Asset Prices and Investor Behavior under Randomized Supply Shocks*

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Abstract

Although supply shocks are central to identifying demand elasticity in other areas of economics, the asset pricing literature has relied on demand-side instruments. We fill this gap by exploiting a unique shock to shares outstanding: the 2016 Tick Size Pilot. While treatment and control firms announced similar levels of repurchases, treatment firms ultimately bought 20% fewer shares due to unforeseen conflicts between the pilot and repurchase regulations. The random assignment of stocks also allows us to account for price spillovers. We estimate a price multiplier of 2.01 and show that households and investment advisors (e.g., hedge funds) absorb most of supply shocks.

Keywords: Exogenous supply shock, price multiplier, portfolio rebalancing, Tick Size Pilot, share repurchase

JEL Classification: G11, G12, G20, G35

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1. Introduction

A fundamental principle in economics is that identifying the slope of the demand curve typically requires exogenous shocks to the supply curve, such as weather shocks in agriculture or changes in input prices. In contrast, the literature in demand system asset pricing often assumes a fixed supply curve and relies on exogenous demand-side instruments: time-series shocks such as index inclusions (Shleifer, 1986),[1] or cross-sectional variations in mandate-driven demand (Koijen and Yogo, 2019). This methodological divergence reflects the difficulty of finding exogenous shocks to the supply of outstanding shares, as firms tend to issue equity when prices are high and repurchase shares when prices are low (Brav et al., 2005). While demand-side instruments provide an ingenious workaround, unbiased estimation requires clearly identifying both shocked investors and affected assets. Moreover, demand-side instruments are silent on how investors respond to supply shocks, which is an important but underexplored dimension at the intersection of asset pricing and corporate decisions.

This paper fills these gaps by exploiting an exogenous supply shock to directly estimate the stock-level aggregate price multiplier and to trace the heterogeneous responses across investor groups. Supply shocks circumvent the empirical challenges faced by demand-side instruments: rather than requiring the econometrician to identify the shocked investors, a supply shock affects all investors' holdings through market clearing. In addition, because a firm can alter only the supply of its own shares, the set of shocked assets is directly observed under a supply shock. These features deliver clean identification of aggregate price multipliers and investors' portfolio rebalancing in equilibrium.

Empirically, we exploit the 2016 Tick Size Pilot (TSP) as a rare and randomized experiment that generates an exogenous supply shock to the treatment stocks without affecting their close substitutes in the control group. The TSP randomly assigned 1,200 stocks to treatment groups, where the minimum tick size was increased from one cent to five cents, while another 1,199 stocks served as controls with no change in tick size. Surprisingly, this seemingly minor adjustment in trading friction led to a 20% drop in share repurchases for

[1]Common demand shocks also include mutual fund flows (Coval and Stafford, 2007; Edmans et al., 2012), dividend reinvestment (Kvamvold and Lindset, 2018), asset purchase program by central bank or government (Koijen et al., 2021).

the treatment firms, an outcome that was unanticipated by firms, regulators, and academics alike. *Ex post*, Li et al. (2024) uncover that the first-order effect arises from an unforeseen conflict between the TSP and an existing regulation: SEC Rule 10b-18, which governs open-market share repurchases. To prevent firms from manipulating their stock prices, Rule 10b-18 imposes a price ceiling, often the prevailing bid price, on repurchase transactions. It effectively requires firms to submit limit orders. The TSP, however, removed 4 out of each 5 price grids, forcing investors who would submit limit orders at different price levels at a finer grid to cluster at the same price under the new coarse grid. Since execution priority at a given price depends on speed, the limit orders from firms may go unfilled because they are outpaced by high-frequency traders (HFTs). This mechanical disadvantage led to the sharp decline in realized repurchase activity of treatment firms. Thus, treatment firms effectively faced a *de facto* positive supply shock relative to control firms.

The reduction in share repurchases during the TSP is unanticipated by both managers and market participants. Specifically, we find no significant changes in announced repurchase dollar volume or in the cumulative abnormal returns (CARs) around repurchase announcements by treatment firms relative to control firms. Since announced repurchase volume reflects managerial intentions, our findings suggest that the TSP does not alter managers' intention to buy back shares. Similarly, the insignificant changes in announcement CARs indicate that the market's interpretation of repurchase announcements remains unaffected by the TSP. Therefore, the observed decline in actual repurchases for treatment firms is uninformed and exogenously stems from a lower completion rate of repurchase programs.

An exogenous supply shock to one stock can propagate to the prices of other stocks through investors' portfolio rebalancing (Fuchs et al., 2024). To address the complicated spillover effects, our empirical specification exploits the randomization of the TSP: only treatment stocks are subject to supply shocks, while control stocks are not. We match each treatment stock to its closest substitute based on observable characteristics. Under the assumption that matched treatment and control stocks share the same cross-price multipliers, differencing the price changes between treatment and control stocks before and after the TSP removes spillover effects from stocks outside the matched pair. We then construct the measure of supply shock as the double-difference in repurchases between matched treatment and control stocks before and after the TSP. This approach intuitively aligns with Haddad et al. (2025) to estimate the relative price multiplier. We additionally control for the double-differences in observed firm characteristics to absorb potential confounders that may induce price pressure within the matched pair.

We estimate an average stock-level price multiplier of 2.01, indicating that a 1 percent increase in uninformed share supply (scaled by book equity) lowers the stock price by 2.01 percent. The magnitude remains similar after controlling for industry–time fixed effects, differences in fundamentals, and changes in liquidity. The robustness suggests that the estimated price multiplier reflects the effect of supply shock itself, rather than changes in fundamentals or liquidity.

A unique feature of TSP further rules out the liquidity and demand-side effect on stock prices. As part of the pilot design, the Securities and Exchange Commission (SEC) divided the 1200 treatment stocks into 3 groups, where 400 stocks in test group 3 were subject to an additional constraint known as the "trade-at rule," which required that dark pools could only execute orders if they improved the National Best Bid and Offer (NBBO) by at least 2.5 cents. Albuquerque et al. (2020) find that this rule reduces liquidity in the dark pool but has limited impact on market liquidity as a whole. Intuitively, the trade-at rule is a zero-sum game that harms the dark pool but benefits the lit market. Despite limited change in market liquidity, share repurchases of test group 3 are reduced by 59% more than group 1 and 2. This surprising decline arises because the trade-at rule unexpectedly destroys dark pools as the last resort for share repurchases. As dark pools do not impose time priority, they provide a viable execution venue for firms outpaced by HFTs in the lit market. However, Rule 10b-18 would consider a repurchase price 2.5 cents above the best bid as a sign of price manipulation. The unintended conflicts between the trade-at rule and Rule 10b-18 effectively banned firms from repurchasing shares through dark pools. This setting provides an ideal environment to examine how estimate of price multiplier behave in the absence of market liquidity shock. We separately estimate the price multiplier for group 1 & 2 and group 3 stocks, and find no statistically significant differences in estimated price multipliers across these subgroups and compared to our baseline estimate. This finding also explains the puzzle documented in Albuquerque et al. (2020), where Group 3 stocks experienced larger price declines than group 1 & 2 stocks (-3.2% vs -1.75%) without corresponding liquidity reductions. Our analysis demonstrates that the greater price decline in group 3 stocks compared to groups 1 & 2 is primarily attributable to the additional reduction in share repurchases.

We next study how investors adjust their holdings in response to supply shocks. With respect to the specific supply shocks induced by the TSP, we find households raise their holdings of treatment stocks by 1.006 percent when facing 1 percent positive supply shock relative to the closest substitute in control group, followed by investment advisors (primarily hedge funds) of 0.452 percent, and insurance companies of 0.065 percent. By contrast, smaller funds reduce their relative holdings by 0.189 percent, and other investor groups show no significant responses. These results indicate that households and investment advisors absorb most of the supply shocks, whereas small funds exacerbate them by selling shares.

Intuitively, investors with higher demand elasticities are more likely to absorb supply shocks. To explore this mechanism further, we analyze the contribution of investor groups to share repurchases in normal time. We apply the variance decomposition approach as per Koijen et al. (2021), who investigate the portfolio rebalancing to quantitative easing in euro area. We find that mutual funds, households, and investment advisors are the largest share sellers, consistent with our finding that households and investment advisors absorb most of the exogenous supply shocks. The only exception is mutual funds, who do not significantly alter their relative holdings in response to supply shocks. A possible explanation is that mutual funds view treatment and control stocks as close substitutes and adjust proportionally. In contrast, small funds tend to purchase shares when firms repurchase, which aligns with their selling behavior during TSP. Pension funds and banks show little response, while insurance companies absorb only a small fraction of supply shocks, underscoring their limited roles in response to supply changes.

We conclude our analysis using the end of TSP as a reversed supply shock. On October 1, 2018, the SEC reverted the tick size of treatment stocks to 1 cent also repealed the trade-at rule. Following this policy reversal, we find that the repurchases of treatment firms increased relative to control firms after the end of the TSP and fully reversed to the pre-treatment level. The reversal of supply shock yields a price multiplier of 1.008, which is still far from a flat demand curve. Moreover, we find relatively large price multipliers in larger firms, which may reflect the limited availability of close substitutes for them.

Contributions to Related Literature. To our best knowledge, this paper is the first to exploit exogenous supply shocks in equity market to estimate price multiplier. While theoretical frameworks in demand system asset pricing demonstrate the intuition using shocks to the supply (Yogo, 2025), the empirical implementation, however, have predominantly focused on demand shocks, such as index inclusion/deletion (Chang et al., 2015), dividend reinvestment (Schmickler and Tremacoldi-Rossi, 2023; Hartzmark and Solomon, 2024; Chen, 2024), and regulatory regime shifts (Cassella et al., 2024). Although these demand shocks are plausibly exogenous to specific investors, most shock-based approach can only identify the elasticity of other investors absorbing the demand shock as the total supply is fixed. An exceptional condition is to estimate the aggregate price multiplier using demand shifters. For example, Chaudhary et al. (2023) construct the hypothetical demand changes of all investors using mutual fund flows to estimate aggregate price multiplier in the bond market. However, an unbiased estimate still requires identifying shocked investors. Our supply-based approach avoids these empirical challenges because supply shocks affect all investors simultaneously.

Koijen and Yogo (2019) use investment mandates as a creative demand-side instrument to identify each investor's demand elasticity. Their identification strategy relies on an exogenous investment universe, which is defined by a predetermined rule on the set of investable assets. The challenge for this approach is that most investors, except for index funds or a few mutual funds, do not publicly disclose their investment mandate. Therefore, Koijen and Yogo (2019) construct the investment universe based on each institution's observed holdings over the previous 11 quarters. To make the instrument universe robust, they exclude the household sector and aggregate only over institutions with little variation in the investment universe. Yet this method may incorrectly attribute zero holdings to the mandate, making Koijen and Yogo (2019) call for better data or methodology to measure the investment universe. We contribute to literature by highlighting the investment universe of firms, which is not only exogenous but singular. Unlike other investors, firms usually invest only in their own stocks.

Although the investment mandate approach has the strength to estimate the individual demand curve, it needs to impose downward-sloping demand curve for many large investors to guarantee the existence of equilibrium (van Binsbergen et al., 2025). This constraint mechanically amplifies the bias of elasticity (multiplier) estimates at the aggregate level. Our supply-based approach enables a direct, one-shot identification of aggregate demand elasticity, which avoids the need to impose filters or parametric investor-by-investor.

Beyond estimating the price multiplier, we extend the demand system framework, which explains the *levels* of investor holdings (Koijen and Yogo, 2019), by examining how investors *change* their holdings responding to supply shifts. Specifically, we show that investors with higher demand elasticities are more likely to absorb supply shocks, thereby broadening the application of the demand system to corporate events such as share repurchases.

This paper also contributes to the recent discussion on causal inference in asset pricing. Haddad et al. (2025) assume all stocks are potentially shocked and demonstrate that identifying the relative price multiplier with cross-sectional instruments requires the assumption of a constant relative price multiplier across stock pairs. We relax this assumption using the random assignment of the TSP: there is no spillover effect from control stock to its matched treatment stock because control stocks do not face supply shocks. This feature, together with both the time-series and cross-sectional variations in the supply shock, allows us to estimate an average relative price multiplier that accommodates potential heterogeneity across pairs. In addition, we empirically document that the average idiosyncratic risk in our sample stocks far exceeds their market risk exposure, thereby validating our theoretical condition under which the estimated relative price multiplier approximates the own-price multiplier.

Finally, our findings provide new insights to the literature in share repurchases. Traditional views attribute the price increase after share repurchases as evidence of signaling undervaluation (Bonaimé and Kahle, 2024). Our results show that a reduction in share outstanding may also mechanically contribute to an increase in price. As a result, the secular increase in share repurchases (Kahle and Stulz, 2021), particularly the part that led by the change in market microstructure reform (Li et al., 2024) may lead to a higher share price in recent years. Moreover, our evidence suggests that supply shocks involving stocks with larger household and investment-advisor ownership are more easily absorbed, implying that these firms can repurchase shares with less price impact.

The rest of the paper is structured as follows. Section 2 establishes theoretical foundations on our identification method. Section 3 describes the institutional backgrounds and sample construction. Section 4 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, excludes the confounding liquidity effect, and validates the empirical approximation of relative price multiplier to the own-price multiplier. Section 6 reports the portfolio rebalancing behaviors by investors when faced supply changes. We investigate robustness checks and heterogeneous distribution of price multipliers in Section 7. Finally, Section 8 concludes.

2. Conceptual Framework

We consider a financial market with two periods indexed by $t = 0, 1$. The market consists of a riskless asset with an interest rate normalized to zero and N risky stocks, indexed by $n = 1, \ldots, N$, with share supply vector $\boldsymbol{S} = (S(1), \ldots, S(N))'$. Investors, indexed by $i = 1, \ldots, I$, form portfolios comprising these N stocks. In period $t = 0$, investor i chooses to hold $q_i(n)$ shares of stock n, summarized by the holdings vector $\boldsymbol{q}_i = (q_i(1), \ldots, q_i(N))'$. In period $t = 1$, each stock pays a terminal dividend, denoted by $\boldsymbol{d}_i = (d_i(1), \ldots, d_i(N))'$, where the subscript i captures investor-specific beliefs about future payoffs. Throughout the paper, subscripts denote investors, and parentheses denote individual stocks.

2.1 Optimal Portfolio and Equilibrium Prices

Investor i's terminal wealth at $t = 1$ equals her initial wealth at $t = 0$, $A_{i,0}$, plus the return on her stock holdings:

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

where $\boldsymbol{P} = (P(1), \cdots, P(N))'$ is the vector of the stock price at $t = 1$ and $\boldsymbol{d}_2 - \boldsymbol{P}$ is thus the return vector.

Investor i chooses an optimal portfolio holding $\boldsymbol{q}_i$ at $t = 0$ to maximizes her expected CARA utility at $t = 1$:

$$\max_{\boldsymbol{q}_i} \mathbb{E}_i \left[-\exp\left(-\gamma_i A_{i,1}\right) \right] \tag{2}$$

where γ_i denotes the risk aversion coefficient of investor i.

Each investor i has heterogeneous beliefs in future payoff $\boldsymbol{d}_i$ with the following normal distribution:[2]

$$\boldsymbol{d}_i \sim N(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \tag{3}$$

in which $\boldsymbol{\Sigma}_i$ is full rank. Under assumption (3), the standard mean-variance optimal portfolio of investor i is

$$\boldsymbol{q_i} = \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\left(\boldsymbol{\mu_i} - \boldsymbol{P}\right) \tag{4}$$

We delegate detailed proof in the Appendix A.1. Market clearing condition determines the equilibrium prices. Define the aggregate demand from investors as $\boldsymbol{Q} \triangleq \sum_{i=1}^{I} \boldsymbol{q}_i$, the market clears when the aggregate demand equals the total supply of shares at $t = 0$:

$$\boldsymbol{Q} = \boldsymbol{S} \tag{5}$$

Equation (5) solves the market equilibrium price

$$\boldsymbol{P} = \boldsymbol{\mathcal{M}}\left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\boldsymbol{\mu}_i - \boldsymbol{S}\right), \quad \boldsymbol{\mathcal{M}} \triangleq \left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\right)^{-1} \tag{6}$$

where $\boldsymbol{\mathcal{M}}$ is the price multiplier matrix, characterizing how marginal changes in aggregate demand across investors $i = 1, ..., I$ translate into marginal price changes. In particular, the diagonal elements $[\boldsymbol{\mathcal{M}}]_{n,n}$ represent the aggregate own-price multipliers for each stock, capturing each stock's price response to the change in its aggregate demand. The off-diagonal elements $[\boldsymbol{\mathcal{M}}]_{n,m}$ are the aggregate cross-price multipliers, measuring the extent to which a change in the aggregate demand for stock m affects the price of stock n. That is,

$$-\frac{\partial P(n)}{\partial Q(n)} = [\boldsymbol{\mathcal{M}}]_{n,n}, \quad -\frac{\partial P(n)}{\partial Q(m)} = [\boldsymbol{\mathcal{M}}]_{n,m}, m \neq n \tag{7}$$

[2]In the CAPM, all investors hold the same belief, so that $\boldsymbol{\mu}_i = \boldsymbol{\mu}_j = \boldsymbol{\mu}$ and $\boldsymbol{\Sigma}_i = \boldsymbol{\Sigma}_j = \boldsymbol{\Sigma}$.

2.2 Identification with Supply Shocks

We introduce supply shocks to our framework by first defining the supply shock vector $\Delta \boldsymbol{S} = (\Delta S(1), ..., \Delta S(N))'$. After the supply shocks, the total supply changes to

$$\boldsymbol{S}^{\text{new}} = \boldsymbol{S} - \Delta \boldsymbol{S} \tag{8}$$

Thus, $\Delta S(n) > 0$ reflects a supply shock reducing share outstanding for stock n, $\Delta S(n) < 0$ indicates a supply shock increasing share outstanding, and $\Delta S(n) = 0$ implies no supply shocks.[3] Given the new supply $\boldsymbol{S}^{\text{new}}$, the market-clearing condition in equation (5) determines the new equilibrium price $\boldsymbol{P}^{\text{new}}$. Then, taking the difference between the new and the initial equilibrium prices in equation (6) and denoting $\Delta \boldsymbol{P} = \boldsymbol{P}^{\text{new}} - \boldsymbol{P}$ yield the price change:

$$\Delta \boldsymbol{P} = \boldsymbol{\mathcal{M}} \, \Delta \boldsymbol{S} \tag{9}$$

Considering a setting with simultaneous exogenous supply shocks like the TSP, we can generally express the total price change in a treatment stock n as

$$\Delta P(n) = \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n} \Delta S(n)}_{\text{Direct Effect}} + \underbrace{\sum_{m \neq n} [\boldsymbol{\mathcal{M}}]_{n,m} \Delta S(m)}_{\substack{\text{Spillover Effects from} \\ \text{other Supply Shocks}}} \tag{10}$$

Equation (10) reveals that the total price change consists of both a direct effect and spillover effects. The first term captures the sensitivity of stock n's price to changes in its own supply. The second term represents spillover effects given by the product of supply shocks in other stocks $\Delta S(m)$ and the cross-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,m}$. It measures the extent to which stock n's price responds to supply shocks in another stock m (Chaudhary et al., 2023; Haddad et al., 2025).

Advantages of Supply Shocks. We first discuss the benefits of supply shocks compared to the identification using demand-side instruments. Such instrument includes demand

[3] In Koijen and Yogo (2019), they do not include supply changes in their model, so $\Delta \boldsymbol{S} \equiv \boldsymbol{0}$, which is a special case.

shifter or demand shock.[4] Consider a general price change formula, analogous to equation (10):[5]

$$\Delta P(n) = [\boldsymbol{\mathcal{M}}]_{n,n} \left(\sum_{i=1}^{I} Z_i(n) \right) + \sum_{m \neq n} [\boldsymbol{\mathcal{M}}]_{n,m} \left(\sum_{i=1}^{I} Z_i(m) \right) \tag{11}$$

in which $Z_i(n)$ represents the demand-side instrument for investor i in stock n. Two empirical challenges arise: obtaining an unbiased estimate of the own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ requires the knowledge of both (1) the set of all shocked investors ($Z_i(n) \neq 0$ for all $i = 1, .., I$), and (2) the set of all assets that are simultaneously shocked ($\sum_{i=1}^{I} Z_i(m) \neq 0$ for all $m = 1, ..., N$).

The demand-shock approach faces one additional challenge: it typically assumes a fixed supply curve ($\sum_{i=1}^{I} \Delta q_i(n) = 0$), which means that the aggregate price multiplier cannot be identified—only the multiplier with respect to unshocked investors. We provide detailed discussion on demand-side instruments in Appendix A.4.

In contrast, identification using supply shocks offers two key advantages. First, because all investors respond simultaneously to a supply shock, it enables the direct identification of the aggregate, stock-level price multiplier without requiring us to track which investor groups are shocked. By market clearing, we observe $\Delta \boldsymbol{S}(n) = \sum_{i=1}^{I} Z_i(n)$. Second, the supply-based approach provides clean identification of the shocked assets, since each firm can only alter the supply of its own shares. The random assignment of treatment and control stocks in the TSP allows us to clearly separate firms with supply shocks from those without.

The creative demand system developed by Koijen and Yogo (2019) not only explains investor holdings but can also estimate the aggregate price multipliers. However, to ensure a unique equilibrium in their structural model, they impose the constraint that each investor's demand curve must be downward sloping. This requirement may bias the estimates by truncating negative elasticities (e.g., for momentum traders) to zero (van Binsbergen et al.,

[4]One of the examples of demand shifter is that a mutual fund i rebalances its portfolio due to unexpected inflows or outflows (Lou, 2012; Chaudhary et al., 2023); while examples of demand shocks include index inclusions and deletions (Shleifer, 1986; Chang et al., 2015; Pavlova and Sikorskaya, 2023), regulatory regime shifts (Cassella et al., 2024), or dividend reinvestment (Schmickler and Tremacoldi-Rossi, 2023; Hartzmark and Solomon, 2024; Chen, 2024).

[5]Specifically, if $Z_i(n)$ represents the demand shock $\Delta q_i(n)$, we can express the total price change as $\Delta P(n) = [\boldsymbol{\mathcal{M}}]_{n,n}(\sum_{i=1}^{I} \Delta q_i(n)) + \sum_{m \neq n}[\boldsymbol{\mathcal{M}}]_{n,m}(\sum_{i=1}^{I} \Delta q_i(m))$. If $Z_i(n)$ represents the demand shifter $u_i(n)$, we can express the total price change as $\Delta P(n) = [\boldsymbol{\mathcal{M}}]_{n,n}(\sum_{i=1}^{I} u_i(n)) + \sum_{m \neq n}[\boldsymbol{\mathcal{M}}]_{n,m}(\sum_{i=1}^{I} u_i(m))$.

2025). Moreover, measurement errors in their instruments may also bias the price multiplier estimates. By contrast, estimation based on supply shocks allows us to recover aggregate price multipliers without truncating potentially upward-sloping individual demand curves and avoids concerns about measurement errors in instrument (supply shocks), since firms can only repurchase their own shares. We provide detailed discussions in Appendix A.5 and A.6.

Unshocked Close Substitute Eliminates Spillover Effects. An unbiased estimates of own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ using supply shocks still requires controlling the spillover effects.[6] Otherwise, the price change would be over-attributed to the own supply shock. To eliminate spillover effects, we exploit the random assignment of treatment and control stocks in the TSP. Specifically, we perform a one-to-one matching procedure based on observed characteristics to identify a control stock n' *without* a supply shock (*i.e.*, $\Delta S(n') = 0$). The matched control stock n' serves as the closest substitute to the treatment stock n. The price change in control stock n' is thus

$$\Delta P(n') = \underbrace{[\boldsymbol{\mathcal{M}}]_{n',n'}\Delta S(n')}_{\substack{\text{Direct Effect }=0 \\ \text{because } \Delta S(n')=0}} + \underbrace{[\boldsymbol{\mathcal{M}}]_{n',n}\Delta S(n)}_{\substack{\text{Spillover Effect from} \\ \text{the Closest Substitute}}} + \underbrace{\sum_{m\neq n,n'} [\boldsymbol{\mathcal{M}}]_{n',m}\Delta S(m)}_{\substack{\text{Spillover Effects from} \\ \text{All Other Stocks}}} \tag{12}$$

We can now decompose the spillover effects into the one from closest substitute and those from all other stocks after matching. Since stock n and the matched stock n' are similar in observed characteristics, we assume stocks n and n' share the homogeneous substitution patterns compared to all other stocks, i.e., $[\mathcal{M}]_{n,m} \approx [\mathcal{M}]_{n',m}$ for $m \neq n, n'$. Intuitively, we assume that all investors, on average, view the matched pair (n, n') as the closest substitutes.[7] With the decomposition of spillover effects, the price change in treatment stock n can be

[6] Structural and demand-side instrument approaches also face this challenge. Koijen and Yogo (2019) solve it by imposing the homogeneous substitution pattern relative to outside assets based on the property of logit demand. Chaudhary et al. (2023) and Koijen and Yogo (2024) specify the spillover patterns using nested logit demand.

[7] Our identification only need they agree on the *ranking* of substitutions. We do allow investors disagree on the *level* of substitutions, as reflected in the heterogeneous variance-covariance matrix $\boldsymbol{\Sigma}_i$. We also provide a microfoundation to it in Section 2.3.

expressed as:

$$\Delta P(n) = \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n}\Delta S(n)}_{\text{Direct Effect}} + \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n'}\Delta S(n')}_{\substack{\text{Spillover Effect from} \\ \text{the Closest Substitute=0} \\ \text{because } \Delta S(n')=0}} + \underbrace{\sum_{m\neq n,n'} [\boldsymbol{\mathcal{M}}]_{n,m}\Delta S(m)}_{\substack{\text{Spillover Effects from} \\ \text{All Other Stocks}}} \tag{13}$$

Taking the difference between equations (13) and (12), we obtain:

$$\Delta P(n) - \Delta P(n') = \underbrace{([\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n',n})}_{\text{Relative Price Multiplier } \mathcal{M}_r(n)} \Delta S(n) - \underbrace{([\boldsymbol{\mathcal{M}}]_{n',n'} - [\boldsymbol{\mathcal{M}}]_{n,n'})\,\Delta S(n')}_{=0 \text{ because } \Delta S(n')=0} \tag{14}$$

$$\Longrightarrow \Delta P(n) - \Delta P(n') = \mathcal{M}_r(n)\ \Delta S(n) \tag{15}$$

The double-differences of price between stock n and its closest unshocked substitute n' eliminates spillover effects from supply shocks in all other stocks outside the matched pair. The remaining spillover effect from closest substitute is induced by the supply shock to stock n multiplied by the cross-price multiplier term $[\boldsymbol{\mathcal{M}}]_{n',n}$. As a result, supply shocks $\Delta S(n)$ identifies the *relative* price multiplier between matched pair (n, n'): $\mathcal{M}_r(n) = [\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n'n}$. Relative price multiplier measures what would be the price change relative to a stock's closest substitute given an exogenous aggregate demand change (Haddad et al., 2025).

Compared to the IV approach in Haddad et al. (2025), our identification strategy for the relative price multiplier does not rely on the assumption that the multiplier is constant across all matched pairs (Assumption 2 in Haddad et al. (2025)). This is because the matched control stock n' does not experience a supply shock during the TSP ($\Delta S(n') = 0$), ensuring that there is no spillover effect from n' to n and allowing us to simplify equation (14) to equation (15). Haddad et al. (2025) consider the case in which both stocks n' and n face supply shocks, and the double difference would only yield equation (14). To proceed, they assume a constant relative price multiplier across any matched pairs (n, n'), such that $[\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n',n} = [\boldsymbol{\mathcal{M}}]_{n',n'} - [\boldsymbol{\mathcal{M}}]_{n,n'} \equiv \mathcal{M}_r$, which allows them to further simplify equation

(14) as $\Delta P(n) - \Delta P(n') = \mathcal{M}_r\left(\Delta S(n) - \Delta S(n')\right)$.[8]

Guided by equation (15), we propose the following empirical regression specification:

$$\Delta p = \bar{\mathcal{M}}\Delta s + \boldsymbol{\gamma}'\Delta \boldsymbol{x} + \varepsilon \tag{16}$$

where $\bar{\mathcal{M}}$ is the regression coefficient intended to identify the average relative price multiplier across shocked stocks. The outcome variable $\Delta p = \Delta P(n) - \Delta P(n')$ denotes the double-difference in stock prices between a shocked stock n and its matched control n'. We detail the construction of the supply shock variable Δs in Section 5.1. We also include the double differences in observables that could also affect the returns such as liquidity, size, growth opportunity, profitability, etc. In Appendix A.3, we justify this setting and show that including the double differences in observables helps control for potential confounders affecting stock returns during the TSP.

2.3 Approximation to the Own Price Multiplier

In this section, we show that the estimated relative price multiplier in equation (16) approximates the own-price multiplier under a factor structure and an empirically testable condition. We subsequently evaluate the validity of this condition in our empirical analysis.

Factor Structure of Asset Payoffs. In addition to assumption (3), we assume that each investor i's belief about the stock's future payoff follows a factor structure following Koijen et al. (2023):

$$\boldsymbol{d}_i = \boldsymbol{\mu}_i + \boldsymbol{b}_i F + \boldsymbol{\eta} \tag{17}$$

Here, $\boldsymbol{\mu}_i$ denotes investor i's expectation of the future payoff; $\boldsymbol{b}_i$ is a $N \times 1$ vector, in which the nth entry represents investor i's belief about the factor loadings on the risk factor F of stocks n. The risk factor follows a standard normal distribution with mean zero and unit variance.[9] The vector $\boldsymbol{\eta} \sim \mathcal{N}(0, \sigma^2 \boldsymbol{I})$ captures idiosyncratic risk that are independent

[8]They do discuss an extension to relaxing such assumption by assuming the relative price multiplier depends linearly on observed characteristics $\boldsymbol{X}$: $\boldsymbol{\mathcal{M}}_{relative} = \mathcal{M}_r \boldsymbol{X}$. A constant $\mathcal{M}_r$ is still required for identification. In contrast, identification using randomized supply shock does not require this relaxed assumption either.

[9]This standardization facilitates tractability. We focus on a single-factor structure for simplicity, but our main results remain robust under multiple independent factors.

of F.[10]

Under this factor structure, the variance-covariance matrix of $\boldsymbol{d}_i$, denoted by $\boldsymbol{\Sigma}_i$, can be expressed as $\boldsymbol{\Sigma}_i = \sigma_F^2 \boldsymbol{b}_i \boldsymbol{b}_i' + \sigma^2 \boldsymbol{I}$. This representation enables us to derive an explicit expression for the price multiplier matrix $\boldsymbol{\mathcal{M}}$, as stated in the following lemma.

Lemma 1 (Price Multiplier under Factor Structure). *Under the factor structure in equation (17), the price multiplier matrix* $\boldsymbol{\mathcal{M}}$ *defined in equation (6) is*

$$\boldsymbol{\mathcal{M}} = \frac{\sigma^2}{r}\boldsymbol{I} + \frac{\sigma^2}{r^2}\boldsymbol{BLB}' \tag{18}$$

where

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

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

$$\begin{aligned} [\boldsymbol{\mathcal{M}}]_{n,n} &= \frac{\sigma^2}{r} + \frac{\sigma^2}{r^2}\, \boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_n, \quad [\boldsymbol{\mathcal{M}}]_{n,m} = \frac{\sigma^2}{r^2}\, \boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_m \\ \mathcal{M}_{relative} &= \frac{\sigma^2}{r} + \frac{\sigma^2}{r^2}\, \boldsymbol{\rho}_n'\boldsymbol{L}(\boldsymbol{\rho}_n - \boldsymbol{\rho}_m) \\ \textit{where } \boldsymbol{\rho}_n &= \left(\frac{\boldsymbol{b}_1(n)}{\sqrt{\gamma_1(\sigma^2 + \boldsymbol{b}_1'\boldsymbol{b}_1)}}, \cdots, \frac{\boldsymbol{b}_I(n)}{\sqrt{\gamma_I(\sigma^2 + \boldsymbol{b}_I'\boldsymbol{b}_I)}} \right)' \end{aligned} \tag{19}$$

Proof: See Appendix A.2.

Intuitively, the scalar r represents the aggregate risk aversion coefficient across investors. The ith element of the I-dimensional vector $\boldsymbol{\rho}_n$ captures investor i's perceived factor exposure of stock n relative to the total factor exposure across all stocks. The $I \times I$ matrix $\boldsymbol{L}$ reflects spillover pattern arising from investors' portfolio rebalancing in response to factor exposures.

The own-price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ comprises two components: the idiosyncratic risk term

[10]We assume homogeneous idiosyncratic risk for tractability but the heterogeneous idiosyncratic risk as $\sigma^2(n)$ does not change the main results.

σ^2 and a systemic risk component that aggregates through the factor exposure vector $\boldsymbol{\rho}_n$. In contrast, the cross-price multiplier between stocks m and n, $[\boldsymbol{\mathcal{M}}]_{n,m}$, only consists of the systemic risk component through the factor exposure vectors $\boldsymbol{\rho}_n$ and $\boldsymbol{\rho}_m$.

Constant Cross-Price Multipliers Outside the Pairs. Our identification strategy relies on the assumption of constant cross-asset substitution outside the matched stock pair (n, n'). This condition is particularly transparent under the factor structure: assuming that the matched stocks with similar firm characteristics have similar factor exposures satisfying $\boldsymbol{\rho}_n \approx \boldsymbol{\rho}_{n'}$, we have that $[\boldsymbol{\mathcal{M}}]_{n,m} \approx [\boldsymbol{\mathcal{M}}]_{n',m}$ for all $m \neq n, n'$ from Lemma 1. Therefore, taking the difference in the price changes of stocks n and n' would cancel out the spillover effects from shocked stocks outside the matched pair. Section 5.3 empirically tests the similar factor exposure assumption between matched pair in our sample.

Moreover, for a given matched pair with $\boldsymbol{\rho}_n \approx \boldsymbol{\rho}_{n'}$, the relative price multiplier would be $[\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n,n'} \approx \frac{\sigma^2}{r}$. Recall that $[\boldsymbol{\mathcal{M}}]_{n,n} = \frac{\sigma^2}{r} + \frac{\sigma^2}{r^2}\ \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n$. Hence, if the second term $\frac{\sigma^2}{r^2}\ \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_n$ is negligible compared to the first term $\frac{\sigma^2}{r}$, the relative price multiplier is approximated to the own price multiplier. In the following proposition, we provide a sufficient condition for such approximation.

Proposition 1 (Relative Price Multiplier is Approximated to Own Price Multiplier). *For a given stock pair (n, n'), if $\forall i \in \{1, \cdots, I\}$, $\boldsymbol{b}_i(n) \approx \boldsymbol{b}_i(n')$ and $\boldsymbol{b}_i^2(n) \ll \sigma^2$, then $[\boldsymbol{\mathcal{M}}]_{n',m} \approx [\boldsymbol{\mathcal{M}}]_{n,m}$ for $m \neq n, n'$ and $[\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n,n'} \approx [\boldsymbol{\mathcal{M}}]_{n,n}$.*

Proof: See Appendix A.2.

Proposition 1 establishes that when each investor's perceived factor exposure risk in stock n, denoted by $\boldsymbol{b}_i^2(n)$, is sufficiently small relative to the idiosyncratic risk σ^2, the second term in the own-price multiplier becomes negligible. Consequently, the relative price multiplier serves as a close approximation to the own-price multiplier.

CAPM case. While we provide detailed proofs of Lemma 1 and Proposition 1 in Appendix A.2, we illustrate the intuition behind the price multiplier using the CAPM model with a representative investor: $\gamma_i = \gamma_j = \gamma$, $\boldsymbol{b}_i = \boldsymbol{b}_j = \boldsymbol{b}$, and $I = 1$. We can simplify the price multiplier matrix as follows:

$$
\begin{aligned}
&[\boldsymbol{\mathcal{M}}]_{n,n} = \gamma\sigma^2 + \gamma\ \boldsymbol{b}^2(n) \\
&[\boldsymbol{\mathcal{M}}]_{n,m} = \gamma\ \boldsymbol{b}(n)\boldsymbol{b}(m) \\
&\mathcal{M}_{relative} = \gamma\sigma^2 + \gamma\ \boldsymbol{b}(n)\left[\boldsymbol{b}(n) - \boldsymbol{b}(m)\right]
\end{aligned}
\tag{20}
$$

Intuitively, the own price multiplier consists of the idiosyncratic volatility and the stock's beta. Cross-stock price multipliers depend on the product of two stocks' market betas. If two stocks' betas are similar, that is, $\boldsymbol{b}(n) \approx \boldsymbol{b}(m)$, they are close substitutes and have similar cross-price multipliers to all other stocks outside themselves. The sufficient condition described in Proposition 1 for the relative price multiplier being approximated to the own price multiplier of stock n is that $\boldsymbol{b}^2(n) \ll \sigma^2$, that is, the exposure to the market risk is much less than the idiosyncratic risk.

The Importance of Eliminating Spillover Effects. It is noteworthy that Proposition 1 does not imply that the spillover effects captured in equation (10) are negligible. Specifically, the condition $\boldsymbol{b}_i^2(n) \ll \sigma^2$ does not ensure that the aggregate spillover effects, $\sum_{m=1}^{N} \boldsymbol{b}_i(n)\boldsymbol{b}_i(m)\Delta S(m)$, is also small relative to the direct effect $\gamma\left(\sigma^2 + \boldsymbol{b}^2(n)\right)\Delta S(n)$, particularly when N, the number of shocked stocks in the market, is large and the simultaneous supply shocks $\Delta S(m)$ are positively correlated. In the case of TSP, there are 1,200 treatment stocks facing reduction in share repurchases ($\Delta S(m) < 0, m = 1, \cdots, 1{,}200$). Failing to eliminate spillover effects would therefore over-attribute the price change to own supply shocks and thus bias the estimation of relative price multiplier.

2.4 Investor Response to Supply Shocks

Koijen and Yogo (2019) provide an innovative explanation of equilibrium stock holdings through a demand system. This raises a natural follow-up question: how do investors' holdings evolve over time as the supply of shares changes? This section studies this question by examining *changes* in equilibrium holdings when investors are faced with supply shocks. We begin with an investor i's demand function described by equation (4) and plug in the equilibrium price defined by equation (6):

$$\boldsymbol{q_i} = \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\left(\boldsymbol{\mu_i} - \boldsymbol{\mathcal{M}}\left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\mu}_i - \boldsymbol{S}\right)\right) \tag{21}$$

Therefore, investor i's holding change $\Delta\boldsymbol{q}_i = \boldsymbol{q}_i - \boldsymbol{q}_i^{\text{new}}$ given the supply shock $\Delta\boldsymbol{S} = \boldsymbol{S} - \boldsymbol{S}^{\text{new}}$ is

$$\Delta\boldsymbol{q}_i = \boldsymbol{\mathcal{A}}_i \times \Delta\boldsymbol{S}, \quad \boldsymbol{\mathcal{A}}_i \triangleq \underbrace{\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}}_{\text{Investor } i\text{'s Elasticity Matrix}} \times \underbrace{\boldsymbol{\mathcal{M}}}_{\text{Price Multiplier Matrix}} \tag{22}$$

Here, we define the absorption matrix $\boldsymbol{\mathcal{A}}_i$ as the product of investor i's elasticity matrix and the price multiplier matrix. Intuitively, the absorption matrix captures how does investor i change her holdings to absorb supply shocks. A supply shock first moves stock prices through the multiplier matrix $\boldsymbol{\mathcal{M}}$. Given these exogenous price changes, investor i rebalances her portfolio according to her elasticity matrix $\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}$. Investors with lower demand elasticity absorb a smaller fraction of the shock. The form of absorption matrix $\boldsymbol{\mathcal{A}}_i$ naturally correlates to Haddad et al. (2025), who argue that investors will strategically adjust their portfolio based on not only individual demand elasticity but also aggregate elasticity.

Investors' absorption satisfies the market clearing condition that the aggregate changes in holdings exactly equal the supply shocks:

$$\sum_{i=1}^{I}\Delta\boldsymbol{q}_i = \sum_{i=1}^{I}\boldsymbol{\mathcal{A}}_i\Delta\boldsymbol{S} = \Big(\sum_{i=1}^{I}\tfrac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\Big)\boldsymbol{\mathcal{M}}\Delta\boldsymbol{S} = \Delta\boldsymbol{S},$$

since by definition $\boldsymbol{\mathcal{M}} = \left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\right)^{-1}$. Because an investor chooses a portfolio rather than a single asset, a supply shock in asset m generally leads her to rebalance across many assets. Thus, investor i's absorption matrix includes both own-asset absorption terms $[\boldsymbol{\mathcal{A}}_i]_{n,n}$ and cross-asset rebalancing terms $[\boldsymbol{\mathcal{A}}_i]_{n,m}$ for $n \neq m$. In particular, for a matched stock pair

(n, n'), investor i's quantity changes are

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

Similar to our discussion in Section 2.2, simply regressing the holding changes on the supply shock cannot recover the actual absorption pattern $[\boldsymbol{\mathcal{A}}_i]_{n,n}$ because of the spillover effects $\sum_{m \neq n,n'} [\boldsymbol{\mathcal{A}}_i]_{n,m} \Delta \boldsymbol{S}(m)$. To eliminate the spillover effects, we consider the relative holding changes between close substitutes in the matched pair (n, n'). Under the individual elasticity implied by factor structure discussed in Section 2.3, we have[11]

$$\Delta \boldsymbol{q}_i(n) - \Delta \boldsymbol{q}_i(n') = \left([\boldsymbol{\mathcal{A}}_i]_{n,n} - [\boldsymbol{\mathcal{A}}_i]_{n',n} \right) \Delta \boldsymbol{S}(n) \tag{23}$$

Again, we rely on the unique feature of the TSP that control stocks do not face supply shocks ($\Delta S(n') = 0$) to simplify the expression. Equation (23) describes how investor i changes her holdings in stock n relative to a close substitute stock n' when facing a supply shock to stock n. We provide empirical results to equation (23) in Section 6.

3. Institutional Settings, Data, and Sample

3.1 Institutional Background

In 2014, the SEC instructed the Financial Industry Regulatory Authority (FINRA) and national securities exchanges (NSEs) to collaborate on developing a pilot program aimed at testing the effects of varying tick sizes on market performance. The TSP program officially commenced on October 3, 2016, and ran until October 1, 2018. The program involved 2,399 stocks from the Regulation National Market System (Reg NMS) that met specific criteria,

[11] Note that assumptions of factor structure in equation (17) and that stocks with similar characteristics have similar factor exposures, we would have that $\boldsymbol{\Sigma}_i^{-1} \boldsymbol{\mathcal{M}} = \frac{1}{\gamma_i \sigma^2} (\boldsymbol{\mathcal{M}} - \frac{\boldsymbol{b}_i \boldsymbol{b}_i' \boldsymbol{\mathcal{M}}}{\sigma^2 + \boldsymbol{b}_i' \boldsymbol{b}_i})$. Denote $\boldsymbol{v}_i = \boldsymbol{b}_i' \boldsymbol{\mathcal{M}}$, we have that $\left[\boldsymbol{\Sigma}_i^{-1} \boldsymbol{\mathcal{M}}\right]_{n,m} = \frac{1}{\gamma_i \sigma^2} ([\boldsymbol{\mathcal{M}}]_{n,m} - \frac{\boldsymbol{b}_i(n) \boldsymbol{v}_i'(m)}{\sigma^2 + \boldsymbol{b}_i' \boldsymbol{b}_i})$. For a matched stock pair (n, n') with similar characteristics, we have that $\boldsymbol{b}_i(n) = \boldsymbol{b}_i(n')$, and therefore, we have that $\left[\boldsymbol{\Sigma}_i^{-1} \mathcal{M}\right]_{n,m} \approx \left[\boldsymbol{\Sigma}_i^{-1} \boldsymbol{\mathcal{M}}\right]_{n',m}$ for $m \neq n, n'$.

including a minimum share price of $1.50, an average daily trading volume of fewer than one million shares, and a market capitalization of less than $3 billion.

The stocks were then divided into four groups: one control group and three test groups. The control group consisted of 1,199 stocks that continued to be traded and quoted at the standard 1-cent tick size. Test group 1 stocks could only be quoted in $0.05 increments but could still be traded in $0.01 increments. Test group 2 stocks were both quoted and traded in $0.05 increments. Test group 3 adhered to the same rules as test group 2 but also fell under the Trade-at Rule, which barred dark-pool executions unless they improved the NBBO by 2.5 cents.[12]

Since repurchasing firms typically assign valuations well above the prevailing market price (Li et al., 2023), a modest increase in tick size should have limited direct impact on share repurchase. Surprisingly, Li et al. (2024) find that the 2016 TSP significantly reduced share repurchases for treatment firms relative to controls. This unexpected outcome stems primarily from an unintended interaction between the TSP and an existing regulation SEC Rule 10b-18, which regulates open-market share repurchase. Rule 10b-18 imposes a price ceiling on share repurchase transactions to prevent firms from manipulating their stock prices. The price ceiling prohibits firms to bid above the highest independent bid or the last transaction price, and effectively requires 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 trade 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 thereby lowering their realized repurchase volume *ex post*. As we report later, the effect of TSP on repurchase is unanticipated by firm managers as treatment and control firms continued to announce similar amounts of share repurchases after the commencement of TSP, making the resulting decline in repurchases an exogenous supply shock to treatment firms.

Notably, firms often buy back shares using dark pools. Although dark pools are not specifically designed for share repurchases, their execution mechanism—matching orders

[12]See, for example, 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.

passively based on reference prices from public exchanges—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. Moreover, dark pools do not impose time priority, which help firms to bypass the speed competition. 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 conducting share repurchases through dark pools. In other words, firms in test group 3 face more stringent constraints on share purchase compared to test group 1 and 2.

3.2 Data and Sample

Our sample comprises all common stocks (CRSP share codes 10 or 11) in the TSP from the FINRA website and are included in both the quarterly Compustat database and the Center for Research in Security Prices (CRSP).[13] The sample period spans from 2014Q4 to 2018Q3, allowing for eight quarters of data both before and after the implementation of the TSP. We collect firm-level financial information from Compustat's North America Fundamentals Quarterly files, daily and monthly stock data from CRSP. We collect percent quote spread data from Daily Trade and Quote (TAQ). Firms' repurchase announcement dates and values are collected from the SDC Platinum. The holdings of institutional investors are from the Thomson Reuters Institutional (13f) Holdings dataset, Following the payout literature, we exclude firms in the utility (SIC code 4200–4299) and financial industries (SIC code 6000–6999) because these companies face additional regulations that might generate divergent payout behavior (Fama and French, 2001). We also require non-missing value for variables used in the payout specification. Our final sample includes 611 firms in the three test groups and 651 firms in the control group.

Table 1 presents summary statistics for main variables employed in our analysis. For an average firm in our sample, the total expenditures in common stock repurchase, equity

[13]The TSP security lists and changing lists are available on https://www.finra.org/rules-guidance/key-topics/tick-size-pilot-program/data-collection-securities-and-pilot-securities-files.

Table 1
Summary Statistics

Variables	N	Mean	*SD*	Q1	Median	Q3
Repurchase Payout	19,548	0.629	1.924	0.000	0.000	0.078
Equity Issuance	19,548	0.641	1.649	0.000	0.022	0.299
Dividend Payout	19,548	0.422	1.026	0.000	0.000	0.475
Price ($)	19,548	27.759	33.678	7.950	18.000	36.620
Shares (million)	19,548	34.041	28.318	15.758	28.477	45.277
Size	19,548	5.853	1.420	4.849	5.930	6.942
Profitability	19,548	0.090	0.260	0.008	0.045	0.095
Growth	19,548	2.308	1.863	1.204	1.648	2.637
Investment	19,548	2.632	15.378	-2.968	0.336	3.619
Beta	19,503	1.225	1.092	0.644	1.165	1.717
Quote Spread	19,548	0.790	1.189	0.170	0.314	0.788

Note. This table presents the summary statistics for the primary variables in our empirical specifications. Definitions for variables can be found in Appendix B. To mitigate the potential influence of extreme values, the continuous variables are winsorized at the top and bottom 1% percentile.

issuance, and common stock dividends account for 0.629%, 0.641%, and 0.422% of the book equity, respectively. As mentioned, our sample consists of small and medium firms, whose stock price and total shares outstanding are $27.759 and 34.041 million on average.

4. Exogenous Supply Shock

We show that the TSP significantly and exogenously reduced share repurchases for treatment firms relative to control firms, without affecting managerial intentions or market expectations.

4.1 Reduction in Share Repurchases

Our empirical analysis begins by investigating the effect of TSP on firm's share repurchase. Following Li et al. (2024), the difference-in-differences specification is

$$Y_{n,t} = \beta \times Treatment_n \times Post_t + \boldsymbol{\gamma}' \boldsymbol{X}_{n,t} + u_t + u_n + \varepsilon_{n,t} \tag{24}$$

where n indexes firms, t indexes year-quarters. $Y_{n,t}$ is the dependent variables of interests, including share repurchase, defined by the total expenditures in common stock repurchases divided by lagged book equity;[14] equity issuance, defined as the sale of common and preferred stocks minus any increase in preferred stocks divided by lagged book equity; dividend payouts, defined as common stock dividends divided by lagged book equity. $Treatment_n$ 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, as in 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 shocks. The main coefficient of interest is β, which estimates the average treatment effects of TSP on share repurchase. All continuous and unbounded variables are winsorized at the 1% and 99% levels. The standard errors are robust to heteroskedasticity and are clustered at the firm level.

Table 2 presents the results. Column (1) indicates that, relative to control firms, the repurchase volume of treatment firms is substantially reduced by 0.143%, about 20% of the pre-treatment sample mean. The significant decrease in share repurchase is consistent with Li et al. (2024): The price ceiling under Rule 10b-18 constrains firms to outbid others and incentivizes firms to place limit orders on repurchase transactions. The widened tick size by the TSP, however, intensifies the competition of time priority between firms and other investors at the price ceiling, leading firms' limit orders to fall behind faster HFTs with lower execution probability. This intersection of price ceiling and intensified competition of time priority results in the unexpected reduction of share repurchase.

The insignificant coefficient on β in column (2) suggests 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 payments, which occur outside the secondary market and are therefore unaffected by the TSP or the price

[14] We select book equity as the scale variable following Fama and French (2015). In untabulated results, we also use lagged total assets as the scale variable and obtain identical results as Li et al. (2024).

Table 2
Supply Shock

	Repurchase Payout$_{n,t}$ (1)	*Equity Issuance*$_{n,t}$ (2)	*Dividend Payout*$_{n,t}$ (3)
$\boldsymbol{Treatment_n \times Post_t}$	**-0.143****	**-0.014**	**-0.006**
	(0.07)	**(0.05)**	**(0.03)**
$Size_{n,t}$	-0.043	0.393***	-0.050*
	(0.06)	(0.05)	(0.03)
$Profitability_{n,t}$	0.573***	0.130	0.146**
	(0.13)	(0.11)	(0.07)
$Growth_{n,t}$	-0.007	0.445***	0.021**
	(0.01)	(0.02)	(0.01)
Firm FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Obs.	19,548	19,548	19,548
Adj. R^2	0.332	0.345	0.662

Note. This table presents the effect of 2016 Tick Size Pilot program on repurchase payouts, equity issuance, and dividend payouts. 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 the 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. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

ceiling rule. The negligible effect on dividend payouts provides indirect evidence of the exogeneity of the supply shock as managers did not alter the dividend policy to compensate the reduction of share repurchase.

4.2 Repurchase Announcement

In this section, we validate the effect of the TSP on share repurchase is exogenous and unexpected by both firm managers and market participants. We verify that the implementation of TSP does not alter firms' intentions regarding share repurchases nor affect the market reaction surrounding repurchase program announcements. Specifically, we replace the de-

Table 3
Announced Repurchase Dollar Volume

	log($Announced\ Repurchase\ Dollar\ Volume_{n,t}$)	
	(1)	(2)
$\boldsymbol{Treatment_n \times Post_t}$	**-0.117**	**-0.106**
	(0.21)	**(0.20)**
Pre-treatment mean of LHS	10.376	10.376
Controls	No	Yes
Firm FE	Yes	Yes
Announcement quarter FE	Yes	Yes
Obs.	579	579
Adj. R^2	0.606	0.619

Note. This table presents the effects of TSP on planned share repurchase. The dependent variable is the natural logarithm of announced repurchased dollar volume. 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 firm level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

pendent variables in equation (24) with the logarithmic value of the announced repurchase dollar volume and the three-day CAR[-1, +1] around repurchase announcements.

Table 3 presents our empirical results on the impact of the TSP on announced repurchase volumes. Column (1) shows that the TSP does not lead to a statistically significant reduction in announced repurchase dollar volumes without control variables. Column (2) confirms this finding remains robust after controlling for firm-specific fundamentals. The announced repurchase dollar volume reflects the maximum amount managers indicate they may allocate to a specific share repurchase program and thus serves as a proxy for repurchase intentions. Therefore, the observed decline in realized share repurchases is not driven by changes in managerial intent, but rather by a lower completion rate of repurchase programs.

Another concern is that TSP may affect market reactions to repurchase announcements, potentially triggering price fluctuations. Table 4 explores this issue by examining three-day cumulative abnormal returns (CARs) surrounding repurchase announcements. Columns (1),

Table 4
Announcement Effect

	CAPM	FF3	FF5
	(1)	(2)	(3)
$\boldsymbol{Treatment_n \times Post_t}$	**-0.543**	**-0.408**	**-0.309**
	(2.33)	**(2.27)**	**(2.20)**
Pre-treatment mean of LHS	1.040%	1.126%	1.093%
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Announcement quarter FE	Yes	Yes	Yes
Obs.	571	571	571
Adj. R^2	0.124	0.138	0.139

Note. This table presents the effects of TSP on announcement returns. In column (1), (2), and (3), the dependent variable is the cumulative abnormal return (%) around [-1,+1] event window based on CAPM, Fama-French three-, and five-factor model. Treatment is a dummy variable that equals one if a stock is in one of the three test groups and zero if it is in the control group. Post is an indicator variable that equals one if the year-quarter falls into the post-treatment period (2016Q4–2018Q3) and zero if it falls into the pre-treatment period (2014Q4–2016Q3). The robust standard errors clustered at firm and announcement quarter level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(2), and (3) present CAR estimates adjusted using the CAPM, the Fama-French three-factor model, and the Fama-French five-factor model, respectively. None of these models reveal significant differences in CARs around repurchase announcements for treatment firms during the TSP period. These results indicate the market participants did not foresee the negative effect of the TSP on repurchase and thus did not alter their response to new repurchase announcements from treatment firms.

Together with the findings on announced repurchase volumes, our evidence validates that the observed reductions in share repurchases among treatment firms during the TSP reflect exogenous shifts of the supply curve: treatment firms encountered lower *ex post* completion rates for the similar share repurchase programs relative to control firms. These results also extend the findings of Li et al. (2024), who remain silent on whether the TSP affected firms' repurchase intentions or market expectations.

5. Estimation of Price Multiplier

We outline our identification strategy, and present baseline estimates of the relative price multiplier. We next exploit the dark pool constraint imposed exclusively on test group 3 but not on test groups 1 and 2. This constraint leads to an additional decline in share repurchases for test group 3, while maintaining similar liquidity conditions across all test groups. This differential treatment enables us to isolate the impact of repurchase-driven supply shocks from general liquidity effects on stock price. We finally present the empirical evidence that the relative price multiplier approximates the own-price multiplier.

5.1 Estimation of Relative Price Multiplier

Having validated the TSP as an exogenous supply shock, this section estimates the price multiplier using this supply shift and the specification discussed in Section 2.2. The TSP randomly assigns treatment and control stocks, and only treatment stocks face supply shocks. We exploit this unique feature by matching each treatment stock with a close substitute control stock. Matching a treatment stock to a control stock is critical to absorb the price spillover effects induced by simultaneous supply shocks from other treatment stocks, as discussed in Section 2.2.

We match each treatment firm with one control firm from the same industry (2-digit SIC code) based on size, profitability, growth, and repurchase payout, using a nearest-neighbour propensity-score method. We use the average characteristics in the pre-treatment period (2014Q4 to 2016Q3) to mitigate the concern that the TSP may affect firm characteristics *ex post*. Our matched sample consists of 546 pairs of treatment and control firms. Table 5 compares the average value of various firm characteristics between treatment and matched control, and indicates that they share identical observables.

Construction of Supply Shocks. For each matched pair j, we construct the supply shock at quarter t during the TSP period (2016Q4–2018Q3) as follows:

$$\begin{aligned}\Delta s_{j,t} = &\big(Repurchase\ Payout^{treatment}_{j,t} - Repurchase\ Payout^{treatment}_{j,0}\big) \\ &- \big(Repurchase\ Payout^{control}_{j,t} - Repurchase\ Payout^{control}_{j,0}\big)\end{aligned} \tag{25}$$

Table 5
Propensity Score Matching Sample

	Treatment	Control	t-test
Repurchase Payout	0.751	0.631	1.431
Size	5.759	5.778	0.223
Profitability	0.092	0.084	0.656
Growth	2.214	2.187	0.289
Investment	2.290	2.158	0.320
Dividend Payout	0.433	0.386	0.867
Beta	1.285	1.202	1.398
Price ($)	24.475	24.073	0.242
Shares Outstanding ($m)	32.836	32.364	0.312

Note. This table compares the average observables between matched treatment and control stocks in the pre-treatment period (2014Q4-2016Q3). The matching procedure is based on four characteristics: size, profitability, growth opportunity, and repurchase payout. Each treated firm is matched to a control firm in the same industry (SIC 2-digit), using the one-to-one nearest neighbour matching method. The t-test column presents the t-statistics based on the null hypothesis that the mean value is not different between treatment and control stocks. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

where $Repurchase\ Payout_{j,0}^{treatment}$ and $Repurchase\ Payout_{j,0}^{control}$ denote the average repurchase payouts over eight quarters prior to the TSP for the treatment firm and its matched control firm in a matched pair j, respectively. Intuitively, the first difference between the post- and pre-TSP periods accounts for potential time trends in repurchase activity, while the second difference between treatment and control groups further isolates the exogenous decline in repurchase payouts.

Regression Specification. Motivated by Equation (16), we estimate the following panel regression:

$$\Delta p_{j,t} = \bar{\mathcal{M}} \Delta s_{j,t} + \boldsymbol{\gamma}' \Delta \boldsymbol{x}_{j,t} + u_t \times u_g + \varepsilon_{j,t} \tag{26}$$

where j indexes matched pairs, t indexes quarters, and g indexes industries. $\Delta p_{j,t}$ denotes the difference-in-differences of stock prices for a matched pair j, i.e., $\Delta p_{j,t} = \log\left(p_{j,t}^{treatment}/p_{j,0}^{treatment}\right) - \log\left(p_{j,t}^{control}/p_{j,0}^{control}\right)$, where $p_{j,t}^{treatment}$ ($p_{j,t}^{control}$) is the quarter-end closing price of the treatment (control) stock of pair j at a post-treatment quarter t. $p_{j,0}^{treatment}$ ($p_{j,0}^{control}$) is the pre-treatment average quarter-end prices of the treatment (control) stock of pair j. $\Delta s_{j,t}$ denotes the supply shocks defined in Equation (25). Intuitively, $\Delta p_{j,t}$ captures the return on a long-short portfolio constructed for each matched pair j at time t, where the portfolio takes a long position in the treatment stock and a short position in the corresponding control stock. The coefficient $\bar{\mathcal{M}}$ identifies the average relative price multiplier (the reciprocal of relative demand elasticity) across treatment firms, reflecting how much would the price decrease given 1% increase in share supply.

$\Delta \boldsymbol{x}_{j,t}$ denotes the difference-in-differences of firm fundamentals that are known to explain stock returns (Fama and French, 2015; Koijen and Yogo, 2019), constructed as Equation (25). Specifically, we control for firm size, profitability, growth opportunities, investment, dividend payout, liquidity (measured by percentage quoted spread), and market beta. In addition, we include industry-by-time fixed effects ($u_t \times u_g$). The set of control variables and fixed effects allow us to account for potential confounders that could also affect the return differences between treatment and control stocks. In Appendix A.3, we formally show that including these controls alleviates concerns that the TSP may have altered firm fundamentals or liquidity in ways that could otherwise bias our results. The standard errors are robust to heteroskedasticity and are clustered at the industry-by-time level.[15]

Table 6 reports the baseline estimates of the relative price multiplier. In column (1), we include only time fixed effects, and the estimated average relative price multiplier, $\bar{\mathcal{M}}$, is 2.010, statistically significant at the 5% level. This estimate effectively presents the relative price multiplier as Haddad et al. (2025), i.e., $\mathcal{M}_r(n) = [\boldsymbol{\mathcal{M}}]_{n,n} - [\boldsymbol{\mathcal{M}}]_{n',n}$. It interprets how the price of treatment stocks relative to comparable control stocks respond to the relative change in supply. In column (2), we include pair-specific double-differences in firm fundamentals and industry-by-time fixed effects to further control the potential confounders that could affect the price differences within each pair. The estimated average relative price multiplier, $\bar{\mathcal{M}}$, remains stable as of 2.010 with a higher adjusted R-square. This magnitude implies that

[15] $\bar{\mathcal{M}}$ effectively reflects the average relative price multiplier over different horizons. Unlike temporary demand shocks, e.g., mutual fund flows, the supply shocks induced by the TSP are stable over time (see Figure C.2). As shown in Figure C.3, our estimate of relative price multiplier is generally stable over different horizons.

Table 6
Estimation of Price Multiplier

	$\Delta p_{j,t}$	
	(1)	(2)
$\boldsymbol{\Delta s_{j,t}}$	**2.010****	**2.010*****
	(0.82)	**(0.34)**
$\Delta \boldsymbol{x}_{j,t}$	No	Yes
Year-quarter FE	Yes	No
Industry-Time FE	No	Yes
Obs.	4,156	4,059
Adj. R^2	0.004	0.567

Note. This table presents the baseline estimation of relative price multipliers. The dependent variable is $\Delta p_{j,t}$. For each quarter in the post-treatment period (2016Q4-2018Q3), $\Delta p_{j,t}$ is calculated as the log difference-in-differences of quarter-end closing prices and pre-treatment average prices (2014Q4-2016Q3), between treatment and control stock in a matched pair j. The main independent variable is denoted by $\Delta s_{j,t}$, estimated by the difference-in-differences of share repurchase of matched pair j. $\Delta \boldsymbol{x}_{j,t}$ includes double-differences of size, profitability, growth opportunity, investment, dividend payout, percentage quoted spread, and market beta. The robust standard errors clustered at industry-by-time level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

a 1% relative decrease in share repurchases (scaled by book equity) leads to a 2.01% relative decrease in stock price. While additional controls modestly increases the explanatory power of the return differences within matched pairs, it does not affect the estimated magnitude of the relative price multiplier. This finding indicates that matching a shocked treatment stock with an unshocked control stock already absorbs most price pressure driven by fundamentals, leaving the remaining variation attributable to supply shocks. Additionally, our results further support the validity of our identification strategy by indicating that the constructed supply shocks, $\Delta s_{j,t}$, are orthogonal to changes in firms' fundamentals and liquidity, as discussed in Appendix A.3.

5.2 Rule out Liquidity Effect on Price Pressure

A major concern with the TSP to estimate relative price multiplier is that the price reduction of treatment stocks is also driven by the TSP's adverse effects on liquidity (transaction costs), instead of supply-side effect. Though our estimate of relative price multiplier is robust after controlling the change in liquidity, we further address this concern using a unique feature of the TSP. The three test groups are subject to different changes to the trading environment. In addition to being subject to the rules applying to stocks in test group 1 (G1) and test group 2 (G2), the stocks in test group 3 (G3) are subject to the "trade-at" provision, which requires that orders be executed in lit venues unless dark venues can improve the NBBO by more than 2.5 cents.

Firms can bypass the intensified competition of time priority using dark pools, which do not impose time-priority rule. However, Rule 10b-18 regards the dark orders improving the best bid by 2.5 cents as a signal of price manipulation. As a result, the "trade-at" provision combined with Rule 10b-18 effectively banned G3 firms to repurchase using dark pools, and the TSP decreased repurchase volume more for G3 stocks compared to G1&2 stocks (Li et al., 2024). We confirm this channel by replicating Equation (24) for G1&2 and G3 stocks, respectively. Panel A of Table 7 shows that G3 stocks encountered more decrease in repurchase relative to G1&2 stocks.

Meanwhile, Albuquerque et al. (2020) document an empirical puzzle: while the "trade-at" rule had little impact on market liquidity across three groups, G3 stocks encountered more price decline compared to G1&2 stocks. This setting provides an ideal environment to examine how estimates of price multiplier behave after controlling liquidity effect. If the liquidity-induced effect does not drive our estimate, the discrepancy in price pressure between G1&2 and G3 stocks should be mainly attributed to the differentiated decrease in share repurchase. In other words, we should expect similar estimate of relative price multiplier between G1&2 and G3 stocks and compared to the baseline estimate. To testify, we re-estimate the relative price multiplier using G1&2 and G3 stocks with their corresponding matched control firms, respectively. Panel B of Table 7 shows that the estimates in column (1) and (2) are significant and are almost identical with each other and with the baseline

Table 7
G1&2 v.s. G3 Stocks

Panel A: Effect of TSP on share repurchase

	$Repurchase\ Payout_{n,t}$	
	G1&2	G3
	(1)	(2)
$Treatment_n \times Post_t$	-0.150*	-0.239**
	(0.09)	(0.11)
p-value for difference	**0.001*** **	
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-quarter FE	Yes	Yes
Obs.	12,416	5,532
Adj. R^2	0.329	0.409

Panel B: Price multiplier of G1&2 and G3

	$\Delta p_{j,t}$	
	G1&2	G3
	(1)	(2)
$\Delta s_{j,t}$	2.133***	1.792**
	(0.45)	(0.89)
p-value for difference	**0.266**	
$\Delta \boldsymbol{x}_{j,t}$	Yes	Yes
Industry-Time FE	Yes	Yes
Obs.	2,783	1,206
Adj. R^2	0.574	0.535

Note. This table presents the subgroup analysis excluding the general liquidity effect on price changes. In Panel A, we respectively repeat Equation (24) for group 1&2 and group 3. 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. In Panel B, we respectively repeat Equation (26) for group 1&2 and group 3. $\Delta \boldsymbol{x}_{j,t}$ include difference-in-differences of size, profitability, growth opportunity, investment, dividend payout, percentage quoted spread, and market beta. Industry-by-year-quarter fixed effects are included. The robust standard errors clustered at industry-by-time level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. The reported p-value for difference is based on 1,000 bootstrap iterations. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

estimate in Table 6. Taking together, the results in Table 7 provide an explanation for the puzzle documented in Albuquerque et al. (2020): the additional price decline of G3 stocks compared to G1&2 is primarily attributable to the additional reduction in share repurchases.

5.3 Relative Price Multiplier Approximates Own-Price Multiplier

As discussed in Section 2, Equation (26) identifies the relative price multiplier à la Haddad et al. (2025). Building on Proposition 1, we conduct two empirical tests to assess whether the estimated relative price multiplier closely approximates the own-price multiplier under the factor structure assumption in Equation (17). Specifically, we examine the following conditions: (1) the matched treatment and control stock pair (n, n') exhibit similar factor exposures, i.e., $\boldsymbol{b}(n) \approx \boldsymbol{b}(n')$; and (2) factor exposure risk is small enough relative to idiosyncratic risk, i.e., $\boldsymbol{b}^2(n) \ll \sigma^2$.[16]

5.3.1 Similar Factor Exposures

We begin by constructing a long-short portfolio for each matched stock pair j, going long the treatment stock and short the corresponding control stock. We take the market excess return as the risk factor in our factor structure assumption in equation 17. For each year-month, we regress the daily returns of the long-short portfolio on the daily market excess return $R_{m,t}$ to estimate the factor loading β_j. We also record the corresponding t-statistic associated with β_j to assess the statistical significance of differential factor exposures within each matched pair.

$$r_{j,t}^{treatment} - r_{j,t}^{control} = \alpha_j + \beta_j R_{m,t} + \nu_j \tag{27}$$

Let n and n' denote the treatment and control stocks within matched pair j, since we normalize the variance of the factor as one in our factor assumption, we would have that $\beta_j = (\boldsymbol{b}_j(n) - \boldsymbol{b}_j(n'))\,\sigma(R_m)$, in which $\sigma(R_m)$ is the standard deviation of the market excess return. In Figure 1, we plot the time series of the average $\hat{\beta}_j$ across matched pairs, along

[16] Empirically, we cannot identify each investor i's factor exposure to stock n, $\boldsymbol{b}_i(n)$, without additional assumptions. Therefore, we assume homogeneous (or average) factor exposures across investors and suppress the subscript i in our empirical implementation. We also assume a constant idiosyncratic risk across stocks. We provide empirical evidence on this in Appendix C.1.

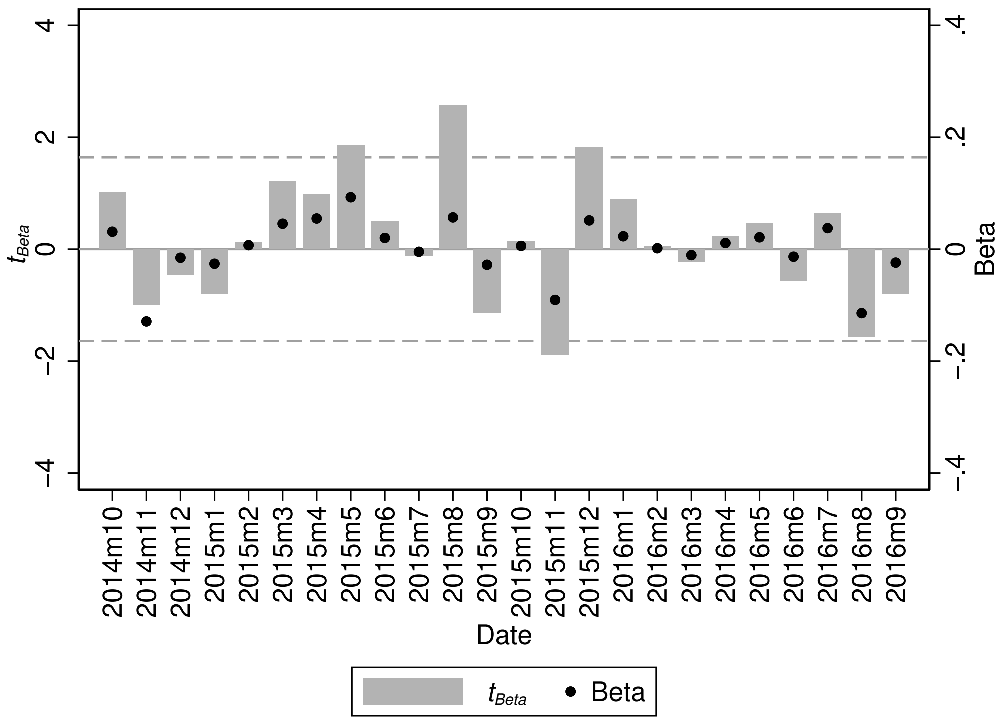

Figure 1. Balance on variances: exposure of long-short portfolio to stock market returns. This figure plots the exposure of a long-short portfolio between treatment and control stocks to the excess stock market returns. At each month, we obtain the market beta and the corresponding t-statistics by regressing the long-short portfolio returns on excess stock market returns. The time series is the pre-treatment period from October 2014 to September 2016.

with the corresponding t-statistics, computed for each year-month. We find that the average coefficients fluctuate around zero and are statistically indistinguishable from zero (mean t-statistic = 0.02). This finding suggests that the treatment and control stocks within each pair exhibit similar factor exposures, i.e., $\boldsymbol{b}(n) \approx \boldsymbol{b}(n')$.

Therefore, treatment and control stocks share similar cross-price multipliers with respect to other stocks in the market, supporting the validity of our empirical strategy that relies on differencing price changes between matched pairs.[17]

[17] Recall from Lemma 1 that the cross-price multiplier between stocks n and m is given by $[\boldsymbol{\mathcal{M}}]_{n,m} = \frac{\sigma^2}{r^2}\boldsymbol{\rho}_{n'}\boldsymbol{L}\boldsymbol{\rho}_m$. If $\boldsymbol{b}(n) \approx \boldsymbol{b}(n')$, then $\boldsymbol{\rho}_n \approx \boldsymbol{\rho}_{n'}$, implying $[\boldsymbol{\mathcal{M}}]_{n,m} \approx [\boldsymbol{\mathcal{M}}]_{n',m}$ for all $m \neq n, n'$.

5.3.2 Relatively Large Idiosyncratic Risk

We take the market excess return as the risk factor and estimate the time-series regression of stock n's daily return:[18]

$$r_t(n) = \alpha(n) + \beta(n)R_{m,t} + \varepsilon_t(n) \tag{28}$$

where $r_t(n)$ denotes the daily return of stock n on day t, and $R_{m,t}$ represents the daily return of the market factor. For each year-month T, we compute the idiosyncratic risk $\sigma_T^2(n)$ as the variance of the residuals $\varepsilon_t(n)$ from Equation (28). Since our model normalizes the variance of the market factor to one, the factor exposure risk $\boldsymbol{b}_{i,T}^2(n)$ referenced in Proposition 1 corresponds to the square of the estimated loading $\beta^2(n)$ times the variance of the market factor:

$$\hat{\beta}_T^2(n)\mathrm{Var}(R_{m,T})$$

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

$$H_0 : \ln\left(\frac{\hat{\beta}_T^2(n)\mathrm{Var}(R_{m,T})}{\sigma_T^2(n)}\right) \geq \ln(c) \tag{29}$$

Panel A of Table 8 reports summary statistics for idiosyncratic risk, factor exposure risk, and the t-test results. The average idiosyncratic risk is 5.32×10^{-4}, which is around 6.7 times larger than the average factor exposure risk, measured at 7.93×10^{-5}.[19]

Panel B further exploits the distribution information and reports one-sided p-values from the test in (29) for different thresholds c. We can reject the null hypothesis under the threshold of 0.1 (0.077) at 1% (10%) significance level. That is, on average, the factor

[18] We also report the idiosyncratic risk calculated from Fama-French three factors, Carhart four factors, and Fama-French five factors in Appendix C.1 and they all exhibit the same magnetites.

[19] This relative size matches with the previous empirical findings. For example, Table 2 of Bartram et al. (2019) report that the average of $\sigma^2/\mathrm{Var}(R_m)$ (assuming average the $\boldsymbol{b}(n)$ of 1) from 1961 to 2017 ranges from 4.60 to 10.41 under different CRSP Index Volatility periods. 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.

exposure risk is less than 10% (7.7%) of idiosyncratic risk at 1% (10%) significance level. These results confirm that factor exposure risk is substantially smaller than idiosyncratic risk, satisfying the condition $\boldsymbol{b}^2(n) \ll \sigma^2$ stated in Proposition 1.

This inequality implies that the own-price multiplier is much larger than a *singular* cross-price multiplier. However, it does not imply that *aggregate* spillover effects from cross-price multipliers can be ignored. To see this, consider a special case of CAPM and we can express the spillover effects to a TSP treatment stock n as in Equation (20):

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

The number of simultaneously shocked stocks in TSP was $N = 1,200$ and so the spillover effects come from other 1,199 treatment stocks. Moreover, all treatment stocks experienced negative reduction in share repurchases such that $\Delta S(m) < 0,\ m = 1, \cdots, 1{,}200$. As a result, the *aggregate* spillover effect is not negligible. Failing to account for these *aggregate* spillover effects would therefore bias the estimated relative price multiplier due to omitted-variable bias, as discussed in Section 2.

In summary, the empirical evidence in this section supports the approximation of the relative price multiplier by the own-price multiplier under the factor structure (17). At the same time, our results underscore the necessity of controlling for *aggregate* spillover effects, as their contribution to price impact is economically significant and cannot be ignored.

6. Investor Responses to Share Repurchases

We begin by examining portfolio rebalancing during the TSP to see which investors absorb the the specific exogenous supply shocks induced by the TSP. Motivated by Equation (23) in Section 2.4, we estimate the following panel regression:

$$\Delta q^i_{j,t} = \beta^i \Delta s_{j,t} + \gamma^i \Delta \boldsymbol{x}_{j,t} + u_t \times u_g + \varepsilon^i_{j,t} \tag{30}$$

Table 8
The Sizes of Idiosyncratic and Factor Exposure Risk

Variables	N	Mean	*SD*	Q1	Median	Q3
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Idiosyncratic Risk ($\sigma^2_T(n)$)	26,179	$5.32e^{-4}$	$4.88e^{-4}$	$1.87e^{-4}$	$3.81e^{-4}$	$7.14e^{-4}$
Factor Exposure Risk ($\hat{\beta}^2_T(n)\text{Var}(F_T)$)	26,180	$7.93e^{-5}$	$1.09e^{-4}$	$1.14e^{-5}$	$4.12e^{-5}$	$1.02e^{-4}$
Panel B						
	$c = 0.10$	$c = 0.09$	$c = 0.08$	$c = 0.079$	$c = 0.077$	$c = 0.075$
$p-$value	0.000***	0.000***	0.002***	0.008***	0.062*	0.139

Note. Panel A presents the summary statistics of estimated idiosyncratic risk and factor exposure risk, and the relative size of idiosyncratic risk. Idiosyncratic risk is calculated as the variance of regression residual from Equation (28) in each year-month T. Factor exposure risk is calculated as the product of estimated betas from Equation (28) and the variance of market factor in at time T. Panel B reports the one-side p-value under different threshold level c and the null hypothesis specified in Equation (29). The robust standard errors clustered at stock level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

where j indexes matched pair; i indexes investor type, including banks, insurance companies, investment advisors, mutual funds, pension funds, other small funds, and households as per Koijen and Yogo (2019); and t indexes year-quarter. We includes the same control variables and industry-time fixed effects as in Equation (26). For each investor type i, we calculate the double differences in their holdings, scaled by lagged total share outstanding, in the matched stock pair j as $\Delta q^i_{j,t} = (q^{i,treatment}_{j,t} - q^{i,treatment}_{j,0}) - (q^{i,control}_{j,t} - q^{i,control}_{j,0})$. $\Delta s_{j,t}$ is similarly defined as in Equation (26) but scaled by lagged total share outstanding. Therefore, coefficient β^i estimates the average relative holding changes in investor type i responding to the supply shock $\Delta s_{j,t}$. In the case of exogenous increase in share supply like the TSP with $\Delta s < 0$, a negative coefficient implies an relative increase in holdings of shocked stocks, suggesting the absorption of the supply shocks.

Table 9 reports the estimation results. Household, investment advisors (e.g., hedge funds), and insurance companies statistically significantly increase their holdings in treatment stocks relative to the matched control stocks. In terms of economic significance, household and investment advisors absorb most of the supply shocks. For a 1% reduction in relative share repurchases in treatment stocks compared to matched control stocks, i.e., a

Table 9
Estimation of Investor Responses

	Bank	Insurance	Investment Advisors	Mutual Funds	Pension Funds	Other Funds	Household
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta s_{j,t}$	-0.048	-0.065*	-0.452**	0.238	0.021	0.189*	-1.006***
	(0.07)	(0.04)	(0.21)	(0.26)	(0.02)	(0.11)	(0.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,059	4,059	4,059	4,059	4,059	4,059	4,059
Adj. R^2	0.067	0.012	0.032	0.110	0.004	-0.001	0.121

Note. This table estimates the relative holding changes in each investor type during the TSP, specified in Equation (30). The dependent variable is $\Delta q^i_{j,t}$, which is the double differences in holding changes between treatment and control stocks, before and after the shock for investor type i. We consider seven types of investors from 13F files: banks, insurance companies, investment advisors, mutual funds, pension funds, other funds, and household. For each quarter in the post-treatment period (2016Q4-2018Q3), $\Delta q^i_{j,t}$ is calculated as the log difference-in-differences of quarter-end holdings and pre-treatment average holdings (2014Q4-2016Q3), between treatment and control stock in a matched pair j. The main independent variable is denoted by $\Delta s_{j,t}$, estimated by the difference-in-differences of share repurchase of matched pair j, scaled by lagged total share outstanding. $\Delta \boldsymbol{x}_{j,t}$ includes double-differences of size, profitability, growth opportunity, investment, dividend payout, percentage quoted spread, and market beta. The robust standard errors clustered at industry-by-time level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

1% increase in relative share supply, household increases its relative holdings in treatment stocks, compared with matched control stocks, by 1.006%, investment advisors increase relative holdings by 0.452%, and insurance companies increase by 0.065%. In contrast, other (small) funds reduce the relative holdings by 0.189%. We do not find statistically significant changes in the relative holdings banks, mutual funds, or pension funds. Since we measure the relative response, the insignificant changes could either because inelastic investors do not change their holdings at all, or investors change holdings in the treatment and control stocks with the same magnitude. In summary, during the TSP, household absorb most of the relatively additional shares, followed by investment advisors and insurance companies. Other small funds amplify the supply shock by selling relative more shares to the market.

Equation (22) implies that investors with higher demand elasticity tend to absorb more supply shocks. We therefore investigate portfolio rebalancing of different investor types during normal-time repurchases in our sample stocks, examining which investors sell to firms and generalizing the conclusion above. Our approach follows Koijen et al. (2021), who employ the variance decomposition to study portfolio rebalancing under quantitative easing in the euro area. This approach reveals the relative ranking of demand elasticity across investors.

Let $S_t(n)$ be the number of total shares outstanding of stock n at quarter t. The intensity of share repurchase and equity issuance are respectively denoted by

$$Rep_t(n) = \frac{Repurchase_t(n)}{S_{t-1}(n)}, \; Iss_t(n) = \frac{Issuance_t(n)}{S_{t-1}(n)} \tag{31}$$

Let $Q_{it}(n)$ be investor i's holdings of stock n at quarter t. The market clearing condition is

$$Rep_t(n) = Iss_t(n) - \sum_{i=1}^{I} \frac{Q_{it}(n) - Q_{it-1}(n)}{S_{t-1}(n)} = Iss_t(n) - \sum_{i=1}^{I} D_{it}(n) \tag{32}$$

which implies the share repurchase must be offset by equity issuance and investors' rebalancing:

$$\frac{Cov(Iss_t(n), Rep_t(n)) - \sum_{i=1}^{I} Cov(D_{it}(n), Rep_t(n))}{Var(Rep_t(n))} = 1 \tag{33}$$

This variance decomposition examines which investors sell to firms when firms repurchase shares in normal times. We use the same investor classification as in Table 9. Investor i's contribution to the variance of firm repurchases is estimated over 2013Q4–2016Q3.[20] Figure 2 shows that investment advisors (e.g., hedge funds), mutual funds, and households contribute the most to repurchases by selling shares to firms. By contrast, other (smaller) funds tend to purchase shares when firms repurchase, consistent with Table 9, which shows that other funds reduce their relative holdings in treatment firms when repurchases decline.

These results highlight that households and investment advisors exhibit relatively higher demand elasticity, consistent with Table 9 showing that they absorb most of the supply shocks during the TSP by increasing their relative holdings in treatment stocks. The only exception

[20] We follow common practice to use 12 quarters to ensure sufficient observations for calculating (co)variances. Results are similar when restricting to 8 quarters (2014Q4–2016Q3).

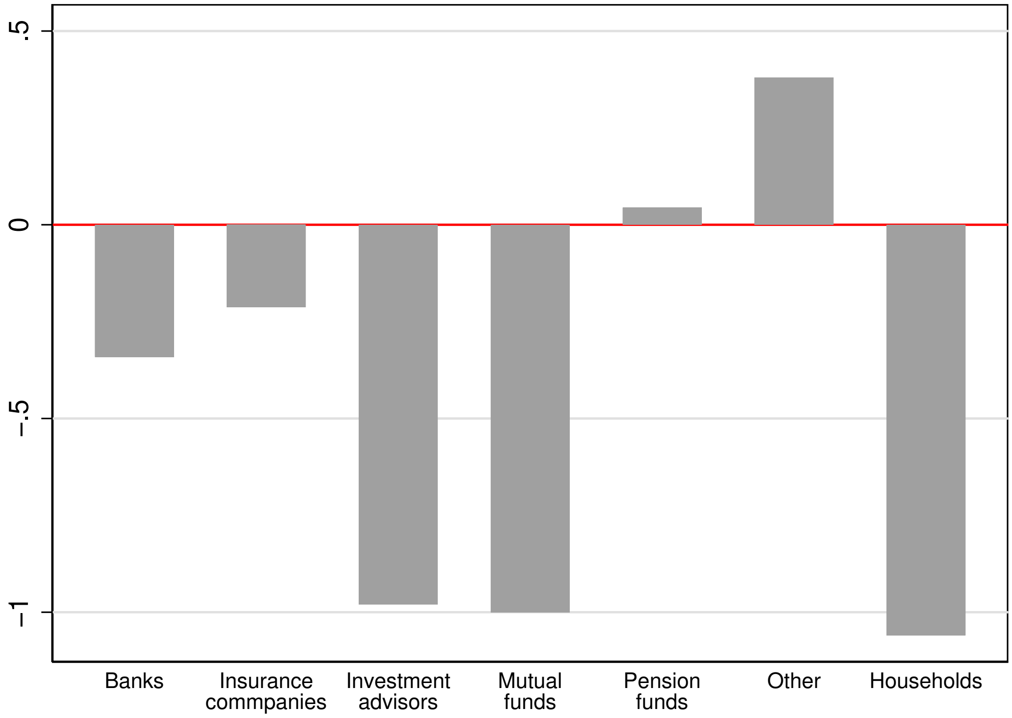

Figure 2. Variance decomposition of repurchases from 2013Q4 to 2016Q3 for our sample firms. The gray bar plots each investor's contribution to the variance of share repurchase estimated by Equation (33). The definition of investor sectors follows Koijen and Yogo (2019).

is mutual funds: although they sell aggressively to firms in normal repurchases, they do not increase their relative holdings when treatment firms reduce repurchases during the TSP. A possible explanation is that mutual funds view matched treatment and control stocks as close substitutes and rebalance symmetrically across them, such that $[\boldsymbol{\mathcal{A}}_{\text{mutual funds}}]_{n,n} - [\boldsymbol{\mathcal{A}}_{\text{mutual funds}}]_{n',n} \approx 0$. Another explanation is that mutual funds recognize the TSP as a relatively short-lived regulation change compared with their investment horizons, and thus choose not to adjust their holdings during the TSP.

7. Additional Tests on the Price Multiplier

We present additional robustness checks and subgroup analyses. First, we confirm the robustness of our estimate by using repurchasing firms only and alternative metrics of price and quantity. Second, we use the end of TSP as a reversed supply shock, which recovered the realized repurchase volume for treatment stocks. We estimate a significant price multiplier of 1.008. Finally, we provide evidence that the price multiplier tends to be greater for (relatively) larger firms. This heterogeneous pattern is consistent with Koijen and Yogo (2019) and Haddad et al. (2025), that the disproportionately more inelastic investors holding large firms create this discrepancy.

7.1 Robustness Checks

We first conduct several robustness tests for our estimate of price multiplier. First, the supply shock arises due to the reduction of realized share repurchase. Firms never buy back shares could bias the estimate by capturing unobservables driving the price pressure. To address this concern, we re-match only repurchasing firms in treatment and control groups and re-estimate the price multiplier with repurchasing sample. The repurchasing firms are defined as firms ever engaged in share repurchase in the pre-treatment period. Column (1) of Table 10 reports the results. The estimate of price multiplier remains significant and is slightly (but insignificantly) smaller than the baseline estimation. This magnitude is less likely to be biased by the non-repurchasing firms.

Next, we repeat our estimation using an alternative measure of $\Delta s_{j,t}$ in Equation (26). In column (2) of Table 10, $\Delta s_{j,t}$ is the difference-in-differences of the number of common shares repurchased by firms, instead of repurchase dollar volume, divided by lagged total shares outstanding. The new estimate is 1.810, which is close to the baseline estimate. Similarly, we use an alternative measure of $\Delta p_{j,t}$ in Equation (26). In column (3) of Table 10, following Koijen and Yogo (2019), $\Delta p_{j,t}$ is the difference-in-differences of market capitalization. The new estimate of price multiplier is 1.400, suggesting that a 1% increase in share supply reduces the market capitalization by 1.4% in treatment firms.

7.2 A Reversal of Supply Shock

The TSP concluded on October 1, 2018, when tick sizes for treatment stocks reverted to the original 1-cent level. This change leads to a rebound in share repurchases, effectively decreasing the supply of shares for treatment stocks. We treat this as a *de facto* negative

Table 10
Robustness Checks

	$\Delta p_{j,t}$		
	Repurchasing firms only (1)	Alternative quantity (2)	Alternative price (3)
$\boldsymbol{\Delta s_{j,t}}$	**1.724*** (0.38)**	**1.810** (0.87)**	**1.400*** (0.31)**
$\Delta \boldsymbol{x}_{j,t}$	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes
Obs.	2,142	4,059	4,059
Adj. R^2	0.538	0.565	0.643

Note. This table presents the robustness checks related to our estimate of price multiplier. In column (1), we repeat the estimation using repurchasing firms only. The repurchasing firms are defined as firms ever engaged in share repurchase in the pre-treatment period. In column (2), $\Delta s_{j,t}$ denotes the difference-in-differences of number of shares repurchased relative to total shares outstanding. In column (3), $\Delta p_{j,t}$ denotes the difference-in-differences of market capitalization. The robust standard errors clustered at industry-by-time level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

supply shock and re-estimate the aggregate price multiplier.

Panel A of Table 11 presents the effect of TSP end on share repurchase. The end of TSP restored the share repurchase payout, with a significantly positive coefficient of 0.148 on $Treatment_n \times Post_t$. Next, following Equation (26), we re-estimate the price multiplier using four quarters before to four quarters after the end of TSP (2018Q4-2019Q3), based on the same sample of matched treatment and control stocks in Section 5.1.[21] Panel B of Table 11 presents a estimated price multiplier of 1.008, which is 49% lower than the baseline estimate of 2.010. One possible explanation is that the TSP increased tick size for treatment firms, and mechanically increase the bid-ask spread and transaction costs. The tighter liquidity conditions subsequently constrain investors' willingness to trade. In other words, compared to "normal" market condition, the demand curve during the TSP could

[21]We choose a post-treatment period of four quarters here to avoid the market complication during COVID-19 pandemic.

Table 11
The End of TSP

Panel A: Effect of TSP end on share repurchase	*Repurchase Payout$_{n,t}$*	Panel B: Estimation of Price Multiplier using TSP end	$\Delta p_{j,t}$
	(1)		(2)
$\boldsymbol{Treatment_n \times Post_t}$	**0.148****	$\boldsymbol{\Delta s_{j,t}}$	**1.008****
	(0.07)		**(0.40)**
Controls	Yes		
Firm FE	Yes	$\Delta \boldsymbol{x}_{j,t}$	Yes
Year-quarter FE	Yes	Industry-Time FE	Yes
Obs.	9,765	Obs.	1,898
Adj. R^2	0.448	Adj. R-squared	0.318

Note. This table presents the empirical results using TSP end. Panel A reports the effect of TSP end on share repurchase. Controls include size, profitability and growth opportunity. The robust standard errors clustered at firm level are in parentheses. Panel B presents the estimate of price multiplier using TSP end as a reverse supply shock. $\Delta \boldsymbol{x}_{j,t}$ include difference-in-differences of size, profitability, growth opportunity, investment, dividend payout, and market beta. The robust standard errors clustered at industry-by-time level are in parentheses. All continuous and unbounded variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

have a deeper slope.[22] Nevertheless, the magnitude of this new estimate is still far from an elastic stock market (i.e., flag demand curve).

This finding highlights the importance of microfoundation in demand elasticity estimation. When trading frictions are elevated, such as during the TSP, price impact per unit of supply change is magnified, consistent with models of inelastic markets under liquidity constraints (Gabaix and Koijen, 2023). Conversely, under more relaxed trading conditions, the aggregate demand curve appears more elastic, though still far from a flat demand curve. While our baseline estimates capture the upper bound of price multiplier under constrained market conditions, the new estimate provides a more conservative benchmark for price multiplier in typical market environments. Taken together, the reversal of the supply shock

[22] We have shown that our estimate of price multiplier is immune to the liquidity change during the TSP. The liquidity, however, could determine the magnitude of time-varying price multiplier under different market environment.

Table 12
Small v.s. Large Firms

	$\Delta p_{j,t}$	
	Large firms (1)	Small firms (2)
$\Delta s_{j,t}$	3.109***	1.872**
	(0.53)	(0.43)
p-value for difference	**0.055***	
$\Delta \boldsymbol{x}_{j,t}$	Yes	Yes
Industry-Time FE	Yes	Yes
Obs.	1,917	2,044
Adj. R^2	0.586	0.553

Note. This table presents the subgroup analysis related to the firm size. We bifucate the full sample into two subgroups based on stock's pre-treatment average total assets (2014Q4-2016Q3). A stock is assigned as large (small) group if its pre-treatment average total assets is above (below) the cross-sectional median. The reported p-value for this difference is based on 1,000 bootstrap iterations. $\Delta \boldsymbol{x}_{j,t}$ include difference-in-differences of size, profitability, growth opportunity, investment, dividend payout, and market beta. All variables are winsorized at (1%, 99%) levels. The robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

suggests that the price multiplier, or the slope of a stock's aggregate demand curve, can vary over time as market conditions change.

7.3 Firm Size

A debated determinant of price multiplier is firm size. Wurgler and Zhuravskaya (2002) argue that the stocks without close substitutes (e.g. small stocks) convey larger arbitrage risks, thus encounter larger price jumps in S&P 500 index inclusion events. In contrast, Koijen and Yogo (2019) and Haddad et al. (2025) suggest larger price multiplier for larger firms, because they are disproportionately held by large players and passive investors with inelastic demand. To investigate these competing hypotheses, we bifurcate the full sample into two subgroups based on firm's pre-treatment average total assets. A firm is assigned as a large (small) firm if its pre-treatment average total assets is above (below) the cross-sectional median. We separately estimate the price multiplier in Equation (26) within two subgroups, respectively. Table 12 presents the results. We obtain that the estimated price multiplier is significantly higher for larger firms than smaller firms. While the results above support the patterns documented in Haddad et al. (2025), we argue it is more like a suggestive evidence: the 2016 TSP exclusively focuses on small and medium-size firms, which may constrain the generality of this pattern.

8. Conclusions

Exploiting the SEC's 2016 Tick Size Pilot (TSP) as an exogenous and randomized supply shock, we develop and implement the first supply-based approach to estimate the stock-level price multiplier. The TSP unintentionally reduced treatment firms' share repurchases by 20 percent through an unexpected conflict with the Rule 10b-18 and, for firms in G3, the additional "trade-at rule." Importantly, we show that the TSP did not change repurchase announcements and announcement abnormal returns, suggesting the TSP-induced supply shock was not anticipated by managers or market participants.

Empirically, we find that a 1 percent increase in repurchases (as a share of book equity) raises stock prices by 2.01 percent relative to their closest substitutes. We further document that factor exposure risk is sufficiently small compared with idiosyncratic risk in our sample stocks, validating that our estimated relative price multiplier approximates the own-price multiplier. In addition, we show that G3 stocks experienced a larger decline in share repurchases during the TSP but exhibit a similar price multiplier estimate, thereby ruling out liquidity effects on the estimate of price multiplier.

Unlike demand-side instruments, exogenous supply shocks allow us to track the heterogeneous portfolio rebalancing across investor types. We find households and investment advisors primarily absorb the supply shocks. Pension funds, banks, and insurance companies exhibit little response, consistent with their low demand elasticities as Koijen and Yogo (2019), while some small funds exuberate. These patterns underscore the role of investor heterogeneity in interpreting price multiplier and its implication on share repurchase.

Beyond the specific context of the TSP, our findings have several broader implications. First, we highlight that stock-level price multiplier can be estimated using supply shocks and call for more estimation based on supply-side instruments. Second, we show that even an uninformed supply change can mechanically affect share prices, suggesting that the secular rise in U.S. share repurchases may mechanically contribute to the increase in stock valuation. Finally, we extend the demand system framework by documenting heterogeneous adjustments in investor holdings to supply shifts. Future research may investigate how investors adjust their portfolios and trade with one another, and how these interactions affect asset prices.

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A. Supplementary Proofs and Discussions

A.1 Proofs and Assumptions on the Future Payoff

Given our assumption on the future asset payoff, $\boldsymbol{d}_i \sim N(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$, the investor's objective function (2) can be expressed as:

$$\mathbb{E}_i\left[-\exp\left(-\gamma_i A_{i,1}\right)\right] = -\exp\left(-\gamma_i\left(\mathbb{E}_i(A_{i,1}) + \frac{1}{2}\mathbb{V}\mathrm{ar}_i(A_{i,1})\right)\right)$$

$$= -\exp\left(-\gamma_i\left(A_{i,0} + \left(\boldsymbol{\mu_i} - \boldsymbol{P}\right)'\boldsymbol{q}_i\right) + \frac{\gamma_i^2}{2}\left(\boldsymbol{q}_i'\boldsymbol{\Sigma}_i\boldsymbol{q}_i\right)\right)$$

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

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

We can then solve for the optimal portfolio choice:

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

From equation (4), we can explicitly express market clearing condition (5) as

$$\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\Big(\boldsymbol{\mu}_i - \boldsymbol{P}\Big) = \boldsymbol{S} \tag{A.2}$$

Rearranging equation (A.2) yields the equilibrium price vector in equation (6).

A.2 Proofs on Lemma 1 and Proposition 1

Recall from equation (A.2) that $\boldsymbol{\mathcal{M}} = \left(\sum_{i=1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\right)^{-1}$ and also note that under the factor structure (17), we have that $\boldsymbol{\Sigma}_i = Var(\boldsymbol{d}_i) = \sigma^2\boldsymbol{I} + \boldsymbol{b}_i\boldsymbol{b}_i'$. Also note that $\boldsymbol{\Sigma}_i^{-1} =$

$\frac{1}{\sigma^2}\Big(\boldsymbol{I} - \frac{\boldsymbol{b}_i\boldsymbol{b}_i'}{\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i}\Big)$. Therefore,

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

where

$$\alpha = \frac{1}{\sigma^2}\sum_i \frac{1}{\gamma_i}, \qquad w_i = \frac{1}{\gamma_i\sigma^2(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)}.$$

Denote the vectors as an $N \times I$ matrix $R = [\sqrt{w_1}\boldsymbol{b}_1, \cdots, \sqrt{w_I}\boldsymbol{b}_I]$, so that $\sum_{i=1}^{I} w_i\boldsymbol{b}_i\boldsymbol{b}_i' = \boldsymbol{R}\boldsymbol{R}'$ and $\boldsymbol{\mathcal{M}} = (\alpha\boldsymbol{I} - \boldsymbol{R}\boldsymbol{R}')^{-1}$.

By the Woodbury matrix identity, we have

$$(\alpha\boldsymbol{I} - \boldsymbol{R}\boldsymbol{R}')^{-1} = \frac{1}{\alpha}\boldsymbol{I} + \frac{1}{\alpha^2}\boldsymbol{R}\Big(\boldsymbol{I} - \frac{1}{\alpha}\boldsymbol{R}'\boldsymbol{R}\Big)^{-1}\boldsymbol{R}'$$

Finally, define

$$r = \sum_{i=1}^{I}\frac{1}{\gamma_i}, \qquad \boldsymbol{B} = \left(\frac{\boldsymbol{b}_1}{\sqrt{\gamma_1(\sigma^2+\boldsymbol{b}_1'\boldsymbol{b}_1)}}, \cdots, \frac{\boldsymbol{b}_I}{\sqrt{\gamma_m(\sigma^2+\boldsymbol{b}_I'\boldsymbol{b}_I)}}\right)_{N\times I}, \boldsymbol{L} = \Big(\boldsymbol{I} - \frac{1}{r}\boldsymbol{B}'\boldsymbol{B}\Big)^{-1}$$

Then $\boldsymbol{R} = \frac{1}{\sqrt{\sigma^2}}\boldsymbol{B}$ and $\alpha = \frac{r}{\sigma^2}$, so

$$\boldsymbol{\mathcal{M}} = (\alpha\boldsymbol{I} - \boldsymbol{R}\boldsymbol{R}')^{-1} = \frac{\sigma^2}{r}\boldsymbol{I} + \frac{\sigma^2}{r^2}\boldsymbol{B}\boldsymbol{L}\boldsymbol{B}'$$

This ends the proof of Lemma 1. Now, we can express the (n, n) component of matrix $\boldsymbol{\mathcal{M}}$ as

$$[\boldsymbol{\mathcal{M}}]_{n,n} = \frac{\sigma^2}{r} + \frac{\sigma^2}{r^2}\,\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_n$$

Define the relative difference between the second term and the first term as

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

Ignoring the second term 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

$$\frac{1}{c}\boldsymbol{\rho}_n'\boldsymbol{L}\boldsymbol{\rho}_n \leq \frac{1}{c}\cdot\lambda_{\max}(\boldsymbol{L})\cdot\|\boldsymbol{\rho}_n\|^2 \tag{A.3}$$

$$= \frac{1}{c-\lambda_{\max}(\boldsymbol{B}'\boldsymbol{B})}\cdot\|\boldsymbol{\rho}_n\|^2 \tag{A.4}$$

The first inequality follows the Rayleigh-Ritz theorem and the second line uses the fact that $\lambda_{\max}(\boldsymbol{L}) = 1/\lambda_{\min}(\boldsymbol{I}-\boldsymbol{B}'\boldsymbol{B}) = 1/\left(1-\frac{1}{c}\lambda_{\max}(\boldsymbol{B}'\boldsymbol{B})\right)$. Therefore, a sufficient condition for $\frac{1}{c}\boldsymbol{s}_n'\boldsymbol{L}\boldsymbol{s}_n \ll 1$ is

$$\frac{1}{c-\lambda_{\max}(\boldsymbol{B}'\boldsymbol{B})}\cdot\|\boldsymbol{\rho}_n\|^2 \ll 1 \tag{A.5}$$

$$\Rightarrow \|\boldsymbol{\rho}_n\|^2 \ll c-\lambda_{\max}(\boldsymbol{B}'\boldsymbol{B}) \tag{A.6}$$

To satisfy equation (A.6), it is sufficient to show that

$$\|\boldsymbol{\rho}_n\|^2 \ll c-\mathrm{trace}(\boldsymbol{B}'\boldsymbol{B}) \leq c-\lambda_{\max}(\boldsymbol{B}'\boldsymbol{B}) \tag{A.7}$$

where we use the fact that $\lambda_{\max}(\boldsymbol{X}) \leq \mathrm{trace}(\boldsymbol{X})$. Finally, note that

$$\mathrm{trace}(\boldsymbol{B}'\boldsymbol{B}) = \sum_{i=1}^{I}\frac{\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \tag{A.8}$$

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

$$\|\boldsymbol{\rho}_n\|^2 = \sum_{i=1}^{I}\frac{\boldsymbol{b}_i^2(n)}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \ll c-\sum_{i=1}^{I}\frac{\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \tag{A.9}$$

Recall that $c=\sum_{i=1}^{I}\frac{1}{\gamma_i}$, and rearrange equation (A.9)

$$\sum_{i=1}^{I}\frac{\boldsymbol{b}_i^2(n)+\boldsymbol{b}_i'\boldsymbol{b}_i}{\gamma_i(\sigma^2+\boldsymbol{b}_i'\boldsymbol{b}_i)} \ll \sum_{i=1}^{I}\frac{1}{\gamma_i} \tag{A.10}$$

A sufficient condition for equation (A.10), and also $R_n \ll 1$, is

$$\frac{\boldsymbol{b}_i^2(n) + \boldsymbol{b}_i'\boldsymbol{b}_i}{\sigma^2 + \boldsymbol{b}_i'\boldsymbol{b}_i} \ll 1 \tag{A.11}$$

$$\Rightarrow \boldsymbol{b}_i^2(n) \ll \sigma^2 \tag{A.12}$$

Finally, consider the off-diagonal element (n, m) for $m \neq n, n'$:

$$[\boldsymbol{\mathcal{M}}]_{n,m} = \frac{\sigma^2}{r} + \frac{\sigma^2}{r^2}\, \boldsymbol{\rho}_n' \boldsymbol{L} \boldsymbol{\rho}_m$$

If we have that $\boldsymbol{b}_i(n) \approx \boldsymbol{b}_i(n')$ for all $i = 1, \cdots, I$, we would have that $\boldsymbol{\rho}(n) \approx \boldsymbol{b}(n')$ and therefore $[\boldsymbol{\mathcal{M}}]_{n,m} \approx [\boldsymbol{\mathcal{M}}]_{n',m}$.

This ends the proof of Proposition 1.

A.3 Further Addressing the Endogeneity Concerns

Although we have verified the endogeneity of supply shocks, a potential concern is that such uninformative shock may still correlate with the assets' future payoffs through the changes in firms' fundamentals or liquidity. In this section, we show that this concern could be further addressed by adding the difference-in-difference in the control variables in our baseline regression, as we specified in equation 16.

We begin by express the equilibrium price in equation (6) in total differential:

$$d\boldsymbol{P} = \boldsymbol{\mathcal{M}} \left(\sum_{i=1}^{I} \frac{1}{\gamma_i} \boldsymbol{\Sigma}_i^{-1} d\boldsymbol{\mu}_i - d\boldsymbol{S} \right) \tag{A.13}$$

In our main context, we have assumed $d\boldsymbol{\mu}_i \equiv \boldsymbol{0}$ while the potential concern is that the supply shock $d\boldsymbol{P}$ could still be correlated $d\boldsymbol{\mu}_i$, that is, $Cov(d\boldsymbol{P}, d\boldsymbol{\mu}_i) \neq 0$. Motivated by equation (A.13) and define $\Delta S(n) > 0$ as the exogenous amount of share repurchases and $\Delta S(n) < 0$ as the amount of increased share supplies, we can express the price change in stock n as

$$\Delta P(n) = \sum_{m=1}^{N} [\boldsymbol{\mathcal{M}}]_{n,m} \left(\sum_{i=1}^{I} \frac{1}{\gamma_i} \sum_{k=1}^{N} [\boldsymbol{\Sigma}_i^{-1}]_{m,k} \Delta \boldsymbol{\mu}_i(k) \right) + \sum_{m=1}^{N} [\boldsymbol{\mathcal{M}}]_{n,m} \Delta S(m) \tag{A.14}$$

Therefore, the double differences between the matched stock pairs (n, n') is

$$\begin{aligned} \Delta P(n) - \Delta P(n') = &\sum_{m=1}^{N} \left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \left(\sum_{i=1}^{I} \frac{1}{\gamma_i} \sum_{k=1}^{N} [\boldsymbol{\Sigma}_i^{-1}]_{m,k} \Delta \boldsymbol{\mu}_i(k) \right) \\ &+ \sum_{m=1}^{N} \left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \Delta S(m) \end{aligned} \tag{A.15}$$

Given the assumptions that $[\boldsymbol{\mathcal{M}}]_{n,m} \approx [\boldsymbol{\mathcal{M}}]_{n',m}$, $[\boldsymbol{\Sigma}_i^{-1}]_{n,m} \approx [\boldsymbol{\Sigma}_i^{-1}]_{n',m}$ for any $m \neq n, n'$, and that $[\boldsymbol{\mathcal{M}}]_{n,n} \approx [\boldsymbol{\mathcal{M}}]_{n',n'}$, $[\boldsymbol{\Sigma}_i^{-1}]_{n,n} \approx [\boldsymbol{\Sigma}_i^{-1}]_{n',n'}$,[23] we can simplify equation (A.15) as

$$\begin{aligned} &\Delta P(n) - \Delta P(n') = \left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \Delta S(n) + \\ &\left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \left\{ \sum_{i=1}^{I} \frac{1}{\gamma_i} \left[\sum_{k=1}^{N} \left(\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n,k} - \left[\boldsymbol{\Sigma}_i^{-1}\right]_{n',k} \right) \right] \Delta \boldsymbol{\mu}_i(k) \right\} \end{aligned} \tag{A.16}$$

$$\begin{aligned} &= \left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \Delta S(n) + \\ &\left([\boldsymbol{\mathcal{M}}]_{n,m} - [\boldsymbol{\mathcal{M}}]_{n',m} \right) \left\{ \sum_{i=1}^{I} \frac{1}{\gamma_i} \left(\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n,n} - \left[\boldsymbol{\Sigma}_i^{-1}\right]_{n',n} \right) \left(\Delta \boldsymbol{\mu}_i(n) - \Delta \boldsymbol{\mu}_i(n') \right) \right\} \end{aligned} \tag{A.17}$$

To motivate an empirically tractable regression settings, we can proxy $\Delta \boldsymbol{\mu}_i(n) - \Delta \boldsymbol{\mu}_i(n') = \boldsymbol{\gamma}_i \Delta \boldsymbol{X}(n, n') + \varepsilon_i$ in which $\Delta \boldsymbol{X}(n, n')$[24] represents the double differences in observables such as size, growth opportunity, profitability, dividend payouts, market's beta, etc., between the treatment and controls, before and after the supply shocks. $\boldsymbol{\gamma}_i$ and ε_i represent investor specific preference on observables and latent demand, similar to Koijen et al. (2023).

[23] Such conditions can be satisfied based on our microfoundation of price multipliers in section 2.3.

[24] We can also add industry fixed effects as control variables and repeat the deviation to get the regression with fixed effects.

Therefore, we can further simplify equation (A.17) as

$$
\begin{aligned}
&\underbrace{\left([\boldsymbol{\mathcal{M}}]_{n,m}-[\boldsymbol{\mathcal{M}}]_{n',m}\right)}_{\bar{\mathcal{M}}}\Delta S(n)+\\
&\underbrace{\left([\boldsymbol{\mathcal{M}}]_{n,m}-[\boldsymbol{\mathcal{M}}]_{n',m}\right)\left\{\sum_{i=1}^{I}\frac{1}{\gamma_i}\left(\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n,n}-\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n',n}\right)\boldsymbol{\gamma}_i\right\}}_{\gamma}\Delta\boldsymbol{X}(n,n')+\\
&\underbrace{\left([\boldsymbol{\mathcal{M}}]_{n,m}-[\boldsymbol{\mathcal{M}}]_{n',m}\right)\left\{\sum_{i=1}^{I}\frac{1}{\gamma_i}\left(\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n,n}-\left[\boldsymbol{\Sigma}_i^{-1}\right]_{n',n}\right)\varepsilon_i\right\}}_{\varepsilon}
\end{aligned}
\tag{A.18}
$$

which is aligned with our specification in equation (16). Empirically, we compare the regression results before and after adding the controls of observables and find nearly identical estimated coefficient, implying that the supply shocks in our sample likely do not correlate with the changes in firms' fundamentals or liquidity.

A.4 Discussion on Demand-side Instruments

Suppose researchers aim to identify the price multiplier for stock n using a demand-side instrument, $\sum_{i=1}^{I} Z_i(n)$. We can broadly divide demand-side instruments into demand shifter and demand shock approaches. Demand shifter captures the hypothetical shift in aggregate demand curve. Investors hold optimal portfolio by internalizing demand shifters. Such shifters may come from, for instance, the unexpected inflows or outflows into mutual fund sectors(Lou, 2012; Chaudhary et al., 2023). Demand shock, however, reflects the actual equilibrium quantity change resulted from, for example, index inclusions and deletions (Shleifer, 1986; Chang et al., 2015; Pavlova and Sikorskaya, 2023), regulatory regime shifts (Cassella et al., 2024), or dividend reinvestment (Schmickler and Tremacoldi-Rossi, 2023; Hartzmark and Solomon, 2024; Chen, 2024).

Similar to equation (10), we can generally express the analytical price change with respect to the demand-side instruments as:

$$\Delta P(n) = \underbrace{[\boldsymbol{\mathcal{M}}]_{n,n} \times \left(\sum_{i=1}^{I} Z_i(n)\right)}_{\text{Direct Effect}} + \underbrace{\sum_{m \neq n}^{N} \left([\boldsymbol{\mathcal{M}}]_{m,n} \times \sum_{i=1}^{I} Z_j(m)\right)}_{\text{Spillover Effects}} \tag{A.19}$$

As we discuss in Section 2.2, the total price change in stock n consists of direct effect and spillover effects. We list two empirical identification challenges here.

A.4.1 Special Challenge to Demand Shock Approach

We first discuss a special challenge faced by demand shock approach: it can only identify the residual price multiplier because the total demand change is zero under the fixed supply assumption. To see this point, suppose a subgroup of investors $j = 1, ..., J$ $(1 \leq J < N)$ experiences exogenous shocks to their demands, captured by the shock vector $\Delta\tilde{\boldsymbol{q}}_j = (\Delta\tilde{q}_j(1), ..., \Delta\tilde{q}_j(N))'$. As a result, their portfolio holdings shift from the initial optimal allocation $\boldsymbol{q}_j^{\text{optimal}}$ to a new portfolio $\boldsymbol{q}_j^{\text{new}}$ (not necessarily optimal):

$$\boldsymbol{q}_j^{\text{new}} = \boldsymbol{q}_j^{\text{optimal}} + \Delta\tilde{\boldsymbol{q}}_j,\ j \in \{1, ..., J\} \tag{A.20}$$

Therefore, the demand-side instrument $\boldsymbol{Z}_j$ now is $\Delta\tilde{\boldsymbol{q}}_j$. We can then divide investors into two groups. The residual supply is the total supply out of the aggregate demand of shocked investors $j = 1, ..., J$, while the aggregate demand of the remaining investors, $i = J + 1, \ldots, N$, constitutes the residual demand:

$$\underbrace{\boldsymbol{S} - \sum_{j=1}^{J} \boldsymbol{q}_j}_{\text{Residual Supply}} = \underbrace{\sum_{j=J'+1}^{I} \boldsymbol{q}_i}_{\text{Residual Demand}} \tag{A.21}$$

The exogenous change in residual supply is therefore given by:

$$\underbrace{\left(\boldsymbol{S} - \sum_{j=1}^{J} \boldsymbol{q}_j^{\text{new}}\right)}_{\text{New Residual Supply}} - \underbrace{\left(\boldsymbol{S} - \sum_{j=1}^{J} \boldsymbol{q}_j^{\text{optimal}}\right)}_{\text{Previous Residual Supply}} = -\sum_{j=1}^{J} \Delta\tilde{\boldsymbol{q}}_j \tag{A.22}$$

Equation (A.22) shows that exogenous changes in the holdings of a subgroup of investors generate variation in the residual supply faced by the remaining investors.

With the change in residual supply, the market equilibrium prices adjust to $\boldsymbol{P}^{\text{new}}$ so that each of the remaining investor $i \in \{J+1, ..., I\}$ holds a new optimal portfolio $\boldsymbol{q}_i^{\text{new}}$:

$$\boldsymbol{q}_i^{\text{new}} = \frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{\mu}_i - \boldsymbol{P}^{\text{new}}),\ i \in \{J+1, ..., I\} \tag{A.23}$$

Define equilibrium price change vector $\Delta\boldsymbol{P} = \boldsymbol{P}_1^{\text{new}} - \boldsymbol{P}_1$, we can express the demand changes in each of the remaining investors as

$$\Delta\boldsymbol{q}_i = -\frac{1}{\gamma_i}\boldsymbol{\Sigma}_i^{-1}\Delta\boldsymbol{P},\ i \in \{J+1, ..., I\} \tag{A.24}$$

Since the asset supply is fixed, market clearing condition (5) implies that the total changes in investors' portfolio holdings equal zero. Separated by investor groups, we have

$$\sum_{j=1}^{J}\Delta\tilde{\boldsymbol{q}}_j + \sum_{i=J+1}^{I}\Delta\boldsymbol{q}_i = 0 \tag{A.25}$$

Combined with equation (A.24), we can then express equation (A.25) as

$$\underbrace{\sum_{i=J+1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_{\boldsymbol{i}}^{-1}\Delta\boldsymbol{P}}_{\text{Changes in Residual Demand}} \quad = \quad \underbrace{\sum_{j=1}^{J}\Delta\tilde{\boldsymbol{q}}_j}_{\text{Changes in Residual Supply}} \tag{A.26}$$

The exogenous variation in residual supply, $\sum_{j=1}^{J}\Delta\tilde{\boldsymbol{q}}_j,\ j \in \{1, ..., J\}$, together with the observed price changes $\Delta\boldsymbol{P}$, identifies only the price multiplier of the unshocked investors. The residual price multiplier matrix is given by:

$$\boldsymbol{\mathcal{M}}^{\text{res}} \ \triangleq\ -\frac{\partial\boldsymbol{P}}{\sum_{i=J+1}^{I}\partial\boldsymbol{q}_i} = \left(\sum_{i=J+1}^{I}\frac{1}{\gamma_i}\boldsymbol{\Sigma}_{\boldsymbol{i}}^{-1}\right)^{-1} \tag{A.27}$$

An unbiased estimate of the residual price multiplier still requires knowledge of the shocked investors and affected assets, as discussed above. For example, Pavlova and Sikorskaya (2023) obtains a lower residual price multiplier estimates than Chang et al. (2015) after including mutual funds as the shocked investors.

Intuitively, the investors in residual demand, indexed by $J+1,\ldots,I$, collectively absorb the changes in residual supply. The residual price multiplier $[\boldsymbol{\mathcal{M}}^{\text{res}}]_{n,n}$, identified from equation (A.27), is generally *different* from the aggregate price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$, because $[\boldsymbol{\mathcal{M}}^{\text{res}}]_{n,n}$ excludes the investors contributing to the residual supply. Consequently, empirical studies that exploit residual supply variation identify the price multiplier contributed by specific investor subgroups rather than by the entire market. For example, Pavlova and Sikorskaya (2023) estimates the price multipliers of investors without index benchmark using the index inclusion as demand shocks. This approach therefore leads to substantial heterogeneity in empirical estimates.

A.4.2 Challenges to Demand Shifter and Demand Shock Approaches

Now, we discuss two general challenges faced by both demand shifter and demand shock approaches. The only difference is that the demand shifter approach is aim to identify the stock-level own price multiplier while the demand shock approach can only identify the price multiplier of residual demand curve (unshocked investors). For simplicity, we consider a demand shifter approach aiming to identify the aggregate price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ in the following context. All discussions hold if we replace the $[\boldsymbol{\mathcal{M}}]_{n,n}$ with the residual price multiplier $[\boldsymbol{\mathcal{M}}^{\text{res}}]_{n,n}$ under a demand shock approach.

Challenge I: Bias from omitted shocked investors. An unbiased estimates of price multiplier $[\boldsymbol{\mathcal{M}}]_{n,n}$ requires a clear classification of shocked investors, which is empirically challenging. For example, if only a stock n faces a shift in aggregate demand curve and researchers observe only a subset of $J<I$ investors' demand shifters but ignore the remaining $I-J$ investors', a mis-specified regression would be:

$$\Delta P(n) = \hat{\mathcal{M}}_{n,n} \times \underbrace{\left(\sum_{i=1}^{J} u_i(n)\right)}_{\text{Observed Shocked Investors}} + \varepsilon(n) \tag{A.28}$$

Here, the demand-side instruments are the demand shifters in stock n by investors ($Z_i(n) = u_i(n)$). Such specification suffers the measurement errors in the independent variable:

$$\underbrace{\sum_{i=1}^{J} u_i(n)}_{\text{Observed Shocked Investors}} = \underbrace{\sum_{i=1}^{I'} u_i(n)}_{\text{All Shocked Investors}} + \underbrace{\left(-\sum_{i=J+1}^{I'-J} u_i(n)\right)}_{\text{Measurement Errors: Unobserved Shocked Investors}} \tag{A.29}$$

Intuitively, if omitted all investors' holding changes, specification (A.28) would attribute the price change solely to the demand changes in a subset of investors, $\sum_{i=1}^{J} u_i(n)$, thus bias the estimate of own-price multiplier.[25]

Challenge II: Bias from correlated shocked assets. Even if researchers can accurately observe all shocked investors, correct identification still requires controlling for holding changes across all simultaneously shocked assets $m \neq n$, i.e., $\sum_{i=1}^{I} Z_i(m)$ for $m = 1, \ldots, N$. Consider, for example, only a mutual fund (investor 1) experiencing a capital outflow and responding by liquidating a portfolio of assets simultaneously (Coval and Stafford, 2007). In this case, multiple assets are sold at the same time, resulting in positively correlated holding changes across the shocked assets. If researchers consider only the change in holdings of stock n after observing its price change $\Delta P(n)$, a mis-specified regression would be:

$$\Delta P(n) = \hat{\mathcal{M}}_{n,n}\ u_1(n) + \varepsilon(n) \tag{A.30}$$

Here, again, the demand-side instrument is the demand shifter constructed from investor 1's unexpected outflow ($Z_1(n) = u_1(n)$). This specification suffers from omitted-variable bias because it ignores the concurrent demand shifts in other assets, that is, $u_1(m)$ for all $m \neq n$. The accurate specification should be:

$$\Delta P(n) = \hat{\mathcal{M}}_{n,n} \times u_1(n) + \underbrace{\left(\sum_{m \neq n}^{N} \hat{\mathcal{M}}_{n,m} \times u_1(m)\right)}_{\text{Omitted Variables: Spillover Effects}} + \tilde{\varepsilon}(n) \tag{A.31}$$

in which $\hat{\mathcal{M}}_{n,n}$ and $\hat{\mathcal{M}}_{n,m}$ are the regression coefficients aiming to identify the own-price and

[25] Analytically, denote $\sum_{i=1}^{I} u_i(n)$ as x, $\sum_{i=J+1}^{I} u_i(n)$ as u, we can express the bias as $\hat{\mathcal{M}}_{n,n} - \mathcal{M}_{n,n} = \frac{\text{Cov}(\varepsilon(n),u) - [\boldsymbol{\mathcal{M}}]_{n,n} \times [\text{Var}(u) - \text{Cov}(x,u)]}{\text{Var}(x) + \text{Var}(u) + 2\text{Cov}(x,u)}$ as in Wooldridge (2010).

cross-price multipliers, $[\boldsymbol{\mathcal{M}}]_{n,n}$ and $[\boldsymbol{\mathcal{M}}]_{n,m}$, respectively. Intuitively, if stock n and other assets $m \neq n$ experience positively correlated demand shocks, that is, $\mathrm{Cov}\left(u_1(n), u_1(m)\right) > 0$, then specification (A.30) will upwardly bias the estimated own-price multiplier, as it fails to account for price spillover effects from other shocked assets.[26] Chaudhary et al. (2023) provides a similar evidence on corporate bond market that controlling correlated demand shocks yields a lower price multiplier.

A.5 Identification of Demand Curve in Koijen and Yogo (2019)

We present detailed discussions on the aggregate demand elasticity measure from Koijen and Yogo (2019). We show that they estimate aggregate elasticity in two steps: first, estimate individual elasticity from individual demand function; and second, aggregate all investors' demand elasticities to stock level.

Step 1: They estimate the following demand function to obtain coefficient $\beta_{0,i}$:

$$\frac{w_i(n)}{w_i(0)} = \delta_i(n) \; = \; \exp\left(\beta_{0,i}\, me(n) \; + \; \sum_{k=1}^{K-1} \beta_{k,i}\, x_k(n) \; + \; \beta_{K,i}\right) \varepsilon_i(n) \tag{A.32}$$

in which $w_i(n)$ is the investor i's weights on stock n in her portfolio, and $w_i(0)$ is her weight on outside assets. $me(n)$ is the market value in stock n and $x_k(n)$ is the kth characteristics in stock n.

Step 2: After obtaining the coefficient $\beta_{0,i}$, they calculate the aggregate demand elasticity as in the equation (15) of Koijen and Yogo (2019):

$$[\boldsymbol{\mathcal{E}}]_{n,n} = -\frac{\partial q(n)}{\partial p(n)} = 1 - \frac{1}{\sum_{i=1}^{I} A_i w_i(n)} \sum_{i=1}^{I} A_i \beta_{0,i} \left[w_i(n) - w_i^2(n)\right] \tag{A.33}$$

in which A_i is the wealth level of investor i.

[26] Specifically, if we denote $x \triangleq u_1(n)$ and $z_m \triangleq u_1(m), m \neq n$, we can express the bias as $\mathrm{Sign}(\hat{\mathcal{M}}_{n,n} - \mathcal{M}_{n,n}) = \mathrm{Sign}(\sum_{m \neq n} [\boldsymbol{\mathcal{M}}]_{m,n} \times \mathrm{Cov}(x, z_m))$, as shown in Wooldridge (2010). Therefore, if $\mathrm{Cov}(x, z_m) > 0$, that is, the mutual fund liquidates multiple assets simultaneously, we would get an upwardly biased estimates.

Similarly, they calculate the aggregate cross-elasticity as

$$[\boldsymbol{\mathcal{E}}]_{n,m} = -\frac{\partial q(n)}{\partial p(m)} = \frac{1}{\sum_{i=1}^{I} A_i w_i(n)} \sum_{i=1}^{I} A_i \beta_{0,i} w_i(n) w_i(m) \tag{A.34}$$

To ensure a unique market-clearing price exists, Koijen and Yogo (2019) impose the coefficient constraint $\beta_{0,i} < 1$ in the step 1, which implicitly assume all investor's demand curves are downward sloping. This assumption is critical, as investor-level demand elasticity is defined by equation (14) in Koijen and Yogo (2019):

$$\begin{aligned}\left[\boldsymbol{\mathcal{E}^i}\right]_{n,n} &= -\frac{\partial q_i(n)}{\partial p(n)} = 1 - \frac{1}{A_i w_i(n)} A_i \beta_{0,i} \left[w_i(n) - w_i^2(n)\right] \\ &= 1 - \beta_{0,i} + \beta_{0,i} w_i(n) \end{aligned} \tag{A.35}$$

Thus, the condition $\beta_{0,i} < 1$ is sufficient to ensure that $\left[\boldsymbol{\mathcal{E}^i}\right]_{n,n} > 0$, i.e., each investor's demand curve is downward sloping. However, imposing this constraint may exclude certain investors with demand elasticity is negative, $\left[\boldsymbol{\mathcal{E}^i}\right]_{n,n} < 0$, such as momentum funds, meaning their holdings $q_i(n)$ increase with price $p(n)$. van Binsbergen et al. (2025) find that around 50% of estimates are negative if removing such coefficient restriction. As a result, the structural approach in Koijen and Yogo (2019) effectively identifies the elasticity only for investors with downward-sloping demand curves, biasing the estimation of aggregate elasticity by truncating negative individual elasticities to zero. In contrast, supply shocks offer a one-shot identification of aggregate demand curve without assumptions above.

A.6 Mis-measurement in Koijen and Yogo (2019)'s Instrument

For each investor i, Koijen and Yogo (2019) construct an instrumental variable for market equity $me(n)$ to estimate the demand function specified in equation (A.32). The instrument is derived from the investment mandates of all other investors $j \neq i$:

$$\hat{me}_i(n) = \sum_{j \neq i} A_j \cdot \frac{\mathbb{1}\left\{n \in N_j\right\}}{1 + |N_j|} \tag{A.36}$$

where N_j is investor j's investment mandate and $\mathbb{1}\{n \in N_j\}$ equals one if stock n is in investor j's investment mandate and zero otherwise. The cross-sectional variation in the instrument thus arises from the number of investors who include stock n in their investment mandates. That is, each stock is included in a different number of investors' investment mandates. Intuitively, if stock n is part of investor j's mandate, it is treated as being "shocked" by investor j's demand. Therefore, $\mathbb{1}\{n \in N_j\} = 1$ corresponds to $Z_j(n) > 0$ in our discussion in Appendix A.4. In this sense, their instrument exploits $\sum_{j \neq i}^{N} Z_j(n)$, the variation in residual supply generated by all other investors j, when estimating the demand curve of investor i.

As noted in Koijen and Yogo (2019), most institutions do not disclose their investment mandates, and researchers must therefore infer them from observed portfolio holdings. In each quarter, Koijen and Yogo (2019) define an investor's mandate as the set of stocks currently held or ever held in the previous 11 quarters. However, if investor i chooses not to hold stock n—despite it being within her mandate—due to her latent demand $\varepsilon_i(n)$, the method in Koijen and Yogo (2019) would incorrectly classify stock n as outside her mandate. This mis-classification results in a mis-measurement of the investment mandate. As the authors acknowledge, "any correlation between this mis-measurement and latent demand through correlated demand shocks across investors could threaten identification."

To explicitly see this point, suppose an investor j chooses not to hold the stock n in her mandate due to her low latent demand $\varepsilon_j(n)$, the construction instrument for investor i, $\hat{me}_i(n)$, would assign $\mathbb{1}\{n \in N_j\} = 0$, resulting a lower value of $\hat{me}_i(n)$. Therefore, $\text{Cov}(\hat{me}_i(n), \varepsilon_j(n)) > 0$. If investors i and j exhibit positively correlated latent demand, that is, $\text{Cov}(\varepsilon_i, \varepsilon_j) > 0$, we would have $\text{Cov}(\hat{me}_i(n), \varepsilon_i) > 0$. In other words, the instrument is positively correlated with investor i's latent demand, resulting an upward bias of $\beta_{0,i}$ in equation (A.32). An upwardly biased $\beta_{0,i}$ implies a downward bias of demand elasticity in equation (A.35). In contrast, a firm is a special trader whose investment mandate only consists of its own stock. Therefore, using supply shocks avoids the concern of mis-measuring the investment mandates.

B. Variable Definition

Variable	Definition
Repurchase Payout	Share repurchase payouts, estimated by the total expenditures in common stock repurchases (CSHOPQ$\times$PRCRAQ), divided 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, depending on the availability in the order of redemption (PSTKRQ) and capital (pstkq). It is expressed in percentage point.
Equity Issuance	Equity issuance, estimated by the sales of common and preferred stocks (SSTKQ) minus any increase in preferred stocks, scaled by lagged book equity. It is expressed in percentage point.
Dividend Payout	Dividend payouts, estimated by common stock dividends (DVQ - DVPQ), divided by lagged book equity. 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.
Size	Natural logarithm of total assets (ATQ).
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. It is expressed in percentage point.

Growth	Growth opportunity, estimated by the market value of equity (PRCCQ$\times$CSHOQ) plus book value of total assets (ATQ) minus the book value of common equity (CEQQ) minus the deferred taxes from balance sheet (TXDBQ), divided by the lagged total assets (ATQ).
Investment	Quarterly growth of total assets (ATQ). 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.
Quote Spread	The average of daily percent quote spread in the pre-treatment period (2014Q4-2016Q3). Percent 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 percent quoted spread is the time weighted average percent quoted spread computed over all time intervals.

C. Additional Empirical Results

C.1 Tests of Homogeneous Idiosyncratic Volatility

We test whether the idiosyncratic volatility is similar between treatment and control stocks. To do so, for each year-month, we respectively regress the daily excess stock returns of treatment and control stocks, on the market excess return factor. Next, we calculate the average idiosyncratic volatility as the equal-weighted average variance of residuals. Consistent with our assumption of constant idiosyncratic volatility, Figure C.1 shows the nearly identical patterns of idiosyncratic volatility (t-statistics = -0.6914) between matched treatment and control stocks conditional on observables.

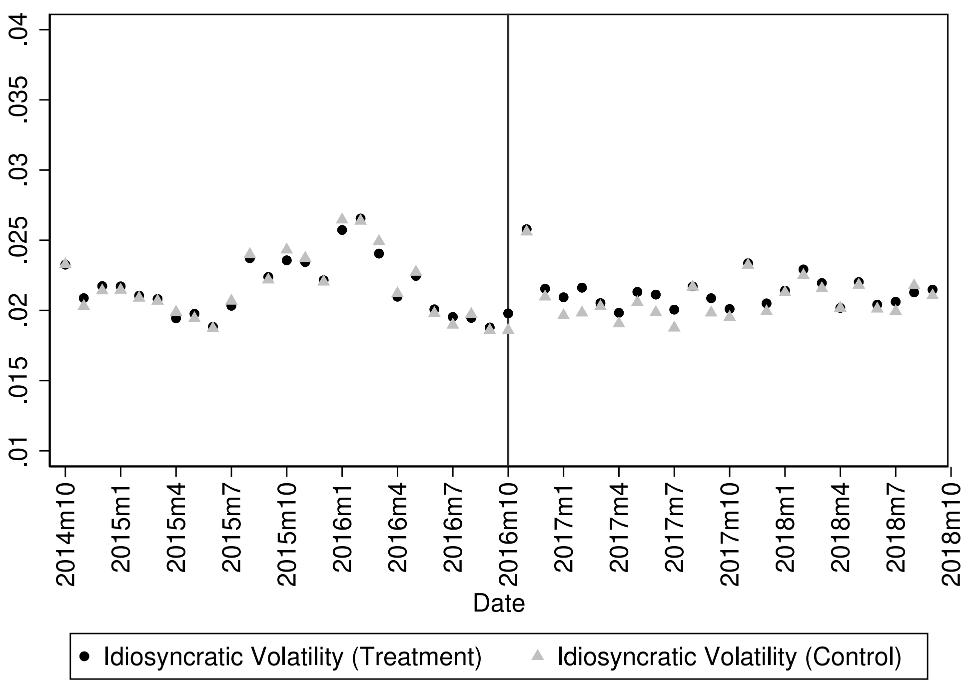

Figure C.1. Balance on variances: average idiosyncratic volatility. This figure testifies our assumption of constant volatility, by comparing the average idiosyncratic volatility between treatment and control stocks. At each month, we calculate the equal-weighted average idiosyncratic volatility by regressing daily excess stock returns on market excessive return. The time series is the pre-treatment period from October 2014 to September 2018.

Table C.1 reports t-tests under alternative factor structures. In addition to the market factor, we compute idiosyncratic volatility using the Fama–French three-factor model, the

Carhart four-factor model, and the Fama–French five-factor model. Across all specifications, we find no statistically significant differences in idiosyncratic volatility between treatment and control firms in our sample.

Table C.1
t-test for the Differences in Idiosyncratic Volatility

Idiosyncratic Volatility	Treatment	Control	t-statistics
Market Factor	0.0212	0.0215	-0.691
Fama-French Three Factors	0.0193	0.0195	-0.832
Carhart Four Factors	0.0185	0.0188	-0.861
Fama-French Five Factors	0.0178	0.0181	-0.881

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

C.2 Dynamic Tests

A key identifying assumption in DID estimates is the parallel trends assumption. It posits that, prior to the TSP, the treatment and control groups should exhibit similar trends in share repurchase, or show an insignificant decremental effect of treatment over the control group. Following the shock, a notable divergence is expected, indicating a significant decremental effect in share repurchase (incrumental effect in share supply).

To test this assumption, we replace $Post_t$ in Equation (24) with event-time dummy variables, defined relative to the commencement quarter of TSP. Displayed in Figure C.2 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. Furthermore, the figure demonstrates a significant drop in share repurchase following the implementation and remains robust from the second quarter after the implementation of TSP.

Our baseline specification (26) estimates the aggregate price multiplier averaging over post-treatment period. To ensure our estimate is not driven by short- or long-run horizons,

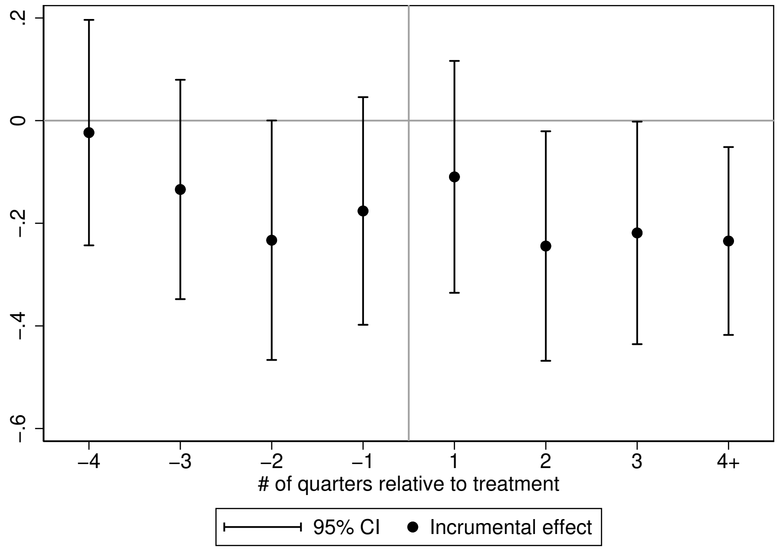

Figure C.2. Event study. This figure presents the results from an event-time analysis of the effect of TSP on share repurchase. We re-estimate the Equation (24) by replacing the dummy variable $Post_t$ with a set of indicators for the quarters around the implementation of TSP for each firm in our sample. Quarter -h (h) refers to the h-th quarter before (after) the closing auction is implemented. Quarter 0 refers to the quarter when the TSP is implemented. Quarter 4+ refers to four or more quarter after the TSP is implemented. The figure reports the coefficient estimates on the interactions between each event quarter indicator and $Treatment_i$, along with their 95% confidence intervals.

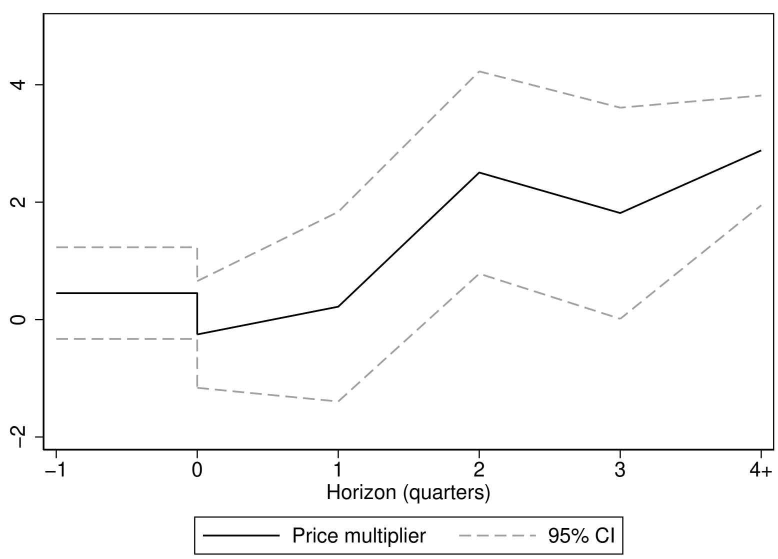

Figure C.3. Dynamic effect. This figure presents the estimates of aggregate price multiplier by horizons (quarters) using Equation (C.1). Quarter -h (h) refers to the h-th quarter before (after) the closing auction is implemented. Quarter 0 refers to the quarter when the TSP is implemented. Quarter 4+ refers to four or more quarter after the TSP is implemented. The figure reports $\mathcal{M}_h$ along with their 95% confidence intervals.

we re-estimate the aggregate price multiplier by quarters (horizons):

$$\Delta p_{j,h} - \Delta p_{j,0} = \mathcal{M}_h(\Delta s_{j,h} - \Delta s_{j,0}) + \text{Controls} + \varepsilon_{j,h} \tag{C.1}$$

where quarter -h (h) refers to the h-th quarter before (after) the closing auction is implemented. Quarter 0 refers to the quarter when the TSP is implemented. Figure C.3 presents the results. The estimated price multiplier becomes significantly positive and stable after the first quarter since the commencement of TSP.

C.3 Placebo Tests

Table C.2
Placebo Test

	$\Delta p_{j,t}$	
	Placebo (1)	Pre-treatment (2)
$\boldsymbol{\Delta s_{j,t}}$	**-0.025**	**0.108**
	(0.27)	**(0.18)**
Controls	Yes	Yes
Industry-Time FE	Yes	Yes
Obs.	1,762	3,891
Adj. R^2	0.529	0.369

Note. This table presents the tests of the effects of cross-asset spillover on our estimation of price multiplier. In column (1), we use a counterfactual shock, with pre- and post-treatment period as 2013Q4–2014Q3 and 2014Q4–2015Q3, respectively. In column (2), we estimate the demand elasticity in pre-treamt period only (2014Q4-2016Q3). Controls include the difference-in-differences of size, profitability, growth opportunity, investment, dividend payout, and market beta. Industry-by-year-quarter fixed effects are included. The robust standard errors clustered at industry-by-time level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 1 shows the price of treatment stocks and matched control stocks comove with each other when there's no exogenous supply shock. It indicates that the matching procedure find close substitute with no supply shock for treatment stock. In this section, we conduct placebo tests to further support this argument. If there's no exogenous supply shock between treatment and control, we should obtain no variation in both stock prices and share repurchase, and subsequently insignificant estimate of price multiplier.

In column (1) of Table C.2, we report the results using two years before the Pilot implementation as a placebo shock. The pre-treatment and post-treatment period is 2013Q4–2014Q3 and 2014Q4–2015Q3, respectively. In column (2), we repeat the estimation of Equation (26) in pre-treatment period only (2014Q3 - 2016Q3), $\bar{\mathcal{M}}$ is insignificant. Taking together, Table C.2 indicates that the price of treatment and matched control comove with each other when there's no exogenous supply shocks.

C.4 Aggregate Elasticity Estimates from Koijen and Yogo (2019)

Following Equation (14) in Koijen and Yogo (2019), the individual demand elasticity is estimated by

$$-\frac{\partial \mathbf{q}_{i,t}}{\partial \mathbf{p}_t^{'}} = \mathbf{I} - \beta_{0,i,t}\mathrm{diag}(\mathbf{w}_{i,t})^{-1}\mathbf{G}_{i,t} \tag{C.2}$$

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 (A.32). And $\mathbf{G}_{i,t} = \mathrm{diag}(\mathbf{w}_{i,t}) - \mathbf{w}_{i,t}\mathbf{w}_{i,t}'$.

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

$$-\frac{\partial \mathbf{q}_t}{\partial \mathbf{p}_t^{'}} = \mathbf{I} - \sum_{i=1}^{I} \beta_{0,i,t} A_{i,t}\mathbf{H}_t^{-1}\mathbf{G}_{i,t} = \sum_{i=1}^{I} \frac{A_{i,t}\mathbf{w}_{i,t}}{\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}} \left(-\frac{\partial \mathbf{q}_{i,t}}{\partial \mathbf{p}_t^{'}}\right) \tag{C.3}$$

Table C.3 reports the estimated aggregate and investor-type specific demand elasticities following the same approach in Koijen and Yogo (2019) for our treatment firms and sample periods from 2016Q4 to 2018Q3.

Table C.3
Demand Elasticity by Investor Types

Variable	N	Mean	SD	Min	p10	p50	p90	Max
Banks	4,150	0.592	0.158	0.454	0.454	0.497	0.948	0.948
Insurance companies	4,198	0.144	0.097	0.010	0.010	0.140	0.272	0.607
Investment advisors	3,494	0.086	0.071	0.010	0.010	0.080	0.154	1.020
Mutual funds	4,237	0.418	0.082	0.010	0.332	0.412	0.513	0.995
Pension funds	4,241	0.164	0.071	0.010	0.064	0.167	0.250	0.455
Other	3,893	0.096	0.062	0.010	0.010	0.097	0.171	0.458
Households	3,735	0.233	0.131	0.010	0.040	0.235	0.375	0.950
Aggregate	4,399	0.386	0.158	0.078	0.205	0.365	0.594	0.970

C.5 Instrument Variable Regression for Reduction in Repurchases

In Section 5, we exploit two sources of randomness in the TSP, the assignment of treatment stocks and the exogenous reduction in share repurchases during the TSP, to construct the supply shock as the difference-in-difference between matched treatment and control stocks, before and after the TSP. An alternative approach is to only leverage the randomness of the stock assignment as instrument for share repurchases. A caveat is that 2SLS-IV regression cannot fully control for spillover effects from the simultaneous supply shocks faced by all treatment stocks. Nevertheless, we specify the first-stage regression as follows:

$$Repurchase\ Payout_{n,t} = \beta D_{n,t} + +\boldsymbol{\gamma}'\boldsymbol{X}_{n,t} + u_n + u_{(g)t} + \varepsilon_{n,t} \tag{C.4}$$

where $Repurchase\ Payout_{n,t}$ is the quarterly repurchase payout scaled by lagged book equity in stock n at quarter t. We use the exogenous $D_{n,t}$ to instrument for the share repurchases, which is the dummy variable equal to one for treatment stock n at quarter t during the TSP period and zero otherwise. We include the following control variables $\boldsymbol{X}$ in both stages: size, growth, profitability, percentage quoted spread, stock's beta, and the inverse of price level. Finally, u_n is the stock fixed effects, and $u_{(g)t}$ is the (group by) time fixed effects. We consider three specifications with finer definition of stock groups: (1) only time fixed effects, (2) SIC-2 digit industry by time fixed effects, and (3) SIC-4 digit industry by time fixed effects. We take the industry classification as the one in last quarter before the TSP.

In the second stage, we estimate the following regression:

$$\Delta p_{n,t} = \lambda \widehat{\Delta s}_{n,t} + \boldsymbol{\gamma}' \boldsymbol{X}_{n,t} + u_n + u_{(g)t} + \nu_{n,t} \tag{C.5}$$

where $\Delta p_{n,t}$ is the quarterly stock return, $\widehat{\Delta s}_{n,t}$ is the predicted value of quarterly repurchases from the first stage equation (C.4). By construction, $\widehat{\Delta s}_{n,t}$ reflects only the exogenous variation in share repurchases, serving as supply shocks. We also include the stock fixed effect and group by time fixed effects as in the first stage. Chaudhary et al. (2023) show that, group by time fixed effects capture heterogeneous cross-asset-group substitution effects while assuming the within group cross-asset substitution pattern the same. Thus, adding group by time fixed effects can absorb the spillover effects by other treatment stocks in different industry groups while assuming stocks in the same industry have the same cross-asset substitution pattern.

Table C.4
IV-2SLS Estimation of Price Multiplier: First Stage

	Repurchase Payout$_{n,t}$		
Fixed Effects	Time (1)	SIC 2 Digit by Time (2)	SIC 4 Digit by Time (3)
$D_{n,t}$	-0.123** (0.05)	-0.117** (0.05)	-0.175*** (0.06)
Controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
F-Statistics	11.70	10.86	9.88
Obs.	16,777	16,772	13,961
Adjusted R^2	0.354	0.361	0.346

Note. This table presents the first stage regression specified in equation (C.4). We consider time fixed effect only, SIC 2 Digit industry by time fixed effects, and SIC 4 Digit industry by time fixed effects. Control variables include size, growth, profitability, percentage quoted spread, stock's beta, and the inverse of price level. The robust standard errors clustered at stock or group-by-time depending on the specification. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Tables C.4 and C.5 report the estimation results from the first and second stages, respectively. The first stage F-statistics ranges from 9.88 to 11.70, indicating a relatively strong instrument (Stock and Yogo, 2005). As Haddad et al. (2025) note, the IV regression can only recover the relative price multiplier. Therefore, under time fixed effects, we estimate the relative price multiplier to the market portfolio returns. In other words, a 1% increase in the treatment stocks' share repurchases relative to the market average would increase the stock by 2.089%. Similarly, under SIC 2 and four digit industry by time fixed effects, we estimate the relative (to industry average) price multiplier of 2.501 and 1.285, respectively.

Table C.5
IV-2SLS Estimation of Price Multiplier: Second Stage

	$\Delta p_{n,t}$		
Fixed Effects	Time	SIC 2 Digit by Time	SIC 4 Digit by Time
$\widehat{\Delta s_{n,t}}$	2.089	2.501	1.285
	(4.88)	(4.70)	(3.84)
Controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Obs.	16,775	16,770	13,959
Adj. R^2	0.188	0.206	0.191

This table presents the first stage regression specified in equation (C.5). We consider time fixed effect only, SIC 2 Digit industry by time fixed effects, and SIC 4 Digit industry by time fixed effects. Control variables include size, growth, profitability, percentage quoted spread, stock's beta, and the inverse of price level. The robust standard errors clustered at stock or group-by-time depending on the specification. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.