# Asset Prices and Portfolio Adjustment under Supply Shocks*

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**Abstract**

We provide the first estimate of the price impact of exogenous changes in share supply: a 1% uninformed reduction in shares outstanding lowers stock prices by 2.6%. Our identification exploits the 2016 SEC Tick Size Pilot. Although treatment and control firms announced similar repurchase programs, treatment firms repurchased 22% fewer shares due to an unforeseen conflict between the pilot and repurchase regulations. Unshocked control stocks allow us to absorb price spillovers and estimate a relative price multiplier, approximating the own-price multiplier at the stock level. Investment advisors and mutual funds absorb most shocks, followed by banks and other 13F institutions.

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# 1. Introduction

A traditional interpretation of long-run abnormal returns following 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 share 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 share repurchases 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. We find no significant changes in the announced repurchase dollar volume between treatment and control firms, suggesting that the TSP did not alter managers' intent to repurchase shares. Similarly, the (absolute) cumulative abnormal returns (CAR) around repurchase announcements show no significant differences, indicating the supply shocks induced by the TSP were uninformed and unanticipated to the market. *Ex post,* Li, Ye, and Zheng (2024) show that the reduction in share repurchase stems from the unexpected conflict between the TSP and the SEC Rule 10b-18, a regulation on open-market repurchases.[1]

[1]To prevent price manipulation, Rule 10b-18 effectively requires that firms use limit orders to repurchase at the bid price. The TSP removed four-fifths of price grids and thus lengthened queues at remaining prices.

The randomized design of the TSP 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),[2] 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 prices, capturing cumulative return differences between matched firms; the key explanatory variable is the corresponding within-pair double differences in cumulative shares repurchased. This 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 share repurchases 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.[3]

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.

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]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.

[3]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.

Because the relative multiplier captures only 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 repurchases represent a continuous flow over multiple years (Stephens and Weisbach, 1998), information about firm fundamentals is revealed discretely at quarterly reporting dates. If the price effect induced by the TSP stems from these confounding fundamental shifts 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 statements are 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.

A unique feature of the TSP further controls for liquidity effects on treatment prices. The TSP divided the 1,200 treatment stocks into three test groups. The 400 stocks in test group 3 exogenously repurchased 14% fewer shares relative to the pre-treatment mean than groups 1 and 2, owing to an unanticipated restriction on the use of dark pools for share repurchases.[4] However, this restriction did not impair overall market liquidity for group 3 stocks; 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

[4]Group 3 stocks were additionally subject to the "trade-at" rule, which required dark-pool executions to improve 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.

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 further controls for potential liquidity effects on treatment prices, as all three groups experienced the same decrease 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 group 3 stocks experienced a greater price decline than groups 1 and 2 primarily because of the additional reduction in share repurchases.

Finally, we examine how investors adjust their holdings in response to supply shocks. Intuitively, given the 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 during the first three quarters, but gradually decrease their holdings by selling shares to other investors after the fourth quarter, thereby amplifying the supply shocks alongside the treatment firms.

**Contribution to Related Literature.** We contribute to the share repurchase literature 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;[5] instead, they interpret these returns as evidence of market underreaction. In contrast, our

[5]The long-run abnormal returns 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).

findings alternatively suggest a coherent explanation: abnormal returns may arise mechanically from reductions 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). To rationalize why managers do not repurchase entire undervalued firms, prior studies assume an exogenous price impact of repurchases (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 supply shocks. While economic principles suggest that identifying a demand curve requires exogenous supply shocks, reduced-form studies rely largely on demand shocks.[6] Assuming a fixed supply, the demand-shock approach implicitly partitions investors into shocked and unshocked groups and identifies the residual price multiplier of unshocked investors.[7] 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 con-

[6]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)

[7]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.

straint by constructing and rotating hypothetical "shocks'' across investors via investment mandates. 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 complements theirs by directly identifying the demand curve faced by firms without parametric assumptions 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) explains cross-sectional investor holdings through a demand system. Koijen et al. (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 individual bond price multipliers. Structurally, Koijen and Yogo (2019) controls for spillover effects through a cross-sectional instrumental variables estimator under the 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 em-

pirically 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. Section 3 establishes a conceptual framework for our identification method. Section 4 outlines the sample construction, and presents the effect of TSP on share supply and the tests of exogeneity of the supply shock. Section 5 presents the estimation of 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 rebalancing behaviors by investors when faced with supply changes. Finally, Section 7 concludes.

## 2. Tick Size Pilot Design and Institutional Background

In this section, we describe the institutional background of the TSP, a unique RCT in U.S. equity markets. We further explain the mechanism through which the TSP induced exogenous supply shocks.

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, an average daily trading volume of fewer than one million shares, and a market capitalization below $3 billion.

After selecting the eligible TSP stocks, FINRA and NSEs first sorted all eligible stocks into 27 buckets based on three characteristics: (1) low, medium, or high share prices, (2) low, medium, or high volume, and (3) low, medium, or high market capitalization. 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.[8]

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. 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 and thus lowering 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.

Notably, firms often buy back shares using dark pools for two reasons. First, dark

[8]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

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, 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 larger decline in share repurchases.

# 3. Conceptual Framework

To motivate our empirical specification, we first develop a simple demand system with supply shocks. It builds on the static CARA-Normal framework with heterogeneous beliefs following Lintner (1969).[9] This model motivates the identification of relative price multiplier, 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 rebalancing behaviors 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

[9]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).

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., $\boldsymbol{d}_i \sim \mathcal{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$.[10]

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:

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

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

[10] 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 $\boldsymbol{\Sigma}$.

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 $\Delta \boldsymbol{S} = (\Delta S(1), ..., \Delta S(N))'$.[11] 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 $i$). We later validate this assumption in our sample by showing no differences in CAR around the report date of 10-K/10-Q file during the TSP in Section 4.4.

[11] Here, "exogenous" means that $\Delta S(n)$ is independent from share price $P(n)$.

### 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.[12] 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

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

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

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., $[\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\mathcal{M}}]_{n',m}$, $\forall m \neq n, n'$.[13] 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 (aggregate demand) shifts. $\mathcal{M}_{relative}(n, n')$ can be heterogeneous across matched pairs. Equation (8) motivates the following DID empirical specification:

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

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

where $\mathcal{M}$ identifies the 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 repurchase payouts 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, such as liquidity, size, growth opportunities, profitability, 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). However, firm managers value the own-price multiplier, which 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 the 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 $\boldsymbol{\eta} \sim \mathcal{N}(0, \sigma^2 \boldsymbol{I})$ is independent of $F$.[14]

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

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

$\boldsymbol{b}_i\boldsymbol{b}_i' + \sigma^2\boldsymbol{I}$. 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*

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

*where*

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

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

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

*Proof.* See Appendix A.2. □

Intuitively, the own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ consists of an idiosyncratic component ($\sigma^2$), scaled by investors' aggregate risk tolerance $\tau$, and a systematic component that aggregates across investors through $\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_n$. In contrast, the cross-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,m}$ arises from systematic comovement between assets through $\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_m$. Hence, the relative price multiplier $\mathcal{M}_{relative}$ isolates the idiosyncratic component plus the difference in systematic exposure between the two assets. We later illustrate this intuition under the CAPM case.

**Constant Cross-Price Multipliers Outside the Pairs.** Our identification strategy follows Haddad et al. (2026) by assuming constant cross-price multipliers with other stocks

outside each matched pair $(n, n')$. Since matched firms share similar characteristics, we assume they share similar factor exposures ($\boldsymbol{\rho}_n = \boldsymbol{\rho}_{n'}$).[15] Then, under Lemma 1, we have $[\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\mathcal{M}}]_{n',m}$ for all $m \neq n, n'$. Taking differences in price changes between $n$ and $n'$, therefore, cancels the spillover effects from all other shocked stocks as we show in equation (7).

For a given matched pair with $\boldsymbol{\rho}_n = \boldsymbol{\rho}_{n'}$, the relative price multiplier simplifies to $[\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n,n'} = \frac{\sigma^2}{\tau}$. Intuitively, since $[\boldsymbol{\mathcal{M}}]_{n,n} = \frac{\sigma^2}{\tau} + \frac{1}{\tau^2}\boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n$, the relative price multiplier closely approximates the own-price multiplier if the second term $(\frac{1}{\tau^2}\boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n)$ is negligible. This occurs when the contribution of systematic risk exposure is sufficiently small relative to the idiosyncratic risk. The following proposition formalizes this intuition.

**Proposition 1 (Condition for the Relative Price Multiplier to Approximate 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 multiplier)*** $[\boldsymbol{\mathcal{M}}]_{n,m} = [\boldsymbol{\mathcal{M}}]_{n',m}$ *for all* $m \neq n, n'$.

(ii) ***(Approximation to own-price multiplier)*** *Furthermore, if* $\dfrac{\boldsymbol{b}_i^2(n)}{\sigma^2} \to 0$ *for all investor* $i$, $\dfrac{\mathcal{M}_{relative}(n, n')}{[\boldsymbol{\mathcal{M}}]_{n,n}} \to 1$.

*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 $\sigma^2$ ($\boldsymbol{b}_i^2(n)/\sigma^2 \to 0$), 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

[15] One of the microfoundations of this assumption is to model the factor exposure as a linear function of characteristics, as in Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2023). Thus, similar characteristics between stocks imply similar factor exposures.

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*

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

*Proof.* See Appendix A.4. □

The own-price multiplier combines the idiosyncratic risk, $\sigma^2$, 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 $\boldsymbol{b}_i^2(n) \ll \sigma^2$ ensures 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 (1) the number of shocked assets $N$ is large, and (2) 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

This section studies the changes in equilibrium holdings across investor types in 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.[16]

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-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

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

particular, for a matched stock pair $(n, n')$, investor $i$'s holding changes are

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

Similar to the spillover effects discussed in Section 3.2, the observed holding changes reflect both the 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[17]

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

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 the relative adjustment between treatment stock $n$ and its matched control stock $n'$. We provide corresponding empirical evidence in Section 6.

# 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

[17] 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 $m \neq n, n'$.

relative to controls. We then show that this reduction is exogenous, as neither corporate managers nor the market anticipated the TSP's impact on repurchase activity.

## 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; 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.[18] $Treatment_n$ is an indicator that equals one if a firm is 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 $\beta$, which estimates the average

[18] 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 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.

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.[19] 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). The final sample comprises 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' repurchase announcement dates and values from the SDC Platinum; the filing dates of 10-K and 10-Q forms from SEC Analytics Suite on Wharton Research Data Services (WRDS); and institutional investor holdings from the LSEG Institutional (13F) Holdings dataset.

Table 1 reports summary statistics for the main variables used in our analysis. To mitigate the potential influence of extreme values, we winsorize the continuous variables at the top and bottom 1% percentile. 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 and percent quoted spread is 1.227 and 0.849%, respectively.

[19]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**

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.

| Variables | N | Mean | *SD* | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| Repurchase | 19,590 | 0.259 | 0.715 | 0.000 | 0.000 | 0.052 |
| 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 (million) | 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 |

## 4.2 Reduction in Share Repurchase

Table 2 presents the results from estimating equation (15). Column (1) shows that treatment firms repurchase 0.077% less outstanding shares per quarter relative to controls, representing 22% of the pre-treatment sample mean. Though this quarterly repurchase effect is still modest relative to the number of common shares outstanding, Section 5.1 later shows that the cumulative impact is economically meaningful over multiple quarters.

The significant decrease in share repurchase is consistent with Li, Ye, and Zheng (2024): the price ceiling under Rule 10b-18 incentivizes firms to submit limit orders for repurchases rather than market orders. However, the wider tick increments introduced by the TSP intensify speed competition between firms and other investors at the price ceiling. 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 lower fill rate of repurchase programs.

**Table 2**
**Supply Shocks**

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.

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

The $\beta$ in column (2) is insignificant and close to zero, suggesting that the TSP affected share supply through constraints on share repurchases, rather than equity issuance. Similarly, column (3) 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 do not adjust dividend policy to compensate for reduced share repurchases.

### 4.3 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 two measures to gauge managers' intent to repurchase: first, the announced repurchase dollar volume in a new repurchase program ($Volume_{n,t}$), reflecting the maximum amount a firm can repurchase within the program; second, an indicator equals one if firm $i$ initiates a new repurchase program in quarter $t$ ($\mathbb{1}_{n,t}$). Panel A of Table 3 shows no statistically significant results for any of the two 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.[20] 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.

Taken together, the decline in repurchases among treatment firms during the TSP reflects an exogenous, unexpected shift in the supply curve. As described in Section 2, treat-

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

**Table 3**
**Effect of the TSP on Share Repurchase Announcement**

This table presents the effects of the 2016 Tick Size Pilot on planned share repurchases. In Panel A, the dependent variables are 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 based on CAPM, Fama and French (1993) three-, and Fama and French (2015) five-factor model, respectively. 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.

Panel A: Repurchase Announcement

| | $Volume_{n,t}$ | $\mathbb{1}_{n,t}$ |
|---|---|---|
| | (1) | (2) |
| $\boldsymbol{Treatment_n \times Post_t}$ | **0.130** | **0.001** |
| | **(0.10)** | **(0.01)** |
| Pre-treatment mean of LHS | 3.487 | 0.039 |
| Controls | Yes | Yes |
| Firm FE | Yes | Yes |
| Year-quarter FE | Yes | Yes |
| Observations | 668 | 19,589 |
| Adj. $R^2$ | 0.846 | 0.071 |

Panel B: Cumulative Abnormal Returns

| | $\lvert CAR_{n,t}\rvert$ | | |
|---|---|---|---|
| | CAPM | FF3 | FF5 |
| | (1) | (2) | (3) |
| $\boldsymbol{Treatment_n \times Post_t}$ | **0.659** | **0.686** | **0.701** |
| | **(0.78)** | **(0.80)** | **(0.76)** |
| Pre-treatment mean of LHS | 5.555% | 5.539% | 5.535% |
| Controls | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Year-quarter FE | Yes | Yes | Yes |
| Observations | 656 | 656 | 656 |
| Adj. $R^2$ | 0.129 | 0.131 | 0.128 |

ment 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.

## 4.4 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.[21] 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. Unlike repurchase programs, which unfold continuously and gradually over time (Stephens and Weisbach, 1998), the information about firm fundamentals is typically disclosed at discrete dates every quarter. If the TSP materially altered fundamentals of treatment firms, it should lead to significant changes in the CAR for treatment firms around the filing dates of financial statements.[22] By contrast, a null effect on the CAR differences around filing dates would suggest that the exogenous reduction in repurchases does not materially affect firm fundamentals or the market's perception of them, thereby reinforcing the validity of the TSP-induced supply shocks.

Analogous to Section 4.3, 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 files, 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 is insignificant and close to zero for treatment firms during the TSP.

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

[22] Prior studies support this interpretation. For instance, Gomes, Gorton, and Madureira (2007) use the absolute CAR around earnings announcement to capture information transmission from firms to the market.

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

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 variable is 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.

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 |

We next examine the effect of the TSP on raw CAR instead of absolute value, and further split the filing events to two categories. An event is assigned as "negative" ("positive") if the corresponding CAR is smaller (greater) than zero. Panel B of Table 4 presents the results for CAR adjusted by CAPM. Similarly, we find no statistically and economically significant change in CAR, neither in full sample nor two subsamples.

These results suggest that the exogenous reduction in repurchases induced by the TSP does not statistically meaningfully change firm fundamentals or the way the market perceives them. This alleviates the concern that our price multiplier estimates are confounded by shifts in other fundamentals rather than the effect of reduced repurchases.

# 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. Finally, we exploit the regulatory dark-pool constraint, which applies exclusively to test group 3. This restriction induced an additional decline in share repurchases and stock prices for test group 3, while leaving overall liquidity conditions unchanged. This unique setting helps us to isolate the price impact of supply shocks from broader liquidity effects.

## 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. 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.[23] 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 price, total shares outstanding, and percentage quoted spread.

**Construction of Supply Shocks.** To ensure the supply shocks are of sufficient magnitude for identification, we cumulate the quarterly reduction 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):

$$\Delta s_j = \sum_{t=1}^{8} \left[ \left( Repurchase_{j,t}^{T} - \overline{Repurchase_j^{T}} \right) - \left( Repurchase_{j,t}^{C} - \overline{Repurchase_j^{C}} \right) \right] \tag{16}$$

where $Repurchase_{j,t}^{T}$ and $Repurchase_{j,t}^{C}$ denote the percentage of shares repurchased in quarter $t$ by the treatment firm and its matched control, respectively; $\overline{Repurchase}j^{T}$ and $\overline{Repurchase}j^{C}$ denote their corresponding pre-treatment eight-quarter averages. The first difference removes firm-specific trends in repurchase 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 trend of our constructed supply shocks, suggesting the stable reduction in repurchases for treatment firms. This pattern suggests that the lower repurchase fill rate for treatment firms persists throughout the TSP. The initial reduction is small but cumulates

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

**Table 5**
**Test of Balance on Covariates**

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.

| | 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 |

over time; by the end of the TSP, the cumulative supply shock reaches −0.25%, −0.09%, and −0.62% for all treatment stocks, treatment groups 1 and 2, and treatment group 3, respectively. These magnitudes are comparable to those documented in related studies. For example, Shleifer (1986) reports an average abnormal volume of 0.34% on index-addition announcement dates; Li and Lin (2026) document an absolute quarterly order flow imbalance of 0.58% relative to total shares outstanding.[24]

[24]The relatively moderate size of our supply shocks also mitigates concerns that investor demand might 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.

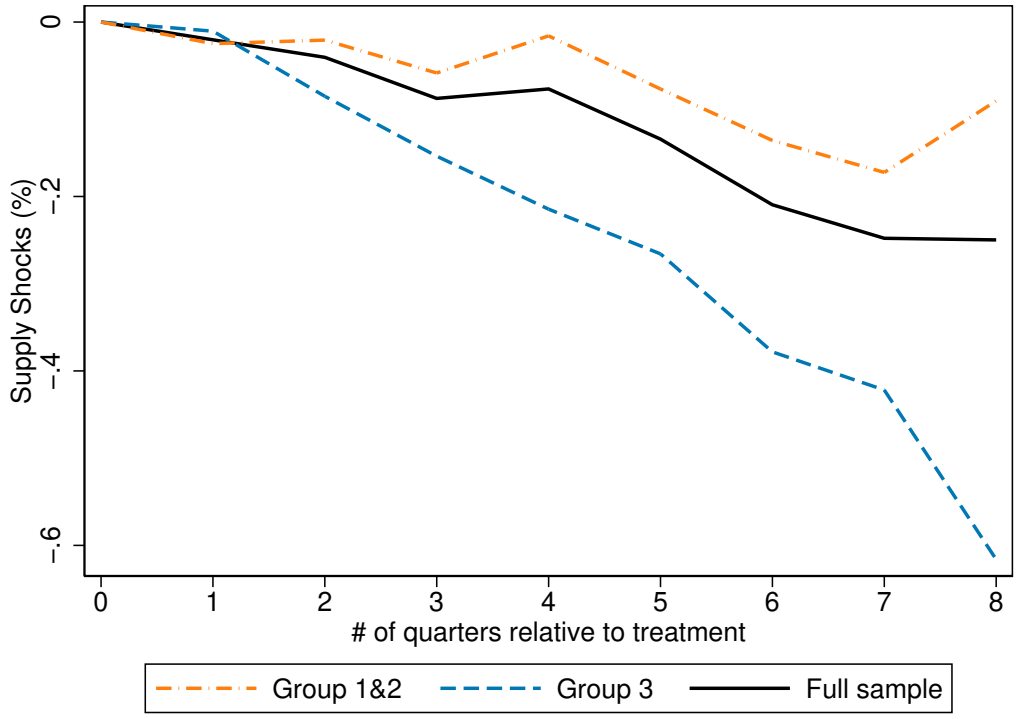



**Figure 1. Dynamics of supply shocks.** This figure presents the dynamics of constructed supply shocks over time. The lines represent the full sample (solid), pairs where the treatment stock is in Groups 1 & 2 (dash-dotted), and pairs where the treatment stock is in Group 3 (dashed). The horizontal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

**Regression Specification.** Motivated by equation (9) and Haddad et al. (2026), we estimate the following regression:

$$\Delta p_j = \mathcal{M}\Delta s_j + \boldsymbol{\gamma}'\Delta\overline{\boldsymbol{x}}_j + u_g + \epsilon_j \tag{17}$$

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

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

$$\Delta p_j = 100\% \times \left[\left(\log Price_{j,8}^{T} - \overline{\log Price_{j}^{T}}\right) - \left(\log Price_{j,8}^{C} - \overline{\log Price_{j}^{C}}\right)\right] \tag{18}$$

where $\log Price_{j,8}^{T}$ and $\log Price_{j,8}^{C}$ 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. $\overline{\log Price_{j}^{T}}$ and $\overline{\log Price_{j}^{C}}$ 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, $\Delta p_j$ 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 $\Delta\overline{\boldsymbol{x}}_j$ 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 post-treatment 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 firm fundamentals and industry fixed

**Table 6**
**Estimation of Price Multiplier**

This table presents the estimates of relative price multipliers. The dependent variable is $\Delta p_j$. For the post-treatment quarter 2018Q3, $\Delta p_j$ 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 $\Delta s_j$, 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 ($\Delta \overline{\boldsymbol{x}}_j = \bar{x}_j^T - \bar{x}_j^C$) in firm fundamentals, including size, profitability, growth opportunity, dividend payout, market beta, and percentage quoted spread. Column (3) alternatively controls for double differences ($\Delta \boldsymbol{x_j} = (x_{j,8}^T - \bar{x}_j^T) - (x_{j,8}^C - \bar{x}_j^C)$) in firm fundamentals. The robust standard errors clustered at the industry level are in parentheses. The robust standard errors clustered at the industry level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | $\Delta p_j$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\boldsymbol{\Delta s_j}$ | **2.578*** ** | **2.575** ** | **2.359** ** |
| | **(0.90)** | **(0.97)** | **(0.94)** |
| Control | No | $\Delta \overline{\boldsymbol{x}}_j$ | $\Delta \boldsymbol{x}_j$ |
| Industry FE | No | Yes | Yes |
| Observations | 508 | 501 | 504 |
| Adj. $R^2$ | 0.007 | 0.122 | 0.306 |

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 shares repurchased lowers the treatment stock price by 2.575%, to which we refer as the baseline estimate of the relative price multiplier.[25] In column (3), we use post-treatment differences in firm fundamentals and industry fixed effects as the alternative set of control variables. The estimated $\mathcal{M}$ has a similar magnitude of 2.359. The stability of $\mathcal{M}$ across columns

[25]This magnitude closely matches that reported by Koijen and Yogo (2019). Applying their approachin our sample yields an average demand elasticity of 0.390, corresponding to a price multiplier of 2.564. We provide detailed discussions in Appendix IA.5 and IA.6.

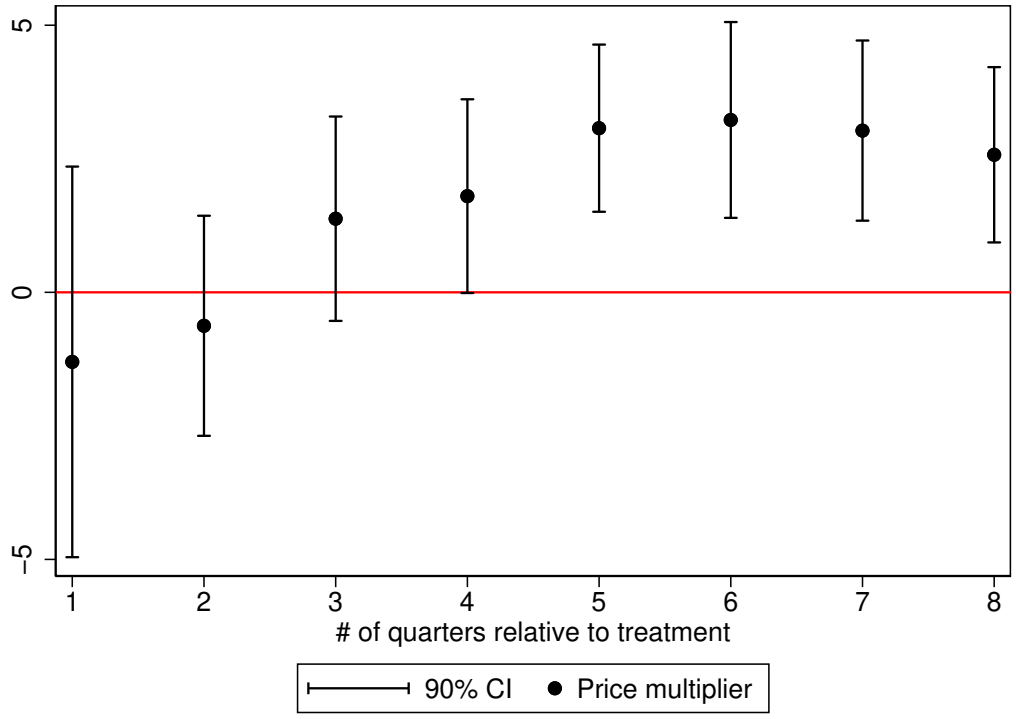



**Figure 2. Dynamic estimates of the relative price multiplier.** This figure plots the evolution of the relative price multiplier estimated using Equation (19) over varying time horizons. The dots represent point estimates, while the capped vertical lines indicate 90% confidence intervals. The horizontal axis denotes the number of quarters following the implementation of the TSP.

(1) to (3) suggests that the matching procedure effectively removes most confounding price effects from fundamentals, isolating the component attributable to supply shocks.[26]

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

[26]Measurement errors in supply shocks induced by scaling, or firms' endogenous responses to price declines, could bias the price multiplier. To address these concerns, we instrument the quarterly percentage of shares repurchased and re-estimate the model using a two-stage least squares (2SLS) approach. As reported in Table IA.1, we find statistically similar results. However, the IV regression may under-control for spillover effects relative to our baseline. We provide a detailed discussion in Appendix IA.2.

using supply shocks cumulated to different horizons:

$$\Delta p_{j,h} = \mathcal{M}_h \Delta s_{j,h} + \boldsymbol{\gamma}' \Delta \overline{\boldsymbol{x}}_j + u_g + \epsilon_{j,h} \tag{19}$$

where quarter $h$ refers to the $h$-th quarter after the TSP is implemented. Figure 2 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.

## 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). However, the own-price multiplier is more informative for firm managers, 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., $\boldsymbol{b}^2(n) \ll \sigma^2$.[27]

[27] Empirically, identifying individual investor $i$'s systematic risk exposure to stock $n$, $\boldsymbol{b}_i(n)$, requires additional assumptions. We therefore assume average factor exposures across investors and suppress the subscript $i$ in our empirical implementation. We also assume constant idiosyncratic risk across stocks and provide empirical support for this assumption in Appendix IA.3 and Figure IA.2.

### 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 $\beta_j$:

$$r_{j,t}^T - r_{j,t}^C = \alpha_j + \beta_j r_{m,t} + \nu_j \tag{20}$$

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

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

in which $\sigma(r_m)$ is the standard deviation of the market excess return. Therefore, $\beta_j$ captures the difference in the systematic risk exposure between the matched treatment and control stocks. Figure 3 plots the cross-sectional average of $\hat{\beta}_j$ 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 each matched pair.

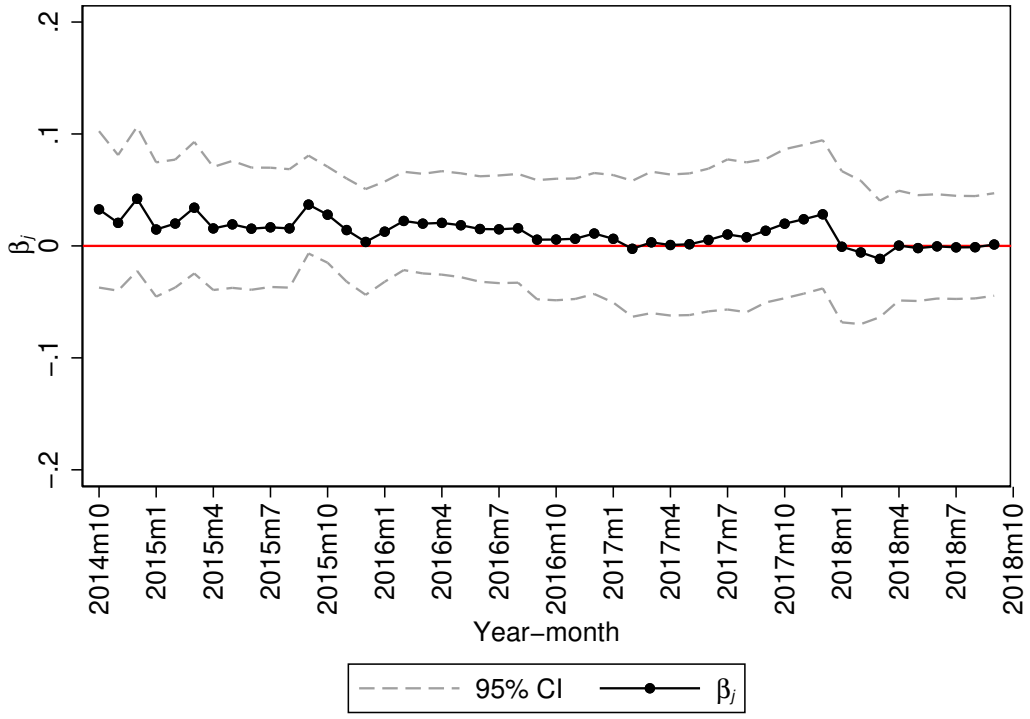



**Figure 3. Test of balance on systematic risk exposure.** This figure plots the average systematic exposure of long-short portfolio returns between matched treatment and control stocks to the excess stock market returns. At each month, we obtain the market beta of each matched pair, and then calculate 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% levels.

### 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:

$$r_t(n) = \alpha(n) + \beta(n) r_{m,t} + \varepsilon_t(n) \tag{21}$$

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 (21) over the past 12 months.[28] 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:

$$\boldsymbol{b}_i^2(n) = \hat{\beta}^2(n)\sigma^2(r_m)$$

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

$$H_0 : \ln\left(\frac{\hat{\beta}^2(n)\sigma^2(r_m)}{\sigma^2(n)}\right) \geq \ln(c) \tag{22}$$

Panel A of Table 7 reports summary statistics for annualized idiosyncratic risk and systematic risk exposure for our sample stocks during the two-year TSP periods. The average idiosyncratic risk (5.704 b.p.) is approximately 8.4 times larger than the average systematic risk exposure (0.676 b.p.).[29]

Panel B reports one-sided $p$-values from the test in (22) for various thresholds $c$. We reject the null hypothesis at the $c = 0.07$ ($c = 0.059$) threshold, corresponding to 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

[28] We also report the idiosyncratic risk calculated from Fama-French three factors, Carhart four factors, and Fama-French five factors in Table IA.2 of Appendix IA.3; the results are quantitatively similar.

[29] 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.

**Table 7**
**Idiosyncratic Risk v.s. Systematic Risk Exposure**

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 (21) multiplied by 252. Systematic risk exposure is calculated as the product of estimated betas from equation (21) 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 (22) 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.

| | 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 ($\hat{\beta}^2(n)\sigma^2(r_m) \times 10^{-4}$) | 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* |

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:

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

Since $N$=1,200 stocks were simultaneously shocked in the TSP, the spillover effects arise from the other 1,199 treatment stocks. Moreover, all treatment stocks experienced a reduction in share repurchases ($\Delta S(m) < 0,\ m = 1, \cdots, 1{,}200$). Therefore, the spillover effects from all other shocked stocks are non-negligible. Failing to account for them would overestimate the relative price multiplier, as discussed in Section 3.2.

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 concern is that the TSP also affected 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 further evidence that the estimated relative price multiplier in Table 6 identifies the price effect of supply shocks after controlling for liquidity. 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 required that orders be 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 suspected as "manipulative". As a result, the "trade-at" rule, in conjunction with Rule 10b-18, effectively discouraged G3 firms from repurchasing shares in dark pools. We validate this channel by replicating Li, Ye, and Zheng (2024). We estimate equation (15) separately for G1&2 and G3 stocks, respectively. Panel A of Table 8 shows that G3 stocks reduce repurchase by 0.116% per quarter (33% of the pre-treatment mean), while G1&2 stocks reduce repurchase by 0.066% per quarter (19% of the pre-treatment mean). The difference is both economically (14%) 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 three groups, G3 stocks experienced larger price decline than G1&2 stocks. This setting provides an ideal environment to examine the behavior of price multiplier estimates when liquidity is held constant. As the liquidity is dampened by the same magnitude, the price discrepancy between G1&2 and G3 should be largely attributable to the differential reduction in share repurchases. Accordingly, the relative price multipliers for G1&2 and G3 should be similar. Furthermore, if our identification captures the price effect mainly driven by share repurchases rather than liquidity, both price multiplier estimates should be similar to the baseline estimate.

**Table 8**
**G1&2 v.s. G3 Stocks**

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 differentiate the double-differences of all variables, and re-estimate equation (17). 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.

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: Price multiplier of G1&2 and G3

| | $\Delta p_j$ | | |
|---|---|---|---|
| | G1&2 | G3 | Long G1&2 Short G3 |
| | (1) | (2) | (3) |
| $\Delta s_j$ | 2.695** | 3.188* | 3.359* |
| | (1.12) | (1.65) | (1.73) |
| **Test of difference** | **0.393** | | |
| **Test of = 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 |

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. Column (1) shows that the estimated 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 indistinguishable. The row "Test of = 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 estimates are statistically different from the baseline magnitude.

Using equation (19), Figure 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 insignificant 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 the 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.

Finally, we match each G3 stock with a stock from G1&2. We then differentiate the pair-level variables and re-estimate our baseline regression.[30] We refer this specification to "long-G1&2-and-short-G3." Since G1&2 and G3 stocks exhibit the same 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 most of the variation in the additional price decrease of G3 compared to G1&2 stocks. The row "Test of = baseline" shows that this

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

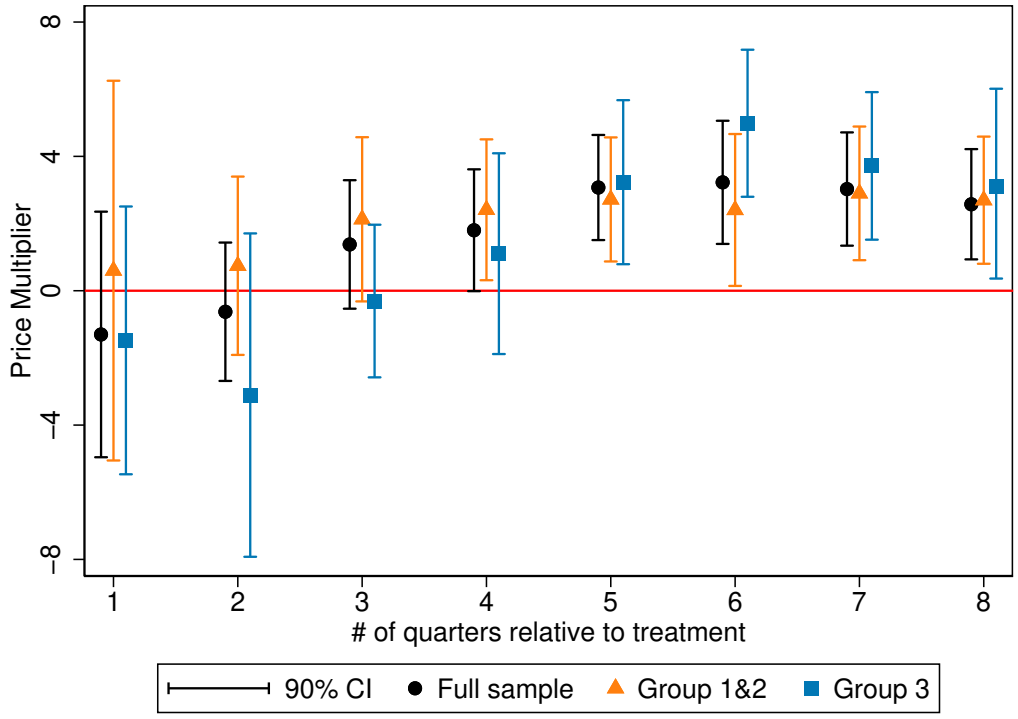



**Figure 4. Estimates of relative price multiplier by treatment groups.** This figure presents the estimates of relative price multiplier by horizons (quarters) using equation (19). The dots, triangles, and squares show the estimates of relative price multiplier using treatment stocks in the full sample, 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 TSP is implemented.

estimate is not statistically different from the baseline magnitude.

Taken together, these results help reconcile the puzzle documented in Albuquerque, Song, and Yao (2020): the larger price decline observed for G3 relative to G1&2 is primarily driven by a larger reduction in share repurchases rather than liquidity.

# 6. Investor Responses to Supply Shocks

In this section, we examine portfolio rebalancing 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 panel regression:

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

where $\Delta s_{j,t}$ denotes the double-difference in percentage of shares 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 and industry–time fixed effects as in equation (17). $\Delta q_{i,j,t}$ is the double difference in investor $i$'s quarterly holding change as of each TSP quarter $t$:

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

$q^T_{i,j,t}$ ($q^C_{i,j,t}$) denotes investor $i$'s holding changes in treatment (control) stock in pair $j$ at quarter $t$, scaled by lagged total shares outstanding. Accordingly, the regression coefficient $\overline{\mathcal{A}}_i$ in equation (23) captures the average percentage change in holdings of investor type $i$ in response to every 1% exogenous shock in supply $\Delta s_{j,t}$, 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 9 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

**Table 9**
**Estimation of Investor Responses**

This table estimates the relative holding changes in 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 main independent variable is denoted by $\Delta s_{j,t}$, the double-differences of quarterly shares repurchased of matched pair $j$. Control variables include double-differences of size, profitability, growth opportunity, dividend payout, market beta, and percentage quoted spread. 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.

| | $\Delta q_{i,j,t}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | 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 |

of insurance companies, pension funds, and households.

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

Figure 5 displays the cumulative portfolio adjustments ($\sum_{l=1}^{t} \overline{\mathcal{A}}_{i,l}$) of each investor sector $i$. Consistent with Table 9, investment advisers and mutual funds exhibit the strongest responses. For example, assuming an exogenously increased cumulative share supply of 8%

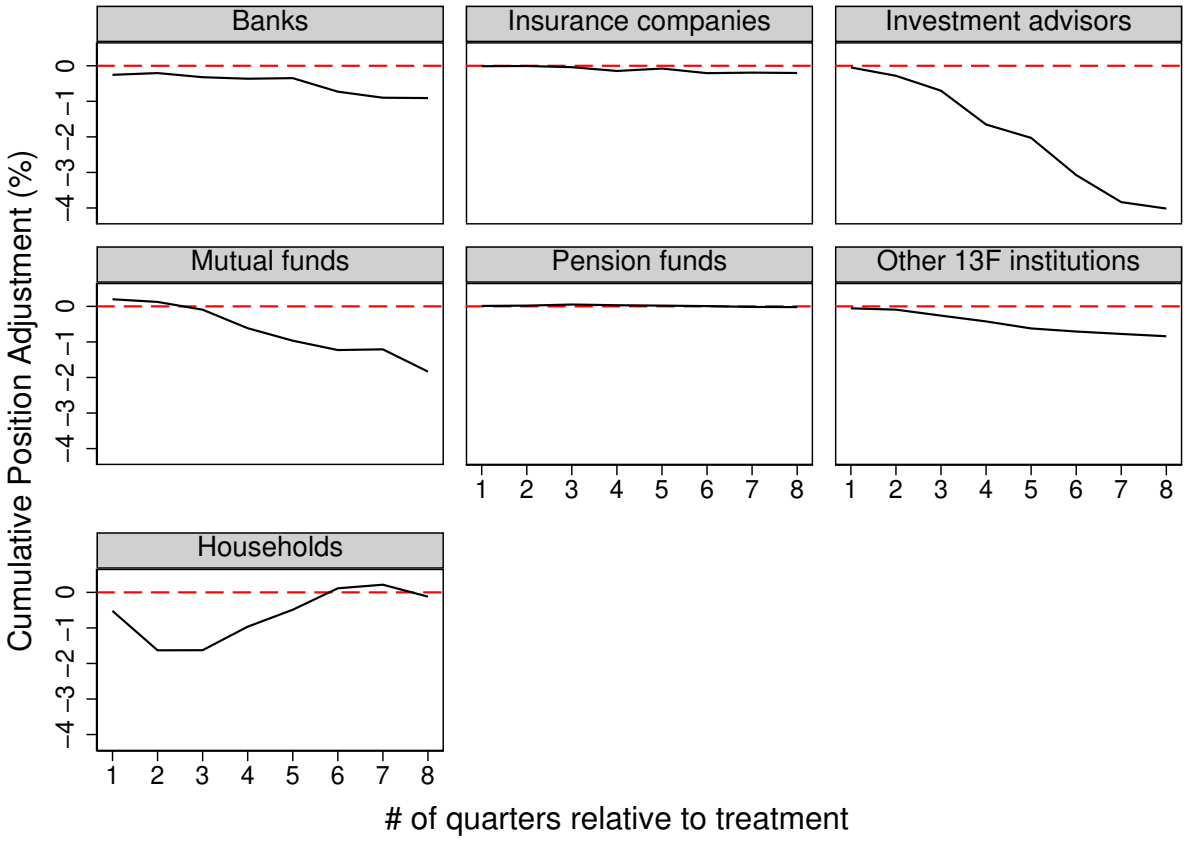



**Figure 5. Cumulative portfolio adjustments by investor sectors.** This figure depicts the cumulative relative holding changes in each investor type during 2016 Tick Size Pilot. At each post-treatment quarter (2016Q4-2018Q3), we estimate $\bar{\mathcal{A}}_i$ using equation (23), and then cumulative the coefficient across quarters. The definition of investor sectors follows Koijen and Yogo (2019).

over eight-quarter TSP period (1% per quarter), investment advisers and mutual funds cumulatively absorb around 4% and 2% of the additional shares, respectively. Banks and other 13F institutions respond more modestly by absorbing 1%, while insurance companies and pension funds show little change in their holdings. Importantly, the insignificant coefficient for households in column (7) of Table 9 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.

# 7. Conclusions

We develop the first supply-based approach to estimate the stock-level price multiplier. We exploit the SEC 2016 TSP as exogenous and uninformed supply shocks that reduced treatment firms' share repurchases by 22%.

Taking the double differences in prices between treatment and control stocks within each matched pair controls for spillover effects from 1,198 treatment stocks outside the pair. We then estimate a relative price multiplier of 2.575. We theoretically derive and empirically validate the conditions such that our estimated relative price multiplier approximates the own-price multiplier. In addition, because G1&2 and G3 stocks experience identical liquidity changes but different supply shocks, we estimate price multipliers separately for the two groups and obtain similar results, thereby controlling for the liquidity effects on price.

Exogenous supply shocks also allow us to track investors' portfolio rebalancing in response to supply shifts. We find investment advisors, mutual funds, and households primarily absorb the supply shocks, followed by banks and other 13F institutions. Insurance companies and pension funds exhibit little response. These patterns underscore the role of different investor types in responding to corporate events like share repurchases.

Beyond the specific context of the Tick Size Pilot, 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. 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.

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# A. Supplementary Proofs and Discussions

## A.1 Proofs of Optimal Portfolio Choice and Equilibrium Prices

Using our assumption on the 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

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

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

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

For tractability, denote a scalar $\tau = \sum_{i=1}^{I} \frac{1}{\gamma_i}$ 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:

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

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

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

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

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

□

## 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 $\lambda_{\max}(\boldsymbol{L}) = 1/\lambda_{\min}(\boldsymbol{I} - \frac{1}{\tau\sigma^2}\boldsymbol{\rho}'\boldsymbol{\rho}) = 1/\left(1 - \frac{1}{\tau\sigma^2}\lambda_{\max}(\boldsymbol{\rho}'\boldsymbol{\rho})\right)$. 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:

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

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 |
|---|---|
| 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. |
| 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). Preferred stocks depend on the availability in the order of redemption (PSTKRQ) and capital (PSTKQ). 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. |
| 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. |
| 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). |
| Size | Natural logarithm of total assets (ATQ). |
| Growth | Growth opportunity, estimated by the quarterly growth of total assets (ATQ). It is expressed in percentage point. |
| 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. |
| Volume | The natural logarithm of announced repurchased dollar volume. |
| $\mathbb{1}$ | An indicator that equals one if a stock announces a repurchase announcement at the quarter and zero otherwise. |

| | |
|---|---|
| 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. |
| 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 (NBBO) 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. |
| 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. |
| 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). |
| 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). |

# **Internet Appendix** for

"Asset Pricing and Portfolio Adjustment under Supply Shocks"

by Shidong Shao, Chen Yao, Mao Ye, and Jason J. Zou

# IA. Additional Empirical Results

## IA.1 Event Study

We replace $Post_t$ in equation (15) with event-time dummy variables, defined relative to the implementation date of 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).

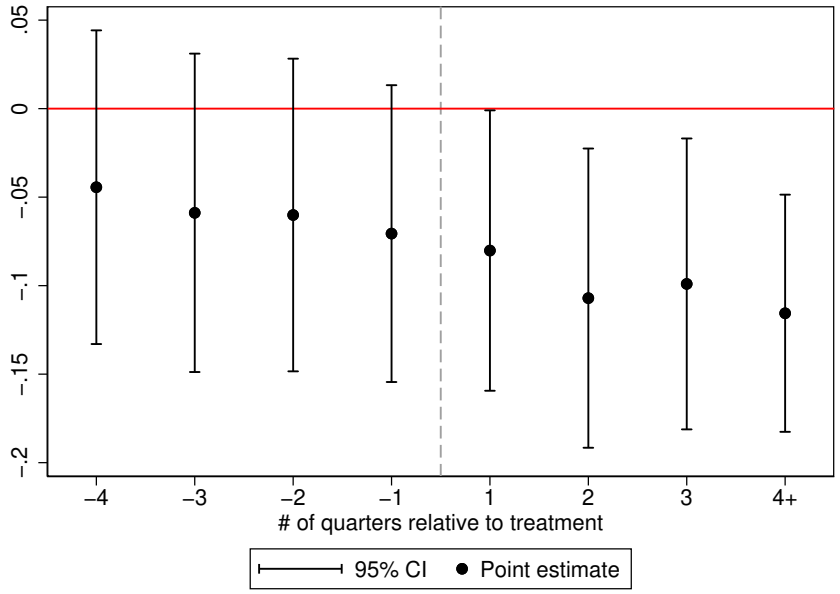



**Figure IA.1. Event study.** This figure presents an event-time analysis of the effect of TSP on share repurchases. We re-estimate the equation (15) by replacing the dummy variable $Post_t$ with a set of indicators for the quarters around the implementation of TSP for each firm in our sample. Quarter $-h$ ($h$) denotes the $h$-th quarter before (after) implementation, and Quarter 4+ aggregates all observations occurring 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 Two Stage Least Squares (2SLS) Regression

In our baseline specification, we construct supply shocks as the double difference in share repurchases 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 such changes may still reflect firms' endogenous responses to price declines (as we cannot exhaust all firm characteristics). To further mitigate this concern, we instrument the quarterly percentage of shares repurchased ($\Delta s_{n,t}$) using treatment assignment and its interaction with the post-TSP indicator, and estimate the following 2SLS regression:

$$\begin{aligned} \text{First stage: } \Delta s_{n,t} =& \boldsymbol{\beta}' \begin{pmatrix} Treatment_n \\ Treatment_n \times Post_t \end{pmatrix} + \boldsymbol{\gamma}' \boldsymbol{X_{n,t}} + u_g \times u_t + \epsilon_{n,t} \\ \text{Second stage: } \Delta p_{n,t} =& \mathcal{M} \times \widehat{\Delta s}_{n,t} + \boldsymbol{\gamma}' \boldsymbol{X_{n,t}} + u_g \times u_t + \varepsilon_{n,t} \end{aligned} \tag{IA1}$$

where $\Delta p_{n,t}$ denotes quarterly abnormal returns adjusted using the Fama and French (1993) three-factor model.[1] The control vector $\boldsymbol{X}_{n,t}$ includes the firm size, inverse of stock price, liquidity (percentage quoted spread), Tobin's Q, profitability, growth opportunities, dividend payout, and market beta. We also control for past returns over quarter $t-1$, $t-2$, and $t-3$ to $t-4$ to account for return momentum and reversal, and industry-by-time fixed effects to absorb common shocks within each industry-quarter (Cassella et al., 2026). Additionally, following Chaudhary, Fu, and Li (2025), we include the average return of peer firms in the same Fama–French 48 industry to control for spillover effects from a stock's close substitutes.

Table IA.1 reports the 2SLS estimates. The first-stage $F$-statistic of 13.23 exceeds conventional weak-instrument thresholds (Stock and Yogo, 2005), supporting instrument relevance. The second stage yields a statistically significant relative price multiplier of 3.460, implying that, relative to TSP control firms, a 1% exogenous reduction in shares repurchased

[1] The FF3-adjusted abnormal return removes common factor-driven variation in returns.

**Table IA.1**
**Estimation of Price Multiplier: Two Stage Least Squares Approach**

This table reports the 2SLS IV regression results. The dependent variable is the quarterly abnormal returns using Fama and French (1993) three-factor model. $\widehat{\Delta s}_{n,t}$ is the instrumented quarterly shares repurchased estimated by regressing shares repurchased on treatment and DID dummies. Control variables consist of inverse of stock price, turnover, percentage quoted spread, size, profitability, growth opportunity, dividend payout, market beta, past stock returns, and average return of peer stocks in the same Fama-French 48 industry. The robust standard errors clustered at year-quarter level in column (4). All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | $\Delta p_{n,t}$ |
|---|---|
| | (1) |
| $\boldsymbol{\widehat{\Delta s}_{n,t}}$ | **3.460*** |
| | **(1.81)** |
| $F$-stat. | 13.23 |
| Control | Yes |
| Industry *times* Time FE | Yes |
| Observations | 19,341 |
| Adj. $R^2$ | 0.255 |

lowers abnormal returns of TSP treatment firms by 3.460%. Although this estimate is not statistically different from the baseline,[2] its larger magnitude reflects the stronger substitution structure implicit in the 2SLS specification. In particular, the IV approach assumes that stocks within the same industry are close substitutes and share identical cross-price multipliers with respect to stocks outside the industry (Chaudhary, Fu, and Li, 2025). By contrast, our DID baseline requires only that each matched treatment-control pair constitute close substitutes, without imposing homogeneity of cross-price multipliers at the industry level. Under this more restrictive notion of close substitutes, the baseline estimate provides a more conservative measure of the relative price multiplier.

[2] A bootstrap test with 1,000 repetitions under the null that the IV and baseline estimates are equal yields a $p$-value of 0.871.

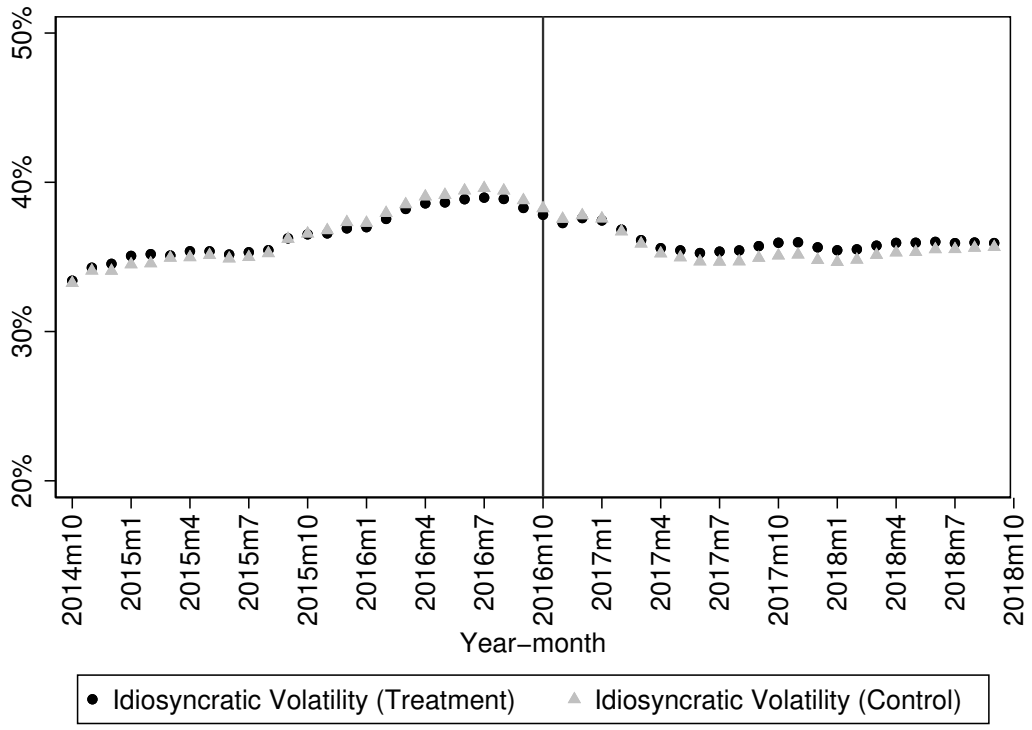



**Figure IA.2. Balance on variances: average annualized idiosyncratic volatility.** This figure testifies our assumption of constant volatility, by comparing the average idiosyncratic volatility between treatment and control stocks. At each month, we calculate the equal-weighted average idiosyncratic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

## IA.3 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 constant idiosyncratic volatility, Figure IA.2 shows the nearly identical patterns of idiosyncratic volatility ($t$-statistics = 0.624) between matched treatment and control stocks conditional on observables.

**Table IA.2**
**The Test of Difference in Annualized Idiosyncratic Volatility**

This table reports the $t$-test for the idiosyncratic volatility calculated from different factor models. We consider 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 equal-weighted average variance of residuals from the daily regression of stock returns on factors.

| 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 |

Table IA.2 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.4 Subsample Analyses

This section presents two subsample analyses. 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 and the subsequent four quarters. We re-estimate the announcement effect separately for each period. Columns (1) and (2) of Table IA.3 show that the effect of the TSP on repurchase announcements remains insignificant in both the early and later post-TSP periods. 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.

**Placebo Tests.** We further conduct placebo tests by changing the time of the TSP

**Table IA.3**
**Subsample Analyses**

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.

| | $\lvert CAR_{n,t}\rvert$ | | | |
|---|---|---|---|---|
| Subsample = | Earlier | Later | G1&2 | G3 |
| | (1) | (2) | (3) | (4) |
| $\boldsymbol{Treatment_n \times Post_t}$ | **0.794** | **0.331** | **0.340** | **2.027** |
| | **(1.00)** | **(1.16)** | **(1.08)** | **(1.48)** |
| Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year-quarter FE | Yes | Yes | Yes | Yes |
| Observations | 479 | 466 | 444 | 164 |
| Adj. $R^2$ | 0.143 | 0.104 | 0.027 | 0.462 |

implementation. If no exogenous supply shock exists between treatment and control, we should obtain no significant variation in stock prices or share repurchases, and subsequently, an insignificant estimate of the price multiplier. In column (1) of Table IA.4, we use the two years before the Pilot implementation as a placebo shock. The 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.

**Table IA.4**
**Placebo Tests**

This table presents the placebo tests. In column (1), we use a counterfactual 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.

| | $\Delta p_j$ | |
|---|---|---|
| | 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 |

## IA.5 Heterogeneity Analyses

The first heterogeneity analysis begins by examining the effect of TSP conditional on the tick constraints. As discussed in Section 2, 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, which exogenously reduces the fill rate of firms' limit buy orders as they are slower than HFTs. Therefore, this effect should concentrate on tick-constrained firms, i.e., whose dollar quote spread is below 5 cents. If a firm is tick unconstrained ex ante, the TSP should have minimal impact on share repurchases. Li, Ye, and Zheng (2024) confirm this prediction by showing that the TSP only dampens share repurchases by tick constrained firms.[3] Therefore, we expect that our specification can only generate significant price multiplier estimate for tick-

[3] Albuquerque, Song, and Yao (2020) also find that only firms with small spreads experience significant reduction in stock returns.

**Table IA.5**
**Heterogeneity Analyses**

This table presents the heterogeneity analyses. We bifurcate the full sample into two subgroups based on stock's pre-treatment characteristics. A stock is assigned as tick-constrained (tick-unconstrained) group if its average daily time-weighted dollar quoted spread from July 1 to September 30, 2016 is below (above) 5 cents. A stock is assigned as having high (low) KY price multiplier if its median Koijen and Yogo (2019) demand elasticity in 2016 is below (above) the cross-sectional median. A stock is assigned as high (low) risk group if its pre-treatment idiosyncratic volatility in 2016Q3 is above (below) the cross-sectional median. The reported $p$-value for this difference is based on 1,000 bootstrap iterations. The robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | $\Delta p_j$ | | | | | |
|---|---|---|---|---|---|---|
| | Tick cons. | Tick uncons. | High KY | Low KY | High risk | Low risk |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta s_j$ | 3.698** | 1.420 | 4.605* | 0.708 | 4.708** | 1.535 |
| | (1.71) | (1.57) | (2.38) | (3.43) | (2.05) | (1.25) |
| Test of difference | **0.022**** | | **0.056*** | | **0.007***** | |
| Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 222 | 271 | 107 | 75 | 254 | 238 |
| Adj. $R^2$ | 0.108 | 0.140 | −0.039 | 0.070 | 0.174 | 0.037 |

constrained firms. To testify this prediction, we split the full sample into two subgroups based on firm's average time-weighted dollar quoted spread in 2016Q3. Following Li, Ye, and Zheng (2024), a firm is assigned as tick-constrained (unconstrained) if its pre-treatment average dollar quoted spread is below (above) 5 cents. We estimate the price multiplier in equation (17) for two subgroups, respectively. Column (1) and (2) of Table IA.5 presents the results. The estimated price multiplier is only significant for tick-constrained firms, and is significantly larger than tick-unconstrained firms.

Our second heterogeneity analysis correlates to Koijen and Yogo (2019). Our baseline

price multiplier estimate of 2.575 implies a demand elasticity of $1/2.575 = 0.388$, which is close to the average demand elasticity of 0.390 by Koijen and Yogo (2019) (see Table IA.6). To further explore the connection between our estimate and Koijen and Yogo (2019), we bifurcate the tick-constrained firms into two subgroups based on firm's median demand elasticity estimated from Koijen and Yogo (2019) in 2016. A firm is assigned as having high (low) KY price multiplier if its demand elasticity is below (above) the cross-sectional median. We separately estimate the price multiplier in equation (17) for two subgroups. Column (3) and (4) shows that for firms with higher price multiplier in Koijen and Yogo (2019), our specification generates significantly larger price multiplier as well.

Finally, Corollary 1 suggests that the matched pairs whose treatment stock has higher idiosyncratic risks present a larger price multiplier. To testify this prediction, we split the full sample into two subgroups based on firm's idiosyncratic volatility in 2016Q3. A firm is assigned as a high-risk (low-risk) firm if its pre-treatment idiosyncratic volatility is above (below) the cross-sectional median. Section IA.3 details the construction and summary statistics of idiosyncratic volatility. We estimate the price multiplier in equation (17) for two subgroups, respectively. Column (5) and (6) of Table IA.5 presents the results. The estimated price multiplier is only significant for firms with higher idiosyncratic risks, and is significantly larger than the counterpart.

## IA.6 Demand Elasticity Estimate from Koijen and Yogo (2019)

Following equation (14) in Koijen and Yogo (2019), the individual demand elasticity is

$$-\frac{\partial \mathbf{q}_{i,t}}{\partial \mathbf{p}_t^{'}} = \mathbf{I} - \beta_{0,i,t}\text{diag}(\mathbf{w}_{i,t})^{-1}\mathbf{G}_{i,t} \tag{IA2}$$

where $\mathbf{I}$ is an identity matrix. $\mathbf{w}_{i,t}$ is a vector of portfolio weights that investor $i$ chooses at time $t$. $\beta_{0,i,t}$ is the coefficient of market capitalization in equation (10) in Koijen and Yogo (2019). And $\mathbf{G}_{i,t} = \text{diag}(\mathbf{w}_{i,t}) - \mathbf{w}_{i,t}\mathbf{w}_{i,t}'$.

**Table IA.6**
**Demand Elasticity by Investor Sectors**

This table presents the summary statistics of the aggregate demand elasticities by investor sectors estimated by Koijen and Yogo (2019). The sample consists of our sample treatment stocks. The sample period is from 2016Q4 to 2018Q3. 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).

| Variable | N | Mean | *SD* | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Banks | 3,612 | 0.592 | 0.158 | 0.454 | 0.471 | 0.497 | 0.656 | 0.948 |
| Insurance companies | 3,656 | 0.143 | 0.098 | 0.010 | 0.067 | 0.139 | 0.210 | 0.607 |
| Investment advisors | 3,040 | 0.085 | 0.071 | 0.010 | 0.037 | 0.078 | 0.126 | 1.020 |
| Mutual funds | 3,691 | 0.417 | 0.083 | 0.010 | 0.373 | 0.412 | 0.456 | 0.995 |
| Pension funds | 3,695 | 0.165 | 0.071 | 0.010 | 0.119 | 0.168 | 0.213 | 0.455 |
| Other 13F institutions | 3,378 | 0.095 | 0.063 | 0.010 | 0.040 | 0.095 | 0.138 | 0.458 |
| Households | 3,252 | 0.232 | 0.131 | 0.010 | 0.152 | 0.235 | 0.307 | 0.950 |
| Aggregate | 3,842 | 0.390 | 0.159 | 0.078 | 0.262 | 0.371 | 0.486 | 0.970 |

Following equation (15) in Koijen and Yogo (2019), the aggregate demand elasticity is the weighted average of individual demand elasticity and is estimated by

$$-\frac{\partial \mathbf{q}_t}{\partial \mathbf{p}_t'} = \mathbf{I} - \sum_{i=1}^{I} \beta_{0,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t} = \sum_{i=1}^{I} \frac{A_{i,t}\mathbf{w}_{i,t}}{\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}} \left(-\frac{\partial \mathbf{q}_{i,t}}{\partial \mathbf{p}_t'}\right) \tag{IA3}$$

Table IA.6 reports the estimated aggregate and investor-type-specific demand elasticities following the same approach as in Koijen and Yogo (2019) for our treatment firms over the sample period from 2016Q4 to 2018Q3. Our findings in Section 6 suggest that investors with higher demand elasticities absorb a larger share of supply shocks. We find consistent results using Koijen and Yogo's approach: mutual funds, households, and banks have higher demand elasticities than insurance companies and pension funds, and accordingly absorb a larger share of supply shocks.