Asset Prices and Portfolio Adjustment under Supply Shocks*

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August 26, 2026

Abstract

We provide the first price impact estimate of exogenous changes in share supply: a 1% exogenous increase in shares outstanding lowers stock prices by 2.6%. Our identification exploits unforeseen conflicts between the 2016 SEC Tick Size Pilot and repurchase regulations. Though announcing similar repurchase programs, treatment firms repurchased 22% fewer shares than control firms due to lower completion rates. Unshocked control stocks allow us to absorb price spillovers and estimate a relative price multiplier, which we show approximates the own-price multiplier at the stock-level. Investment advisors and mutual funds absorb most shocks, followed by banks and other 13F institutions.

Keywords: Exogenous supply shock, price multiplier, share repurchase, Tick Size Pilot, demand-based asset pricing, portfolio rebalancing
JEL Classification: G11, G12, G20, G35

*We are grateful to John Campbell, Stefano Cassella (discussant), Manav Chaudhary (discussant), Haiwei Chen (discussant), Will Cong, Carter Davis, Chuck Fang, Zhiyu Fu, William Fuchs, Xavier Gabaix, Valentin Haddad, Zhiguo He, Kewei Hou, Paul Huebner (discussant), Lawrence Jin, Mahyar Kargar, Ralph Koijen, Jens Kvaerner (discussant), Jane Li, Jiacui Li, Sida Li, Erik Loualiche, Daniel Neuhann, David Ng, Neil Pearson, Nikolai Roussanov, David Solomon, Fred Sun, Yicheng Wang, Rüdiger Weber (discussant), Kairong Xiao, Xiao Yin (discussant), Motohiro Yogo, Scott Yonker, Jiaqi Zhang (discussant), Xinran Zhang (discussant), Jing Zhao (discussant), Miles Zheng, and Haonan Zhou, as well as conference and seminar participants at 2nd Big Data and Market Microstructure Conference, 9th CCER Summer Institute, 12th SAFE Asset Pricing Workshop, 14th Helsinki Finance Summit, 2025 China Fintech Research Conference, 2025 CICF, 2025 CUHK-RAPS-RCFS Conference, 2025 Esade Spring Workshop, 2025 FMA, 2026 FIRS, Bayes Junior Asset Management and Asset Pricing Workshop, The Microstructure Exchange, Cornell University, Singapore Management University, Stockholm Business School, Tsinghua PBCSF, University of British Columbia, University of South Florida, and Vienna Graduate School of Finance for insightful comments. Ye acknowledges support from National Science Foundation grant 1838183. Send correspondence to Mao Ye, my87@cornell.edu.

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1. Introduction

A traditional interpretation of long-run abnormal returns following share repurchase announcements is market underreaction to the information conveyed by repurchase programs (Ikenberry, Lakonishok, and Vermaelen, 1995). Recently, Gabaix and Koijen (2023) conjecture that repurchases may mechanically raise stock prices beyond any informational channel due to market inelasticity. However, isolating this uninformed price impact of repurchases is empirically challenging because managers tend to time the market, rendering repurchases endogenous (Baker and Wurgler, 2013). In this paper, we exploit a rare exogenous supply shock and document an economically significant price multiplier: a 1% uninformed reduction in repurchases relative to shares outstanding decreases stock prices by 2.6%.

The supply shock arises from the SEC's 2016 Tick Size Pilot (TSP). As a randomized controlled trial (RCT) in the equity market, the TSP randomly assigned 1,200 stocks to treatment groups, increasing the minimum tick size from one cent to five cents, while the remaining 1,199 stocks served as the control group. Surprisingly, this seemingly minor change in tick size reduced quarterly share repurchases by 22% among treatment firms, thereby generating exogenous supply shocks.

Neither managers nor the market anticipated the reduction. During the TSP, the percentage of shares outstanding sought in the new repurchase program, the announced dollar volume of repurchase, and the probability of initiating a new repurchase program remained unchanged across treatment and control firms, implying that the TSP did not alter managers' intent to repurchase shares. Similarly, the cumulative abnormal returns (CAR) around re-

purchase announcements show no significant differences, indicating the supply shocks were unanticipated to the market. *Ex post,* Li, Ye, and Zheng (2024) show that the reduction stems from an unexpected conflict between the TSP and SEC Rule 10b-18, a regulation on open-market repurchases.[1] We further show that the conflict results in a lower completion rate of repurchase programs at the execution stage: during the TSP, the completion rate of treatment firms' repurchase programs was 9.6% lower than that of control firms.[2]

Besides generating exogenous shocks on share supply, the randomized design of the TSP also allows us to explicitly control for spillover effects. Without this control, the price change of a treatment stock reflects not only its own supply shock but also the collective shocks from 1,199 other treatment stocks. Because control stocks faced no supply shocks, we match each treatment stock to a paired control stock with similar observables. Since the matched treatment and control share the same cross-price multipliers with all other stocks outside the matched pair (Haddad, He, Huebner, Kondor, and Loualiche, 2026),[3] the double-differences in prices removes spillovers from the remaining 1,199 treatment stocks.

Our regression specification then follows the theoretical framework of Haddad et al. (2026). The dependent variable is the within-pair double differences in log stock prices, capturing cumulative return differences between matched firms; the key explanatory variable is the corresponding within-pair double differences in cumulative shares repurchased. This

[1]To prevent price manipulation, Rule 10b-18 effectively requires firms to use limit orders to repurchase shares at the bid price. The TSP removed four-fifths of the available price grids, thereby lengthening queues at the remaining price points, as reflected in a 112% increase in displayed dollar depth at the national best bid relative to the pre-TSP mean. Time-priority execution prevented firms from competing with high frequency traders, mechanically reducing the fill rate of repurchases for treatment firms. See more details in Section 2.

[2]Firms are not obligated to repurchase the full announced share or dollar volume; the announced amount is an upper limit. Bonaimé (2012) shows that the average completion rate of repurchase programs is 72.57%.

[3]This parallels the assumption of homogeneous cross-elasticities conditional on observables in Haddad et al. (2026). We empirically validate it under a factor structure of asset payoffs in Section 5.2.

specification identifies the relative price multiplier (Haddad et al., 2026) with an empirical magnitude of 2.575. This estimate implies that, relative to its matched substitute, a 1% uninformed reduction in repurchases relative to shares outstanding lowers the treatment stock's price by 2.575%.

We then show that the estimated *relative* price multiplier closely approximates the *own*-price multiplier. Intuitively, the relative price multiplier retains only the one-to-one spillover from a treatment stock to its matched control. We find that this spillover is negligible relative to the direct effect of the treatment stock's own supply shock.[4]

To formalize this intuition, we build a simple demand system in which asset payoffs follow a single-factor structure (Koijen, Richmond, and Yogo, 2023). Theoretically, the own-price multiplier consists of an idiosyncratic-risk and a systematic-risk-exposure component. Because the relative multiplier captures the idiosyncratic component, it approximates the own-price multiplier when idiosyncratic risk dominates systematic exposure. Empirically, we find strong supportive evidence: the average idiosyncratic risk is 8.4 times larger than average systematic exposure, and a t-test indicates that systematic exposure is less than 7% of idiosyncratic risk at the 1% significance level. In other words, the residual spillover effect is less than 7% of the direct effect in our relative multiplier estimate for an *individual* stock.

Although our baseline regression controls for differences in firm fundamentals, a potential concern is that the exogenous reduction in share repurchases may affect treatment firms' fundamentals, such as cash holdings, thereby affecting stock prices. While firms repurchase shares continuously and gradually over time (Stephens and Weisbach, 1998), information

[4]Importantly, this does not imply that spillovers from all treatment firms are negligible. During the Tick Size Pilot, 1,200 treatment stocks experienced positively correlated supply shocks, so aggregate spillovers can be substantial even when spillovers at the *individual*-stock level are small.

about both firm fundamentals and realized repurchases is disclosed only at discrete quarterly reporting dates. If the price effect induced by the TSP primarily stems from the confounding changes in firm fundamentals instead of supply shocks, the return differences between treatment and control firms should be concentrated around the filing dates of 10-K/10-Q forms, in which the detailed financial and repurchase information is disclosed. However, we find no statistically and economically significant difference in CAR over the filing windows. This evidence suggests that our estimated price multipliers are unlikely to be contaminated by changes in firm fundamentals.[5]

A unique feature of the TSP further addresses the concern of changes in liquidity contaminating the multiplier estimate. The TSP divided the 1,200 treatment stocks into three test groups. The 400 stocks in test group 3 exogenously repurchased 14% fewer shares than groups 1 and 2, owing to an unanticipated restriction on the use of dark pools for share repurchases.[6] However, this restriction did not induce larger reduction in aggregate liquidity for group 3 stocks compared to stocks in group 1 and 2, because it merely redistributed liquidity across exchanges and dark pools (Albuquerque, Song, and Yao, 2020). We first estimate price multipliers separately for groups 1&2 and for group 3, finding no statistically significant differences from each other and from the baseline estimate. We also directly match each treatment firm in group 3 with a treatment firm in group 1 or 2. This additional layer of differencing directly eliminates potential liquidity effects on treatment prices, as three

[5]Quarterly filings also disclose the prices and quantities of repurchases during the preceding quarter. Therefore, the absence of the CAR difference around filing dates further suggests that the market does not materially revise its valuations upon receiving the information about repurchases.

[6]Group 3 stocks were additionally subject to the "trade-at" rule, which conferred execution priority to displayed orders unless nondisplayed liquidity improves the Nationl Best Bid and Offer (NBBO) by 2.5 cents, while Rule 10b-18 treated such price improvement for repurchase orders as an indicator of price manipulation. This unintended conflict effectively banned Group 3 firms from repurchasing shares through dark pools.

groups experienced similar decreases in liquidity. We re-estimate the price multiplier and again find no statistically significant differences from the baseline estimate. Taken together, our findings suggest that the three treatment groups have the same price multipliers, and the price effect mainly stems from supply shocks instead of liquidity changes.[7] Group 3 experienced a greater price decline than groups 1 and 2 primarily because of the additional reduction in share repurchases.

To further alleviate concerns about the potential endogeneity of realized repurchases, we also instrument realized quarterly repurchases. A two-stage least squares (2SLS) specification regressing quarterly stock returns on instrumented repurchases yields a relative price multiplier statistically indistinguishable from our baseline result.

Finally, we examine how investors adjust their holdings in response to supply shocks. Intuitively, given a price change through the price multiplier, investors with higher demand elasticities absorb more supply shocks. We find that for each 1% additional exogenous supply, investment advisors (e.g., hedge funds) purchase 0.501%; mutual funds purchase 0.249%; banks and other 13F institutions purchase 0.102% and 0.104%, respectively. Insurance companies and pension funds do not actively respond to supply shocks. Households exhibit a dynamic response: they initially absorb the supply shocks, but gradually decrease their holdings by selling shares to other investors afterwards, thereby amplifying the supply shocks alongside the treatment firms.

Contribution to Related Literature. We contribute to the share repurchase liter-

[7]These tests strengthen our inference in two ways for the TSP as a reused experiment (Heath et al., 2023). First, while most existing research using the TSP as an experiment relies on variation in treatment assignment, we additionally exploit the random assignment of G1&2 and G3 stocks to provide corroborating evidence for our supply channel. Second, by showing that the liquidity does not contaminate the multiplier estimate, we alleviate the compound exclusion restriction concern.

ature by showing that market inelasticity provides an additional explanation for why stock prices rise with share repurchases. A large body of corporate finance research attributes abnormal returns around repurchase announcement to managerial signaling of undervaluation (Dann, 1981; Vermaelen, 1981; Ofer and Thakor, 1987; Constantinides and Grundy, 1989; Billett and Yu, 2016). However, Ikenberry, Lakonishok, and Vermaelen (1995) argue that signaling theory alone cannot explain the post-announcement long-run abnormal returns;[8] instead, they interpret these long-run returns as an evidence of market underreaction. In contrast, our findings suggest an alternative explanation: the long-run abnormal returns arise mechanically from the reduction in shares outstanding. Since a repurchase program typically takes years to complete (Stephens and Weisbach, 1998), the continuous reduction in shares outstanding then contribute to the long-run abnormal returns after the announcement.

An important strand of behavioral corporate finance literature examines how rational managers correct mispricings by issuing overvalued securities and repurchasing undervalued ones (Baker and Wurgler, 2013). The theoretical models in this literature often assumes an exogenous price impact of repurchases to prevent managers from buying back the entire firm (e.g., Stein, 1996). We provide an empirical foundation for this assumption by showing that market inelasticity alone generates economically significant price impact, even in the absence of asymmetric information.

Our paper complements a rich literature estimating price multipliers by providing the first estimate based on exogenous supply shocks. While economic principles suggest that identifying a demand curve requires exogenous supply shocks, reduced-form studies rely

[8]The long-run abnormal returns following repurchase announcements are well documented over time and across different countries (e.g., Ikenberry, Lakonishok, and Vermaelen, 1995; Peyer and Vermaelen, 2009; Manconi, Peyer, and Vermaelen, 2019).

largely on demand shocks.[9] Assuming a fixed supply, the demand-shock approach implicitly partitions investors into shocked and unshocked groups and identifies the price multiplier of unshocked investors.[10] In contrast, managers value the price multiplier across all investors. Under an exogenous supply shock, the shocked agent is the firm itself and unshocked agents are all investors; the supply shock therefore identifies the demand curve faced by the firm, yielding a price multiplier directly relevant to corporate decision-making.

On the structural side, Koijen and Yogo (2019) innovatively bypass the fixed-supply constraint by constructing and rotating hypothetical "shocks" for each investor via investment mandates of all other investors. Their approach identifies *every* investor's demand curve and then aggregates them to form the stock-level demand curve. However, they impose downward-sloping demand curves on each investor to ensure a unique equilibrium. This restriction may top-code investors with negative demand elasticities (e.g., momentum traders), thereby attenuating the aggregate elasticity estimate (Binsbergen, David, and Opp, 2026). Our supply-shock approach directly identifies the demand curve faced by firms without top-coding upward-sloping demand curve at the investor level.

The demand-shock approach does not study investors' equilibrium holdings because it relies on exogenous changes in the holdings of a subset of investors. In contrast, Koijen and Yogo (2019) explain cross-sectional investor holdings through a demand system. Koijen et al.

[9]Typical demand shocks include index inclusions and deletions (Shleifer, 1986; Chang, Hong, and Liskovich, 2015; Pavlova and Sikorskaya, 2023), mutual fund flows (Coval and Stafford, 2007; Lou, 2012; Chaudhary, Fu, and Li, 2025), dividend reinvestment (Kvamvold and Lindset, 2018; Schmickler and Tremacoldi-Rossi, 2023; Chen, 2024; Hartzmark and Solomon, 2025), regulatory regime shifts (Cassella et al., 2026), and central bank asset purchase programs (Koijen et al., 2021; Haddad, Moreira, and Muir, 2025).

[10]Recent work also shows that firms may endogenously respond to anticipated demand shocks by adjusting equity supply, including issuing shares following index inclusion (Sammon and Shim, 2026) or mutual fund inflows (Wang, 2025). Fang and Xiao (2025) also show that corporations issue new bonds when the Fed conducts QE. As a result, estimates based on exogneous but anticipated demand shocks may also confound investor demand elasticity with supply elasticity.

(2021) study time-series portfolio rebalancing by bond market investors under quantitative easing by the European Central Bank. We provide the first equity market evidence of investors rebalancing their holdings in response to exogenous supply shifts, finding that investment advisors and mutual funds absorb most of the supply shocks, followed by banks and other 13F institutions.

Our paper also contributes to the discussion of spillover effects in estimating price multipliers. Fuchs, Fukuda, and Neuhann (2025) theoretically argue that spillover effects can bias estimates. Chaudhary, Fu, and Li (2025) empirically show that ignoring spillovers leads to overestimation of bond-level price multipliers. Structurally, Koijen and Yogo (2019) control spillover effects through a logit demand system. For a general reduced-form setting, Haddad et al. (2026) develop a theoretical framework for controlling spillovers and identifying relative price multipliers. To the best of our knowledge, we are the first to implement their framework empirically in the equity market: the randomized assignment of shocked and unshocked stocks under the TSP enables us to absorb spillover effects within a difference-in-differences (DID) design. In addition to estimating the relative price multiplier, we show both theoretically and empirically that when idiosyncratic risk dominates systematic risk exposure, the relative price multiplier closely approximates the own-price multiplier at the individual stock level. This result is particularly relevant for corporate managers, who cannot trade correlated stocks with similar characteristics and therefore care about own-price multipliers.

The rest of the paper is structured as follows. Section 2 describes the institutional background on the TSP and regulations on share repurchases. Section 3 establishes a conceptual framework for our identification method. Section 4 outlines the sample construction, presents the effect of TSP on share supply, and examines the exogeneity of the supply shock.

Section 5 estimates the relative price multiplier, shows the empirical approximation of relative price multiplier to the own-price multiplier, and controls for the confounding liquidity effect. Section 6 reports the portfolio adjustment behavior by investors when faced with supply changes. Finally, Section 7 concludes.

2. Institutional Background

In this section, we describe the institutional background of the TSP, a unique RCT in the U.S. equity market. We further explain the existing regulations on repurchases through which the TSP generated exogenous supply shocks.

2.1 The Tick Size Pilot

In 2014, the SEC instructed the Financial Industry Regulatory Authority (FINRA) and National Securities Exchanges (NSEs) to develop a pilot program to test the effects of varying tick sizes on market performance. The TSP officially commenced on October 3, 2016, and concluded on October 1, 2018. The program selected 2,399 stocks that met specific criteria in the three months before the launch: a minimum share price of $1.50 each day, a volume-weighted average price of at least $2, an average trading volume of fewer than one million shares, market capitalization below $3 billion, and a closing price above $2 on the last day of this period.

After selecting the eligible TSP stocks, FINRA and NSEs first sorted all eligible stocks into 27 buckets based on three characteristics: (i) low, medium, or high share prices, (ii) low, medium, or high market capitalization, and (iii) low, medium, or high volume. They

then randomly selected stocks from each of the 27 categories to form three test groups, each containing 400 stocks. The remaining 1,199 eligible stocks served as the control group.

The control group continued to trade and quote at the standard 1-cent tick size. Stocks in test group 1 could only be quoted in $0.05 increments, but they could still be traded in $0.01 increments. Stocks in test group 2 were both quoted and traded in $0.05 increments. Stocks in test group 3 followed the same rules as test group 2 but also fell under the "trade-at" Rule, which granted execution priority to displayed orders unless nondisplayed liquidity (e.g., dark-pool executions) improved the NBBO by 2.5 cents.[11]

2.2 Regulations on Repurchases and the Exogenous Supply Shocks

Since repurchasing firms typically assign valuations well above the prevailing market price (Li, Ye, and Zheng, 2023), a modest increase in tick size should have limited direct impact on the intent of share repurchases. Surprisingly, Li, Ye, and Zheng (2024) find that the TSP significantly reduced share repurchases for treatment firms. This unexpected outcome stems primarily from an unintended conflict between the TSP and an existing regulation: SEC Rule 10b-18, which regulates open-market share repurchase. Rule 10b-18 sets a price ceiling on share repurchase to prevent firms from manipulating their stock prices. The price ceiling asks firms to buy their shares at prices that do not exceed the highest independent bid or the last transaction price, effectively encouraging firms to place buy limit orders at the bid price on repurchase transactions. The TSP removes four out of every five quote levels, forcing investors who previously quoted at finer intervals to cluster their bids at coarser levels.

[11] More details of the TSP are in https://www.govinfo.gov/content/pkg/FR-2015-05-13/pdf/2015-11425.pdf and https://www.sec.gov/files/rules/sro/nms/2015/34-74892-exa.pdf

Because executions of limit orders quoted at the same price follow the time-priority rule, faster HFTs may outpace firms, reducing firms' order execution probability. The execution slippage thus lowers their realized repurchase volume *ex post*. As we report later, the effect of TSP on repurchase was unanticipated by firms or the market, making the resulting decline in repurchases an exogenous supply shock to treatment firms.

Crucially, even if firms were aware of this shortfall, they could not easily make it up. This is because firms may also structure their open-market repurchase programs to satisfy SEC Rule 10b5-1 to obtain an affirmative defense against claims that the repurchases were made on the basis of material nonpublic information. Repurchase programs satisfying Rule 10b5-1 specify the amount, price, and timing of trades, or a formula or algorithm that determines them, *before* the firm becomes aware of material nonpublic information.[12] Once a plan is in force, the firm may not exercise any subsequent influence over how, when, or whether trades are executed. Any modification to the amount, price, or timing of the purchase of shares underlying an original plan is treated as a termination of such plan and the adoption of a new one, which must independently satisfy the conditions of Rule 10b5-1. In effect, these adjustment frictions make it more difficult for firms to frequently change their repurchase plans. Because neither firms nor the market anticipated that the TSP would interfere with repurchase execution, and because Rule 10b5-1 limits firms' ability to adjust their pre-committed plans even if they were aware of the shortfall, the induced reduction in repurchases was arguably an exogenous supply shock to treatment firms. Later in Section 5.1, we show that the reduction in repurchases accumulates over the TSP period.

[12] During our sample period, this principle rested on Exchange Act Rules, Questions 120.16 and 120.19 and Securities Act Release No. 7881. The principle was subsequently codified as Rule 10b5-1 by the December 2022 amendments.

Notably, firms often repurchase shares through dark pools for three reasons. First, dark pools match orders passively based on reference prices from public exchanges, which aligns naturally with the requirements of Rule 10b-18. For instance, when a dark pool uses the bid price to match buy and sell orders, it inherently satisfies the price constraint imposed by Rule 10b-18. Second, many brokers operate affiliated dark pools and therefore have incentives to route repurchase orders there. Li, Ye, and Zheng (2024) show that many dark pools explicitly cater to issuers repurchasing their shares. Finally, dark pools allow firms to bypass speed competition by not imposing the time priority in trade execution.

However, the TSP introduced an additional "trade-at" Rule specifically for test group 3, which restricted dark pool executions unless they improved the NBBO by more than 2.5 cents. Since Rule 10b-18 regards outbidding the best bid by 2.5 cents as a signal of price manipulation, it unintentionally blocked firms in test group 3 from repurchasing shares through dark pools. Consequently, firms in test group 3 faced more stringent constraints on share repurchases than test groups 1 and 2, and thus experienced a larger decline in share repurchases.

3. Conceptual Framework

To motivate our empirical specifications, we first develop a simple demand system with supply shocks. It builds on the static CARA-Normal framework with heterogeneous beliefs following Lintner (1969).[13] This model motivates the identification of relative price multi-

[13]We choose CARA-Normal framework because it captures the relationship between price and quantity in *levels*. Literature studying other changes in quantity level also applies this framework, such as Pavlova and Sikorskaya (2023) and Cassella et al. (2026).

plier, the control for spillover effects using the TSP's randomized control, the approximation of relative price multiplier to own-price multiplier, and the characterization of investors' portfolio adjustment behavior under supply shocks.

3.1 Model

We consider a securities market with trading at $t = 0$ and payoffs realized at $t = 1$. The market consists of one riskless asset with a risk-free rate normalized to zero and N risky assets indexed by $n = 1, \ldots, N$. Investors, indexed by $i = 1, \ldots, I$, allocate available funds across these assets. Each stock n has an exogenously share supply $S(n)$ and delivers a per-share terminal payoff $d(n)$ at $t = 1$. Each investor i holds heterogeneous beliefs over the payoff vector $\boldsymbol{d}_i = (d_i(1), \ldots, d_i(N))'$, following a joint-normal distribution with finite first and second moments, i.e., $\boldsymbol{d}_i \sim \mathcal{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$.[14]

Let $A_{i,0}$ denote investor i's initial wealth. Let $\boldsymbol{P}$ and $\boldsymbol{q}_i$ be the endogenously determined, N-dimensional vectors of asset prices and the number of shares held by investor i at $t = 0$, respectively. Investor i's terminal wealth at $t = 1$ is

$$A_{i,1} = A_{i,0} + (\boldsymbol{d}_i - \boldsymbol{P})' \boldsymbol{q_i}$$

At $t = 0$, each investor i chooses portfolio holdings $\boldsymbol{q}_i$ to maximize her expected constant absolute risk aversion (CARA) utility over the terminal wealth:

$$\max_{\boldsymbol{q}_i} \mathbb{E}_i \left[- \exp \left(-\gamma_i A_{i,1} \right) \right]$$

[14]The variance-covariance matrix, $\boldsymbol{\Sigma}_i \in \mathbb{R}^{N \times N}$, has full rank. In the CAPM, all investors hold homogeneous beliefs with the same $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$.

where $\gamma_i > 0$ is investor i's coefficient of absolute risk aversion. As shown in Appendix A.1, investor i's optimal demand is

$$\boldsymbol{q}_i = \frac{1}{\gamma_i} \boldsymbol{\Sigma}_i^{-1} \left(\boldsymbol{\mu_i} - \boldsymbol{P} \right) \tag{1}$$

Let $\boldsymbol{S}$ be an N-dimensional vector of share supply at $t = 0$. By clearing markets for risky assets, $\sum_i^I \boldsymbol{q}_i = \boldsymbol{S}$, we obtain equilibrium asset prices:

$$\boldsymbol{P} = \boldsymbol{\mathcal{M}} \left(\sum_{i=1}^{I} \frac{1}{\gamma_i} \boldsymbol{\Sigma}_i^{-1} \boldsymbol{\mu}_i - \boldsymbol{S} \right), \text{ where } \boldsymbol{\mathcal{M}} \triangleq \left(\sum_{i=1}^{I} \frac{1}{\gamma_i} \boldsymbol{\Sigma}_i^{-1} \right)^{-1} \tag{2}$$

$\boldsymbol{\mathcal{M}} \in \mathbb{R}^{N \times N}$ is the price multiplier matrix, characterizing the equilibrium relationship between shifts in supply (aggregate demand) and asset prices. The diagonal elements $[\boldsymbol{\mathcal{M}}]_{n,n}$ represent the own-price multipliers, measuring how asset n's price responds to a shift in its own aggregate demand, holding other prices fixed. The off-diagonal elements $[\boldsymbol{\mathcal{M}}]_{n,m}$ represent the cross-price multipliers, measuring how asset n's price responds to a shift in aggregate demand for asset m. Formally,

$$[\boldsymbol{\mathcal{M}}]_{n,n} = -\frac{\partial P(n)}{\partial \sum_i^I q_i(n)} \quad \text{and} \quad [\boldsymbol{\mathcal{M}}]_{n,m} = -\frac{\partial P(n)}{\partial \sum_i^I q_i(m)}, \ \forall m \neq n$$

3.2 Identification with Supply Shocks

We now introduce supply shocks to our framework. Suppose the exogenous supply shocks shift the supply curve by a wedge of $\Delta \boldsymbol{S} = (\Delta S(1), ..., \Delta S(N))'$. The total supply therefore changes to

$$\boldsymbol{S}^{\text{new}} = \boldsymbol{S} - \Delta \boldsymbol{S}$$

Thus, $\Delta S(n) > 0$ reflects a reduction in shares outstanding for stock n; $\Delta S(n) < 0$ indicates an increase in shares outstanding; and $\Delta S(n) = 0$ implies no supply shock. Equation (2) with $\boldsymbol{S}^{\text{new}}$ determines the new equilibrium price $\boldsymbol{P}^{\text{new}}$. The equilibrium price change $\Delta \boldsymbol{P} = \boldsymbol{P}^{\text{new}} - \boldsymbol{P}$ satisfies

$$\Delta \boldsymbol{P} = \boldsymbol{\mathcal{M}}\, \Delta \boldsymbol{S} \tag{3}$$

This transformation requires the assumption of uninformedness: supply shocks contain no information about assets' future payoffs (i.e., $\Delta \boldsymbol{\mu}_i = 0$ for all investors i). This is because the supply shocks originate from the unforeseen conflict between the repurchase regulation and the TSP. We further validate this assumption in our sample by showing no differences in CAR around (i) the new repurchase program announcement and (ii) the filing date of 10-K/10-Q filings during the TSP in Sections 4.2 and 4.3, respectively.

3.2.1 Controlling for Spillover Effects

This section demonstrates how the randomized design of the TSP controls for spillover effects. Based on equation (3), the equilibrium price change for asset n decomposes as direct and spillover effects:

$$\Delta P(n) = \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n} \Delta S(n)}_{\text{direct effect}} + \underbrace{\sum_{m \neq n} [\boldsymbol{\mathcal{M}}]_{n,m} \Delta S(m)}_{\substack{\text{spillover effects from} \\ \text{other supply shocks}}} \tag{4}$$

The direct effect $[\boldsymbol{\mathcal{M}}]_{n,n} \Delta S(n)$ captures asset n's price response to its own supply shock. Spillover effects characterize how a supply shocks to asset m affects assent n's price through the cross-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,m}$.

Consider the TSP that induced simultaneous supply shocks to all 1,200 treatment firms.

Estimating an unbiased own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ requires controlling for spillover effects from all other 1,199 treatment stocks.[15] Otherwise, price change induced by a treatment stock's own supply shock would be overestimated and partially reflect shocks to other treatment firms. We exploit the randomized assignment of treatment and control stocks in the TSP to difference out these spillover effects.

For each TSP treatment stock n, we match an unshocked TSP control stock n' (i.e., $\Delta S(n') = 0$) with similar characteristics. From equation (4), we further express the equilibrium price change in the treatment stock n as

$$\Delta P(n) = \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n}\Delta S(n)}_{\text{direct effect}} + \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n'}\Delta S(n')}_{\substack{\text{spillover effect from} \\ \text{the matched stock}}} + \underbrace{\sum\nolimits_{m\neq n,n'}[\boldsymbol{\mathcal{M}}]_{n,m}\Delta S(m)}_{\substack{\text{spillover effects from} \\ \text{other stocks}}} \tag{5}$$

where spillover effects are further decomposed into the effect from matched stock and the effect from all other stocks. Similarly, the price change in the matched control stock n' is

$$\Delta P(n') = \underbrace{[\boldsymbol{\mathcal{M}}]_{n',n'}\Delta S(n')}_{\text{direct effect}} + \underbrace{[\boldsymbol{\mathcal{M}}]_{n',n}\Delta S(n)}_{\substack{\text{spillover effect from} \\ \text{the matched stock}}} + \underbrace{\sum\nolimits_{m\neq n,n'}[\boldsymbol{\mathcal{M}}]_{n',m}\Delta S(m)}_{\substack{\text{spillover effects from} \\ \text{other stocks}}} \tag{6}$$

Because stock n and n' have similar observables, we assume, following Haddad et al. (2026), that they share homogeneous cross-price multipliers with all other assets, i.e., $[\boldsymbol{\mathcal{M}}]_{n,m} =$

[15] Identification using demand-side instruments face the same challenge. Koijen and Yogo (2019) address it through homogeneous substitution patterns implied by logit demand. Koijen and Yogo (2026) specify spillovers under a nested-logit structure. Chaudhary, Fu, and Li (2025) find larger spillover effects for bonds within the same rating category as close substitutes, and weaker spillovers for other bonds.

$[\boldsymbol{\mathcal{M}}]_{n',m}$, $\forall m \neq n, n'$.[16] Under this assumption, differencing equations (5) and (6) yields

$$\Delta P(n) - \Delta P(n') = \left([\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n',n}\right) \Delta S(n) - \left([\boldsymbol{\mathcal{M}}]_{n',n'} - [\boldsymbol{\mathcal{M}}]_{n,n'}\right) \Delta S(n') \tag{7}$$

The double-difference in prices between the TSP treatment stock n and its matched TSP control stock n' eliminates spillover effects from all other 1,199 treatment stocks outside the pair. Because the matched TSP control stock n' was unshocked ($\Delta S(n') = 0$), equation (7) further simplifies to

$$\Delta P(n) = \underbrace{\left([\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n',n}\right)}_{\substack{\text{relative price multiplier} \\ \mathcal{M}_{relative}(n,n')}} \Delta S(n) \tag{8}$$

The remaining bilateral spillover operates through the cross-price multiplier $[\boldsymbol{\mathcal{M}}]_{n',n}$. Therefore, the TSP supply shocks identify the *relative price multiplier* $\mathcal{M}_{relative}(n, n')$ —the difference between the own- and cross-price multipliers (Haddad et al., 2026). It measures how the price of a treatment stock changes relative to its comparable control stock when the relative supply shifts. Equation (8) motivates the following DID empirical specification:

$$\Delta p = \mathcal{M} \Delta s + \boldsymbol{\gamma}' \Delta \boldsymbol{x} + \varepsilon \tag{9}$$

where $\mathcal{M}$ identifies the average relative price multiplier across treatment stocks. The variable $\Delta p = \Delta P(n) - \Delta P(n')$ and $\Delta s = \Delta S(n) - \Delta S(n')$ denote the double-difference in log stock price and shares repurchased between a TSP treatment stock n and its matched TSP control stock n', respectively. We detail the variable construction in Section 5.1. We further include differences in observables, including liquidity, size, growth opportunities, profitability,

[16] Section 3.3 provides a microfoundation for this assumption.

dividend payout, and market beta to absorb confounding price effects.

3.3 Approximation to Own-Price Multiplier

The relative price multiplier measures the relative response in price for two stocks with the same observables to a change in the relative supply of these stocks (Haddad et al., 2026), which is relevant for portfolio management. However, the own-price multiplier is more valuable for corporate decisions, as it measures a stock's price response to its own supply change. In this section, we derive empirical conditions under which the estimated relative price multiplier in equation (9) approximates the own-price multiplier. This approximation builds on a standard single-factor structure on asset payoffs as in Koijen, Richmond, and Yogo (2023).

A Single-Factor Structure on Asset Payoffs. Following Koijen, Richmond, and Yogo (2023), we assume each investor i's belief on asset payoffs follows a single-factor structure:

$$\boldsymbol{d}_i = \boldsymbol{\mu}_i + \boldsymbol{b}_i F + \boldsymbol{\eta} \tag{10}$$

where $\boldsymbol{\mu}_i$ is an $N \times 1$ vector of investor i's expected payoffs. $\boldsymbol{b}_i$ is an $N \times 1$ vector of investor-specific factor loadings, with its element $\boldsymbol{b}_i(n)$ capturing investor i's perceived exposure of stock n to the systematic risk factor F. The risk factor follows a standard normal distribution: $F \sim \mathcal{N}(0, 1)$. The idiosyncratic shock $\boldsymbol{\eta} \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$ is independent of F, in which $\mathbf{I}$ is the identity matrix.[17]

Under assumption (10), the covariance matrix of investor i's perceived payoffs is $\boldsymbol{\Sigma}_i =$

[17] Assuming homoskedastic idiosyncratic variance σ^2 simplifies exposition, though allowing $\sigma^2(n)$ heterogeneity leaves the core results unchanged.

$\boldsymbol{b}_i\boldsymbol{b}_i' + \sigma^2\mathbf{I}$. This structure delivers a closed-form expression for the price multiplier matrix $\boldsymbol{\mathcal{M}}$ defined in equation (2), as stated in the following lemma.

Lemma 1 (Price Multiplier under Factor Structure). *Under the factor structure (10), the price multiplier matrix is*

$$\boldsymbol{\mathcal{M}} = \frac{\sigma^2}{\tau}\mathbf{I} + \frac{1}{\tau^2}\boldsymbol{\rho}\boldsymbol{L}\boldsymbol{\rho}' \tag{11}$$

where

$$\tau = \sum_{i=1}^{I}\frac{1}{\gamma_i}, \quad \boldsymbol{\rho} = \left(\frac{\boldsymbol{b}_1}{\sqrt{\gamma_1(1+\boldsymbol{b}_1'\boldsymbol{b}_1/\sigma^2)}}, \cdots, \frac{\boldsymbol{b}_I}{\sqrt{\gamma_I(1+\boldsymbol{b}_I'\boldsymbol{b}_I/\sigma^2)}}\right)_{N\times I}, \quad \boldsymbol{L} = \left(\mathbf{I} - \frac{1}{\tau\sigma^2}\boldsymbol{\rho}'\boldsymbol{\rho}\right)^{-1}$$

The corresponding own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$*, cross-price multiplier* $[\boldsymbol{\mathcal{M}}]_{n,m}$*, and the relative price multiplier between stocks* n, n'*,* $\mathcal{M}_{relative}(n,n') = [\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n,n'}$*, are*

$$\begin{aligned}
[\boldsymbol{\mathcal{M}}]_{n,n} &= \frac{\sigma^2}{\tau} + \frac{1}{\tau^2}\,\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_n, \quad [\boldsymbol{\mathcal{M}}]_{n,n'} = \frac{1}{\tau^2}\,\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_{n'} \\
\mathcal{M}_{relative}(n,n') &= \frac{\sigma^2}{\tau} + \frac{1}{\tau^2}\,\boldsymbol{\rho}_n'\boldsymbol{L}(\boldsymbol{\rho}_n - \boldsymbol{\rho}_{n'}) \\
\text{where } \boldsymbol{\rho}_n &= \left(\frac{\boldsymbol{b}_1(n)}{\sqrt{\gamma_1(1+\boldsymbol{b}_1'\boldsymbol{b}_1/\sigma^2)}}, \cdots, \frac{\boldsymbol{b}_I(n)}{\sqrt{\gamma_I(1+\boldsymbol{b}_I'\boldsymbol{b}_I/\sigma^2)}}\right)'_{N\times 1}
\end{aligned} \tag{12}$$

Proof. See Appendix A.2. □

For a given matched pair with similar factor exposures ($\boldsymbol{\rho}_n = \boldsymbol{\rho}_{n'}$),[18] Lemma 1 indicates that matched stocks have identical cross-price multipliers with respect to all other stocks, i.e., $[\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\mathcal{M}}]_{n',m}$ for all $m \neq n, n'$. Therefore, taking differences in price changes between n and n' eliminates spillover effects from all other shocked stocks, as shown in equation (7).

[18] One microfoundation is to model factor exposures as linear functions of firm characteristics, as in Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2023), such that similarity in characteristics implies similarity in factor exposures between matched firms.

Moreover, the relative price multiplier simplifies to the idiosyncratic-risk component scaled by investors' aggregate risk tolerance:

$$[\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n,n'} = \frac{\sigma^2}{\tau}$$

By contrast, the own-price multiplier in Lemma 1 reflects both idiosyncratic risk and exposure to systematic risk. Thus, the relative price multiplier closely approximates the own-price multiplier when the systematic-risk component is sufficiently small relative to the idiosyncratic-risk component. The following proposition formalizes this intuition.

Proposition 1 (Conditions under which the Relative Price Multiplier Approximates the Own-Price Multiplier). *Under the single-factor payoff structure in equation (10), consider a matched pair (n, n') such that $b_i(n) = b_i(n')$ for all investors i. Then:*

(i) ***(Homogeneous cross-price multipliers)*** $[\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\mathcal{M}}]_{n',m}$ *for all* $m \neq n, n'$.

(ii) ***(Approximation to the own-price multiplier)*** *In addition, if* $\dfrac{b_i^2(n)}{\sigma^2} \to 0$ *for all investors* i, *then* $\dfrac{\mathcal{M}_{relative}(n, n')}{[\boldsymbol{\mathcal{M}}]_{n,n}} \to 1$.

Proof. See Appendix A.3. □

Proposition 1 shows that when each investor's perceived systematic risk exposure for a stock n, $\boldsymbol{b}_i^2(n)$, is sufficiently small relative to its idiosyncratic risk σ^2 ($\boldsymbol{b}_i^2(n)/\sigma^2 \to 0$), the systematic-driven term in the own-price multiplier is negligible. Consequently, the relative price multiplier $\mathcal{M}_{relative}(n, n')$ of the matched stocks (n, n') provides a close approximation to stock n's own-price multiplier. While formal proofs of Lemma 1 and Proposition 1 are

respectively in Appendix A.2 and A.3, we reveal the intuition under a representative-investor CAPM benchmark.

Corollary 1 (CAPM Illustration). *Under the representative-investor CAPM benchmark with* $\gamma_i = \gamma_j = \gamma$, $\boldsymbol{b}_i = \boldsymbol{b}_j = \boldsymbol{b}$, *and* $I = 1$, *the multiplier matrix in Proposition 1 simplifies to*

$$[\boldsymbol{\mathcal{M}}]_{n,n} = \gamma \left[\sigma^2 + \boldsymbol{b}^2(n)\right]$$

$$[\boldsymbol{\mathcal{M}}]_{n,m} = \gamma\, \boldsymbol{b}(n)\boldsymbol{b}(m)$$

$$\mathcal{M}_{\text{relative}}(n,m) = \gamma \left\{\sigma^2 + \boldsymbol{b}(n)\left[\boldsymbol{b}(n) - \boldsymbol{b}(m)\right]\right\}$$

Proof. See Appendix A.4. □

The own-price multiplier combines the idiosyncratic risk, σ^2, and the systematic risk exposure through the asset's beta, $\boldsymbol{b}^2(n)$. Cross-price multipliers scale with the product of two assets' betas, $\boldsymbol{b}(n)\boldsymbol{b}(m)$. When two assets have the same betas, i.e., $\boldsymbol{b}(n) = \boldsymbol{b}(m)$, they exhibit the same cross-price multipliers to other stocks. Furthermore, when $\boldsymbol{b}^2(n) \ll \sigma^2$, i.e., systematic risk exposure is small relative to idiosyncratic risk, the relative price multiplier approximates the own price multiplier.

The Necessity of Eliminating Spillover Effects. Proposition 1 does not imply that the spillover effects aggregated across all shocked assets in equation (4) are negligible. The condition $\boldsymbol{b}_i^2(n) \ll \sigma^2$ assumes that systematic risk exposure is relatively small in individual asset. However, the spillover from all shocked stocks, $\sum_{m=1}^{N} \boldsymbol{b}_i(n)\boldsymbol{b}_i(m)\Delta S(m)$, can still be large when (i) the number of shocked assets N is large, and (ii) the supply shocks $\Delta S(m)$ are positively correlated. In the TSP, 1,200 treatment stocks experienced positively correlated supply shocks. Ignoring these spillovers would overstate the attribution of price changes to

own shocks, thereby biasing estimates of the price multiplier.

3.4 Investor Response to Supply Shocks

Since the demand system of Koijen and Yogo (2019) explains the cross-sectional stock holdings under fixed supply, a natural question is how investors adjust their portfolios when share supply changes exogenously. Starting from investor i's demand function (1) and substituting the equilibrium price (2), we have:

$$\boldsymbol{q_i} = \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\left(\boldsymbol{\mu_i} - \boldsymbol{\mathcal{M}}\left(\sum_{i=1}^{I}\frac{1}{\boldsymbol{\gamma}_i}\boldsymbol{\mu}_i - \boldsymbol{S}\right)\right)$$

The change in investor i's holdings, $\Delta\boldsymbol{q}_i$, in response to a supply shock $\Delta\boldsymbol{S}$, is thus

$$\Delta\boldsymbol{q}_i = \boldsymbol{\mathcal{A}}_i \times \Delta\boldsymbol{S}, \quad \text{where } \boldsymbol{\mathcal{A}}_i \triangleq \underbrace{\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}}_{\text{investor } i\text{'s elasticity}} \times \underbrace{\boldsymbol{\mathcal{M}}}_{\text{aggregate price multiplier}} \tag{13}$$

We refer to $\boldsymbol{\mathcal{A}}_i \in \mathbb{R}^{N\times N}$ as investor i's absorption matrix, defined as the product of investor i's demand elasticity matrix and the aggregate price multiplier matrix. Intuitively, $\boldsymbol{\mathcal{A}}_i$ describes how investor i adjusts her portfolio given a supply shock: a supply shock alters equilibrium prices through $\boldsymbol{\mathcal{M}}$, and each investor rebalances according to her own elasticity matrix $\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}$. Investors with higher demand elasticity absorb a larger share of the shock.[19]

Because an investor chooses a portfolio of assets, a supply shock to asset m changes prices of all other assets through the price multiplier matrix $\boldsymbol{\mathcal{M}}$, leading to the investor's rebalancing across multiple assets. Thus, investor i's absorption matrix includes both own-

[19] Market clearing condition implies that the demand changes aggregated across investors equal the supply shock, i.e., $\sum_{i=1}^{I}\Delta\boldsymbol{q}_i = \sum_{i=1}^{I}\boldsymbol{\mathcal{A}}_i\Delta\boldsymbol{S} = \Delta\boldsymbol{S}$.

asset rebalancing terms $[\boldsymbol{\mathcal{A}}_i]_{n,n}$ and cross-asset rebalancing terms $[\boldsymbol{\mathcal{A}}_i]_{n,m}$ for $n \neq m$. In particular, for a matched stock pair (n, n'), investor i's holding changes are

$$\Delta \boldsymbol{q}_i(n) = [\boldsymbol{\mathcal{A}}_i]_{n,n} \Delta S(n) + [\boldsymbol{\mathcal{A}}_i]_{n,n'} \Delta S(n') + \sum\nolimits_{m \neq n,n'} [\boldsymbol{\mathcal{A}}_{\boldsymbol{i}}]_{n,m} \Delta S(m)$$
$$\Delta \boldsymbol{q}_i(n') = [\boldsymbol{\mathcal{A}}_{\boldsymbol{i}}]_{n',n'} \Delta S(n') + [\boldsymbol{\mathcal{A}}_i]_{n',n} \Delta S(n) + \sum\nolimits_{m \neq n,n'} [\boldsymbol{\mathcal{A}}_i]_{n',m} \Delta S(m)$$

Similar to the price spillover effects discussed in Section 3.2, the observed holding changes reflect both own-asset rebalancing effect $[\boldsymbol{\mathcal{A}}_i]_{n,n}\Delta S(n)$ and cross-asset substitution effects $[\boldsymbol{\mathcal{A}}_i]_{n,m}\Delta \boldsymbol{S}(m), \forall m \neq n$: a supply shock to asset m changes asset n's price, leading the position adjustment in asset n. To eliminate cross-asset substitution effects, we rely on the TSP's randomized-controlled design, where control stocks face no supply shocks $(\Delta S(n') = 0)$. Differentiating investor i's holding changes between matched treatment and control yields[20]

$$\Delta \boldsymbol{q}_i(n) - \Delta \boldsymbol{q}_i(n') = \left([\boldsymbol{\mathcal{A}}_i]_{n,n} - [\boldsymbol{\mathcal{A}}_i]_{n',n} \right) \Delta \boldsymbol{S}(n) \tag{14}$$

Equation (14) thus characterizes how investor i rebalances her holdings in stock n relative to its matched stock n' when stock n experiences an exogenous supply shock. Similar to the relative price multiplier, the coefficient $\left([\boldsymbol{\mathcal{A}}_i]_{n,n} - [\boldsymbol{\mathcal{A}}_i]_{n',n} \right)$ captures investor i's relative adjustment between treatment stock n and its matched control stock n'. In Section 6, we perform corresponding empirical analysis of holding changes based on equation (14).

[20] This simplification also relies on the factor structure in Section 3.3. Assuming that matched stocks share similar factor exposures, we have $\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mathcal{M}} = \frac{1}{\gamma_i \sigma^2}(\boldsymbol{\mathcal{M}} - \frac{\boldsymbol{b}_i \boldsymbol{b}_i' \boldsymbol{\mathcal{M}}}{\sigma^2 + \boldsymbol{b}_i' \boldsymbol{b}_i})$. Defining $\boldsymbol{v}_i = \boldsymbol{b}_i' \boldsymbol{\mathcal{M}}$, this implies $[\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mathcal{M}}]_{n,m} = \frac{1}{\gamma_i \sigma^2}\left([\boldsymbol{\mathcal{M}}]_{n,m} - \frac{\boldsymbol{b}_i(n)\boldsymbol{v}_i'(m)}{\sigma^2 + \boldsymbol{b}_i' \boldsymbol{b}_i}\right)$. For a matched pair (n, n') with $\boldsymbol{b}_i(n) = \boldsymbol{b}_i(n')$, we have $[\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mathcal{M}}]_{n',m}$ for $m \neq n, n'$.

4. Exogenous Supply Shocks

This section begins by outlining the research specification, data sources, and sample construction. We next show that the TSP significantly reduced shares repurchased by treatment firms relative to controls. We further show that this reduction comes from a lower completion rate of repurchase programs, which is exogenous as neither corporate managers nor the market anticipated the TSP's impact on repurchases.

4.1 Specification, Data, and Sample Selection

We begin by estimating the effect of TSP on share repurchases. Following Li, Ye, and Zheng (2024), we implement the following DID specification:

$$Y_{n,t} = \beta \times Treatment_n \times Post_t + \boldsymbol{\gamma}' \boldsymbol{X}_{n,t} + u_t + u_n + \epsilon_{n,t} \tag{15}$$

where n indexes firms and t indexes year-quarters. $Y_{n,t}$ is the dependent variable of interest, including percentage of shares repurchased ($Repurchase_{n,t}$), defined as the number of common shares repurchased, divided by the number of common shares outstanding at the beginning of the quarter; the average displayed depth at the national best bid in thousands of dollars ($Bid\ Depth_{n,t}$); equity issuance ($Issuance_{n,t}$), defined as the sale of common and preferred stocks minus any increase in preferred stocks divided by beginning-of-quarter total assets; and dividend payouts ($Dividend_{n,t}$), defined as common stock dividends divided by beginning-of-quarter total assets.[21] $Treatment_n$ is an indicator that equals one if a firm is

[21] In untabulated results, we alternatively define: (i) share repurchases as quarterly total expenditures in common stock repurchases divided by beginning-of-quarter assets; (ii) equity issuance as quarterly change

in one of three test groups and zero if it is in the control group. $Post_t$ is an indicator that equals one if an observation is from the post-treatment period (2016Q4–2018Q3) and zero if it is from the pre-treatment period (2014Q4–2016Q3). Controls include size, profitability, and growth opportunity (Fama and French, 2001). We include firm fixed effects (u_n) to control time-invariant heterogeneity across firms, and year-quarter fixed effect (u_t) to control time-varying market-wise shocks. All continuous and unbounded variables are winsorized at the 1% and 99% percentiles. The standard errors are robust to heteroskedasticity and are clustered at the firm level. The main coefficient of interest is β, which estimates the average treatment effects of TSP on share repurchase.

We construct our sample by using all common stocks (CRSP share codes 10 and 11) in the TSP program, utilizing the Pilot Securities and Change files maintained by FINRA.[22] The sample period spans from 2014Q4 to 2018Q3, allowing for eight quarters of data both before and after the TSP implementation. Following conventions in the payout literature (Fama and French, 2001), we exclude firms in the utility (SIC codes 4200–4299) and financial (SIC codes 6000–6999) sectors, as their payout activities are subject to unique regulatory constraints. Furthermore, we require non-missing values for all variables needed to estimate equation (15), resulting in 611 firms in the three treatment groups and 653 firms in the control group. We collect firm-level financial information from Compustat's North America Fundamentals Quarterly files; daily and monthly stock returns from CRSP; intraday transaction data from Daily Trade and Quote (TAQ); firms' open-market repurchase announcement dates and values from the SDC Platinum; the filing dates of 10-K and 10-Q forms from SEC Analytics

in shares outstanding plus quarterly shares repurchased divided by beginning-of-quarter shares outstanding; (iii) dividend payouts as the dividend per share. All conclusions still hold.

[22]The Pilot Securities and Change files are accessible via the FINRA website: https://www.finra.org/rules-guidance/key-topics/tick-size-pilot-program/data-collection-securities-and-pilot-securities-files.

Table 1
Summary Statistics

Variables	N	Mean	*SD*	Q1	Median	Q3
Panel A: Firm characteristics						
Repurchase	19,590	0.259	0.715	0.000	0.000	0.052
Bid Depth	19,590	8.569	6.972	3.878	6.276	10.823
Issuance	19,590	1.939	9.727	0.000	0.016	0.190
Dividend	19,590	0.229	0.549	0.000	0.000	0.243
Price	19,586	27.724	33.668	7.920	17.950	36.600
Shares	19,590	32.443	30.028	12.404	26.431	43.917
Size	19,590	5.850	1.423	4.844	5.928	6.942
Profitability	19,590	0.090	0.261	0.008	0.045	0.095
Growth	19,590	2.627	15.408	−2.979	0.329	3.618
Quoted Spread	19,553	0.849	1.079	0.229	0.406	0.953
Beta	19,544	1.227	1.098	0.644	1.166	1.721
Panel B: Repurchase program characteristics						
Percent	566	6.230	4.817	2.992	5.092	8.226
Volume	566	74.898	100.475	15.000	44.880	100.000
Completion Rate	566	65.979	34.672	37.900	75.219	100.000

This table presents the summary statistics for the main variables in our empirical specifications. Variable definitions are provided in Appendix B. To mitigate the potential influence of extreme values, we winsorize the continuous variables at the 1st and 99th percentiles.

Suite on Wharton Research Data Services (WRDS); and institutional investor holdings from the LSEG Institutional (13F) Holdings dataset.

Table 1 reports summary statistics for main variables. On average, firms repurchase 0.259% of their outstanding common shares per quarter. Equity issuance and common stock dividends amount to 1.939% and 0.229% of total assets, respectively. The average stock price is $27.724, and the average number of shares outstanding is 32.443 million. The average market beta, percent quoted spread, and daily displayed depth at the national best bid are 1.227, 0.849%, and $8,569, respectively. For an average repurchase program in our sample, the shares sought in the repurchase represent for 6.23% of total shares outstanding; the

intended repurchase dollar volume is $74.898 million; and the completion rate of repurchase programs is 66%.[23]

4.2 Exogenous Reduction in Share Repurchases

Table 2 presents the results from estimating equation (15). Column (1) shows that treatment firms repurchased 0.077% less outstanding shares per quarter relative to controls, representing 22% of the pre-treatment sample mean.[24] Column (2) demonstrates that the displayed dollar depth of treatment firms increased by $7,045, accounting for 112% of the pre-treatment sample mean. This result supports the mechanism of our supply shocks: the widened tick size induces a longer queue at the best bid, thereby intensifying the speed competition between firms and other investors. The β in column (3) is insignificant and close to zero, suggesting that the TSP affected share supply through constraints on share repurchases, rather than equity issuance. Similarly, column (4) shows no significant effect of the TSP on dividend payouts. These results are consistent with the institutional features of equity issuance and dividend payouts, which take place outside the secondary market and are therefore unaffected by the TSP or the price ceiling rule. The negligible effect on dividend payouts also provides indirect evidence of the exogeneity of supply shocks, as managers did not adjust dividend policy to compensate for reduced share repurchases.

[23]The estimation of completion rate follows Bonaimé (2012): for each open-market repurchase program, we cumulate the quarterly shares repurchased over 9 quarters beginning the announcement quarter. If the next repurchase program is announced within this 9-quarter window, quarterly shares repurchased will be summed only until the prior quarter-end. This figure is then divided by the number of shares sought in a repurchase program to yield the completion rate. The completion rate is truncated at 100% to prevent double counting following Bonaimé (2012).

[24]The coefficient has a t-statistic of 3.01, exceeding the threshold of 3.0 suggested by Heath et al. (2023) as a heuristic for inference when accounting for multiple-testing problem of a reused natural experiment like the TSP. We also provide corroborating evidence and rule out confounding effects in Section 4.3, Section 5.3 and Appendix IA.2 to further alleviate the concern of reusing natural experiment.

Table 2
Supply Shocks

	$Repurchase_{n,t}$	$Bid\ Depth_{n,t}$	$Issuance_{n,t}$	$Dividend_{n,t}$
	(1)	(2)	(3)	(4)
$\boldsymbol{Treatment_n \times Post_t}$	**−0.077*** **	**7.045*** **	**−0.050**	**−0.009**
	(0.03)	**(0.28)**	**(0.20)**	**(0.01)**
$Size_{n,t}$	0.035*	2.069***	−2.343***	−0.051***
	(0.02)	(0.32)	(0.35)	(0.02)
$Profitability_{n,t}$	0.036	0.241	−1.647***	0.012
	(0.03)	(0.26)	(0.43)	(0.02)
$Growth_{n,t}$	−0.002***	0.003	0.393***	0.000
	(0.00)	(0.00)	(0.02)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	19,589	19,589	19,589	19,589
Adj. R^2	0.286	0.725	0.516	0.702

This table presents the effect of 2016 Tick Size Pilot on repurchase, equity issuance, and dividend payouts, expressed in percentage points. *Treatment* is an indicator that equals one if a stock is in one of the three test groups and zero if it is in the control group. *Post* is an indicator that equals one if a year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). Controls include size, profitability, and growth opportunity. The robust standard errors clustered at the firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Exogenous and Unanticipated Supply Shocks. Next, we test whether the effect of the TSP on share repurchases is unanticipated by both firm managers and the market. We modify equation (15) by replacing the dependent variables with (i) the intent of firm managers to buyback shares, and (ii) the market response to a repurchase announcement.

We use three measures to gauge managers' intent to repurchase: first, the percentage of shares announced to be repurchased relative to the number of total shares outstanding ($Percent_{n,t}$); second, the announced repurchase dollar volume in a new repurchase program ($Volume_{n,t}$), reflecting the maximum amount a firm can repurchase within the program;

third, an indicator equals one if firm i initiates a new repurchase announcement in quarter t ($Annc_{n,t}$). Column (1) to (3) in Panel A of Table 3 shows no statistically significant results for all three measures, suggesting that managers of treatment firms do not alter the intensity and the probability of announcing repurchase during the TSP. Therefore, the observed decline in realized share repurchases is not driven by changes in managerial intent but rather by an exogenous shock that lowered the completion rate of repurchase programs.

Further, we examine the effect of the TSP on market response to repurchase announcements, measured by the absolute three-day CAR around the [−1,+1] announcement window.[25] Panel B of Table 3 reports the results. Columns (1), (2), and (3) present CAR estimated using CAPM, Fama and French (1993) three-factor, and Fama and French (2015) five-factor model, respectively. None of these models reveals a significant change in the absolute value of CAR around repurchase announcements for treatment firms during the TSP. These results indicate the market does not anticipate the adverse effect of the TSP on share repurchases and thus does not adjust its response to new repurchase announcements. These results also imply that the supply shocks induced by the TSP are uninformed to the market.

Lower Completion Rate. As we discuss in Section 2, the wider tick size introduced by the TSP induces a longer queue and intensifies the speed competition between firms and other investors at the best bid. Since firms are generally slower than HFTs, they are at a disadvantage in this speed competition. Consequently, their limit orders suffer from reduced execution probabilities, resulting in a lower fill rate of repurchase programs. Column (4) of Table 3 presents direct evidence. We replace the dependent variable in equation (15) with the completion rate of repurchase programs. The result indicates that the completion

[25] Our conclusion remains similar when using the raw CAR without absolute value.

Table 3
Effect of the TSP on Share Repurchase Program

Panel A: Repurchase Announcement	$Percent_{n,t}$	$Volume_{n,t}$	$Annc_{n,t}$
	(1)	(2)	(3)
$\boldsymbol{Treatment_n \times Post_t}$	**0.216**	**0.138**	**−0.005**
	(0.63)	**(0.10)**	**(0.01)**
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	566	566	19,589
Adj. R^2	0.496	0.888	0.067

Panel B: Cumulative Abnormal Return and Completion Rate	$\lvert CAR_{n,t}\rvert$			$Completion\ Rate_{n,t}$
	CAPM	FF3	FF5	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treatment_n \times Post_t}$	**0.095**	**0.224**	**0.222**	**−9.585***
	(0.84)	**(0.87)**	**(0.84)**	**(5.56)**
Pre-treat Mean of LHS	5.288%	5.157%	5.059%	65.377%
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	559	559	559	566
Adj. R^2	0.181	0.173	0.155	0.160

This table presents the effects of the 2016 Tick Size Pilot on planned share repurchases. In Panel A, the dependent variables are the percentage of shares outstanding sought in the repurchase, the natural logarithm of announced repurchased dollar volume, and an indicator of announcing a repurchase program at a quarter. *Treatment* is a dummy variable that equals one if a stock is in one of the three test groups and zero if it is in the control group. *Post* is an indicator variable that equals one if the year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). The robust standard errors clustered at the firm level are in parentheses. In Panel B, the dependent variables are the absolute CAR (%) around [−1,+1] event window respectively adjusted by CAPM, Fama and French (1993) three-, and Fama and French (2015) five-factor model, and completion rate of repurchase programs. The robust standard errors clustered at the firm and announcement quarter level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

rate of treatment firms' repurchase programs dropped by 9.585% relative to control firms, representing 15.1% of the pre-treatment sample mean.

Taken together, the decline in repurchases among treatment firms during the TSP reflects an exogenous, unexpected shift in the supply curve: treatment firms experienced lower *ex post* completion rates of repurchase programs relative to controls. Our results extend Li, Ye, and Zheng (2024) by showing that the TSP constitutes an exogenous and unexpected supply shock.

4.3 Controlling for Price Effect from Changes in Fundamentals

A remaining concern is that the TSP-induced reduction in share repurchases may affect treatment firms' fundamentals, such as cash holdings, and thus alter the asset prices.[26] While we control for firm fundamentals in our baseline regressions, we further alleviate this concern by examining whether the TSP affects the CAR around the filing dates of 10-K/10-Q forms. While actual repurchases exercise continuously and gradually over time (Stephens and Weisbach, 1998), the disclosure of firm fundamentals, including repurchase activities, happens at discrete dates every quarter. If the market had perceived the changes in firm fundamentals or repurchase quantity of treatment firms at the discrete disclosure dates, there would have been significant changes in the CAR for treatment firms around the filing dates of financial statements.[27] By contrast, a null effect on the CAR differences around filing dates suggests that disclosed repurchase quantities and firm fundamentals do not materially

[26] In untabulated results, we also directly replace the dependent variable in equation (15) with cash holdings and book leverage, and find no significant changes.

[27] Prior studies support this interpretation. For instance, Gomes, Gorton, and Madureira (2007) use the absolute CAR around corporate announcement to capture information transmission from firms to the market. Ye, Zhang, and Zou (2025) show that disclosure of repurchase quantity reveals a firm's private information.

Table 4
Effect of the TSP on CAR around 10-K/10-Q Filings

Panel A: Absolute Cumulative Abnormal Returns

	$\lvert CAR_{n,t}\rvert$					
	CAPM		FF3		FF5	
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treatment_n \times Post_t}$	**−0.148**	**−0.130**	**−0.213**	**−0.192**	**−0.208**	**−0.187**
	(0.26)	**(0.27)**	**(0.25)**	**(0.25)**	**(0.25)**	**(0.26)**
Pre-treat Mean of LHS	5.928%		5.872%		5.877%	
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,121	19,121	19,121	19,121	19,121	19,121
Adj. R^2	0.114	0.114	0.114	0.114	0.114	0.114

Panel B: Cumulative Abnormal Returns by Sentiment

	$CAR_{n,t}$					
	Full Sample		Negative		Positive	
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treatment_n \times Post_t}$	**0.231**	**0.336**	**0.442**	**0.491**	**0.081**	**0.159**
	(0.27)	**(0.28)**	**(0.37)**	**(0.36)**	**(0.27)**	**(0.30)**
Pre-treat Mean of LHS	0.237%		−5.721%		6.133%	
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,121	19,121	9,665	9,665	9,453	9,453
Adj. R^2	−0.001	0.003	0.150	0.154	0.129	0.132

This table presents the effects of the 2016 Tick Size Pilot on cumulative abnormal returns around the filing dates of 10-K/10-Q forms. In Panel A, the dependent variables are the absolute CAR around the [−1,+1] event window based on CAPM, Fama and French (1993) three-, and Fama and French (2015) five-factor model, respectively. In Panel B, the dependent variable is the CAR around the [−1,+1] event window based on CAPM. An event is assigned as "negative" ("positive") if the corresponding CAR is smaller (greater) than zero. The robust standard errors clustered at the firm and filing quarter level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

affect treatment stock prices; rather, the price effect is realized gradually as lower repurchase completion accrues.

Analogous to Table 3, we cumulate the abnormal stock returns (relative to a model-adjusted benchmark) around the [−1,+1] event window for the filing dates of 10-K/10-Q forms, and take an absolute value. Panel A of Table 4 presents the effect of TSP on the absolute CAR estimated by CAPM, Fama and French (1993) three-factor, and Fama and French (2015) five-factor model, respectively. The results without (with) control variables are reported in odd (even) columns. All of these models reveal that the change in the absolute CAR around the disclosure dates of firm fundamentals is insignificant and close to zero for treatment firms during the TSP.

We next examine signed CARs and separately consider filings associated with negative and positive market reactions. A filing is classified as negative (positive) when its corresponding CAR is below (above) zero. Panel B reports the results using CAPM-adjusted CARs. We again find no statistically or economically significant changes, either in the full sample or in the negative- and positive-CAR subsamples. Overall, our results alleviate the concern that the price multiplier estimates are confounded by shifts in firm fundamentals rather than the effect of reduced repurchases, thereby reinforcing the validity of the TSP-induced supply shocks.

5. Estimation of Price Multiplier

In this section, we first outline our identification strategy and present baseline estimates of the relative price multiplier. We then empirically show that the estimated relative price multiplier closely approximates the own-price multiplier.Next, we exploit the regulatory dark-pool constraint, which applies exclusively to test group 3. The restriction induced an additional

decline in share repurchases and stock prices for test group 3, whereas the liquidity changes remain the same across the three test groups. We find that the three test groups share the same relative price multiplier, suggesting their demand curves have the same slope and that our baseline estimate is not confounded by liquidity effects. The larger price decline in test group 3 is thereby attributed to its larger supply shocks. Finally, to address the concern that the realized repurchases might still be endogenous, we instrument quarterly shares repurchased and perform a 2SLS analysis. It yields statistically indistinguishable estimates of relative price multipliers.

5.1 Estimation of Relative Price Multiplier

After validating the TSP as an exogenous and uninformed supply shock, we now estimate the relative price multiplier using the specification developed in Section 3.2. To control for spillover effects, we exploit the TSP's random assignment of treatment and control stocks and match each treatment stock with a closest control stock.

Specifically, we match each TSP-treatment firm to a TSP-control firm within the same Fama-French 48 industry based on shares repurchased and profitability. We implement matching via the nearest-neighbor propensity score method without replacement.[28] We construct the matching covariates using average pre-treatment characteristics over 2014Q4–2016Q3, ensuring comparability while avoiding conditioning on outcomes potentially affected by the TSP. The final sample consists of 524 treatment–control pairs. Table 5 reports the pre-treatment mean of various characteristics for treatment firms and their matched controls. It shows no statistically significant differences across observable dimensions, such as stock

[28]We impose a caliper of 0.05 to restrict matches to the region of common support.

Table 5
Test of Balance on Covariates

	Treatment	Control	t-statistics	p-value
	(1)	(2)	(3)	(4)
Repurchase	0.275	0.257	0.606	0.544
Size	5.788	5.738	0.575	0.566
Profitability	7.807	7.774	0.031	0.975
Growth	2.466	2.201	0.676	0.499
Price ($)	24.348	24.634	−0.166	0.868
Shares Outstanding ($m)	33.218	31.410	1.150	0.250
Dividend	0.220	0.217	0.082	0.935
Beta	1.287	1.222	1.056	0.291
Quoted Spread	0.867	0.935	−0.975	0.330

This table examines the test of balance on observables after the propensity score matching. Matching is conducted one-to-one within the same Fama-French 48 industry using the nearest-neighbor method, based on *ex ante* firm characteristics. Columns (1) and (2) report the pre-treatment average of observables (2014Q4–2016Q3) for matched treatment and control stocks, respectively. Column (3) reports the t-statistics for the null hypothesis of equal means between treatment and control groups, and column (4) reports the corresponding p-value.

price, total shares outstanding, and percentage quoted spread.

Construction of Supply Shocks. To ensure the supply shocks are sufficiently large for identification, we cumulate the quarterly reductions in shares repurchased over eight post-treatment quarters. Specifically, we construct the corresponding supply shock as the cumulative double-difference in share repurchases within the matched pair at the end of the TSP (2018Q3):

$$\Delta s_j = \sum_{t=1}^{8} \left[\left(Repurchase_{j,t}^{T} - \overline{Repurchase}_{j,\text{pre}}^{T} \right) - \left(Repurchase_{j,t}^{C} - \overline{Repurchase}_{j,\text{pre}}^{C} \right) \right] \quad (16)$$

where $Repurchase_{j,t}^{T}$ and $Repurchase_{j,t}^{C}$ denote the percentages of shares outstanding repurchased by the treatment firm and its matched control in quarter t, respectively; $\overline{Repurchase}_{j,\text{pre}}^{T}$

and $\overline{Repurchase}^{C}_{j,\text{pre}}$ denote their average repurchases over the eight quarters before the TSP. The first difference removes firm-specific trends in repurchases between the pre- and post-TSP periods. The second difference, between treatment and control firms, nets out time-varying confounders common to both groups. Together, this double-difference measure captures the exogenous shift in the share supply faced by treatment firms during the TSP.

Figure 1 plots the dynamics of our constructed supply shocks, suggesting a stable reduction in repurchases for treatment firms. The initial reduction is small but cumulates over time; by the end of the TSP, the cumulative supply shock reaches -0.25% on average. As we discuss in Section 2.2, SEC Rule 10b5-1 effectively constrains firms from frequently changing their repurchase plans, making it difficult for them to make up for the lower fill rate by repurchasing more aggressively in the later TSP period. The magnitude of our supply shock is comparable to those documented in related studies. For example, Li and Lin (2026) document an absolute quarterly order flow imbalance of 0.58% relative to shares outstanding.[29] The larger supply shock for test group 3 reflects the unexpected conflict between the additional "trade-at" rule and Rule 10b-18, as discussed in Section 2.

Regression Specification. Motivated by equation (9), we estimate the following regression:

$$\Delta p_j = \mathcal{M}\Delta s_j + \boldsymbol{\gamma}'\Delta\overline{\boldsymbol{x}}_{j,\text{pre}} + u_g + \epsilon_j \tag{17}$$

where j indexes matched pairs and g denotes industries. The dependent variable Δp_j is the double differences in log stock prices between each matched pair j before and after the TSP,

[29]The relatively moderate shock size also mitigates concerns that investor demand may endogenously become more elastic in response to large shocks (Chaudhry and Li, 2026). Moreover, even if the demand function is non-linear, the small shock size justifies a local linear approximation of the demand curve.

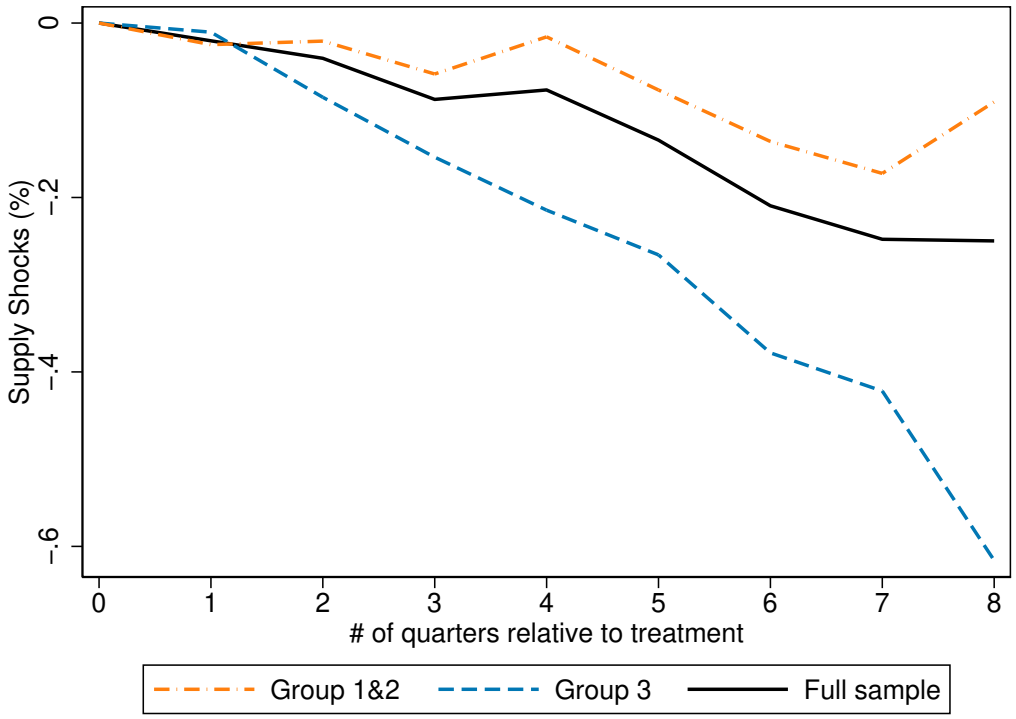


Figure 1. Dynamics of supply shocks. This figure presents the dynamics of constructed supply shocks over time. The lines represent the full sample (solid), pairs where the treatment stock is in Groups 1 & 2 (dash-dotted), and pairs where the treatment stock is in Group 3 (dashed). The horizontal axis denotes the number of quarters following the implementation of the TSP.

capturing the eight-quarter cumulative return difference induced by the TSP:

$$\Delta p_j = 100\% \times \left[\left(\log Price^T_{j,8} - \overline{\log Price}^T_{j,\text{pre}}\right) - \left(\log Price^C_{j,8} - \overline{\log Price}^C_{j,\text{pre}}\right)\right] \tag{18}$$

where $\log Price^T_{j,8}$ and $\log Price^C_{j,8}$ denote the log quarter-end closing price of the treatment and control stocks in the matched pair j at the post-treatment quarter 8 (2018Q3), respectively. $\overline{\log Price}^T_{j,\text{pre}}$ and $\overline{\log Price}^C_{j,\text{pre}}$ denote the pre-treatment average log quarter-end prices of the treatment and control stock of pair j, respectively. The stock price is adjusted for stock splits and stock dividends. Intuitively, Δp_j corresponds to the cumulative return on a long–short portfolio that takes a long position in the treatment stock and a short position

in its matched control stock.

The coefficient $\mathcal{M}$ in regression (9) identifies the *relative* price multiplier: it measures the relative percentage change in the stock price associated with a 1% change in the relative share supply between treatment and control firms (Haddad et al., 2026). Following Cassella et al. (2026), the control vector $\Delta\overline{\boldsymbol{x}}_{j,\text{pre}}$ includes pairwise differences in pre-treatment firm characteristics known to explain cross-sectional stock returns, including firm size (logarithm of total assets), profitability, growth opportunities, dividend payout, market beta, and liquidity (percentage quoted spread). In an alternative specification, we include pairwise double differences in firm characteristics, $\Delta\boldsymbol{x}_j$, to account for potential price effects arising from changes in observables during the TSP. We also control for industry fixed effects (u_g) to absorb common unobservables within the same industry. These controls absorb the potential price changes induced by changes in fundamentals or liquidity during the TSP.

Table 6 presents the estimates of $\mathcal{M}$ under different specifications. In column (1), we estimate equation (17) without control variables or industry fixed effects. The estimated relative price multiplier, $\mathcal{M} = 2.578$, is statistically significant at the 1% significance level. In column (2), we include pre-treatment differences in fundamentals and industry fixed effects. The estimated $\mathcal{M}$ remains stable at 2.575 with a substantial increase in explanatory power. This magnitude implies that relative to its matched control, a 1% decrease in repurchases relative to total shares outstanding lowers the treatment stock price by 2.575%, to which we refer as the baseline estimate of the relative price multiplier.[30] In column (3), we use double differences in firm fundamentals and industry fixed effects as an alternative set of

[30]This magnitude closely matches that reported by Koijen and Yogo (2019). Applying their approach in our sample yields an average demand elasticity of 0.390, corresponding to a price multiplier of 2.564.

Table 6
Estimation of Price Multiplier

	Δp_j		
	(1)	(2)	(3)
$\boldsymbol{\Delta s_j}$	**2.578*** **	**2.575** **	**2.359** **
	(0.90)	**(0.97)**	**(0.94)**
Control	No	Pre-treatment diff.	Double diff.
Industry FE	No	Yes	Yes
Observations	508	501	504
Adj. R^2	0.007	0.122	0.306

This table presents the estimates of relative price multipliers. The dependent variable is Δp_j. For the post-treatment quarter 2018Q3, Δp_j is calculated as the difference-in-differences of log quarter-end stock prices and pre-treatment average log prices (2014Q4-2016Q3), between treatment and control stock in a matched pair j. The main independent variable is denoted by Δs_j, estimated by the difference-in-differences of cumulative shares repurchased of matched pair j. Column (2) controls the industry fixed effects and the pre-treatment differences in average firm fundamentals ($\Delta \overline{\boldsymbol{x}}_{j,\text{pre}} = \overline{\boldsymbol{x}}^T_{j,\text{pre}} - \overline{\boldsymbol{x}}^C_{j,\text{pre}}$), including size, profitability, growth opportunity, dividend payout, market beta, and percentage quoted spread. Column (3) alternatively controls for double differences in firm fundamentals ($\Delta \boldsymbol{x_j} = (\boldsymbol{x}^T_{j,8} - \overline{\boldsymbol{x}}^T_{j,\text{pre}}) - (\boldsymbol{x}^C_{j,8} - \overline{\boldsymbol{x}}^C_{j,\text{pre}})$). The robust standard errors clustered at the industry level are in parentheses. We winsorize all continuous and unbounded variables at the 1% and 99% percentiles. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

control variables. The estimated $\mathcal{M}$ has a similar magnitude of 2.359. The stability of $\mathcal{M}$ across columns (1) to (3) suggests that the matching procedure effectively removes most confounding price effects from fundamentals, isolating the component attributable to supply shocks.

5.2 Relative Price Multiplier Approximates Own-Price Multiplier

As discussed in Section 3, equation (17) identifies the relative price multiplier à la Haddad et al. (2026), which is relevant for portfolio managers. However, the own-price multiplier is more informative for firm managers than the relative price multiplier, who are primarily

concerned with the effect of repurchasing their own equity. Building on Proposition 1, we conduct two empirical tests to assess whether the estimated relative price multiplier empirically approximates the own-price multiplier at the stock level. Specifically, we verify two conditions: (1) the matched treatment and control stock pair (n, n') exhibit the same systematic risk exposure, i.e., $\boldsymbol{b}(n) = \boldsymbol{b}(n')$; and (2) systematic risk exposure is small enough relative to idiosyncratic risk, i.e., $\boldsymbol{b}^2(n) \ll \sigma^2$.[31]

5.2.1 Test of Balance on Systematic Risk Exposure

For each matched pair, we construct a portfolio by going long the treatment stock and shorting the control stock. We use the market excess return as the systematic risk factor in our factor structure assumption (10). For each year-month, we regress the daily excess returns of the long-short portfolio on the daily market excess return $r_{m,t}$ over the past 12 months to estimate the factor loading β_j:

$$r^T_{j,t} - r^C_{j,t} = \alpha_j + \beta_j r_{m,t} + \nu_j \tag{19}$$

Let n and n' denote the treatment and control stocks within matched pair j. Since we normalize the variance of the risk factor to one, we have that

$$\beta_j = \frac{\boldsymbol{b}_j(n) - \boldsymbol{b}_j(n')}{\sigma(r_m)}$$

[31] Identifying individual investor i's perceived systematic risk exposure to stock n, $\boldsymbol{b}_i(n)$ requires experiments and granular data on individual investor beliefs (Giglio et al., 2021; Merkle and Ungeheuer, 2025). We suppress the subscript i in our empirical implementation so that $\boldsymbol{b}(n)$ captures the average factor exposures perceived by investors.

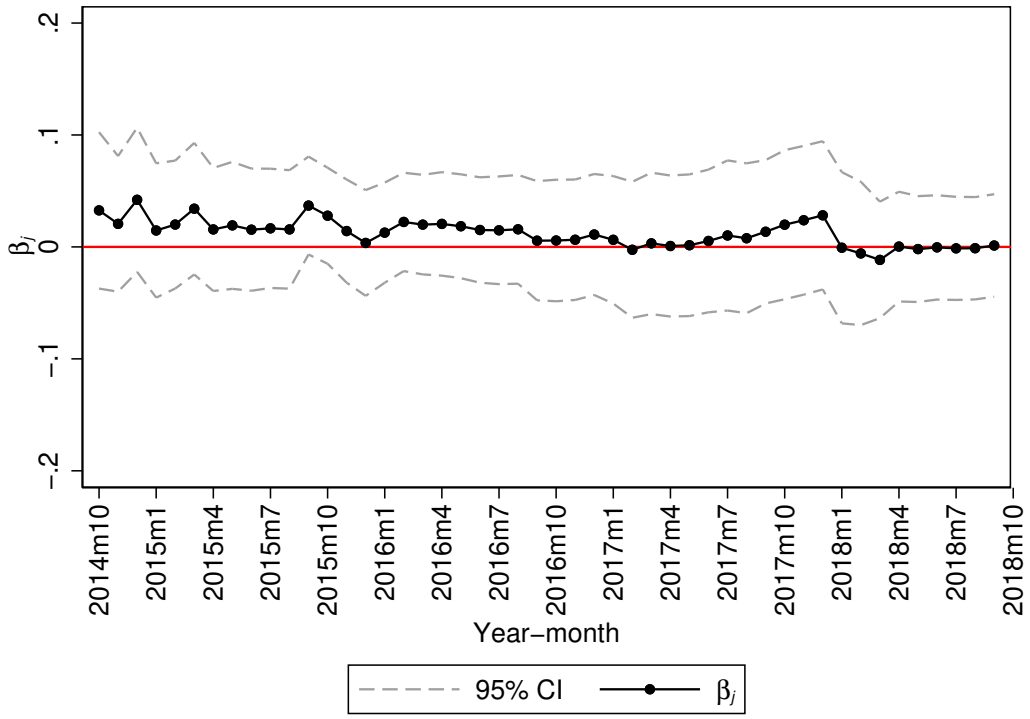


Figure 2. Test of balance on systematic risk exposure. This figure plots the average systematic exposure of long-short portfolio returns between matched treatment and control stocks to the excess stock market returns. At each month, we obtain the market beta of each matched pair, and then calculate the cross-sectional mean across matched pairs and the corresponding 95% confidence interval. The sample period is from October 2014 to September 2018. Estimates are winsorized at the 1% and 99% percentiles.

in which $\sigma(r_m)$ is the standard deviation of the market excess return. Therefore, β_j captures the difference in the systematic risk exposure between the matched treatment and control stocks. Figure 2 plots the cross-sectional average of fitted β_j across matched pairs and the corresponding t-statistics from October 2014 to September 2018. We find that the average coefficients fluctuate around zero and are statistically indistinguishable at 5% significance level for the entire 48 months. This finding suggests that the treatment and control stocks within each pair exhibit the same factor exposures, i.e., $\boldsymbol{b}(n) = \boldsymbol{b}(n')$.

Therefore, under the single-factor structure, treatment and control stocks share similar cross-price multipliers with respect to other stocks outside the matched pair. This result

supports the validity of our empirical strategy, which relies on differencing price changes between matched stocks to remove spillover effects from other stocks outside matched pairs.

5.2.2 Relatively Large Idiosyncratic Risk

We use the market excess return as the systematic risk factor and estimate the time-series regression of stock n's daily excess return:

$$r_t(n) = \alpha(n) + \beta(n) r_{m,t} + \varepsilon_t(n) \tag{20}$$

where $r_t(n)$ is the daily excess return of stock n on day t, and $r_{m,t}$ is the daily market excess return. For each year-month, we compute the idiosyncratic risk $\sigma^2(n)$ as the variance of the residuals $\varepsilon_t(n)$ from equation (20) over the past 12 months.[32] Since our model normalizes the variance of the systematic risk factor to one, the systematic risk exposure $\boldsymbol{b}_i^2(n)$ equals the square of the estimated loading $\beta^2(n)$ multiplied by the market factor variance: $\boldsymbol{b}_i^2(n) = \beta^2(n)\sigma^2(r_m)$.

We then test the null hypothesis that the systematic risk exposure is no smaller than c fraction of the idiosyncratic risk:

$$H_0 : \ln\left(\frac{\beta^2(n)\sigma^2(r_m)}{\sigma^2(n)}\right) \geq \ln(c) \tag{21}$$

Panel A of Table 7 reports the summary statistics for annualized idiosyncratic risk and systematic risk exposure for our sample stocks during the two-year TSP periods. The average

[32]We also report the idiosyncratic risk calculated from Fama-French three factors, Carhart four factors, and Fama-French five factors in Table IA.4 of Appendix IA.4; the results are quantitatively similar.

Table 7
Idiosyncratic Risk vs. Systematic Risk Exposure

	N	Mean	SD	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Summary statistics						
Idiosyncratic ($\sigma^2(n) \times 10^{-4}$)	24,937	5.704	3.924	2.737	4.474	7.778
Systematic ($\beta^2(n)\sigma^2(r_m) \times 10^{-4}$)	24,937	0.676	1.407	0.140	0.320	0.637
Panel B: Statistical tests						
	$c = 0.10$	$c = 0.09$	$c = 0.08$	$c = 0.07$	$c = 0.06$	$c = 0.059$
$p-$value	0.000***	0.000***	0.000***	0.000***	0.040**	0.082*

This table compares the idiosyncratic risk and systematic risk exposure. Panel A presents summary statistics for the estimated annualized idiosyncratic risk and systematic risk exposure. Idiosyncratic risk is calculated as the variance of the daily regression residual from equation (20) multiplied by 252. Systematic risk exposure is calculated as the product of estimated betas from equation (20) and the variance of daily market factor multiplied by 252. Panel B reports the one-sided p-value for the null hypothesis specified in equation (21) under a different threshold level c. The sample period is from October 2014 to September 2018. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

idiosyncratic risk (5.704 b.p.) is approximately 8.4 times larger than the average systematic risk exposure (0.676 b.p.).[33]

Panel B reports one-sided p-values from the test in (21) for various thresholds c. We reject the null hypothesis for $c = 0.07$ ($c = 0.059$) threshold at the 1% (10%) significance level. It indicates that, on average, the systematic risk exposure is less than 7% (5.9%) of idiosyncratic risk at these respective significance levels. These results confirm that systematic exposure risk is substantially smaller than idiosyncratic risk, thus satisfying the condition $\boldsymbol{b}^2(n) \ll \sigma^2$ stated in the CAPM illustration of Proposition 1.

While the relatively large idiosyncratic risk implies that the own-price multiplier is

[33]This relative magnitude is consistent with prior empirical findings. For example, Campbell et al. (2001) show that the idiosyncratic risks are 4.2 (6.2) times larger than the market (industrial) risks on average from July 1962 to December 1997. Goyal and Santa-Clara (2003) extrapolate that the idiosyncratic risks are 6.1 times larger than the systematic risks. Table 2 of Bartram, Brown, and Stulz (2019) reports that the average of $\sigma^2/\sigma^2(r_m)$ (assuming average the $\boldsymbol{b}(n)$ of 1) ranges from 4.60 to 10.41 between 1961 to 2017, under different CRSP Index Volatility periods.

much larger than a singular cross-price multiplier, this does not imply that spillover effects aggregating across all other shocked stocks can be ignored. To demonstrate this, consider the special case of CAPM, and we can express the spillover effects to a TSP treatment stock n as follows:

$$\text{Spillover Effects to Stock } n = \sum_{m=1}^{1,199} \gamma \boldsymbol{b}(n)\boldsymbol{b}(m)\Delta S(m)$$

In the TSP, N=1,200 treatment stocks were simultaneously shocked ($\Delta S(m) < 0$, $m = 1, \cdots, 1{,}200$). The spillover effect is thus non-negligible as it arises from the other 1,199 treatment stocks. Failing to account for them would overestimate the relative price multiplier, as discussed in Section 3.2.1.

In summary, the estimated relative price multiplier in our sample empirically approximates the own-price multiplier according to Proposition 1.

5.3 Controlling for Liquidity Effect on Price

One remaining concern is that the TSP also affects the liquidity of treatment stocks relative to controls. If the observed price differences reflect both changes in liquidity and share repurchases, our estimated multiplier may conflate the two effects. To address this concern, this section provides two pieces of evidence that the estimated relative price multiplier in Table 6 identifies the price effect of supply shocks rather than liquidity changes.

Test Group 1&2 vs. Group 3. We exploit a unique feature of the TSP: stocks in test group 3 (G3) were subject to an additional "trade-at" rule compared to stocks in test group 1 and 2 (G1&2). This rule granted priority to orders executed in lit venues unless dark venues could improve the NBBO by more than 2.5 cents. However, under Rule 10b-18, dark

orders that improve the best bid by 2.5 cents are viewed as "manipulative". As a result, the "trade-at" rule, together with Rule 10b-18, further discouraged G3 firms from repurchasing shares in dark pools, a venue commonly used for repurchases, as discussed in Section 2.

To validate this channel, we estimate equation (15) separately for G1&2 and G3 stocks. Panel A of Table 8 shows that G3 stocks reduce repurchases by 0.116% per quarter (33% of the pre-treatment mean), while G1&2 stocks reduce repurchases by 0.066% per quarter (19% of the pre-treatment mean). The difference is both economically (14% of the pre-treatment mean) and statistically significant at 10% level.

Albuquerque, Song, and Yao (2020) document an empirical puzzle: while the "trade-at" rule had the same negative impact on aggregate liquidity across all three groups, G3 stocks experienced larger price decline than G1&2 stocks. This setting provides an ideal environment to estimate the relative price multiplier while controlling for liquidity effects. Because liquidity is dampened by the same magnitude across groups, if G1&2 and G3 stocks share the same relative price multiplier (i.e., $\mathcal{M}_{\text{G1\&2}} = \mathcal{M}_{\text{G3}}$), the larger supply shocks faced by G3 could explain its larger return reduction compared with G1&2. Furthermore, if this shared relative price multiplier also matches our baseline estimate (i.e., $\mathcal{M}_{\text{G1\&2}} = \mathcal{M}_{\text{G3}} = \mathcal{M}_{\text{baseline}}$), it would suggest that our estimate captures the price effect of supply shocks rather than liquidity changes.

We then re-estimate relative price multipliers for G1&2 and G3 using their corresponding matched control firms. Panel B of Table 8 reports the results. Columns (1) and (2) show that the estimated relative price multiplier for G1&2 and G3 is 2.695 and 3.188, respectively. The difference between the two estimates is not statistically significant (p-value = 0.393), indicating that the relative price multipliers of G1&2 and G3 are statistically indistinguish-

Table 8
G1&2 vs. G3 Stocks

Panel A: Effect of TSP on share repurchase

	$Repurchase_{n,t}$		
	G1&2		G3
	(1)		(2)
$Treatment_n \times Post_t$	−0.066**		−0.116**
	(0.03)		(0.05)
Test of (1)=(2)		**0.060***	
Control	Yes		Yes
Firm FE	Yes		Yes
Year-quarter FE	Yes		Yes
Observations	12,197		5,381
Adj. R^2	0.290		0.261

Panel B: Relative Price multiplier of G1&2 and G3

	Δp_j		
	G1&2	G3	G3 minus G1&2
	(1)	(2)	(3)
Δs_j	2.695**	3.188*	3.359*
	(1.12)	(1.65)	(1.73)
Test of $\mathcal{M}_{\text{G1\&2}} = \mathcal{M}_{\text{G3}}$	**0.393**		
Test of $\mathcal{M}_{\text{G1\&2}} = \mathcal{M}_{\text{G3}} = \mathcal{M}_{\text{baseline}}$	**0.462**	**0.388**	**0.467**
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	346	144	142
Adj. R^2	0.132	0.132	0.735

This table presents the subgroup analyses that isolates price changes from general liquidity influences. Panel A re-estimates equation (15) separately for G1&2 and G3. Controls include size, profitability and growth opportunity. Firm and year-quarter fixed effects are included. The robust standard errors clustered at firm level are in parentheses. Columns (1) and (2) in Panel B re-estimate equation (17) separately for G1&2 and G3. In column (3), we match each pair whose treatment stock is assigned to G3 to a pair whose treatment stock is in G1&2, and then difference all variables in equation (17), and re-estimate the relative price multiplier. The robust standard errors clustered at industry level are in parentheses. The reported p-value for difference is based on 1,000 bootstrap iterations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

able. The row "Test of $\mathcal{M}_{G1\&2} = \mathcal{M}_{G3} = \mathcal{M}_{\text{baseline}}$" reports the p-value of the difference test between each estimate with respect to the baseline relative price multiplier of 2.575 reported in column (2) of Table 6. Neither estimate is statistically different from the baseline magnitude.

G3 minus G1&2. Finally, we match each G3 stock with a stock from G1&2. We then difference the pair-level variables and re-estimate our baseline regression.[34] We refer this specification as "G3 minus G1&2." Since G1&2 and G3 stocks exhibit the same aggregate liquidity conditions, this additional layer of differentiation further controls for the common liquidity effects on prices. Column (3) reports the resulting estimate of 3.359. The sharp increase in adjusted R^2 suggests that the supply-side effect explains a substantial share of the variation in the additional price decrease of G3 compared to G1&2 stocks. The row "Test of $\mathcal{M}_{G1\&2} = \mathcal{M}_{G3} = \mathcal{M}_{\text{baseline}}$" shows that this estimate is not statistically different from the baseline magnitude.

Notably, our design also follows the recommendations of Heath et al. (2023) for strengthening inference when a natural experiment such as the TSP is reused. First, whereas most existing TSP research exploits random treatment assignment, we additionally exploit the random assignment of treatment stocks to G1&2 and G3. This provides corroborating evidence for our inference on the multiplier: although G1&2 and G3 experience different reductions in repurchases, their relative price multipliers are statistically indistinguishable from each other and from the baseline estimate.[35]

[34] For example, for a stock in G3 and its matched stock from G1&2, we construct the supply shock as $\Delta s_j = \Delta S_{G3} - \Delta s_{G1\&2}$, in which Δs_{G3} and $\Delta s_{G1\&2}$ are constructed separately from equation (16).

[35] In Appendix IA.2, we report a further check using only firms with pre-TSP repurchase activity (repurchasers). Relative to non-repurchasers, repurchasers experience an approximately 1.8% larger decline in abnormal returns and a 0.137% larger drop in quarterly shares repurchased. The relative price multiplier estimated for repurchasers is statistically indistinguishable from our baseline estimate, suggesting that the

Second, we show that the TSP-induced liquidity effect on prices documented by Albuquerque et al. (2020) is unlikely to contaminate our multiplier estimate. Because G1&2 and G3 experience similar changes in liquidity, differencing the price changes of G3 from those of matched G1&2 stocks controls the potential liquidity effect. We nevertheless obtain a multiplier similar to our baseline estimate. This result also reconciles our supply channel with the empirical puzzle documented by Albuquerque et al. (2020): although liquidity changes are similar across the three test groups, G3 experiences a larger price decline than G1&2 because it experiences a larger reduction in share repurchases.

5.4 Two-Stage Least Squares Estimates

In our baseline specification, we construct supply shocks as the double differences in realized shares repurchased between matched treatment and control firms. Although the reduction in repurchases stems from the unexpected interaction between the TSP and Rule 10b-18, a remaining concern is that the size of the realized repurchase shortfall might still be endogenous to contemporaneous prices. To further mitigate this concern, we instrument the realized quarterly shares repurchased ($Repurchase_{n,t}$) and perform a 2SLS estimation:

$$\begin{aligned} &\text{First stage: } Repurchase_{n,t} = \boldsymbol{\beta}'\boldsymbol{Z}_{i,t} + \boldsymbol{\gamma}'\boldsymbol{X}_{n,t} + u_n + u_g \times u_t + \epsilon_{n,t} \\ &\text{Second stage: } Return_{n,t} = \mathcal{M} \times \widehat{Repurchase}_{n,t} + \boldsymbol{\gamma}'\boldsymbol{X}_{n,t} + u_n + u_g \times u_t + \varepsilon_{n,t} \end{aligned} \tag{22}$$

In the first-stage, $\boldsymbol{Z}_{i,t}$ denotes a set of instrument variables (IV). The main IV is the treatment assignment and its interaction with the post-TSP indicator ($Treatment \times Post$). Follow-

multiplier estimate is not driven by the inclusion of non-repurchasers.

ing previous market microstructure studies (Sarkar and Schwartz, 2009; Foley and Putniņš, 2016), we also include the lagged level of repurchase ($Repurchase_{n,t-1}$) as the second instrument. The second stage estimates the impact of instrumented shares repurchased on stock prices. $Return_{n,t}$ denotes quarterly abnormal returns adjusted using CAPM, Fama and French (1993) three-factor, and Fama and French (2015) five-factor model. We use abnormal stock returns to control for the potentially different risk exposures among treatment and control firms, following Amihud, Mendelson, and Lauterbach (1997) and Albuquerque, Song, and Yao (2020). The control vector $\boldsymbol{X}_{n,t}$ includes the same variables specified in equation (17). We further include the inverse of stock prices to control for the relative tick size (Albuquerque, Song, and Yao, 2020).[36] We also include industry-by-time fixed effects ($u_g \times u_t$) to absorb common time-varying shocks within each industry. The robust standard errors are clustered at firm and industry-by-time levels.

Table 9 reports the 2SLS estimates. In the first stage, the coefficient of $Treatment_n \times Post_t$ indicates that a treatment firm repurchased 0.059% less shares after the commencement of TSP relative to control firms. The coefficient on $Repurchase_{n,t-1}$ of 0.167 is significantly positive and consistent with the persistence of open-market repurchase programs, which are typically executed gradually over multiple quarters (Stephens and Weisbach, 1998). The first-stage F-statistic of 47.690 exceeds conventional weak-instrument thresholds (Stock and Yogo, 2005), supporting relevance condition of our instruments. Hansen's J tests the validity of the overidentifying restrictions and we fail to reject the null of instrument validity across all three specifications. Given the plausibly exogenous variation in repurchases generated by

[36]The magnitude of estimated price multipliers remains similar without the inverse of stock prices as a control variable.

Table 9
Estimation of Relative Price Multiplier: Two-Stage Least Squares

	First stage	Second stage		
	$Repurchase_{n,t}$	CAPM	FF3	FF5
	(1)	(2)	(3)	(4)
$Treatment_n \times Post_t$	−0.059***			
	(0.02)			
$Repurchase_{n,t-1}$	0.167***			
	(0.02)			
$\widehat{Repurchase}_{n,t}$		**3.107*** **	**3.036*** **	**2.864*** **
		(0.99)	**(0.94)**	**(0.93)**
F-statistics (Kleibergen-Paap)	47.690			
Hansen's J statistic (p-value)		0.738	0.619	0.540
Test of = baseline (p-value)		0.701	0.733	0.830
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-by-time FE	Yes	Yes	Yes	Yes
Observations	19,359	19,356	19,356	19,356
Adj. R^2	0.312	0.058	0.058	0.060

This table reports the estimates of price multiplier using a two-stage least squares regression. The dependent variable is the quarterly abnormal returns using CAPM, Fama and French (1993) three-factor, and Fama and French (2015) five-factor model. *Treatment* is a dummy variable that equals one if a stock is in one of the three test groups and zero if it is in the control group. *Post* is an indicator variable that equals one if the year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). $\widehat{Repurchase}_{n,t}$ is the instrumented quarterly shares repurchased estimated by regressing shares repurchased ($Repurchase_{n,t}$) on treatment of TSP ($Treatment \times Post$) and lagged repurchases ($Repurchase_{n,t-1}$). Control variables consist of size, profitability, growth opportunity, dividend payout, market beta, percentage quoted spread, and the inverse of stock price. The robust standard errors clustered at firm and industry-by-time level are shown in parentheses. We winsorize all continuous and unbounded variables at the 1% and 99% levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

($Treatment_n \times Post_t$), the results suggest that $Repurchases_{n,t-1}$ also satisfies the exclusion restriction. The second stage yields a statistically significant relative price multiplier of 3.107, 3.036, and 2.864, respectively using abnormal returns adjusted by CAPM, Fama and French (1993) three-factor, and Fama and French (2015) five-factor model. These estimates are not

statistically distinguishable from our baseline estimate of 2.575: a statistical test of equality between the 2SLS and baseline coefficients yields z-statistics with p-values of 0.701, 0.733, and 0.830, respectively.

6. Investor Responses to Supply Shocks

In this section, we examine the portfolio adjustment behavior across investor types during the TSP to identify which investors absorb the exogenous supply shocks. Guided by equation (14) in Section 3.4, we estimate the quarterly panel regression:

$$\Delta q_{i,j,t} = \mathcal{A}_i \Delta s_{j,t} + \boldsymbol{\gamma}_i' \Delta \boldsymbol{x}_{j,t} + u_t \times u_g + \epsilon_{i,j,t} \tag{23}$$

where $\Delta s_{j,t}$ denotes the double-difference in percentage of shares outstanding repurchased for matched pair j in quarter t. Investor types i include banks, insurance companies, investment advisors (e.g., hedge funds), mutual funds, pension funds, other 13F institutions (e.g., endowments, foundations, and non-financial corporations), and households following the taxonomy in Koijen and Yogo (2019). We include the same control variables as in equation (17) and industry–time fixed effects to absorb common time-varying shocks within each industry. $\Delta q_{i,j,t}$ is the double difference in investor i's quarterly holding changes as of each TSP quarter t:

$$\Delta q_{i,j,t} = \left(q^T_{i,j,t} - \bar{q}^T_{i,j,\text{pre}}\right) - \left(q^C_{i,j,t} - \bar{q}^C_{i,j,\text{pre}}\right) \tag{24}$$

where $q^T_{i,j,t}$ and $q^C_{i,j,t}$ ($\bar{q}^T_{i,j,\text{pre}}$ and $\bar{q}^C_{i,j,\text{pre}}$) denote investor i's holding changes in treatment and control stock in pair j at quarter t (averaged across pre-treatment quarters), scaled by lagged

Table 10
Estimation of Investor Responses

	$\Delta q_{i,j,t}$						
	Banks	Insurance companies	Investment advisors	Mutual funds	Pension funds	Other 13F institutions	Households
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\boldsymbol{\Delta s_{j,t}}$	**−0.102****	−0.027	**−0.501*****	**−0.249****	−0.003	**−0.104****	−0.025
	(0.04)	(0.03)	**(0.13)**	**(0.11)**	(0.01)	**(0.05)**	(0.20)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
I×T FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,085	4,085	4,085	4,085	4,085	4,085	4,085
Adj. R^2	0.032	0.003	0.071	0.052	−0.010	−0.011	0.001

This table estimates the relative holding changes by each investor type during the 2016 Tick Size Pilot, specified in equation (23). The dependent variable is $\Delta q_{i,j,t}$, which is the double differences in quarterly holding change of investor type i between treatment and control stocks, before and after the shock. We consider seven types of investors: banks, insurance companies, investment advisors, mutual funds, pension funds, other 13F institutions, and households. The definition of investor sectors follows Koijen and Yogo (2019). The independent variable $\Delta s_{j,t}$ is the double-differences of quarterly shares repurchased of matched pair j. Control variables include size, profitability, growth opportunity, dividend payout, market beta, and percentage quoted spread. Industry-by-time fixed effect is included. The robust standard errors clustered at the industry-by-time level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

total shares outstanding, respectively. Accordingly, the regression coefficient $\mathcal{A}_i$ in equation (23) captures the average percentage change in holdings of investor type i in response to every 1% exogenous shock in share supply, relative to the matched control stock. In the case of an exogenous increase in share supply like the TSP (where $\Delta s < 0$), a negative coefficient implies a relative increase in the holdings of treatment stocks versus control stocks, thereby indicating absorption of the supply shock.

Table 10 reports the estimation results. Investment advisors (e.g., hedge funds), mutual funds, banks, and other 13F institutions significantly increase their holdings of treatment stocks relative to control stocks. When treatment firms exogenously increase share supply

by 1%, relative to control firms, investment advisors and mutual funds on average purchase 0.501% and 0.249%, respectively. Banks and other 13F institutions purchase 0.102% and 0.104%, respectively. We do not find statistically significant changes in the relative holdings of insurance companies, pension funds, and households.

Equation (23) estimates the average quarterly change in holdings for each investor sector in response to the supply shocks. To examine the dynamics of portfolio adjustment, we re-estimate equation (23) separately for each post-treatment quarter t and investor type i, yielding the coefficient $\mathcal{A}_{i,t}$; we then cumulate investor i's responses over different post-treatment horizons by calculating $\sum_{l=1}^{t} \mathcal{A}_{i,l}$.

Figure 3 displays the cumulative portfolio adjustments of each investor sector i over different horizon t. Consistent with Table 10, investment advisers and mutual funds exhibit the strongest responses. For an exogenous increase in cumulative share supply of 0.25% over eight TSP quarters, investment advisers and mutual funds cumulatively and persistently absorb around 0.13% and 0.06% of the additional shares, respectively. Banks and other 13F institutions respond modestly by absorbing around 0.03%, while insurance companies and pension funds show little change in their holdings. Importantly, the insignificant coefficient for households in column (7) of Table 10 does not imply inelastic demand. Instead, households initially purchase shares following the implementation of the TSP and subsequently unwind their positions gradually as shares are reallocated to other investor sectors.

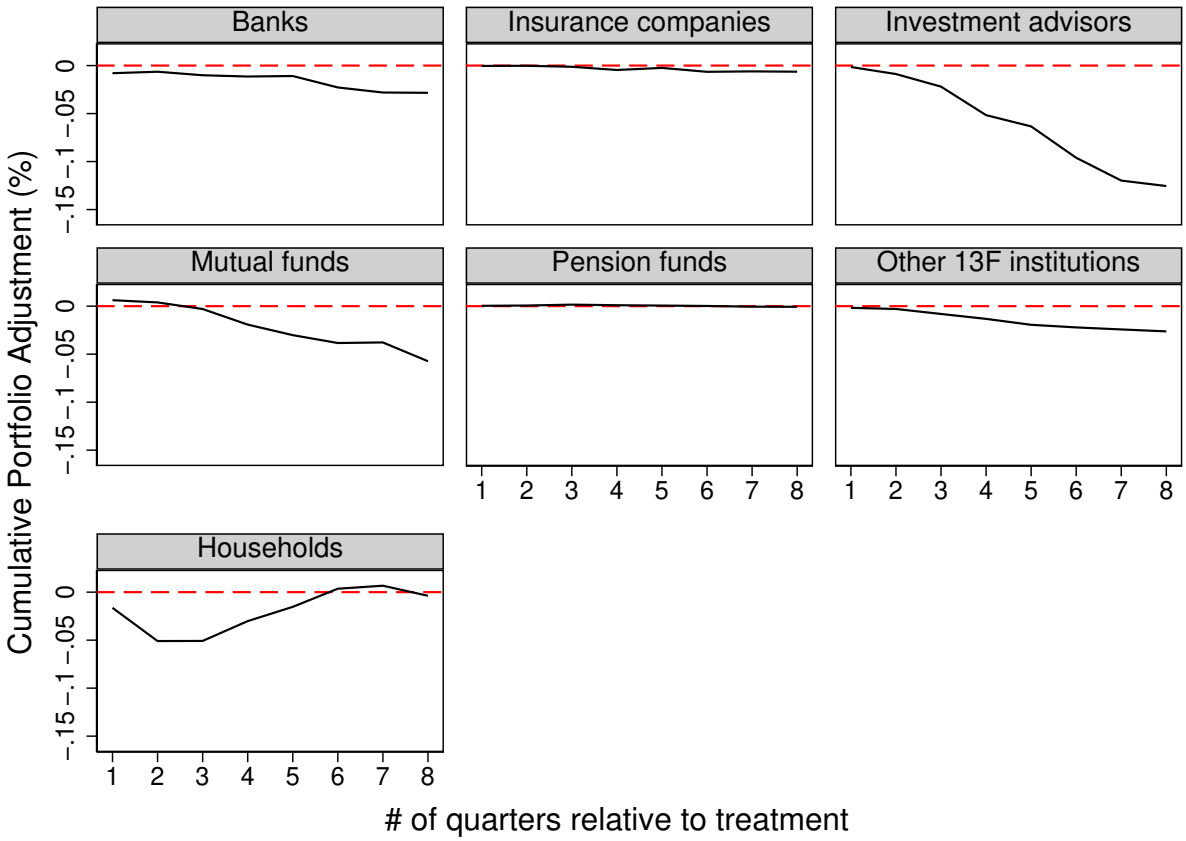


Figure 3. Cumulative portfolio adjustments by investor sectors. This figure depicts the cumulative relative changes in holdings by investor type in response to a 0.25% exogenous supply shock during the Tick Size Pilot. For each post-treatment quarter from 2016Q4 to 2018Q3, we estimate $\mathcal{A}_i$ using equation (23) and then cumulate the estimated coefficients over quarters. The classification of investor sectors follows Koijen and Yogo (2019).

7. Conclusions

This paper provides the first estimate of the price impact of exogenous changes in share supply. We exploit the 2016 SEC Tick Size Pilot as a source of exogenous, uninformed supply shocks. The randomized design of the TSP also allows us to explicitly absorb price spillover effects, yielding a relative price multiplier of 2.575. Because this relative multiplier retains only the one-to-one spillover between matched treatment and control stocks, we

theoretically derive and empirically validate the conditions under which it approximates the own-price multiplier at the individual stock level.

Exogenous supply shocks also allow us to track investors' portfolio adjustment responding to supply shifts. We find investment advisors and mutual funds primarily absorb supply shocks, followed by banks and other 13F institutions. Households also respond actively: they initially increase their holdings but gradually unwind positions over time. By contrast, insurance companies and pension funds exhibit little response. These patterns underscore the heterogeneous response of different investor types to corporate events like repurchases.

Beyond the specific context of the TSP, our findings have several broader implications. First, we provide empirical support for the assumption of repurchase price impact in behavioral corporate finance. Second, we offer an alternative interpretation of abnormal returns following share repurchases: reductions in shares outstanding may mechanically raise stock prices, beyond informational channels such as signaling or market underreaction. Finally, our results suggest that the secular rise in U.S. share repurchases (Kahle and Stulz, 2021) may have mechanically contributed to the increase in aggregate stock valuations.

References

Albuquerque, R., S. Song, and C. Yao (2020). The price effects of liquidity shocks: A study of the SEC's tick size experiment. *Journal of Financial Economics 138*(3), 700–724.

Amihud, Y., H. Mendelson, and B. Lauterbach (1997). Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. *Journal of Finance 45*(3), 365–390.

Baker, M. and J. Wurgler (2013). Behavioral corporate finance: An updated survey. In *Handbook of the Economics of Finance*, Volume 2, pp. 357–424. Elsevier.

Bartram, S. M., G. W. Brown, and R. M. Stulz (2019). Why is there a secular decline in idiosyncratic risk in the 2000s? *Working Paper*.

Billett, M. T. and M. Yu (2016). Asymmetric information, financial reporting, and open-market share repurchases. *Journal of Financial and Quantitative Analysis 51*(4), 1165–1192.

Binsbergen, J. H. v., B. David, and C. C. Opp (2026). How (not) to identify demand elasticities in dynamic asset markets. *Working Paper*.

Bonaimé, A. (2012). Repurchases, reputation, and returns. *Journal of Financial and Quantitative Analysis 47*(2), 469–491.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *Journal of Finance 56*(1), 1–43.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Cassella, S., A. Rizzo, O. Spalt, and L. Zimmerer (2026). Constrained by law: The impact of fiduciary duties on portfolios and prices in us equity markets. *Journal of Financial Economics 177*, 104227.

Chang, Y., H. Hong, and I. Liskovich (2015). Regression discontinuity and the price effects of stock market indexing. *Review of Financial Studies 28*(1), 212–246.

Chaudhary, M., Z. Fu, and J. Li (2025). Corporate bond multipliers: Substitutes matter. *Working Paper*.

Chaudhry, A. and J. Li (2026). Endogenous elasticities: Price multipliers are smaller for larger demand shocks. *Working Paper*.

Chen, H. (2024). Cash induced demand. *Journal of Financial and Quantitative Analysis 59*(1), 195–220.

Constantinides, G. M. and B. D. Grundy (1989). Optimal investment with stock repurchase and financing as signals. *Review of Financial Studies 2*(4), 445–465.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*(2), 479–512.

Dann, L. Y. (1981). Common stock repurchases: An analysis of returns to bondholders and stockholders. *Journal of Financial Economics 9*(2), 113–138.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial Economics 60*(1), 3–43.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Fang, C. and K. Xiao (2025). What do $40 trillion of portfolio holdings say about monetary policy transmission? *Working Paper*.

Foley, S. and T. J. Putniņš (2016). Should we be afraid of the dark? Dark trading and market quality. *Journal of Financial Economics 122*(3), 456–481.

Fuchs, W., S. Fukuda, and D. Neuhann (2025). Demand-system asset pricing: Theoretical foundations. *Working Paper*.

Gabaix, X. and R. S. Koijen (2023). In search of the origins of financial fluctuations: The inelastic markets hypothesis. *Working Paper*.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus (2021). Five facts about beliefs and portfolios. *American Economic Review 111*(5), 1481–1522.

Gomes, A., G. Gorton, and L. Madureira (2007). SEC Regulation Fair Disclosure, information, and the cost of capital. *Journal of Corporate Finance 13*(2-3), 300–334.

Goyal, A. and P. Santa-Clara (2003). Idiosyncratic risk matters! *Journal of Finance 58*(3), 975–1007.

Haddad, V., Z. He, P. Huebner, P. Kondor, and E. Loualiche (2026). Causal inference for asset pricing. *Working Paper*.

Haddad, V., A. Moreira, and T. Muir (2025). Asset purchase rules: How QE transformed the bond market. *Working Paper*.

Hartzmark, S. and D. Solomon (2025). Marketwide predictable price pressure. *American Economic Review 115*(9), 3171–3213.

Heath, D., M. C. Ringgenberg, M. Samadi, and I. M. Werner (2023). Reusing natural experiments. *Journal of Finance 78*(4), 2329–2364.

Ikenberry, D., J. Lakonishok, and T. Vermaelen (1995). Market underreaction to open market share repurchases. *Journal of Financial Economics 39*(2-3), 181–208.

Kahle, K. and R. M. Stulz (2021). Why are corporate payouts so high in the 2000s? *Journal of Financial Economics 142*(3), 1359–1380.

Koijen, R. S., F. Koulischer, B. Nguyen, and M. Yogo (2021). Inspecting the mechanism of quantitative easing in the euro area. *Journal of Financial Economics 140*(1), 1–20.

Koijen, R. S., R. J. Richmond, and M. Yogo (2023). Which investors matter for equity valuations and expected returns? *Review of Economic Studies 91*(4), 2387–2424.

Koijen, R. S. and M. Yogo (2019). A demand system approach to asset pricing. *Journal of Political Economy 127*(4), 1475–1515.

Koijen, R. S. and M. Yogo (2026). Exchange rates and asset prices in a global demand system. *Journal of Political Economy*, forthcoming.

Kvamvold, J. and S. Lindset (2018). Do dividend flows affect stock returns? *Journal of Financial Research 41*(1), 149–174.

Li, J. and Z. Lin (2026). Price multipliers are larger for less diversifiable order flows. *Journal of Finance*, forthcoming.

Li, S., M. Ye, and M. Zheng (2023). Refusing the best price? *Journal of Financial Economics 147*(2), 317–337.

Li, X., M. Ye, and M. Zheng (2024). Price ceilings, market structure, and payout policies. *Journal of Financial Economics 155*, 103818.

Lintner, J. (1969). The aggregation of investor's diverse judgments and preferences in purely competitive security markets. *Journal of Financial and Quantitative Analysis 4*(4), 347–400.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies 25*(12), 3457–3489.

Manconi, A., U. Peyer, and T. Vermaelen (2019). Are buybacks good for long-term shareholder value? evidence from buybacks around the world. *Journal of Financial and Quantitative Analysis 54*(5), 1899–1935.

Merkle, C. and M. Ungeheuer (2025). Beliefs about beta: upside participation and downside protection. *Review of Finance 29*(5), 1397–1436.

Ofer, A. R. and A. V. Thakor (1987). A theory of stock price responses to alternative corporate cash disbursement methods: Stock repurchases and dividends. *Journal of Finance 42*(2), 365–394.

Pavlova, A. and T. Sikorskaya (2023). Benchmarking intensity. *Review of Financial Studies 36*(3), 859–903.

Peyer, U. and T. Vermaelen (2009). The nature and persistence of buyback anomalies. *Review of Financial Studies 22*(4), 1693–1745.

Sammon, M. and J. J. Shim (2026). Who clears the market when passive investors trade. *Review of Financial Studies*, forthcoming.

Sarkar, A. and R. A. Schwartz (2009). Market sidedness: Insights into motives for trade initiation. *Journal of Finance 64*(1), 375–423.

Schmickler, S. and P. Tremacoldi-Rossi (2023). Spillover effects of payouts on asset prices and real investment. *Working Paper*.

Shleifer, A. (1986). Do demand curves for stocks slope down? *Journal of Finance 41*(3), 579–590.

Stein, J. C. (1996). Rational capital budgeting in an irrational world. *Journal of Business 69*(4), 429–455.

Stephens, C. and M. Weisbach (1998). Actual share reacquisitions in open-market repurchase programs. *Journal of Finance 53*(1), 313–333.

Stock, J. H. and M. Yogo (2005). Testing for weak instruments in linear iv regression. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pp. 80–108. Cambridge: Cambridge Univ. Press.

Vermaelen, T. (1981). Common stock repurchases and market signalling: An empirical study. *Journal of Financial Economics 9*(2), 139–183.

Wang, Y. (2025). Estimating investor demand elasticity with endogenous firm responses: Evidence from mutual fund flow shocks. *Working Paper*.

Ye, M., F. Zhang, and J. Zou (2025). Disclosing share repurchases more frequently? *Working Paper*.

A. Proofs and Discussions

A.1 Proofs of Optimal Portfolio Choice and Equilibrium Prices

Based on the assumption of future asset payoff, $\boldsymbol{d}_i \sim \mathcal{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$, and the expectation properties of log-normal distribution, the investor's objective function can be expressed as

$$\begin{aligned}
&\mathbb{E}_i\left[-\exp\left(-\gamma_i A_{i,1}\right)\right] = -\exp\left(-\gamma_i\left(\mathbb{E}_i(A_{i,1}) + \frac{1}{2}\mathbb{V}\text{ar}_i(A_{i,1})\right)\right) \\
&= -\exp\left(-\gamma_i\left(A_{i,0} + \left(\boldsymbol{\mu_i} - \boldsymbol{P}\right)'\boldsymbol{q}_i\right) + \frac{\gamma_i^2}{2}\left(\boldsymbol{q}_i'\boldsymbol{\Sigma}_i\boldsymbol{q}_i\right)\right)
\end{aligned}$$

The first-order condition of the investor's portfolio choice is

$$-(\boldsymbol{\mu_i} - \boldsymbol{P}) + \gamma_i(\boldsymbol{\Sigma}_i)\boldsymbol{q}_i = 0$$

It solves the optimal portfolio choice in equation (1):

$$\boldsymbol{q_i} = \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\left(\boldsymbol{\mu_i} - \boldsymbol{P}\right)$$

From equation (1), we can explicitly express market clearing condition as

$$\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\Big(\boldsymbol{\mu}_i - \boldsymbol{P}\Big) = \boldsymbol{S} \tag{A1}$$

Rearranging equation (A1) yields the equilibrium price vector:

$$\boldsymbol{P} = \boldsymbol{\mathcal{M}}\left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mu}_i - \boldsymbol{S}\right) \tag{A2}$$

where $\boldsymbol{\mathcal{M}} \triangleq \left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\right)^{-1}$ is the price multiplier matrix. □

A.2 Proof of Lemma 1

Note that under the factor structure (10), we have $\boldsymbol{\Sigma}_i = \mathbb{V}\text{ar}(\boldsymbol{d}_i) = \sigma^2\mathbf{I} + \boldsymbol{b}_i\boldsymbol{b}_i'$. The Woodbury matrix identity yields $\boldsymbol{\Sigma}_i^{-1} = \frac{1}{\sigma^2}\Big(\mathbf{I} - \frac{\boldsymbol{b}_i\boldsymbol{b}_i'}{\sigma^2 + \boldsymbol{b}_i'\boldsymbol{b}_i}\Big)$. Plugging it to $\boldsymbol{\mathcal{M}} = \Big(\sum_{i=1}^I \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\Big)^{-1}$, we have

$$\boldsymbol{\mathcal{M}} = \left(\sum_{i=1}^I \frac{1}{\gamma_i\sigma^2}\Big(\mathbf{I} - \frac{\boldsymbol{b}_i\boldsymbol{b}_i'}{\sigma^2 + \boldsymbol{b}_i'\boldsymbol{b}_i}\Big)\right)^{-1} = \left(\sum_{i=1}^I \frac{1}{\gamma_i\sigma^2}\mathbf{I} - \sum_{i=1}^I \frac{\boldsymbol{b}_i\boldsymbol{b}_i'}{\gamma_i\sigma^2(\sigma^2 + \boldsymbol{b}_i'\boldsymbol{b}_i)}\right)^{-1}$$

Denote the aggregate risk tolerance as $\tau = \sum_{i=1}^I \frac{1}{\gamma_i}$ and an $N \times I$ matrix

$$\boldsymbol{\rho} = \left[\frac{\boldsymbol{b}_1}{\sqrt{\gamma_1(1 + \boldsymbol{b}_1'\boldsymbol{b}_1/\sigma^2)}}, \cdots, \frac{\boldsymbol{b}_I}{\sqrt{\gamma_I(1 + \boldsymbol{b}_I'\boldsymbol{b}_I/\sigma^2)}}\right]_{N\times I}$$

so that we can express the price multiplier matrix $\boldsymbol{\mathcal{M}}$ as:

$$\boldsymbol{\mathcal{M}} = \left(\frac{\tau}{\sigma^2}\mathbf{I} - \frac{1}{\sigma^4}\boldsymbol{\rho}\boldsymbol{\rho}'\right)^{-1}$$

Applying the Woodbury matrix identity, we can express the matrix inverse as

$$\left(\frac{\tau}{\sigma^2}\mathbf{I} - \frac{1}{\sigma^4}\boldsymbol{\rho}\boldsymbol{\rho}'\right)^{-1} = \frac{\sigma^2}{\tau}\mathbf{I} + \frac{1}{\tau^2}\,\boldsymbol{\rho}\Big(\mathbf{I} - \frac{1}{\tau\sigma^2}\boldsymbol{\rho}'\boldsymbol{\rho}\Big)^{-1}\boldsymbol{\rho}'$$

Finally, defining $\boldsymbol{L} = \Big(\mathbf{I} - \frac{1}{\tau\sigma^2}\boldsymbol{\rho}'\boldsymbol{\rho}\Big)^{-1}$, we can simplify the matrix $\boldsymbol{\mathcal{M}}$ as

$$\boldsymbol{\mathcal{M}} = \frac{\sigma^2}{\tau}\,\mathbf{I} + \frac{1}{\tau^2}\,\boldsymbol{\rho}\boldsymbol{L}\boldsymbol{\rho}' \tag{A3}$$

□

A.3 Proof of Proposition 1

Given equation (A3) and $b_i(n) = b_i(n')$ for all investor i, the relative price multiplier and the (n, n) element of matrix $\boldsymbol{\mathcal{M}}$ are

$$\mathcal{M}_{relative}(n, n') = \frac{\sigma^2}{\tau},\ [\boldsymbol{\mathcal{M}}]_{n,n} = \frac{\sigma^2}{\tau} + \frac{1}{\tau^2}\ \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n$$

where $\boldsymbol{\rho}_n = \left(\frac{\boldsymbol{b}_1(n)}{\sqrt{\gamma_1(1+\boldsymbol{b}_1'\boldsymbol{b}_1/\sigma^2)}}, \cdots, \frac{\boldsymbol{b}_I(n)}{\sqrt{\gamma_I(1+\boldsymbol{b}_I'\boldsymbol{b}_I/\sigma^2)}} \right)'$ is the n-th column of matrix $\boldsymbol{\rho}$. Note that

$$\frac{\mathcal{M}_{relative}(n, n')}{[\boldsymbol{\mathcal{M}}]_{n,n}} = \frac{\frac{\sigma^2}{\tau}}{\frac{\sigma^2}{\tau} + \frac{1}{\tau^2}\ \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n} = \frac{1}{1 + \frac{1}{\tau\sigma^2} \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n}$$

Define the ratio

$$R_n = \frac{1}{\tau\sigma^2} \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n$$

Achieving $\dfrac{\mathcal{M}_{relative}(n, n')}{[\boldsymbol{\mathcal{M}}]_{n,n}} \to 1$ requires $R_n \ll 1$. Denote $\lambda_{\max}(\boldsymbol{X})$ and $\lambda_{\min}(\boldsymbol{X})$ as the largest and smallest eigenvalues of matrix $\boldsymbol{X}$, the upper bound of this quadratic form is

$$\begin{aligned} R_n = \frac{1}{\tau\sigma^2} \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n &\leq \frac{1}{\tau\sigma^2} \cdot \lambda_{\max}(\boldsymbol{L}) \cdot \|\boldsymbol{\rho}_n\|^2 \\ &= \frac{1}{\tau\sigma^2 - \lambda_{\max}(\boldsymbol{\rho}'\boldsymbol{\rho})} \cdot \|\boldsymbol{\rho}_n\|^2 \end{aligned}$$

The first inequality follows the Rayleigh-Ritz theorem and the second line uses the fact that $\lambda_{\max}(\boldsymbol{L}) = 1/\lambda_{\min}(\mathbf{I} - \frac{1}{\tau\sigma^2}\boldsymbol{\rho}'\boldsymbol{\rho}) = 1/\left(1 - \frac{1}{\tau\sigma^2}\lambda_{\max}(\boldsymbol{\rho}'\boldsymbol{\rho})\right)$. Therefore, a sufficient condition for $R_n \ll 1$ is

$$\begin{aligned} &\frac{1}{\tau\sigma^2 - \lambda_{\max}(\boldsymbol{\rho}'\boldsymbol{\rho})} \cdot \|\boldsymbol{\rho}_n\|^2 \ll 1 \\ \Rightarrow &\|\boldsymbol{\rho}_n\|^2 \ll \tau\sigma^2 - \lambda_{\max}(\boldsymbol{\rho}'\boldsymbol{\rho}) \end{aligned} \tag{A4}$$

Because $\lambda_{\max}(\boldsymbol{X}) \leq \text{trace}(\boldsymbol{X})$, to satisfy equation (A4), it is sufficient to show that

$$\|\boldsymbol{\rho}_n\|^2 \ll \tau\sigma^2 - \text{trace}(\boldsymbol{\rho}'\boldsymbol{\rho})$$

Finally, note that

$$\text{trace}\,(\boldsymbol{\rho}'\boldsymbol{\rho}) = \sum_{i=1}^{I} \frac{\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(1+\boldsymbol{b}_i'\boldsymbol{b}_i/\sigma^2)} = \sum_{i=1}^{I} \frac{\sigma^2\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)}$$

Therefore, the sufficient condition for $R_n \ll 1$ is

$$\|\boldsymbol{\rho}_n\|^2 = \sum_{i=1}^{I} \frac{\sigma^2\ \boldsymbol{b}_i^2(n)}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \ll \tau\sigma^2 - \sum_{i=1}^{I} \frac{\sigma^2\ \boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \tag{A5}$$

Since $\sigma^2 > 0$ and $\tau = \sum_{i=1}^{I} \frac{1}{\gamma_i}$, rearranging equation (A5) yields:

$$\sum_{i=1}^{I} \frac{\boldsymbol{b}_i^2(n)+\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \ll \sum_{i=1}^{I} \frac{1}{\gamma_i} \tag{A6}$$

A sufficient condition for equation (A6), and also $R_n \ll 1$, is

$$\begin{aligned} &\frac{\boldsymbol{b}_i^2(n)+\boldsymbol{b}_i'\boldsymbol{b}_i}{\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i} \ll 1 \\ \Rightarrow\ &\boldsymbol{b}_i^2(n) \ll \sigma^2 \text{ or } \frac{\boldsymbol{b}_i^2(n)}{\sigma^2} \to 0 \end{aligned} \tag{A7}$$

□

A.4 Proof of Corollary 1

We derive the special case of CAPM to reveal the intuition behind the price multiplier matrix based on Lemma 1. The representative-investor CAPM implies that $\gamma_i = \gamma_j = \gamma$, $\boldsymbol{b}_i = \boldsymbol{b}_j = \boldsymbol{b}$, and $I = 1$. Then, $\tau = 1/\gamma$. The $N \times I$ matrix $\boldsymbol{\rho}$ simplifies to an $N \times 1$ vector:

$$\boldsymbol{\rho} = \left[\frac{b(1)}{\sqrt{\gamma\left(1+\sum_{m=1}^{N} b(m)^2/\sigma^2\right)}}, ..., \frac{b(N)}{\sqrt{\gamma\left(1+\sum_{m=1}^{N} b(m)^2/\sigma^2\right)}} \right]'_{N\times 1}$$

and the $I \times I$ matrix $\boldsymbol{L}$ simplifies to a scalar L:

$$L = \left(1 - \frac{\gamma}{\sigma^2} \sum_{m=1}^{N} \frac{b(m)^2}{\gamma \left(1 + \sum_{m=1}^{N} b(m)^2/\sigma^2\right)}\right)^{-1} = \left(\frac{\sigma^2}{\sigma^2 + \sum_{m=1}^{N} b(m)^2}\right)^{-1}$$

Since $\boldsymbol{L}$ becomes a scalar, $\boldsymbol{\rho L \rho'}$ simplifies to:

$$\boldsymbol{\rho L \rho'} = L \boldsymbol{\rho \rho'} = L \frac{\boldsymbol{b b'}}{\gamma \left(1 + \sum_{m=1}^{N} b^2(m)/\sigma^2\right)} = L \frac{\sigma^2 \boldsymbol{b b'}}{\gamma \left(\sigma^2 + \sum_{m=1}^{N} b^2(m)\right)}$$

Therefore, the price multiplier matrix becomes:

$$\begin{aligned} \boldsymbol{\mathcal{M}} &= \gamma \sigma^2 \mathbf{I} + \gamma^2 \left(\frac{\sigma^2 + \sum_{m=1}^{N} b(m)^2}{\sigma^2}\right) \frac{\sigma^2 \boldsymbol{b b'}}{\gamma \left(\sigma^2 + \sum_{m=1}^{N} b^2(m)\right)} \\ &= \gamma \sigma^2 \mathbf{I} + \gamma \boldsymbol{b b'} \end{aligned}$$

The corresponding own-price, cross-price, and relative price multipliers are:

$$\begin{aligned} [\boldsymbol{\mathcal{M}}]_{n,n} &= \gamma \left[\sigma^2 + \boldsymbol{b}^2(n)\right] \\ [\boldsymbol{\mathcal{M}}]_{n,m} &= \gamma \ \boldsymbol{b}(n) \boldsymbol{b}(m) \\ \mathcal{M}_{relative}(n,m) &= \gamma \left\{\sigma^2 + \ \boldsymbol{b}(n) \left[\boldsymbol{b}(n) - \boldsymbol{b}(m)\right]\right\} \end{aligned} \tag{A8}$$

□

B. Variable Definitions

Variable	Definition
Annc	An indicator that equals one if a stock announces a repurchase announcement at the quarter and zero otherwise.
Beta	Market beta. For each stock-quarter, it is estimated from a regression of monthly stock excess returns over the risk-free rate, onto excess market returns using the past 60-month (five-year) observations.
Bid Depth	The average daily displayed dollar depth at the national best bid over a quarter. It is expressed in thousands of dollars.
CAR	The cumulative abnormal return around $[-1, +1]$ event window based on CAPM, Fama and French (1993) three-, or Fama and French (2015) five-factor model. It is expressed in percentage point.
Completion Rate	The realized number of shares repurchase, scaled by the number of shares sought for a repurchase program. It is expressed in percentage point.
Dividend	Dividend payouts, estimated by common stock dividends (DVQ − DVPQ), divided by lagged total assets (ATQ). Compustat quarterly data only provides the year-to-date dividends (DVY). The quarterly dividend (DVQ) is computed as DVY (in the first fiscal quarter) or the change in DVY (in the second, third, and fourth fiscal quarter). It is expressed in percentage point.
Growth	Growth opportunity, estimated by the quarterly growth of total assets (ATQ). It is expressed in percentage point.
Issuance	Equity issuance, estimated by the sales of common and preferred stocks (SSTKQ) minus any increase in preferred stocks, scaled by lagged total assets (ATQ). Compustat quarterly data only provides the year-to-date sales of common and preferred stocks (SSTKY). The quarterly value (SSTKQ) is computed as SSTKY (in the first fiscal quarter) or the change in SSTKY (in the second, third, and fourth fiscal quarter). Preferred stocks depend on the availability in the order of redemption (PSTKRQ) and capital (PSTKQ). It is expressed in percentage point.
Percent	The number of shares sought for a repurchase program, scaled by the number of shares outstanding at the authorization date. It is expressed in percentage point.
Post	An indicator that equals one if a year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3).
Price	The quarter-end stock prices (PRCCQ). When calculating price differences, it is adjusted for stock splits and stock dividends by dividing to adjust factor (AJEXQ).

Profitability	Profitability, estimated by the quarterly revenues (REVTQ) minus the sum of cost of goods sold (COGSQ) and selling, general, and administrative expenses (XSGAQ) and interest and related expenses (XINTQ), scaled by lagged book equity. Book equity is defined as the book value of stockholders' equity (SEQQ), plus balance sheet deferred taxes and investment tax credit (TXDITCQ), minus the book value of preferred stock.
Quoted Spread	The average daily percentage quoted spread over a quarter. Percentage quoted spread is the difference between the National Best Ask and the National Best Bid at any time interval divided by the midpoint of the two. The daily percentage quoted spread is the time weighted average percentage quoted spread computed during market time. It is expressed in percentage point.
Repurchase	Shares repurchased, estimated by the number of common stock repurchases (CSHOPQ), divided by lagged total number of common shares outstanding (CSHOQ). The number of shares is adjusted by stock split (AJEXQ). It is expressed in percentage point.
Repurchaser	An indicator that equals one if a firm ever engaged in repurchase activities in the pre-treatment period and zero otherwise.
Shares	The quarter-end number of total common shares outstanding (CSHOQ). When calculating share differences, it is adjusted for stock splits and stock dividends by multiplying adjust factor (AJEXQ).
Size	The natural logarithm of total assets (ATQ).
Treatment	An indicator that equals one if a stock is in one of the three test groups and zero if it is in the control group.
Volume	The announced repurchased dollar volume in million.

Internet Appendix for

"Asset Prices and Portfolio Adjustment under Supply Shocks"

IA.1. Parallel Trend

We replace $Post_t$ in equation (15) with event-time dummy variables, defined relative to the implementation quarter of the TSP. Displayed in Figure IA.1 are the coefficients of event quarters intersected with $Treatment_i$, along with their respective 95% confidence intervals. In line with the parallel-trend assumption, no significant trend is observed prior to the implementation, indicating that the treatment and control groups exhibit similar trends in share repurchases prior to the TSP. Following the shock, we observe a notable divergence, indicating a significant decremental (incremental) effect in share repurchase (share supply).

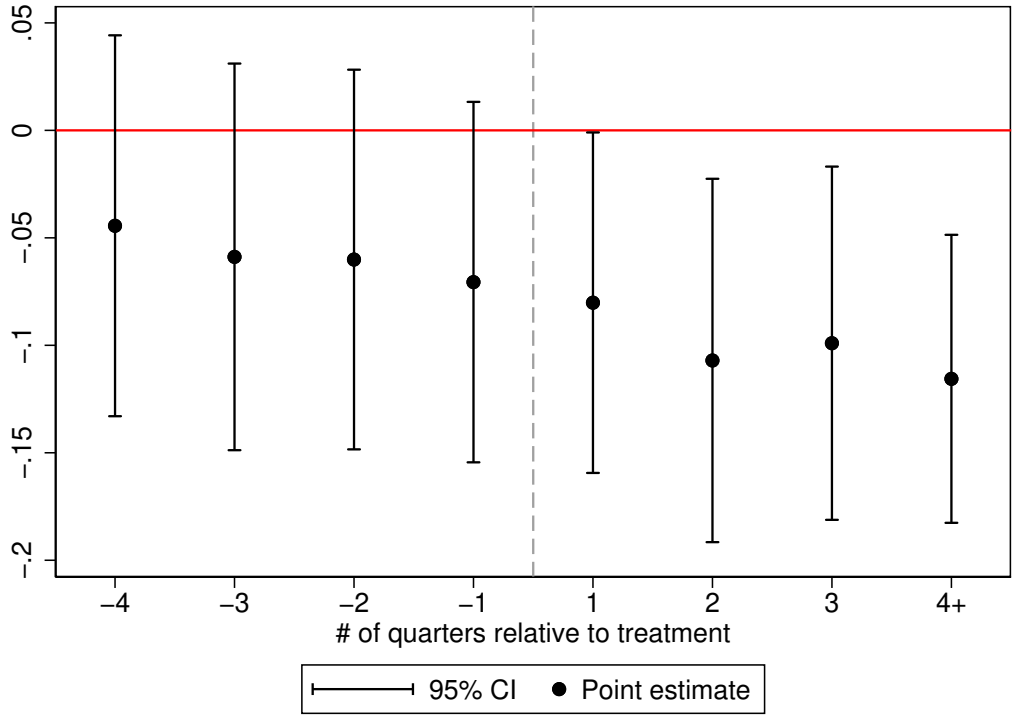


Figure IA.1. Parallel Trend. This figure exmaines the parallel-trend assumption for the effect of TSP on share repurchases. We re-estimate the equation (15) by replacing the dummy variable $Post_t$ with a set of indicators for the quarters around the implementation of TSP for each firm in our sample. Quarter $-h$ (h) denotes the h-th quarter before (after) implementation, and Quarter 4+ denotes four or more quarters after implementation. The dots report the coefficient estimates of $Treatment_i \times Post_h$, and the capped vertical lines report the corresponding 95% confidence intervals.

IA.2. Repurchasers vs. Non-Repurchasers

We provide a further test of the relevance condition. As discussed in Section 2, our supply shock originates from an unexpected reduction in the fill rate of repurchase programs. Since repurchase program usually takes years to complete (Stephens and Weisbach, 1998), firms with pre-TSP repurchases are more likely to continue repurchasing shares during the TSP.[1] The relevance condition therefore implies that firms with greater pre-TSP repurchase activity should experience a larger reduction in repurchases and, correspondingly, a larger price decline. We classify a firm as a repurchaser (non-repurchaser) if it (never) repurchased shares during the pre-treatment period, and estimate the following triple-difference regression:

$$Y_{n,t} = \beta \times Treatment_n \times Post_t \times Repurchaser_n + \boldsymbol{\gamma}' \boldsymbol{X}_{n,t} + u_{(g)\times t} + u_n + \epsilon_{n,t} \qquad \text{(IA1)}$$

where $Repurchaser_n$ is an indicator that equals one if firm n repurchased shares in the eight quarters preceding the TSP and zero otherwise. $\boldsymbol{X}_{n,t}$ contains the lower-order interaction terms ($Treatment_n \times Post_t$ and $Post_t \times Repurchaser_n$), together with total assets, profitability, and growth if $Y_{n,t} = Repurchaser_{n,t}$. We additionally control dividend payout, market beta, and percentage quoted spreads if $Y_{n,t} = CAR_{n,t}$. $u_{(g)\times t}$ and u_n denote (industry-)quarter and firm fixed effects, respectively.

We first set the dependent variable $Y_{n,t}$ to the percentage of shares repurchased and report the estimate in column (1) of Table IA.1. Relative to control firms, treated firms that repurchased before the TSP reduce quarterly repurchases by an additional 0.137% of shares outstanding, indicating that repurchasers face a larger supply shock. This pattern follows consistently from our proposed mechanism: because repurchase programs typically span multiple years (Stephens and Weisbach, 1998), firms with greater pre-TSP repurchase activity are more likely to still be executing purchases when the pilot begins. Therefore, they are more exposed to the speed competition induced by the TSP, and end up repurchasing a smaller fraction of shares outstanding *ex post*.

We next ask whether the firms absorbing the larger supply shock also experience the

[1] In our sample, firms with pre-TSP repurchases buy back an average of 0.34% of shares outstanding every quarter during the TSP, while firms without pre-TSP repurchase activity repurchase an average of 0.039%.

Table IA.1
The Effect of the Tick Size Pilot on Repurchases and Stock Returns

	$Repurchase_{n,t}$	$CAR_{n,t}$		
		CAPM	FF3	FF5
	(1)	(2)	(3)	(4)
$\boldsymbol{Treatment_n \times Post_t \times Repurchaser_n}$	**−0.137*** **	**−1.927***	**−1.861***	**−1.795***
	(0.045)	**(0.997)**	**(1.031)**	**(1.066)**
Controls	Yes	Yes	Yes	Yes
Lower-Order Interaction	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	No	No	No
Industry × Time FE	No	Yes	Yes	Yes
Observations	19,589	19,489	19,489	19,489
Adj. R^2	0.295	0.113	0.071	0.057

This table presents the effects of the 2016 Tick Size Pilot on actual share repurchases and quarterly stock returns. In column (1), the dependent variable is repurchase, the number of shares repurchased in a quarter as a percentage of total shares outstanding. In columns (2) to (4), the dependent variables are the CAR (%) around the [−1,+1] event window, respectively adjusted by the CAPM, Fama and French (1993) three-, and Fama and French (2015) five-factor model. *Treatment* is a dummy variable that equals one if a stock is in one of the three test groups and zero if it is in the control group. *Post* is an indicator variable that equals one if the year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). *Repurchaser* is an indicator variable that equals one if the firm repurchased shares during the pre-treatment period and zero otherwise. All lower-order interactions ($Treatment \times Post$ and $Repurchaser \times Post$) are included. The robust standard errors clustered at the firm level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

larger price decline. Columns (2) to (4) replace $Y_{n,t}$ with quarterly abnormal returns benchmarked to the CAPM, the Fama and French (1993) three-factor model, and the Fama and French (2015) five-factor model, respectively. Relative to control firms, treatment repurchasers experience additional declines of 1.93%, 1.86%, and 1.80%. The estimates are stable across risk adjustments, suggesting that the effect is not driven by a particular set of factor loadings among treatment repurchasers.

Finally, we examine whether repurchaser has the same relative price multiplier as the baseline. A remaining concern is that firms that never repurchased shares could bias the multiplier estimate due to systematic differences in unobserved characteristics correlated to

Table IA.2
Repurchasers vs. Non-Repurchasers

	Δp_j	
	Repurchaser	Non-repurchaser
	(1)	(2)
Δs_j	2.407**	3.135
	(1.08)	(3.00)
Test of = baseline	0.877	
Control	Yes	Yes
Industry FE	Yes	Yes
Observations	270	229
Adj. R^2	0.082	0.154

This table presents the subgroup analyses that isolate price changes induced by repurchase channel. Column (1) re-estimates equation (17) using repurchasers only. Repurchaser is defined as a firm engaged in share repurchases in the pre-treatment period. Column (2) re-estimates equation (17) using non-repurchasers only. Non-repurchaser is defined as a firm never engaged in share repurchases in the pre-treatment period. The robust standard errors clustered at industry level are in parentheses. The reported p-value for difference is based on 1,000 bootstrap iterations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

stock prices. To separate the repurchase channel from direct price effects, we only include repurchaser and then re-estimate equation (17) using this restricted sample. Column (1) of Table IA.2 reports the results. The estimated relative price multiplier remains positive and statistically significant, with a magnitude of 2.407. This estimate is statistically insignificantly different from the baseline estimate of 2.575, confirming that the baseline effect is not driven by firms that do not participate in repurchases. We then reverse the restriction and estimate equation (17) on non-repurchasers alone. Column (2) reports an insignificant price multiplier estimate of 3.135, as expected given that the non-repurchasers have a lower repurchase intensity than repurchases, thereby experiencing less variation in repurchase activity during the TSP. Taken together, our results suggest that the estimated relative price multiplier captures the price effects of TSP-induced supply shocks; and the variation of our identification mainly arises from firms experiencing supply shocks.

Table IA.3
Effect of the TSP on Short-Sale Intensity

	$Short\ Interest_{n,t}$	$BC_{n,t}$	$Borrow\ Fee_{n,t}$
	(1)	(2)	(3)
$\boldsymbol{Treatment_n \times Post_t}$	**−0.063**	**0.003**	**−0.003**
	(0.22)	**(0.01)**	**(0.00)**
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	19,557	19,563	19,537
Adj. R^2	0.672	0.530	0.681

This table presents the effects of the 2016 Tick Size Pilot on short-sale intensity. The dependent variables are short interest ratio, the borrower concentration, and stock borrow fee. *Treatment* is a dummy variable that equals one if a stock is in one of the three test groups and zero if it is in the control group. *Post* is an indicator variable that equals one if the year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). The robust standard errors clustered at the firm level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

IA.3. Effect of the TSP on Short Selling Activities

Our model allows investors to hold negative positions. An potential channel of the price effect is that the TSP-induced reduction in repurchases may leave more shares available to lend and potentially relax short-selling constraints, thereby reducing prices. To examine this hypothesis, we present empirical evidence supporting the null effect of the TSP on short selling activities in this section.

We use three measures to proxy short-sale intensity: first, short interest ratio, defined as the number of shares held short relative to total shares outstanding ($Short\ Interest_{n,t}$), expressed in percentage points; second, the average daily borrower concentration ($BC_{n,t}$). A larger number of borrowers (higher competition) decreases the value of BC from 1 to 0; third, the average daily indicative borrowing fees ($Borrow\ Fee_{n,t}$). The definitions of borrower concentration and indicative borrow fee are provided by Markit. In sum, a higher value of borrower concentration and indicative borrow fee identifies hard-to-borrow stocks.

Table IA.3 presents the regression results. We find no statistically significant changes in all three measures, suggesting that short-selling activities do not significantly change during the TSP periods. The additional float and lendable shares during the TSP did not affect the short-sale intensity as well as stock borrow fee. Therefore, the price effect during the TSP is unlikely to be attributed to more active short-selling activities.

IA.4. Test of Balance on Idiosyncratic Volatility

We test whether the idiosyncratic volatility is similar between treatment and control stocks. For each year-month, we respectively regress the daily excess stock returns of treatment and control stocks, on the market excess return factor over the past 12 months. Next, we calculate the equal-weighted average idiosyncratic volatility as the standard deviation of residuals and annualize it. Consistent with our assumption of the same idiosyncratic volatility between treatment and control stocks, Figure IA.2 shows nearly identical patterns of idiosyncratic volatility (t-statistics = 0.624) between matched treatment and control stocks conditional on observables.

Table IA.4 reports t-tests under alternative factor structures. In addition to the market factor, we compute idiosyncratic volatility using Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2015) five-factor model. Across all specifications, we find no statistically significant differences in idiosyncratic volatility between treatment and control firms in our sample.

IA.5. Subsample Analyses

This section presents two subsample analyses on the effect of the TSP on repurchase announcement CAR.

First, to examine whether the effect of the TSP on repurchase announcements remains insignificant over time, we split the eight post-treatment quarters into two equal subsamples: the first four quarters ("Earlier") and the subsequent four quarters ("Later"). We re-estimate the announcement effect separately for each period. Columns (1) and (2) of Table IA.5 show

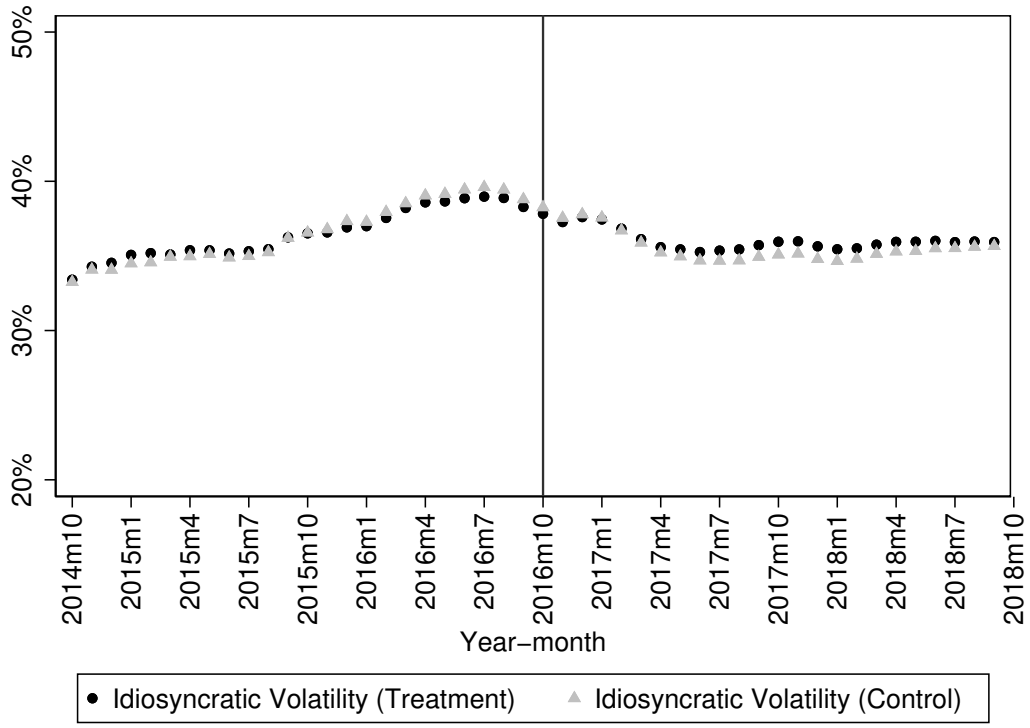


Figure IA.2. Balance on variances: average annualized idiosyncratic volatility. This figure testifies our assumption of the same idiosyncratic volatility between treatment and control stocks. At each month, we calculate the equal-weighted average idiosyncratic volatility by regressing daily excess stock returns on market excessive return. The sample period is from October 2014 to September 2018.

Table IA.4
The Test of Difference in Annualized Idiosyncratic Volatility

Idiosyncratic Volatility	Treatment	Control	t-statistics	p-value
Market Factor	36.279%	36.087%	0.624	0.534
Fama-French Three Factors	34.851%	34.588%	0.951	0.344
Carhart Four Factors	34.578%	34.318%	0.992	0.324
Fama-French Five Factors	34.429%	34.144%	1.034	0.304

This table reports the t-test for the idiosyncratic volatility calculated from different factor models. We consider CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2015) five-factor model. Idiosyncratic volatility is calculated as the annualized equal-weighted average variance of residuals from the daily regression of stock returns on factors.

that the effect of the TSP on repurchase announcements remains insignificant in both the early and later post-TSP periods.

Table IA.5
Subsample Analyses

	$\lvert CAR_{n,t}\rvert$			
Subsample =	Earlier	Later	G1&2	G3
	(1)	(2)	(3)	(4)
$\boldsymbol{Treatment_n \times Post_t}$	**0.862**	**-0.976**	**0.069**	**1.647**
	(1.05)	**(1.18)**	**(1.05)**	**(1.83)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	399	394	386	150
Adj. R^2	0.175	0.150	0.027	0.419

This table presents subsample analyses of the effects of TSP on repurchase announcement. The dependent variable is absolute CAR (%) around [−1,+1] event window based on CAPM. In column (1) and (2), the post-treatment period is split to "Earlier" (the first four quarters after the shock) and "Later" (the second four quarters after the shock) period. In column (3) and (4), we repeat the analysis for G1&2 and G3, respectively. The robust standard errors clustered at firm and announcement quarter level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Second, we conduct the same analysis separately for Groups 1&2 and Group 3. Columns (3) and (4) indicate that the insignificance of the TSP effect persists across these subsamples as well. Taken together, the results suggest that the null effect of the TSP on share repurchase announcements is persistent across different subgroups.

IA.6. Dynamics of Price Multiplier

While our baseline specification (17) estimates the relative price multiplier using the supply shocks cumulated over eight quarters of the TSP effective period, we also examine how the estimate evolves over time. To do so, we re-estimate the relative price multiplier using supply shocks cumulated to different horizons:

$$\Delta p_{j,h} = \mathcal{M}_h \Delta s_{j,h} + \boldsymbol{\gamma}' \Delta \overline{\boldsymbol{x}}_j + u_g + \epsilon_{j,h} \tag{IA2}$$

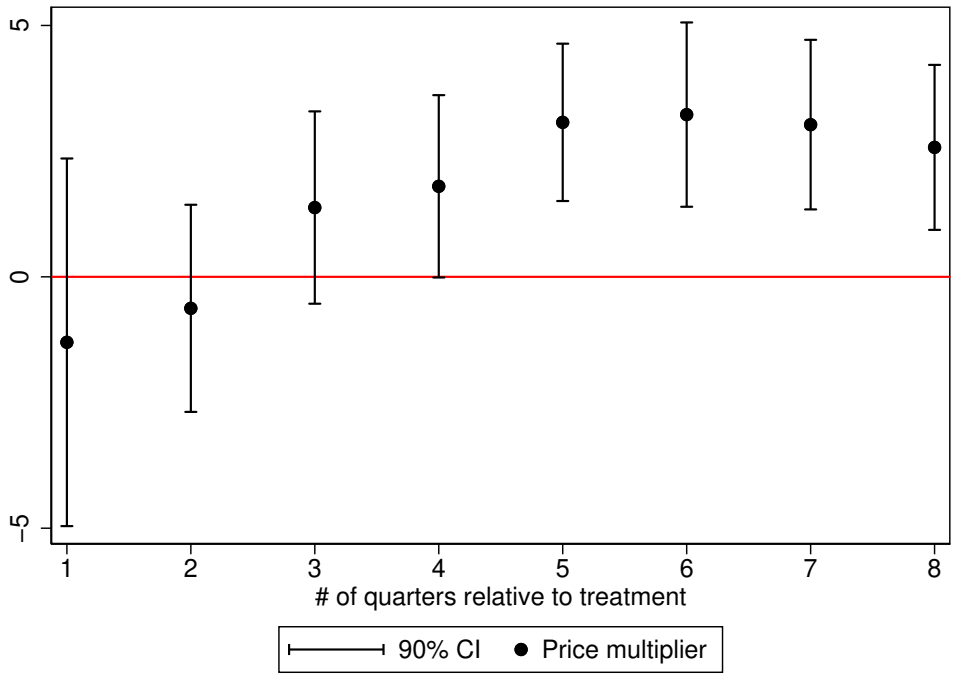


Figure IA.3. Dynamic estimates of the relative price multiplier. This figure plots the evolution of the relative price multiplier estimated using equation (IA2) over varying time horizons. The dots represent point estimates, while the capped vertical lines indicate 90% confidence intervals. The horizontal axis denotes the number of quarters following the implementation of the TSP.

where quarter h refers to the h-th quarter after the implementation of the TSP. Figure IA.3 shows that the estimated relative price multiplier is statistically insignificant over the first four post-treatment quarters but becomes significantly positive and remains stable thereafter. This pattern is consistent with Figure IA.1, which shows limited change in repurchases in the first post-treatment quarter but progressively larger reductions over time. Figure 1 further shows that the quarterly reduction in share repurchases cumulates steadily, with no sign of reversal before the end of the TSP. Together, these patterns indicate that it takes several quarters for cumulative repurchase reductions to generate a statistically significant relative price multiplier estimate.

Using equation (IA2), Figure IA.4 formally visualizes this comparison by plotting the estimated relative price multipliers at each post-treatment horizon for three samples: the full set of treatment stocks (baseline), treatment stocks in G1&2, and treatment stocks in G3. Across all three samples, the point estimates are close to zero and statistically insignif-

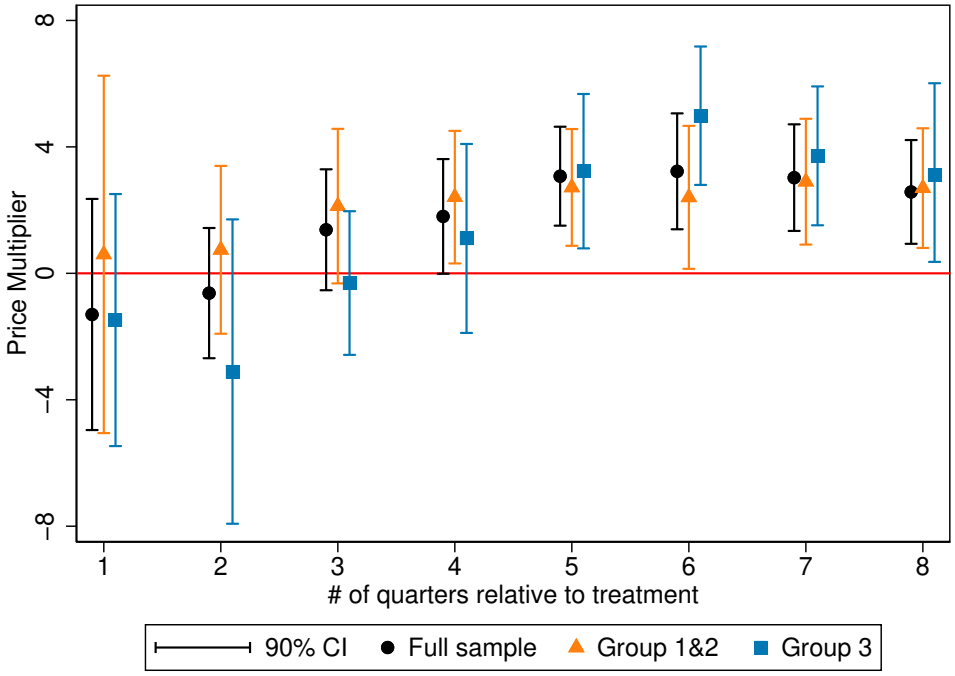


Figure IA.4. Estimates of relative price multiplier by treatment groups. This figure presents the estimates of relative price multiplier by horizons (quarters) using equation (IA2). The dots, triangles, and squares show the estimates of relative price multiplier using treatment stocks in the full sample, group 1&2, and group 3, respectively. The capped vertical lines report the 90% confidence intervals. Quarter h refers to the h-th quarter after the implementation of the TSP.

icant over the first four post-treatment quarters, consistent with the gradual accumulation of repurchase-driven supply shocks. From the fourth quarter onward, the estimates turn significantly positive and remain stable. Importantly, the point estimates across three samples are indistinguishable from one another at every horizon, and their 90% confidence intervals overlap throughout. This pattern reinforces that the estimated price multipliers are driven primarily by supply shocks rather than by a general liquidity effect.

IA.7. Placebo Tests

In this section, we conduct two placebo tests. If no exogenous supply shock exists between treatment and control, we should obtain no significant variation in stock prices and share repurchases, and subsequently, an insignificant estimate of the price multiplier. In column (1) of Table IA.6, we use the two years before the Pilot implementation as a placebo shock. The

Table IA.6
Placebo Tests

	Δp_j	
	Placebo	Pre-treatment
	(1)	(2)
$\boldsymbol{\Delta s_j}$	**−0.155**	**0.641**
	(0.59)	**(2.94)**
Control	Yes	Yes
Industry FE	Yes	Yes
Observations	441	514
Adj. R^2	0.165	−0.006

This table presents the placebo tests. In column (1), we use a placebo shock, with pre- and post-treatment period as 2013Q4–2014Q3 and 2014Q4–2015Q3. The estimation uses the last post-treatment quarter 2015Q3. In column (2), we estimate the relative price multiplier using the pre-treamt quarter 2016Q3 only. The robust standard errors clustered at industry level are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

corresponding pre-treatment and post-treatment periods are 2013Q4–2014Q3 and 2014Q4–2015Q3, respectively. we report the estimate using the last post-treatment quarter 2015Q3. In column (2), we repeat the estimation of equation (17) using the pre-treatment quarter 2016Q3 only. We do not find significant estimate of price multiplier in either case. These results confirm that our estimates of relative price multiplier is mainly driven by the supply shocks induced by TSP.