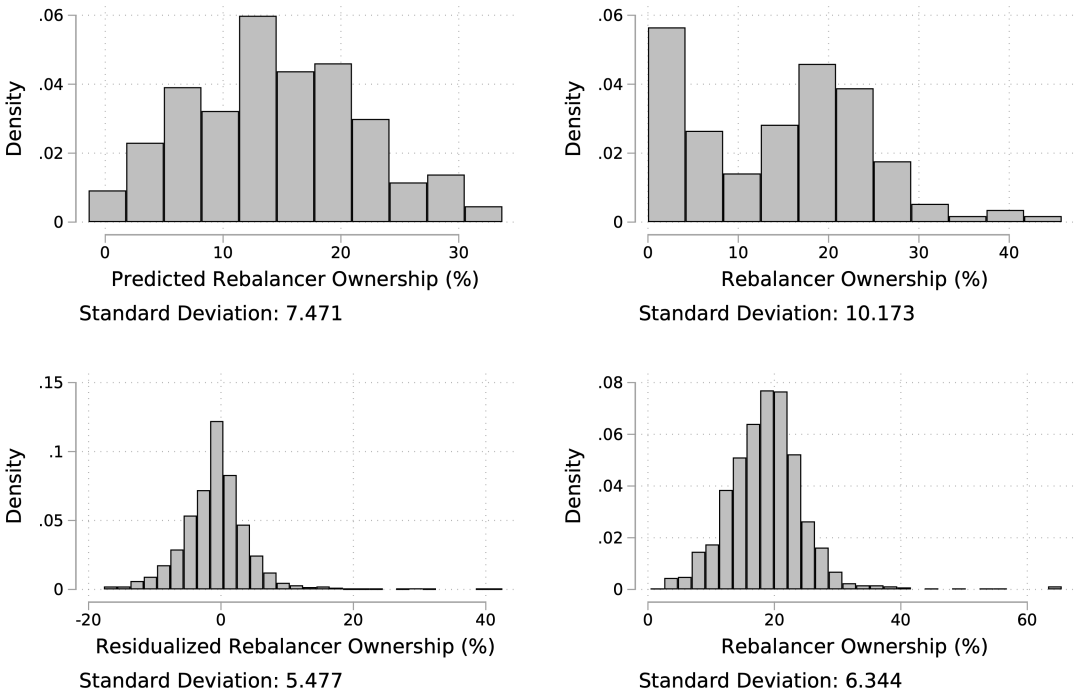
This graph summarizes results from post-selection OLS regressions

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

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

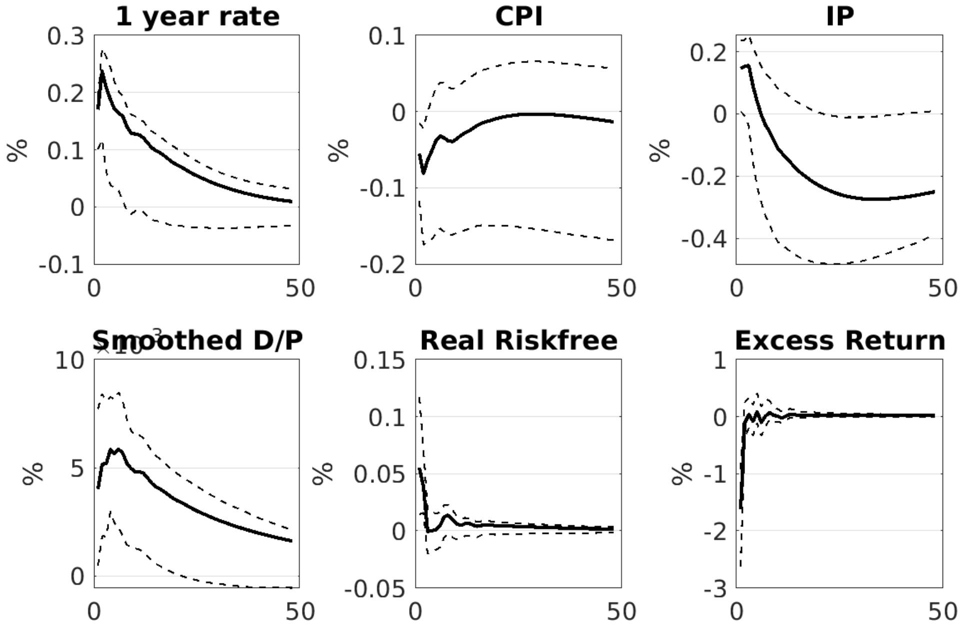
where $\mathrm{E}\, r_i$ is a $N \times 1$ vector that summarizes the average returns for each portfolio i in the sample, $\mathrm{Cov}\left(r_{it}, F_{ownership,t}\right)$ is a $N \times 1$ matrix that captures the covariances between stock returns and the ownership factor, and $\mathrm{Cov}_{i,X}$ 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 (109). Reported numbers should be interpreted as SDF loadings instead of risk premia (65). 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 23: Residual variations in ownership



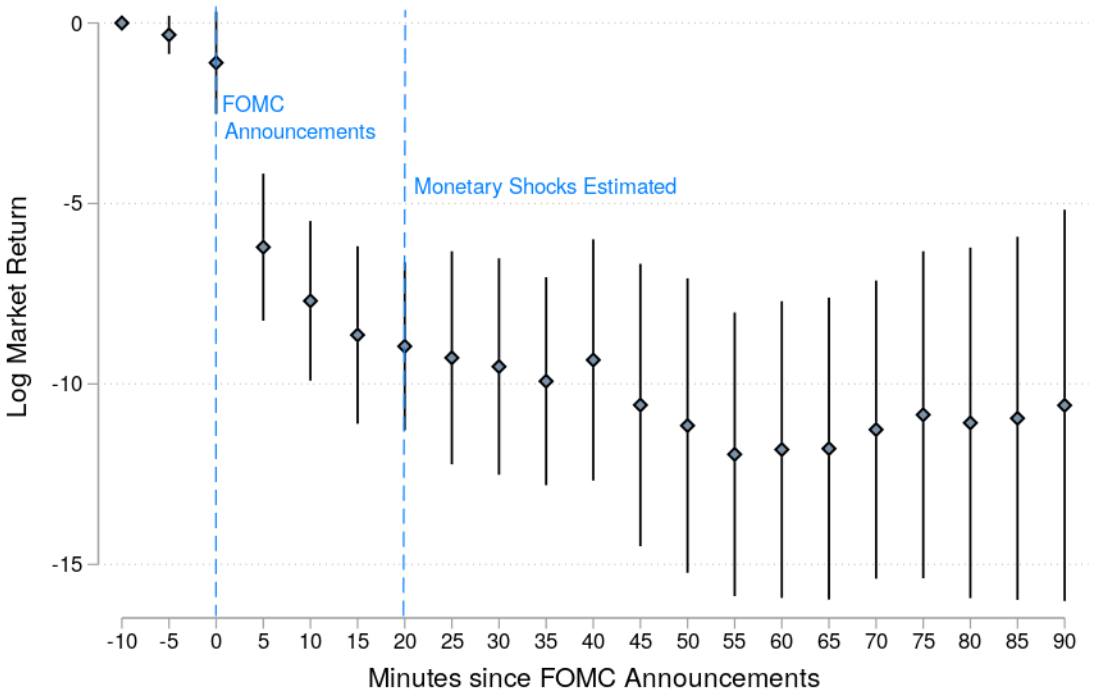
This graph summarizes the cross-sectional variations of rebalancer ownership at the security level. The top two panels capture the average share-class level ownership variations; the top left graph shows that the predicted ownership using voting rights and firm-meeting fixed effects have standard deviations similar to the raw share-class level rebalancer ownership for the dual-class 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(market 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 24: 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 (138), following (113, 75, 135), from October 1995 to September 2019. The 90% confidence intervals are computed at each horizon using the wild bootstrap with 10,000 iterations.

Figure 25: 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.

Table 1: Summary statistics for institutions and funds

			Asset Under Management					Concentration		Active Share (%)		
		N	Mean (bn)	SD (bn)	10th %tile (mn)	Median (bn)	90th %tile (bn)	HHI	CR10	Mean	SD	p50
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	**1,401**	**28.77**	**308.4**	**91.55**	**1.765**	**22.15**	**826.8**	**57.63**	**45.7**	**20**	**47.2**
	2019	**1,947**	**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**
Advisor	2004	1,784	23.2	159.4	41.79	1.506	34.51	270.1	36.72	47.2	19	47.3
	2009	2,083	21.24	126.5	34.89	1.146	31.34	175.1	30.83	45.7	19.2	45.6
	2014	3,306	23.87	167.3	31.68	0.9059	30.62	151.5	29.61	43.7	19.4	44.4
	2019	3,691	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	1,094	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	1,118	10.08	30.65	127.4	1.999	21.79	91.59	23.57	44.9	23.9	49.8
	2019	1,139	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	1,438	78.69	43.7	19.9	45.4
	2019	380	144.5	1431	34.62	0.6731	51.13	2,603	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 type. Statistics are reported separately by category classified based on FactSet codes *entity_type* and *entity_subtype*. We report the HerfindahlHirschman 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 (117). 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.

Table 2: Summary statistics for common stocks in FactSet holdings

	VARIABLES	N	Mean	Median	SD	p10	p90
2004	Advisor %	4,913	22.00	20.50	16.20	1.52	44.60
	Broker %	4,662	0.94	0.54	1.33	0.03	2.20
	Hedge Fund %	4,322	5.59	3.23	6.63	0.46	13.60
	Long-Term Investor %	4,516	2.15	1.38	2.02	0.15	4.84
	Mutual Fund %	4,291	9.92	8.22	8.33	0.81	21.90
	Institutional Wealth Mgmt %	4,849	10.10	8.92	8.34	0.56	20.90
	Market Value ($ million)	4,938	2,536	355.20	8,444	36.23	4,742
	β	3,838	0.918	0.800	0.647	0.170	1.850
	DSS Duration (year)	1,110	18.41	17.53	9.548	14.98	19.26
	Weber Duration (year)	1,137	18.98	21.14	11.31	15.26	23.60
2009	Advisor %	4,398	24.80	24.30	18.10	1.42	49.50
	Broker %	3,919	1.23	0.85	1.49	0.08	2.53
	Hedge Fund %	4,085	6.72	4.14	7.48	0.68	16.20
	Long-Term Investor %	3,996	2.47	2.13	2.03	0.21	5.15
	Mutual Fund %	3,914	10.40	9.11	8.14	0.94	21.70
	Institutional Wealth Mgmt %	4,230	9.77	9.07	7.60	0.68	18.80
	Market Value ($ million)	4,328	2,774	320.94	9,075	23.67	5,260
	β	3,329	0.911	0.843	0.563	0.218	1.681
	DSS Duration (year)	1,336	18.47	16.65	12.76	13.13	20.11
	Weber Duration (year)	1,381	16.64	19.30	14.88	10.23	23.35
2014	Advisor %	4,220	25.70	26	17.70	1.79	49.90
	Broker %	4,101	1.43	0.89	1.62	0.08	3.41
	Hedge Fund %	4,056	9.60	6	10.10	0.91	23.90
	Long-Term Investor %	3,678	2.79	2.51	2.28	0.22	5.84
	Mutual Fund %	3,954	11.20	10.30	8.34	1.40	23.00
	Institutional Wealth Mgmt %	4,171	11.30	10.70	8.54	0.84	21.20
	Market Value ($ million)	4,170	4,798	666.39	12,860	47.39	10,560
	β	2,936	1.329	1.338	0.617	0.438	2.111
	DSS Duration (year)	1,554	19.27	17.40	12.32	14.94	20.22
	Weber Duration (year)	1,604	18.35	20.86	15.39	14.86	23.86
2019	Advisor %	4,149	25.50	25.90	17.80	1.30	49.00
	Broker %	4,016	1.66	1.28	1.62	0.12	3.58
	Hedge Fund %	3,995	10	6.42	10.40	1.04	24.70
	Long-Term Investor %	3,417	2.90	2.68	2.37	0.21	6.04
	Mutual Fund %	3,827	11.20	10.30	8.32	1.22	22.90
	Institutional Wealth Mgmt %	4,072	11.80	11.80	8.37	0.93	20.80
	Market Value ($ million)	4,104	5,950	761.93	14,960	34.75	14,830
	β	2,835	0.929	0.933	0.428	0.351	1.469
	DSS Duration (year)	1,971	19.42	17.65	11.26	14.30	22.46
	Weber Duration (year)	2,018	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 (58), and (174) respectively), market β (71), 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.

Table 3: Dual-class shares: rebalancer ownership and returns under 2SLS

	OLS	1st Stage		2SLS	OLS
	(1) $I_{High\ Rebalancer\ Ownership}$	(2) $I_{High\ Rebalancer\ Ownership}$	(3) MS×$I_{High\ Rebalancer\ Ownership}$	(4) Returns	(5) Returns
$I_{High\ Voting\ Rights}$	-0.282***	-0.291**	0.000573		
	(0.0149)	(0.145)	(0.000616)		
MS×$I_{High\ Voting\ Rights}$		0.371	-0.379***		
		(0.564)	(0.138)		
MS×$I_{High\ Rebalancer\ Ownership}$				-7.324***	-2.765**
				(2.476)	(1.142)
$I_{High\ Rebalancer\ Ownership}$				-0.0914	-0.00133
				(0.0883)	(0.0237)
Firm-Meeting FE	N	Y	Y	Y	Y
N	4,164	4,164	4,164	4,164	
Adj. R^2	0.0796	0.0821	0.568		0.840
CD Wald F				182.9	

This table summarizes the instrumented regressions for dual-class shares and compares the results with OLS regressions. $I_{High\ Rebalancer\ Ownership}$ is an indicator function that equals one when the share class i of firm f at time t has higher rebalancer ownership in $t-1$ than the other share class $-i$ of firm f, and zero otherwise. $I_{High\ Voting\ Rights\ Rights}$ is an indicator function that equals one when the share class i of firm f at time t has higher voting rights in $t-1$ than the other share class $-i$ of firm f, and zero otherwise. Columns (1)–(3) show the relevance between instruments $I_{High\ Voting\ Rights\ Rights}$ and $I_{High\ Voting\ Rights\ Rights} \cdot MS$ and $I_{High\ Rebalancer\ Ownership}$ and $I_{High\ Rebalancer\ Ownership} \cdot MS$. Columns (4) and (5) report the 2SLS estimate of returns on instrumented ownership variables ($\widehat{I_{High\ Rebalancer\ Ownership}}$ and $\widehat{I_{High\ Rebalancer\ Ownership} \cdot MS}$), and the OLS estimate of returns on raw ownership variables ($I_{High\ Rebalancer\ Ownership}$ and $I_{High\ Rebalancer\ Ownership} \cdot MS$).

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%.

Table 4: Does rebalancing demand affect monetary transmission to equity prices?

	Aggregate	*Type* = Rebalancers						
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MS	-8.900*** (1.200)	×	×	×	×	×	×	-3.757 (2.947)
Ownership_{Type}×MS		-2.817* (1.561)	-3.353** (1.590)	-3.413** (1.589)	-3.758** (1.554)	-3.659** (1.565)	-3.718** (1.564)	-6.823*** (1.903)
Ownership_{Type}		×	×	×	×	×	×	×
MPE			×	×	×	×	×	×
MPE×MS			×	×	×	×	×	×
DSS Duration×MS				×	×	×	×	×
DSS Duration				×	×	×	×	×
β×MS					×	×		
β					×	×		
$Log(me)$ ×MS						×	×	×
$Log(me)$						×	×	×
FF4 Factors ×MS							×	×
FF4 Factors							×	×
Meeting FE	N	Y	Y	Y	Y	Y	Y	N
$I\_ind.$× MS	N	Y	Y	Y	Y	Y	Y	N
N	110	58,497	58,497	58,497	58,497	58,497	58,497	58,497
Adj. R^2	0.267	0.592	0.592	0.592	0.594	0.594	0.596	0.153

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

	Cross-Section with Other Institutions					
	(1)	(2)	(3)	(4)	(5)	(6)
MS	×	×	×	×	×	×
$\text{Ownership}_{Others}$×MS	0.332 (0.770)	0.552 (0.768)	0.566 (0.768)	1.079 (0.759)	0.968 (0.791)	0.698 (0.796)
$\text{Ownership}_{Others}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
$Log(me)$ ×MS					×	×
$Log(me)$					×	×
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

(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 (138) estimated from the same 30-minute windows around FOMC announcements:

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

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 (138). 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 investor* for security i at time 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.
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%.

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***	-5.621***		-3.725**	-4.770***	-4.670***		-3.659**
		(1.855)	(1.821)	(1.827)		(1.750)	(1.724)	(1.738)		(1.565)
Ownership of Rebalancers		×	×	×		×	×	×		×
Duration×MS			×	×			×	×		×
DSS Duration			×	×			×	×		×
MPE			×	×			×	×		×
MPE×MS			×	×			×	×		×
β×MS			×	×			×	×		×
β			×	×			×	×		×
$Log(me)$ ×MS				×				×		×
$Log(me)$				×				×		×
Meeting FE	N	Y	Y	Y	N	Y	Y	Y	N	Y
$I\_ind.$× 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 (138) estimated from the same 30-minute windows around FOMC announcements: $r_{it} = \gamma \text{Ownership}_{ijt} \cdot MS_t + \boldsymbol{\phi}' \boldsymbol{X}_{it} \cdot MS_t + \vartheta \text{Ownership}_{ijt} + \boldsymbol{\varphi}' \boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, where i indexes stocks, j indexes types of institutions, 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 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). 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 (138). $Ownership_{ijt}$ sums up the quarterly ownership of institutions in the rebalancer categories (*institutional wealth management* and *long-term investor*) for portfolio i at time 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%.

Table 6: Identifying the effect of mandates: evidence from mutual funds

	Balanced Funds				Pure Equity Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership$_{BalancedFunds}$×MS	-59.55**	-62.32**	-64.15**	-58.90**		
	(29.64)	(29.64)	(29.73)	(29.54)		
Ownership$_{BalancedFunds}$	×	×	×	×		
Ownership$_{EquityFunds}$×MS					2.701	3.334
					(2.563)	(2.729)
Ownership$_{EquityFunds}$					×	×
MPE & MPE ×MS		×	×	×		×
Duration & Duration ×MS			×	×		×
$Log(me)$ & $Log(me)$×MS			×	×		×
β & β×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	0.594	0.594	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 (138) estimated from the same 30-minute windows around FOMC announcements: $r_{it} = \gamma\omega_{it}^F \cdot MS_t + \boldsymbol{\phi}'\boldsymbol{X}_{it} \cdot MS_t + \vartheta\omega_{it}^F + \boldsymbol{\varphi}'\boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, 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 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 meetings; these shocks are normalized based on the daily treasury yield around FOMC dates (138). Mutual funds' ownership is collected from Morningstar; ω_{it}^F 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 at time t, and ω_{it}^F 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 100%. 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%.

Table 7: Summary Statistics of Macro Variables, by City

	Housing Price	Fixed Investment	Real Estate Investment	GDP	ΔGDP	Average Wage
unit	RMB/sq m	RMB mn	RMB mn	RMB bn	RMB bn	RMB
count	195	195	195	195	195	195.00
mean	3750.41	105752.95	21748.16	0.1826	0.0168	31,342.38
std	2166.56	103832.76	33869.33	0.2245	0.0196	7,339.60
min	1657.70	9653.58	773.28	0.0146	0.0008	16,316.36
median	3017.30	66654.79	9738.30	0.1047	0.0097	29,810.69
max	16364.43	679984.85	258079.90	1.7508	0.1200	70,256.63

Table 7: Summary Statistics of Macro Variables, by City (*Continued.*)

	Paved Road	Household Registration	Usual Residence	Govt. Revenue	Govt. Expenditure	Deposits
unit	sq m mn	Person th	Person th	RMB mn	RMB mn	RMB mn
count	195	195	186	195	195	195
mean	0.02	4,769.80	5,023.02	15.82	23,486.48	298,465.74
std	0.03	3,278.12	3,519.75	31.97	36,146.12	655,356.56
min	0.00	553.39	633.81	0.77	3,989.12	23,897.36
median	0.01	3,915.89	4,332.87	7.03	14,843.67	108,967.86
max	0.26	32,745.60	28,922.84	313.28	349,434.69	6,200,904.56

Note: This table shows summary statistics for city-level economic data for 195 cities in sample between 2004 and 2015. Data comes from China National Bureau of Statistics.

Table 8: Promotion, GDP, and Hometown Tie

	Promotion Outcome		
	(1)	(2)	(3)
GDP Growth Rate*Hometown Tie	-3.800***	-3.832***	-3.416**
	(1.449)	(1.426)	(1.327)
Hometown Tie	0.604**	0.657***	0.625***
	(0.247)	(0.240)	(0.227)
Annualized GDP Growth Rate	2.209***	1.982***	1.810***
	(0.668)	(0.628)	(0.601)
Rank		×	×
Dismissal			×
City FE	Y	Y	Y
Prov-Year FE	Y	Y	Y
Turnover FE	Y	Y	Y
Gender FE	Y	Y	Y
Age FE	Y	Y	Y
Birth Province FE	Y	Y	Y
N	411	411	411
Adj. R^2	0.0261	0.0587	0.0835

Note: This table shows estimates for the linear probability model on promotion, GDP growth, hometown tie, and their interactions. The sample includes the universe of city party secretaries who were ever in office between 2003 and 2015. Each observation is a city-year pair. Hometown tie equals one if the province leader is appointed after the city leader and shares the same hometown with the city leader this year or in the last year. Standard errors are two-way clustered at person and province-year. Political data comes from China Political Elite Dataset. City-level economic data is from China National Bureau of Statistics. Standard errors are in parentheses.

Table 9: Hometown Tie and House Price Growth Rate

	House Price Growth Rate		
	(1)	(2)	(3)
L.Hometown Tie	-0.0532***	-0.0514***	-0.0487***
	(0.0164)	(0.0162)	(0.0159)
(Log) GDP		×	×
(Log) Population		×	×
(Log) Fiscal Revenue			×
(Log) Fiscal Expenditure			×
City-Term FE	Y	Y	Y
Prov-Year FE	Y	Y	Y
N	774	774	774
Adj. R^2	0.244	0.242	0.253

This table shows OLS estimates for the effect of hometown tie on house price growth rate. The sample includes prefecture-level cities in mainland China between 2003 and 2015. Hometown tie equals one if the province leader is appointed after the city leader and shares the same hometown with the city leader this year or in the last year. Each observation is a city-year pair. Standard errors are two-way clustered at person and province-year. Political data comes from China Political Elite Dataset. Land data comes from China Real Estate Index System. City-level economic data is from China National Bureau of Statistics. Standard errors are in parentheses.

Table 10: Hometown Tie and Land Supply Ratio

	Land Supply Ratios by Type					
	Residential			Industrial		
	(1)	(2)	(3)	(4)	(5)	(6)
Hometown Tie	0.0553**	0.0528**	0.0526**	-0.0606**	-0.0565**	-0.0532*
	(0.0251)	(0.0261)	(0.0263)	(0.0251)	(0.0261)	(0.0272)
(Log) GDP		×	×		×	×
(Log) Population		×	×		×	×
(Log) Fiscal Revenue			×			×
(Log) Fiscal Expenditure			×			×
City-Term FE	Y	Y	Y	Y	Y	Y
Prov-Year FE	Y	Y	Y	Y	Y	Y
N	504	504	504	504	504	504
Adj. R^2	0.473	0.471	0.467	0.518	0.523	0.523

This table shows OLS estimates for the effect of hometown tie on residential land supply as a ratio of land quota. The sample includes prefecture-level cities in mainland China between 2003 and 2015. Hometown tie equals one if the province leader is appointed after the city leader and shares the same hometown with the city leader this year or in the last year. Each observation is a city-year pair. Standard errors are two-way clustered at person and province-year. Political data comes from China Political Elite Dataset. Land data comes from China Real Estate Index System. City-level economic data is from China National Bureau of Statistics. Standard errors are in parentheses.

Table 11: Hometown Tie and Unit Price of Land by Type

	Residential			Industrial		
	(1)	(2)	(3)	(4)	(5)	(6)
Hometown Tie	-0.213**	-0.224**	-0.228**	0.127**	0.121**	0.116*
	(0.0880)	(0.0888)	(0.0908)	(0.0585)	(0.0586)	(0.0592)
(Log) GDP		×	×		×	×
(Log) Population		×	×		×	×
(Log) Fiscal Revenue			×			×
(Log) Fiscal Expenditure			×			×
City-Term FE	Y	Y	Y	Y	Y	Y
Prov-Year FE	Y	Y	Y	Y	Y	Y
N	523	523	523	523	523	523
$Adj.R^2$	0.875	0.875	0.874	0.702	0.700	0.699

This table shows OLS estimates for the effect of hometown tie on residential land price per unit land area. The sample includes prefecture-level cities in mainland China between 2003 and 2015. Hometown tie equals one if the province leader is appointed after the city leader and shares the same hometown with the city leader this year or in the last year. Each observation is a city-year pair. Standard errors are two-way clustered at person and province-year. Political data comes from China Political Elite Dataset. Land data comes from China Real Estate Index System. City-level economic data is from China National Bureau of Statistics. Standard errors are in parentheses.

Table 12: Hometown Tie and Land Quota

	(Log) Total Land Supply (1)	 (2)	 (3)
Hometown Tie	-0.0538	-0.0385	-0.0396
	(0.116)	(0.117)	(0.120)
(Log) GDP		×	×
(Log) Population		×	×
(Log) Fiscal Revenue			×
(Log) Fiscal Expenditure			×
City-Term FE	Y	Y	Y
Prov-Year FE	Y	Y	Y
N	534	534	534
Adj. R^2	0.835	0.836	0.837

This table shows OLS estimates for the effect of hometown tie on the logarithmic level of land quota. The sample includes prefecture-level cities in mainland China between 2003 and 2015. Each observation is a city-year pair. Standard errors are two-way clustered at person and province-year. Political data comes from China Political Elite Dataset. Land data comes from China Real Estate Index System. City level economic data is from China National Bureau of Statistics. Standard errors are in parentheses.

Table 13: 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 (117). The within-type share stands for the market share within each institutional type.

Table 14: 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.

Table 15: H_0 rejection rate, tests for price gaps of dual-class 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-class shares $g_{f,d,t}$ of any given dual-listed 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-listed firms for which the null hypothesis of a unit root is rejected (in percentage), using the LSDV estimator from (97). 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-listed firms for which the null hypothesis of $c_f = 0$ is rejected (in percentage).

Table 16: Summary statistics for dual-class 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-class shares holdings of FactSet institutions. Dual-class 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-class shares is restricted to 68 companies.

Table 17: An additional liquidity control for dual-class shares

	OLS	1st Stage		2SLS	OLS
	(1)	(2)	(3)	(4)	(5)
	$I_{High\ Rebalancer\ Ownership}$	$I_{High\ Rebalancer\ Ownership}$	MS×$I_{High\ Rebalancer\ Ownership}$	Returns	Returns
$I_{High\ Voting\ Rights}$	-0.282***	-0.248*	0.000794		
	(0.0149)	(0.148)	(0.000711)		
MS×$I_{High\ Voting\ Rights}$		0.530	-0.349**		
		(0.644)	(0.146)		
MS×$I_{High\ Rebalancer\ Ownership}$				-6.913***	-2.707**
				(2.345)	(1.099)
$I_{High\ Rebalancer\ Ownership}$				-0.0684	0.00159
				(0.0795)	(0.0220)
MS× % Realized Spread		-70.42	-17.70**		53.03
		(77.53)	(6.700)		(92.73)
% Realized Spread		-23.54***	-0.0926		1.652
		(5.912)	(0.0632)		(3.236)
Firm-Meeting FE	N	Y	Y	Y	Y
N	4,162	4,162	4,162	4,162	4,162
Adj. R^2	0.0796	0.111	0.574	-0.0368	0.839
CD Wald F				129.4	

This table summarizes the instrumented regressions for dual-class 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 (123, 103) from WRDS millisecond TAQ data. $I_{High\ Rebalancer\ Ownership}$ is an indicator function that equals one when the share class i of firm f at time t has higher rebalancer ownership in $t-1$ than the other share class $-i$ of firm f, and zero otherwise. $I_{High\ Voting\ Rights\ Rights}$ is an indicator function that equals one when the share class i of firm f at time t has higher voting rights in $t-1$ than the other share class $-i$ of firm f, and zero otherwise. Columns (1)–(3) show the relevance between instruments $I_{High\ Voting\ Rights\ Rights}$ and $I_{High\ Voting\ Rights\ Rights} \cdot MS$ and $I_{High\ Rebalancer\ Ownership}$ and $I_{High\ Rebalancer\ Ownership} \cdot MS$. Columns (4) and (5) report the 2SLS estimate of returns on instrumented ownership variables ($\widehat{I_{High\ Rebalancer\ Ownership}}$ and $\widehat{I_{High\ Rebalancer\ Ownership} \cdot MS}$), and the OLS estimate of returns on raw ownership variables ($I_{High\ Rebalancer\ Ownership}$ and $I_{High\ Rebalancer\ Ownership} \cdot MS$).

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%.

Table 18: Robustness tests

	Stock FE	Duration Measure		Ownership Measure	SP500 Index			FF4 Factors	Weighted OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ownership$_{Rebalancers}$×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)
Ownership$_{Rebalancers}$	×	×	×		×	×	×	×	×	×
DSS Duration×MS	×			×	×	×	×	×	×	×
DSS Duration	×			×	×	×	×	×	×	×
MPE	×	×	×	×	×	×	×	×	×	×
MPE×MS	×	×	×	×	×	×	×	×	×	×
$Log(size)$×MS	×	×	×	×	×	×	×	×	×	×
$Log(size)$	×	×	×	×	×	×	×	×	×	×
β×MS	×	×	×	×	×	×	×			
β	×	×	×	×	×	×	×			
GL Duration×MS		×								
GL Duration		×								
Weber Duration×MS			×							
Weber Duration			×							
Rank$_{Rebalancers}$×MS				-0.709*						
				(0.374)						
Rank$_{Rebalancers}$				×						
FF4 Factors×MS								×	×	×
FF4 Factors								×	×	×
Stock FE	Y	N	N	N	N	N	N	N	N	N
I_SP500× MS	N	N	N	N	Y	N	N	N	N	N
Meeting FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$I\_ind.$× 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	0.594	0.594	0.595	0.677	0.579	0.596	0.696	0.658

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 (83) (column 2), and duration using parameters from (174). 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 (71). 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 19: 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 (58) and (174) 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.

Table 20: Rebalancer ownership with *institutional wealth management* category only

	Type = Rebalancers					
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership$_{Type}$×MS	-3.551** (1.657)	-3.956** (1.677)	-4.000** (1.676)	-4.416*** (1.645)	-4.351*** (1.649)	-4.435*** (1.641)
Ownership$_{Type}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
Log(*me*) ×MS					×	×
Log(*me*)					×	×
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

(a)

	Cross-Section with Other Institutions					
	(1)	(2)	(3)	(4)	(5)	(6)
$_{Others}$×MS	0.374 (0.749)	0.553 (0.746)	0.563 (0.746)	1.064 (0.737)	0.958 (0.762)	0.704 (0.766)
Ownership$_{Others}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
Log(*me*) ×MS					×	×
Log(*me*)					×	×
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

(b)

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 (138) estimated from the same 30-minute windows around FOMC announcements:

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

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 (138). Institutional ownership is collected from Factset; $Ownership_{ijt}$ in Panel (a) sums up the quarterly ownership of institution categories *institutional wealth management* for security i at time 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.

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%.

Table 21: Robustness check on the Fed information effect

	Aggregate	*Type* = Rebalancers						
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MS	-11.00*** (1.171)	×	×	×	×	×	×	-4.068 (2.686)
Ownership$_{Type}$×MS		-2.704* (1.628)	-3.407** (1.652)	-3.514** (1.652)	-3.901** (1.604)	-3.837** (1.615)	-4.123** (1.617)	-4.237** (1.815)
Ownership$_{Type}$		×	×	×	×	×	×	×
MPE			×	×	×	×	×	×
MPE×MS			×	×	×	×	×	×
DSS Duration×MS				×	×	×	×	×
DSS Duration				×	×	×	×	×
β×MS					×	×		
β					×	×		
Log(*me*) ×MS						×	×	×
Log(*me*)						×	×	×
FF4 Factors ×MS							×	×
FF4 Factors							×	×
Meeting FE	N	Y	Y	Y	Y	Y	Y	N
I_ind.× MS	N	Y	Y	Y	Y	Y	Y	N
N	70	36,672	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	0.611	0.326

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

	Cross-Section with Other Institutions					
	(1)	(2)	(3)	(4)	(5)	(6)
MS	×	×	×	×	×	×
Ownership$_{Others}$×MS	-0.257 (0.800)	0.0547 (0.797)	0.0796 (0.797)	0.763 (0.786)	0.681 (0.816)	0.331 (0.824)
Ownership$_{Others}$	×	×	×	×	×	×
MPE		×	×	×	×	×
MPE×MS		×	×	×	×	×
DSS Duration×MS			×	×	×	×
DSS Duration			×	×	×	×
β×MS				×	×	
β				×	×	
Log(*me*) ×MS					×	×
Log(*me*)					×	×
FF4 Factors ×MS						×
FF4 Factors						×
Meeting FE	Y	Y	Y	Y	Y	Y
I_ind.× 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 (138) estimated from the same 30-minute windows around FOMC announcements:

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

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 (138). 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 investor* for security i at time 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 (108, 114). 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%.

Table 22: 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	0.465	0.0621	-0.00393	0.848	0.704
	(0.946)	(0.932)	(0.966)	(0.869)	(0.854)	(0.887)
Ownership of Other Institutions	×	×	×	×	×	×
Duration×MS		×	×		×	×
DSS Duration		×	×		×	×
MPE×MS		×	×		×	×
MPE		×	×		×	×
β×MS		×	×		×	×
β		×	×		×	×
$Log(me)$ ×MS			×			×
$Log(me)$			×			×
Meeting FE	Y	Y	Y	Y	Y	Y
$I\_ind.$× 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 (138) estimated from the same 30-minute windows around FOMC announcements: $r_{it} = \gamma Ownership_{it} \cdot MS_t + \boldsymbol{\phi}'\boldsymbol{X}_{it} \cdot MS_t + \vartheta Ownership_{it} + \boldsymbol{\varphi}'\boldsymbol{X}_{it} + \delta_t + \epsilon_{it}$, 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 (138). 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 investor*) for security i at time 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%.

Table 23: 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

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

where $\text{E}\, r_i$ 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 company; fundamental factors refer to the factors in clusters *Accruals, Investment, Debt Issuance, Quality, Profit Growth, Profitability* defined in (109); 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 (65). The estimation period for $\text{E}\, r_i$, $\text{Cov}\left(r_{it}, [F_{ownership,t}, MS_t, F_{ownership,t} \cdot MS_t]\right)$, 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%.

Table 24: 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 (75) using the current month's fed funds futures. Both underlying high-frequency shocks are obtained from (3) 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.

Table 25: Micro and macro elasticity estimates in literature

micro elasticity $\zeta^{\perp}$ (in absolute value)					
	Estimate Type	Market	Event Type	Sample Period	Elasticity
(156)	Drift	US	Dividend payouts	1980-2017	1.25
(85)	Drift	Hong Kong	Fiscal stimuli	2020-2021	0.25-0.5
(132)	Drift	US	Idiosyncratic demand shocks	1980-2006	0.83
(146)	Announcement/Full	US	Index inclusion/deletion	1998-2018	1-3.3
(32)	Announcement/Full	US	Index inclusion/deletion	1996-2012	0.37-1.43
(16)	Announcement	Japan	Equity QE	2013-2017	1
(91)	Structural	US	-	2001-2020	0.5
(118)	Structural	US	-	2017	0.38[a]
macro elasticity ζ (in absolute value)					
(73)	Full/GIV	US	Idiosyncratic demand shocks	1993-2019	0.17
(98)	Drift	US	Dividend payouts	1926-2018	0.43-0.67
(127)	Drift	China	Locked up funds for IPO subscriptions	2006-2018	0.21-0.33
(55)	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; (178) provides a comprehensive review of earlier elasticity estimates. The trade-by-trade elasticity estimate from (69) 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 (116, 25, 73).

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[a] This is the point estimate for a median stock in 2017; (118) reports a time series of micro elasticity estimates from 1980 to 2017 (Figure 6 in their paper).

Table 26: Calibration using alternative elasticity estimates in literature

	(73)		(98)		(127)		(55)	
	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}	$\frac{\zeta^{\perp}}{\zeta}$	r_{mt}
(156)	7.35	6.03	**2.38**	**1.95**	**4.88**	**4.00**	2.78	2.28
(85)	2.21	1.81	0.71	0.58	**1.46**	**1.20**	0.83	0.68
(132)	**4.90**	**4.02**	1.58	1.30	**3.26**	**2.67**	1.85	1.52
(146)	**12.65**	**10.37**	4.09	3.35	8.40	6.89	**4.78**	**3.92**
(32)	**5.29**	**4.34**	1.71	1.40	3.52	2.88	**2.00**	**1.64**
(16)	5.88	4.82	1.90	1.56	3.91	3.20	**2.22**	**1.82**
(91)	2.94	2.41	0.95	0.78	1.95	1.60	1.11	0.91
(118)	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 25.