Anatomy of the Treasury Market: Who Moves Yields?

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Abstract

We develop an empirically tractable model of the U.S. Treasury market that incorporates investors' heterogeneous demand shocks and their responses to macroeconomic factors in determining equilibrium yields. Our estimated model enables us to (i) quantify investors' sensitivities to yields and factors, (ii) decompose yield movements by investors, and (iii) analyze investor responses during specific economic episodes. First, investor demand and factor sensitivities vary significantly across sectors and market conditions, with the overall market being quite inelastic. Second, decomposing yield drivers reveals a structural shift since the financial crisis: Before 2008, foreign investors were the primary drivers of yields, but their influence has declined markedly since then, while the Federal Reserve has stepped in as a state-contingent liquidity provider. Third, contrary to conventional wisdom, we find that foreign investors do not exhibit flight-to-safety behavior for Treasuries during market turmoil; instead, domestic investors drive the countercyclical movement of Treasury prices.

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1 Introduction

There is growing recognition that institutional investor demand is a key determinant of Treasury yields. When arbitrageurs are limited in their risk-bearing capacity, shifts in demand can have persistent effects on equilibrium yields. Studies using regulation changes and other balance sheet shocks confirm that investor demand shifts significantly affect yields. Accordingly, this investor-centric view today underpins explanations for various economic phenomena—ranging from the yield-lowering effects of foreign savings to the portfolio rebalancing mechanisms of quantitative easing and tightening. Yet, despite these insights, we lack a comprehensive understanding of which investors drive yield movements and how their influence has evolved over time.

This paper develops an equilibrium model of the Treasury market's yield that jointly incorporates all investor demand and their heterogeneous responses to yields and macroeconomic conditions. Many models of Treasury yields are, by design, silent on the heterogeneous role of investors. For example, structural approaches often assume representative agents, while factor-based pricing models overlook the role of investors by directly estimating the relationship between yields and factors. While existing investor-centric approaches allow studying the role of investor demand, in practice, they typically zoom into the role of specific investors, limiting their ability to assess aggregate yield effects. Our framework provides a flexible way to quantify and determine the equilibrium influence of all investors on yields.

We use our model to conduct three exercises. First, we estimate price and factor sensitivities at both the market and investor levels, revealing a Treasury market that is quite inelastic with substantial heterogeneity in sensitivities across investor types to changes in yields and macroeconomic factors. Aggregate demand exhibits a macro multiplier of one—a 1% increase in total Treasury demand raises prices by 1%, equivalent to a 15 basis point decline given the Treasury market's average duration of 6.5 years. Second, we decompose historical yield movements into their investor-level determinants and find a notable shift in the Treasury market's structure since the financial crisis. Before the crisis, foreign investors were the primary drivers of yield compression, but their influence has since waned. Meanwhile, U.S. banks and foreign institutions have retreated from their role as liquidity providers, whereas the Federal Reserve has stepped in, providing a liquidity backstop when yields fall too low. Third, we examine investor behavior during flight-to-safety episodes. Contrary to conventional wisdom, we find that domestic private investors increase their demand for Treasuries during market turmoils, whereas

foreign investors, if anything, reduce demand.

Our modelling framework focuses on Treasuries as an asset class, abstracting from substitution and arbitrage across the yield curve. We model investor portfolio allocation as log-linear functions of yields, macroeconomic factors, and investor-specific shocks. This log-linear specification is a first-order approximation for a broad class of portfolio choice problems, allowing us to flexibly incorporate investor-specific differences in objectives, constraints, and beliefs. These factors can vary considerably across investors and interact in complex ways, making them difficult to model explicitly. Our approach provides a tractable solution for capturing these investor heterogeneities.

To estimate the model, we compile quarterly sector-level transactions and Treasury holdings from the Financial Accounts, supplementing them with country-level Treasury International Capital (TIC) data for foreign holders and bank Call Reports. We construct a dataset of Treasury transactions for representative sectors that are mutually exclusive and collectively exhaustive of Treasury market activity. Hence, once we estimate the demand for the sectors, using market clearing, we can fully decompose yield changes into their sector-level drivers.

Estimating the model requires addressing the endogeneity of the sector's holdings and Treasury yields. The standard solution is to find idiosyncratic shocks to one sector's holdings and use these as an instrument for the yield for another sector. Such instruments are exogenous if idiosyncratic shocks across sectors are orthogonal and relevant if the shock-induced reallocation impacts yields. The challenge in our setting is that we require instruments for all sectors. Existing Treasury market instruments—such as regulatory changes and balance sheet shocks—are unsuitable as they are limited to specific sectors or short-lived episodes. Finding appropriate instruments is further complicated by the need to use shocks that meaningfully affect Treasury prices—a significant challenge given the size of the Treasury market. If shocks induce only small price movements, instruments may lack relevance, weakening estimator power and introducing bias due to weak instrument problems.

To address these challenges, we develop an optimal generalized method of moments (GMM) estimator that leverages our model's structure to identify idiosyncratic sector shocks and efficiently estimate parameters. In our framework, a sector's Treasury allocation depends on three components: (i) equilibrium yields, (ii) common drivers such as observed macroeconomic factors and other common unobserved factors, and (iii) id-

iosyncratic sector-specific drivers. Given the considerable heterogeneity in sectoral constraints and objectives, these sector-specific drivers are a significant source of variation in holdings. Our estimation strategy relies on extracting these idiosyncratic sector-specific demand shifters for one sector and using them as instruments for the yield for another sector. Like standard instruments, identification relies on idiosyncratic sector-specific drivers being orthogonal across sectors. More formally, the identifying assumption—that idiosyncratic sector-specific drivers across sectors are orthogonal—admits an overidentified system of equations. To improve efficiency, we optimally weight moment conditions, giving greater weight to shocks from sectors that exert a stronger influence on equilibrium yields e.g. larger sectors with more volatile holdings. Our estimator is an optimal GMM implementation of Granular Instrumental Variables (GIV, Gabaix and Koijen, 2024), allowing for flexible estimation in the presence of heterogeneous investors and time-varying price elasticities.

Once estimated, we use our model to conduct three key exercises. Firstly, we quantify price and factor sensitivities at both the sector and market levels. At the sector level, we find significant heterogeneity in price elasticities across sectors. On the one hand, the household sector—which includes hedge funds, endowment funds, and family offices—is relatively sensitive to yield changes. On the other hand, ETFs and pension funds' allocation and the government's Treasury issuance decisions are very price inelastic, responding minimally to yield changes.

Moreover, price elasticities have changed considerably since the financial crisis for key sectors, suggesting a shift in the "macro structure" of liquidity provision. U.S. banks have retreated from their traditional role as liquidity providers. Their demand has become 60% less price elastic than before the crisis, indicating a reduced willingness to accommodate supply and demand imbalances—consistent with the diminished risk-bearing capacity of banks post-crisis regulatory reforms (Du, Tepper, & Verdelhan, 2018; Favara, Infante, & Rezende, 2024, among others). Similarly, foreign investors have become less price elastic, a significant development given their large share of the Treasury market. In contrast, the Federal Reserve increasingly acts as a state-contingent liquidity provider, purchasing Treasuries when yields and market stress (as measured by the VIX) are high. This pattern aligns with the insurance channel of central bank asset purchases (Haddad, Moreira, & Muir, 2024).

At the market level, the aggregate demand for Treasuries is relatively inelastic. We estimate a macro multiplier of 1.0, meaning that a 1% increase in Treasury demand (as a

percentage of total outstanding) raises the overall market value of Treasuries by 1%. Expressed in yield terms, this corresponds to a 10-basis-point decline in the 10-year Treasury yield.[1]

Secondly, applying market clearing, we link Treasury yields to sector-level allocation decisions, allowing us to decompose yield changes into their sector-level drivers. This decomposition reinforces the notion that there has been a notable shift in the Treasury market structure since the financial crisis. Before 2008, foreign investors were the primary drivers of yield movements, exerting downward pressure of 74 basis points per year between 2003 and 2007—consistent with the literature's emphasis on the global savings glut during this period. However, their influence on U.S. yields has declined markedly since the crisis. Meanwhile, the Federal Reserve has emerged as a central driver of yields through its direct Treasury purchases, particularly during and following crisis episodes via quantitative easing operations. This marks a significant shift from the pre-crisis period when the Fed's influence on yields operated primarily through policy rate decisions rather than Treasury purchases.

Thirdly, we use our model to examine investor behavior in flight-to-safety episodes. These are periods when rising market risk coincides with declining Treasury yields. A common explanation for this pattern is that foreign investors engage in flight-to-quality, increasing their demand for U.S. Treasuries as market risk rises. However, we find no significant evidence that foreign investors increase their Treasury demand when the VIX rises. In fact, we observe net foreign selling pressure of Treasuries during flight-to-safety episodes. This behavior suggests that foreign investors use Treasuries as a hedge against market risk—accumulating them in low-risk periods and selling them in high-risk periods to realize their higher value (Acharya & Laarits, 2024; Acharya & Pedersen, 2005; Brunnermeier, Merkel, & Sannikov, 2024). In contrast, domestic sector significantly increases its Treasury demand in response to rising market risk, consistent with flight-to-quality behavior.

1.1 Related Literature

This paper contributes to the literature studying the role of market participants in shaping Treasury market yields. While an exhaustive review of this literature is beyond the scope

[1] Our estimate is smaller than the equity market macro multiplier of 5 (Gabaix & Koijen, 2022), potentially reflecting greater availability of substitutability between fixed-income asset classes (Chaudhary, Fu, & Li, 2023).

of this work, its overarching finding is that institutional investor demand is a first-order driver of Treasury yields. Research has highlighted the significant influence of the Federal Reserve (Gagnon, Raskin, Remache, & Sack, 2011; Haddad, Moreira, & Muir, 2024; Krishnamurthy & Vissing-Jorgensen, 2011), foreign investors (He, Nagel, & Song, 2022; Jiang, Krishnamurthy, & Lustig, 2021; Kekre & Lenel, 2024; Tabova & Warnock, 2022), banks (Jiang, Matvos, Piskorski, & Seru, 2024), mutual funds (Huang, Jiang, Liu, & Liu, 2020; Selgrad, 2023), insurance companies (Chaudhary, 2024; Koijen & Yogo, 2023), and broker-dealers (Du, Hébert, & Li, 2022; Greenwood & Vayanos, 2014; Vayanos & Vila, 2021). Our central contribution to this literature is to jointly study and quantify the role of all investors in driving the equilibrium yield. Appendix B.6 shows that our Treasury macro-multiplier estimates align with the magnitudes implied by existing price-impact studies.[2]

Specifically, our findings shed light on multiple Treasury market phenomena through three exercises. First, our decomposition of the yield demonstrates that foreign investors were the main drivers of yield compression in the pre-crisis period, in line with the global savings glut hypothesis (Bernanke, 2005; Caballero, 2006; Jiang, Richmond, & Zhang, 2024; Mendoza, Quadrini, & Ríos-Rull, 2009). However, we show that their influence has since considerably diminished. Our finding also echoes the literature documenting that outsized role of the quantitative easing by the Federal Reserve in driving yields down since the financial crisis (Haddad, Moreira, & Muir, 2024; Krishnamurthy & Vissing-Jorgensen, 2011). Third, our analysis of flight-to-safety episodes challenges the conventional view that foreign investors disproportionately increase their demand for U.S. Treasuries during periods of heightened market stress, an assumption often invoked to rationalize the countercyclicality of the U.S. dollar and its associated exorbitant privilege (Jiang et al., 2021; Jiang, Krishnamurthy, & Lustig, 2024). Our finding furthers our understanding of flight-to-safety by tracing the price movement to investors, and sheds light on the mechanism behind the USD exorbitant privilege (Campbell, Pflueger, & Viceira, 2019; He et al., 2022; Kekre & Lenel, 2024).

Broadly, our work builds on the demand-system approach to asset pricing.[3] This paper is the first to study the overall demand of Treasuries as an asset class. We provide

[2]The literature traditionally estimated price impacts, and by making assumptions about the implied size of the quantity changes used in these studies, we can map their price impact estimates to multipliers.

[3]Initially applied to the cross-section of stocks Koijen and Yogo (2019), variants have since been used to study various asset classes, including the equity market (Gabaix & Koijen, 2022), corporate bonds (Chaudhary et al., 2023), and foreign exchange rates (An & Huber, 2024; Camanho, Hau, & Rey, 2022; Jiang, Richmond, & Zhang, 2022).

the first direct macro elasticity estimate for U.S. Treasuries. Moreover, by quantifying this aggregate demand inelasticity, we contribute to the literature highlighting the role of demand shocks in driving the overall Treasury market's yield (Greenwood & Vayanos, 2010; Hanson & Stein, 2015; Krishnamurthy & Vissing-Jorgensen, 2012). Our macro multiplier estimate of 1 suggests that the U.S. Treasury market can more effectively absorb demand shocks compared to the U.S. equity market, which has a macro multiplier closer to 5 (Da, Larrain, Sialm, & Tessada, 2018; Gabaix & Koijen, 2022; Haddad, Huebner, & Loualiche, 2024; Hartzmark & Solomon, 2022; Li, Pearson, & Zhang, 2024; van der Beck, 2022), and the U.S. corporate bond market, which has a portfolio-level multiplier of 3.5 (Chaudhary et al., 2023).

More specifically, our work relates to the burgeoning literature studying the investor's demand for government bonds (Cavaleri, 2023; Eren, Schrimpf, & Xia, 2023; Fang, Hardy, & Lewis, 2022; Jansen, 2021; Jansen, Li, & Schmid, 2024; Jiang, Richmond, & Zhang, 2024; Koijen & Yogo, 2024; Zhou, 2023). Methodologically, we introduce a demand system that allows for the full decomposition of the yield by investor with flexible specifications of price elasticities and factor loadings. In terms of other aggregate bond demand elasticities, Koijen, Koulischer, Nguyen, and Yogo (2017) find Euro area country bonds are more macro elastic than implied by our U.S. Treasury estimates (multiplier of 0.3 vs. 1). This finding is consistent with investors finding debt of Euro Area countries being relatively substitutable amongst each other, compared to U.S Treasuries and other asset classes. In terms of the U.S. Treasury market, Jansen et al. (2024) study institutional investors' demand and substitution patterns across the term structure of the Treasury yield curve, complementing our analysis of investors' aggregate demand for U.S. Treasuries as an asset class relative to other asset classes.

Econometrically, our approach extends the granular instrumental variable (GIV) literature (Gabaix & Koijen, 2024). GIV is increasingly applied in macro-finance settings where it is typically difficult to find market-level instruments (Adrian, Grinberg, Liang, Malik, & Yu, 2022; Camanho et al., 2022; Chodorow-Reich, Gabaix, Koijen, & Viviano, 2024; Kubitza, Sigaux, & Vandeweyer, 2024; Kundu & Vats, 2021). Our GIV extension provides a flexible approach to accommodate heterogeneous price elasticities and factor loadings across investors, without requiring explicit parameterization based on observable characteristics. Moreover, we propose an economically motivated optimal Generalized Method of Moments (GMM) estimator that assigns greater weight to shocks from investors with greater influence on equilibrium yields. The asymptotic efficiency of the estimator helps to ensure demand shocks are relevant instruments for yields, a key chal-

lenge when analyzing a market as large as U.S. Treasuries. Our economically motivated optimal estimator builds upon other variants of efficient GIV estimators, such as Baumeister and Hamilton (2023) and Qian (2024), which characterizes the optimality statistically.

1.2 Roadmap

The paper is organized in five sections. Section 2 introduces an equilibrium model of the Treasury market that can be taken to the data. Section 3 outlines our estimation and identification approach. Section 4 reports our estimate of the Treasury macro market multiplier. Section 5 discusses the sector- and factor-specific drivers of Treasury yield and examines their time variation. Section 6 examines the role of foreign investors in explaining the countercyclical aggregate demand for Treasuries. Section 7 concludes.

2 The Treasury Market: Data and Model Framework

This paper examines how the equilibrium yield of Treasury securities is jointly shaped by investors' allocation and government issuance decisions. We focus on Treasuries as a broad asset class, specifically the demand for the market portfolio of Treasury notes and bonds that have maturities exceeding one year—which we refer to as *Treasury bonds*. Our analysis centers on the overall demand for Treasury bonds relative to other assets, abstracting from investors' substitution and arbitrage across the yield curve.

In this section, we outline our methodology. First, we assemble comprehensive data on Treasury holdings across all investor types and government issuance patterns, capturing the complete Treasury market activity. Second, we develop a flexible but empirically tractable equilibrium model that links Treasury demand and supply drivers to the yield. Third, we outline how to decompose yield changes into the contribution of individual investors and factors.

2.1 Data

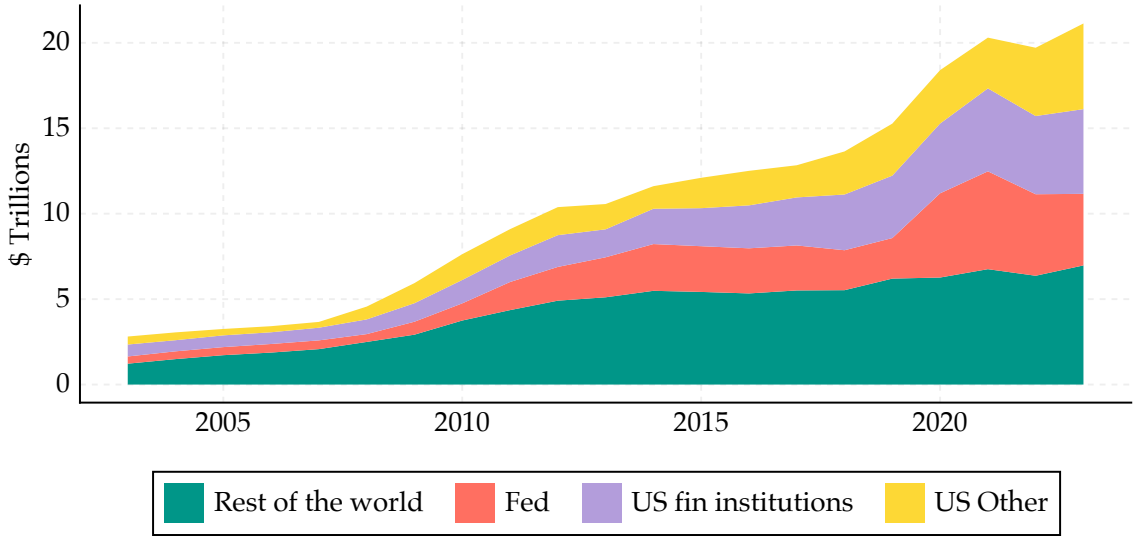
The primary source of our Treasury bonds holdings and issuance data is the Financial Accounts (Z.1). This dataset reports the holdings and flows of Treasury notes and bonds aggregated to the sector level.[4] We then complement this data with a more granular

[4]In the Financial Accounts, not all sectors report separately Treasury bills and notes&bonds. In those cases, we use the total flows and positions in all Treasury securities including bills. See Appendix B.1 for our treatment in more detail.

holding breakdown for banks and the foreign sector.[5] Using Call Reports, we collect holdings and flows of U.S. Treasury securities for individual commercial banks. Using Treasury International Capital (TIC) data, we further disaggregate the foreign holdings by country.

Figure 1 shows the evolution of holdings from 2003Q4 to 2023Q4—we plot the market value of holdings whenever possible. The total supply of Treasury bonds increased from less than $5 trillion in 2003 to more than $20 trillion by the end of 2023, or from around 30% percent of GDP to 70%.[6] Teasuries are held by four major groups: U.S. financial institutions, including banks, mutual funds, insurers, and pension funds; other U.S. investors, mostly covering the household sector and other non-financial institutions; the Federal Reserve; and foreign investors.

Figure 1: **Holdings by Group: U.S. Treasury Notes & Bonds**



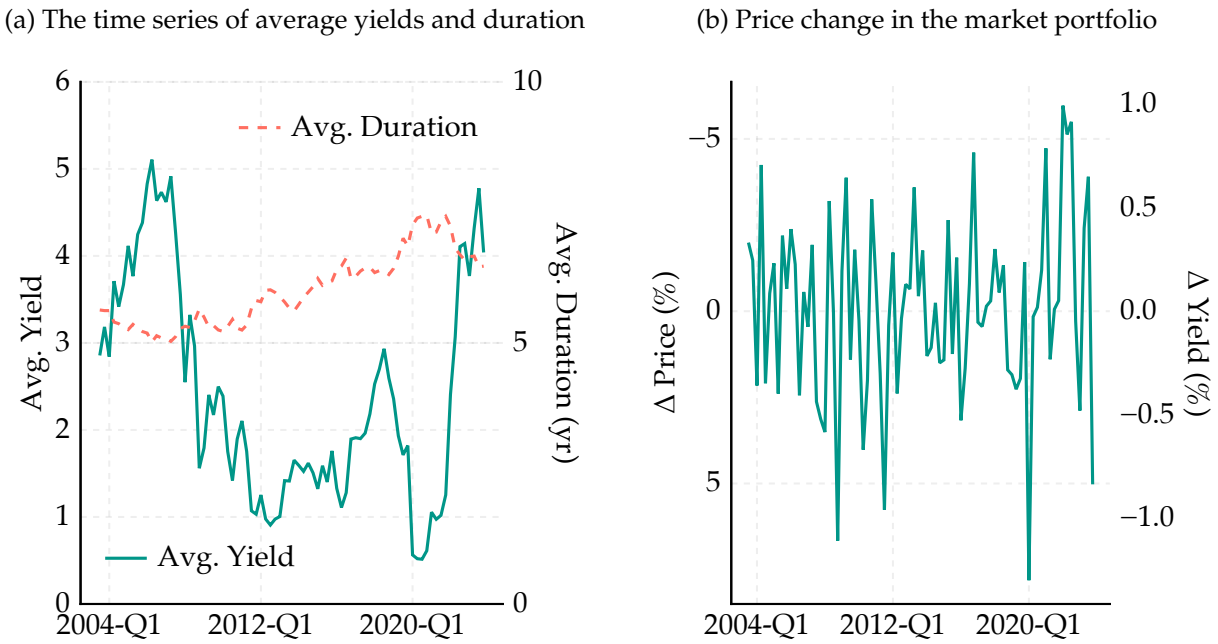
Note: Figure 1 plots the total holding of U.S. Treasury notes and bonds by investor groups (panel (a)). We aggregate investor sectors reported in Financial Account (Z.1) to four investor categories. *US Financial institutions* include banks, ETFs, mutual funds, pension funds, insurance companies, and security brokers and dealers. *US Other* include other smaller domestic categories, most notably households and nonfinancial corporates. Appendix Table B.1 reports the detailed mapping.

We measure the Treasury bond yield using the CRSP US Treasury Database. Using security-level data, we calculate the average yield of a market-weighted portfolio of Trea-

[5]We follow a similar procedure, used by Jansen et al. (2024) and documented in Appendix B.1, to impute Treasury holdings from Treasury and agency holdings of individual banks.

[6]Total Federal debt-to-GDP ratio is around 120% at the end of 2023, comprised of Treasury notes and bonds, bills, and non-marketable Treasury securities.

Figure 2: The path of average yields on U.S. Treasury notes and bonds



Note: Figure 2 plots the path of average yield, duration and price change in the market portfolio of U.S. Treasury bonds and notes from 2004 to 2023. All three objects are aggregated from CRSP from the security level weighted by amount outstanding. In Panel (b), the left y-axis corresponds to price change while the right y-axis corresponds to yield change, defined as price change scaled by average duration.

sury bonds—notes and bonds that have maturities exceeding one year. Figure 2a shows that average yields during our sample period fluctuate between 0.5 and 5 percent, while the average duration of the market portfolio ranges from 5 to 7 years. Figure 2b plots the quarterly changes in the price of the market portfolio. We flip the sign of the y-axis so that a drop in the price, or equivalently, an increase in the yield, corresponds to a rise. We also mark the corresponding changes in average yields on the right axis.

2.2 An Equilibrium Model

In this subsection, we outline our equilibrium model of the Treasury market. The model allows us to connect the yield we observe on Treasury bonds to the data we have collected on sectors' allocation decisions and the government's issuance decisions. The framework is parsimonious yet sufficiently flexible to accommodate the heterogeneity across sectors.

Notations We index sectors by i e.g. insurance sector, the Federal Reserve, etc. The net supply by the Treasury Department is also included and referred to as one of the sectors.

As mentioned, for the banking and foreign sectors, we further disaggregate holdings, so in these cases, the unit of observation is an individual bank or a country. Throughout the text, we use bold symbols to denote vectors or matrices and regular symbols to denote scalars. For example, $\mathbf{q}_t$ is a vector with $q_{i,t}$ being its i-th entry. Following standard notation, we use $Q_{i,t}$ to denote the holdings of Treasuries by sector i at time t, P_t to denote the price of the Treasury market portfolio, and y_t to denote the average yield.

Portfolio choice A key challenge in modeling allocation decisions is capturing the heterogeneity in how different sectors invest in Treasuries. Consider two examples. Hedge funds typically purchase Treasuries to maximize short-term returns, subject to internal value-at-risk limits and also considerations about investor outflows if their performance declines. Insurance companies, on the other hand, buy and hold Treasuries to match their long-duration liabilities while operating under regulatory capital and reserve requirements. Beyond these examples, explicitly characterizing all relevant constraints is challenging as investors face numerous restrictions that can interact in complex ways.

To flexibly capture these diverse drivers of Treasury demand, we leverage the fact that the first-order approximation of any portfolio choice problem can be expressed as a log-linear function of prices and demand shifters:

$$\Delta q_{i,t} = \overline{\Delta q}_i - \zeta_i \Delta p_t + \nu_{i,t}. \tag{2.1}$$

In this equation, $\Delta q_{i,t}$ is the percent change in Treasury bond holdings by sector i at time t, Δp_t is the percent change in the price of the Treasury market portfolio, ζ_i is sector i's price elasticity, and $\nu_{i,t}$ captures demand shifts for sector i in period t. We can derive this expression by log-linearizing any portfolio choice problem around the long-run average and taking the first differences. The main advantage of this approach is that rather than having to model the drivers of portfolio choice decisions explicitly, we can empirically capture them (locally) by estimating the elasticities and demand shifters.

To illustrate how the approximation works, consider two portfolio choice models: (i) bond-in-utility models used to capture investors that hold Treasuries for their convenience services (Krishnamurthy & Vissing-Jorgensen, 2012), and (ii) Kyle, 1985 models used to capture allocation decisions of investors who trade based on their private information. When we log-linearize either of these two models, the elasticity becomes a function of utility function parameters and steady-state values. In the bond-in-utility model, the elasticity of the convenience services pins down the price elasticity. In the Kyle model,

the flow's signal-to-noise ratio pins down the price elasticity.

Demand shifters $\nu_{i,t}$ We model the demand shifters $\nu_{i,t}$ as having a common component $\boldsymbol{\eta}_t$ and an idiosyncratic component $u_{i,t}$. Hence, we can rewrite Equation (2.1) as:

$$\Delta q_{i,t} = \overline{\Delta q}_i - \zeta_i \Delta p_t + \underbrace{\boldsymbol{\lambda}_i \boldsymbol{\eta}_t + u_{i,t}}_{\nu_{i,t}}. \tag{2.2}$$

The common component $\boldsymbol{\eta}_t$ captures demand shifts shared across sectors, such as monetary policy shocks. While all sectors are exposed to these common drivers, they may respond differently to them. We capture this heterogeneity by allowing for sector-specific loadings $\boldsymbol{\lambda}_i$ on these factors. As we discuss in Section 3.1, in our empirical implementation, we allow for both observed common factors, such as macroeconomic variables, and unobserved factors extracted using principal component analysis (PCA). The idiosyncratic component $u_{i,t}$ captures demand shifts specific to sector i, such as sector-specific regulatory changes or idiosyncratic wealth shocks. Which we assume are orthogonal to the common factors.

Equilibrium We connect sector-level Treasury demand and supply to the market's yield using market clearing. Markets must clear every period, and hence the net flow in the total market, including supply, must sum to zero. More formally, as $\Delta q_{i,t}$ is the sector-*i* flow as a percentage of the total holdings—we discuss the construction of the flow measure in detail in Section 3.1—we scale it by the long-run average of their market share S_i to arrive at the market clearing condition,

$$\sum_i S_i \Delta q_{i,t} = 0.$$

In the equilibrium, the Treasury price adjusts to clear the market. We can solve for this price by substituting in the demand equation into the market clearing condition, and rearrange to get:

$$\Delta p_t = \frac{1}{\zeta_S} \left(\overline{\Delta q}_S + \underbrace{\boldsymbol{\lambda}_S \boldsymbol{\eta_t} + u_{S,t}}_{\nu_{S,t}} \right), \tag{2.3}$$

where we use the S subscript to denote the size-weighted aggregation. For example, $\zeta_S \equiv \sum_i S_i \zeta_i$ is the aggregate elasticity, and $\boldsymbol{\lambda}_S \equiv \sum_i S_i \boldsymbol{\lambda}_i$ is the aggregate factor loading.

Equation (2.3) shows that the change in Treasury price is determined by aggregate

demand shifts, scaled by the inverse of the aggregate elasticity, $\frac{1}{\zeta_S}$. The inverse elasticity, $\frac{1}{\zeta_S}$, captures the percentage change in price in response to a 1% change in aggregate net demand. We also refer to the inverse elasticity, $\frac{1}{\zeta_S}$ as the *market multiplier*.

If we can recover sector specific elasticities ζ_i and factor loadings $\boldsymbol{\lambda}_i$, then using Equation (2.3), we can decompose the price changes into the contribution from each sector, the common factors and the idiosyncratic shocks. For example, the contribution of sector i to the price change is,

$$\Delta p_{i,t} = \frac{1}{\zeta_S} S_i \left(\overline{\Delta q}_i + \boldsymbol{\lambda}_i \boldsymbol{\eta}_t + u_{i,t} \right). \tag{2.4}$$

For instance, suppose there is a positive inflation surprise and the Treasury price declines. By applying Equations (2.3) and (2.4), we can determine the extent to which the inflation surprise contributes to the price decline and also determine the investors that transmit this surprise to the Treasury price.

To perform the price decomposition, we need to estimate the elasticities ζ_i and factor loadings $\boldsymbol{\lambda}_i$. However, this is not so straightforward because price and quantities are jointly determined in equilibrium, resulting in a simultaneity bias. In Section 3, we lay out our identification strategy.

3 Identification and Estimation

3.1 Specification Details

In this section, we provide details on the data and implementation of our model. We estimate the following demand function for each sector i, and then connect it to the yield using the market clearing condition:

$$\Delta q_{i,t} = -\zeta_{i,r(t)} \Delta p_t + \boldsymbol{\lambda}_{i,r(t)} \boldsymbol{\eta}_t + \overline{\Delta q}_i + u_{i,t} \tag{3.1}$$

where $\Delta q_{i,t}$ is the percent change in holdings of Treasury bonds by sector i at time t, Δp_t is the percent change in the price of the Treasury market portfolio, $\zeta_{i,r(t)}$ is sector i's price elasticity in regime $r(t)$, $\boldsymbol{\lambda}_{i,r(t)}$ is sector i's factor loading in regime $r(t)$, $\boldsymbol{\eta}_t$ is the common demand shifter, $\overline{\Delta q}_i$ is the sector i fixed effect, and $u_{i,t}$ is the idiosyncratic demand shifter. Below we describe the construction of each component in more detail.

Sample period Our baseline analysis covers the period from 2003Q4 to 2023Q4. In Appendix Table B.4, we report estimates using data starting from 1970Q1, based solely on Financial Accounts data (and not Call Reports or TIC data). Despite the longer time span, the elasticity estimates remain remarkably stable.

Sector definitions We use the sectoral definitions from the Financial Accounts. For ease of interpretability, we often present aggregated sectors in the main text, with the complete list of sectors and their mapping to the aggregated sectors provided in Appendix Table B.1. One sector worth highlighting in the Financial Accounts is the "household sector," which serves as the residual sector to ensure the sum of all sectors' flows equals zero. This sector should be broadly interpreted as a catch-all category for investors not included or observed in other sectors, such as hedge funds, endowment funds, and family offices.

Sector Grouping and Structural Breaks For interpretability and statistical power, we pool coefficients of similar sectors in our estimation. For example, all Call Report banks are assigned the same elasticity parameter, as are all pension fund types from the Financial Accounts (detailed groupings are provided in Appendix Table B.1). Additionally, following the Global Financial Crisis (GFC), there were significant changes in regulations and policymaker behavior. To account for these structural changes, we divide our analysis into two distinct regimes—pre-2009Q1 and post-2009Q1—allowing sectors to exhibit different elasticities and factor loadings in each period. In practice, we find that the structural break is significant for banks, the Federal Reserve, and the foreign sector. Hence, in our baseline specification, we allow for regime-specific elasticities and factor loadings only for these sectors.

Flows and positions The flow measure $\Delta q_{i,t}$ is defined as the net dollar flows $F_{i,t}$ by investor i, normalized by the sector's long-run average market share S_i times the total market values of Treasury bonds outstanding in the last quarter A_{t-1}^{total}:

$$\Delta q_{i,t} \equiv \frac{F_{i,t}}{S_i A_{t-1}^{total}}.$$

More specifically, the long-run average of the market share S_i is constructed as the average market share of each entity throughout the sample period:

$$S_i = \frac{|\sum_t A_{i,t}|}{\sum_t A_t^{total}}.$$

We scale the denominator by the long-run average share rather than the last quarter's share for two main reasons. First, using the long-run average share aligns with our interpretation of the demand system as a first-order approximation of the portfolio choice problem around the steady state (measured by the long-run average). Second, the long-run average offers a statistical advantage as it is not affected by transitory volatility in market shares, which could otherwise lead to noisy estimates. We have also examined the analysis using time-varying market shares and found that the results are generally consistent with our baseline findings.

Supply enters the system as negative demand. We choose the sign convention such that S_i are always positive, and $\Delta q_{i,t}$ follows the sign of the dollar flows $F_{i,t}$, with positive numbers indicating net buying and negative numbers indicating net selling. For example, in 2023Q4, Department of the Treasury issued $\$876.5$ billion of Treasury bonds, and the total outstanding bonds by the end of 2023Q3 is $\$20370.8$ billion, so the supply flow in Q4 is $\Delta q_{supply,2023Q4} = \frac{-\$876.5}{\$20370.8} = -4.3\%$. In this way, the supply and demand can be treated uniformly in this framework: a positive ζ_{supply} means when the Treasury price is higher, supply tends to increase.

Common factors Common factors play two crucial roles in our analysis. First, they enable us to decompose and interpret price changes in the Treasury market. Second, as we will outline later, our identification strategy relies on properly controlling for common factors to isolate idiosyncratic demand shocks.

We aim to incorporate factors that influence Treasury allocation decisions across all sectors. To this end, we include a comprehensive set of common factors. These include several key macro-financial variables: (i) innovations to VIX, which serves as a primary indicator of global risk sentiment and measures "flight to safety" intensity; (ii) quarterly changes in the effective Fed funds rate to account for short-term interest rate movements and their transmission to longer-term rates; (iii) innovations to the USD broad index; and (iv) the gap between quarterly CPI inflation and the inflation target (0.5 percent quarterly or 2 percent annually).[7] We also include consensus forecasts from the Survey of Professional Forecasters (SPF) regarding expected changes in one-quarter and ten-year Treasury yields for the current quarter. These forecasts capture market expectations about yield curve changes not reflected in other variables. Since our model assumes common factors are exogenous to idiosyncratic shocks and Treasury prices, we exclude factors that

[7]More broadly, accounting for macro factors is crucial to understanding Treasury price dynamics because they convey information not captured by the yield cross-section (Ludvigson & Ng, 2009).

are directly related to the Treasury market, such as credit spreads. Our robustness exercises indicate that including additional macro factors provides minimal improvement in explanatory power while increasing the risk of overfitting.

In addition to these macroeconomic factors, we need to account for the fact that policymakers' announcements influence Treasury bond demand across all sectors. Two key policy entities, the Federal Reserve (Fed) and the Department of Treasury (supply), regularly pre-announce their planned purchases and sales to provide transparency and forward guidance to market participants. To capture the anticipatory effects and potential front-running behaviors these announcements may induce, we include predictive variables for their flows in our common factors. Specifically, for the Fed, we control for purchases scheduled a quarter ahead.[8] For the Treasury, we include net issuance in the previous quarter to control for the predictive components in supply. This approach allows us to isolate and measure the flow sensitivity due to deviations from scheduled purchases and sales when estimating coefficients for the Fed and Treasury supply.

To ensure we capture all relevant common factors, we also extract unobserved factors from more granular data that may have been missed by the other included factors. Specifically, we apply principal component analysis (PCA) to extract principal components (PCs) from bank and foreign investor flows, capturing latent common demand shifts. Additionally, we incorporate common investor expectations by extracting factors from the Survey of Professional Forecasters (SPF) panel data on projected one-quarter and ten-year yields. Our baseline specification includes three PCs from banking and foreign flows. In robustness checks, we expand this to include up to five flow-based PCs and two yield forecast PCs, finding that our results remain largely unchanged.

3.2 Identification assumption

The main challenge in estimating the model is addressing the endogeneity between Treasury prices and investors' allocation decisions. The standard approach in the literature is to search for idiosyncratic demand shifters from one sector and use these to instrument the price in another sector's demand equation. These instruments are valid if one sector's idiosyncratic shifters are uncorrelated with both the price and common factors, and importantly, not correlated with other sectors' idiosyncratic shocks. And they are also relevant as long as the idiosyncratic shocks are large enough to have sufficient price impact. For example, flow-induced-trading by mutual funds have been successfully used as

[8] Appendix B.3 discusses the construction of the scheduled purchase series.

a source of idiosyncratic demand shocks to estimate stock and corporate bond elasticities (Chaudhary et al., 2023; Lou, 2012).

The challenge with such approaches in our setting is that we require instruments for all sectors. While previous research has used regulatory changes and balance sheet shocks as sources of idiosyncratic demand shocks, these instruments are unsuitable for our analysis because they are typically limited to particular sectors or short-lived episodes. Furthermore, finding appropriate instruments is especially difficult in the Treasury market due to its enormous size—individual sector shocks often are not large enough to meaningfully affect Treasury prices, resulting in instruments not being relevant.

To address these challenges, we leverage our model's structure to extract idiosyncratic sector shocks. In our model, each sector's Treasury allocation depends on three components: (i) price (Δp_t), (ii) common demand shifters ($\boldsymbol{\eta}_t$), and (iii) idiosyncratic sector-specific shifters ($u_{i,t}$). The considerable heterogeneity in sectoral constraints and objectives makes these idiosyncratic drivers a significant source of variation in holdings. Our estimation strategy extracts these idiosyncratic sector-specific demand shifters from one sector and uses them as instruments for the yield in another sector.

Similar to standard instrumental variable approaches, our identification relies on idiosyncratic sector-specific drivers being orthogonal across sectors. For instance, selling Treasuries by a foreign country may be driven solely by their domestic concerns, and hence this can be used as an instrument for U.S. pension funds' demand. Formally, our identification assumption that idiosyncratic sector-specific shifters ($u_{i,t}$) are independent from each other across sectors:

Assumption 1. *$u_{i,t}$ is independent from $u_{j,t}$ for any $i \neq j$.*

This identification assumption is the same assumption used in Granular Instrumental Variables (GIV, Gabaix and Koijen, 2024) approaches that are increasingly used in the macrofinance literature (Adrian et al., 2022; Camanho et al., 2022; Chodorow-Reich et al., 2024; Kubitza et al., 2024; Kundu & Vats, 2021). Hence, our estimator, which we outline below, can be viewed as an extension of the standard GIV approach.[9] For a more detailed comparison with the standard GIV approach, see Appendix A.4.

[9]The key difference from the standard implementation is that our GIV extension flexiblily accommodates heterogeneous price elasticities and factor loadings across investors, without requiring explicit parameterization based on observable characteristics. Additionally, our optimal GMM implementation more efficiently uses information contained in the idiosyncratic shocks.

In the subsection below, we first develop the optimal GIV estimator based on Assumption 1. In Section 3.4, we return to the identification assumption in the lens of the estimator and discuss its robustness in detail.

3.3 The Optimal GIV Estimator

We propose an economically motivated optimal Generalized Method of Moments (GMM) estimator that weights investor shocks according to their market influence. This approach assigns greater importance to shocks from investors who have more significant impact on equilibrium yields, thereby enhancing the instrument relevance of the idiosyncratic demand shocks.

For ease of exposition, we proceed *as if* there are no common factors in the model. Operationally, this can be achieved by first residualizing $\Delta q_{i,t}$ and Δp_t against the common factors and taking the residuals. We also assume that the elasticities are constant across regimes here, and relaxed it in Appendix A.1.

Our the identification Assumption 1 implies the following moment restrictions,

$$\mathbb{E}\left[u_{i,t}u_{j,t}\right] = 0. \tag{3.2}$$

Notice that these moment conditions give us an overidentified system of equations. Specifically, they place restrictions on the entire off-diagonal covariance matrix of idiosyncratic sector-specific shifters, giving us $N \times (N-1)/2$ moment conditions to identify just N sector-specific price elasticities. We would like to optimally weigh the moment conditions. In theory, we could use a two-step efficient generalized method of moments (GMM). However, we face a practical challenge: the number of moment conditions $N \times (N-1)/2$ far exceeds our time-series sample size T. In such settings, statistical methods of finding the optimal weighting matrix, like the two-step GMM, are known to perform poorly (Han & Phillips, 2006; Newey & Windmeijer, 2009).

Guided by the economics of our model, we derive an optimal weighting scheme for the moment conditions. This optimal estimator assigns greater weight to moment conditions from entities with larger market shares. The rationale is straightforward: entities with larger market shares generate idiosyncratic shocks with greater price impact, making them more relevant as instruments. We refer to this size-weighted approach as the *optimal GIV estimator*.[10]

[10]The package for the optimal GIV estimator can be found at https://github.com/FuZhiyu/OptimalGIV.

Formally, the optimal GIV estimator $\hat{\boldsymbol{\zeta}}$ solves the following sample moment conditions:

Definition 1.

$$\hat{\mathbb{E}}\left[\hat{u}_{i,t}\left(\hat{\zeta}_i\right)\underbrace{\sum_{j\neq i}S_{j,t}\hat{u}_{j,t}\left(\hat{\zeta}_j\right)}_{\hat{u}_{S(-i),t}(\hat{\boldsymbol{\zeta}})}\right]\equiv\hat{\mathbb{E}}\left[\left(\Delta q_{i,t}+\hat{\zeta}_i\Delta p_t\right)\sum_{j\neq i}S_j\left(\Delta q_{j,t}+\hat{\zeta}_j\Delta p_t\right)\right]=0. \tag{3.3}$$

where $\hat{\mathbb{E}}$ denotes the sample mean across the time dimension.

In Appendix A.6 we show that the estimator is asymptotically efficient.

Theorem 1 (Asymptotic efficiency)**.** *Given the moment conditions (3.2), Under regularity conditions,*[11] *the optimal GIV estimator $\hat{\boldsymbol{\zeta}}$ is consistent and asymptotically normal:*

$$\sqrt{T}\left(\hat{\zeta}-\zeta\right)\xrightarrow{d}\mathcal{N}\left(0,\mathbf{V}^{\zeta}\right),$$

for $T\to\infty$. Moreover, its asymptotic variance achieves the semi-parametric efficiency bound (Chamberlain, 1987), given as

$$\mathbf{V}^{\zeta}=\zeta_S^2\times Inv\left(\begin{bmatrix}\frac{1}{\sigma_1^2}\sum_{i\neq1}S_i^2\sigma_i^2 & S_1S_2 & S_1S_3 & \cdots & S_1S_N\\ S_1S_2 & \frac{1}{\sigma_2^2}\sum_{i\neq2}S_i^2\sigma_i^2 & S_2S_3 & \cdots & S_2S_N\\ S_1S_3 & S_2S_3 & \frac{1}{\sigma_3^2}\sum_{i\neq3}S_i^2\sigma_i^2 & \cdots & S_3S_N\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ S_1S_N & S_2S_N & S_3S_N & \cdots & \frac{1}{\sigma_N^2}\sum_{i\neq N}S_N^2\sigma_N^2\end{bmatrix}\right), \tag{3.4}$$

where $\zeta_S\equiv\sum_i S_i\zeta_i$ is the aggregate elasticity and $\sigma_i^2\equiv var(u_{i,t})^2$.

The expression (3.4) illustrates the sources of statistical power in the optimal GIV estimator. First, the standard error of each sector's elasticity, ζ_i, is scaled by the aggregate elasticity, ζ_S. This reflects that demand shocks have greater power when their price impact is larger. In the extreme case where the market is perfectly elastic ($\zeta_S\to\infty$), demand shocks cannot move prices at all, rendering the instruments irrelevant and causing standard errors to approach infinity. Second, standard errors depend on the ratio of other

jl.

[11] See Appendix A for the exact conditions required.

sectors' size-weighted shock volatility, $\sum_{j \neq i} S_j^2 \sigma_j^2$, to the sector's own shock volatility, σ_i^2. Higher volatility in the rest of the market creates larger exogenous price variations that can be used to instrument sector i's demand, enhancing instrument power. Conversely, when $\sum_{j \neq i} S_j^2 \sigma_j^2 \to 0$, there is no exogenous price variation available to estimate sector i's price elasticity.

Below, we provide two ways to think about why our optimal GIV estimator corrects for the simultaneity bias and why size weighting maximizes the power of our estimates.

Instrumental-variable interpretation Our estimator has a natural instrumental variable (IV) interpretation. For each entity i, the moment condition in Equation (3.3) can be rewritten as:

$$\hat{\zeta}_i = -\frac{\hat{\mathbb{E}}\left[\Delta q_{i,t} \hat{u}_{S(-i),t}\left(\hat{\boldsymbol{\zeta}}\right)\right]}{\hat{\mathbb{E}}\left[\Delta p_t \hat{u}_{S(-i),t}\left(\hat{\boldsymbol{\zeta}}\right)\right]}.$$

Note that this is nothing other than an IV estimator where we instrument price using size-weighted idiosyncratic shocks of other investors. Maximizing the power of an IV estimator requires maximum instrument relevance, i.e., maximizing the covariance between price and the instrument. The market clearing condition of our model implies that price is an affine function of the size-weighted aggregation of idiosyncratic shocks, so size weighting achieves maximal relevance.

Bias-corrrected OLS interpretation For an infinitesimal entity—whose idiosyncratic shocks have negligible impact on price—we can estimate its elasticity by simply regressing $\Delta q_{i,t}$ on Δp_t using OLS. Furthermore, under our assumption of temporally homoskedastic idiosyncratic shocks, this OLS estimator would be optimal efficiency. However, when entities are large enough to move the price, OLS becomes biased. An ideal estimator would exploit the efficiency in OLS while correcting the biases. This is exactly what the optimal GIV does. Lemma 1 formally shows that the optimal GIV estimator corrects for the bias arising from OLS estimation.

Lemma 1 (Bias-corrected OLS moment conditions)**.** *The optimal GIV estimator is equivalent to the estimator that solves,*

$$\hat{\zeta}_i = -\frac{\hat{\mathbb{E}}\left[\Delta q_{i,t} \Delta p_t\right]}{\hat{\mathbb{E}}\left[\Delta p_t^2\right] - \frac{1}{\hat{\zeta}_S} S_i \hat{\sigma}_i^2} \tag{3.5}$$

where $\hat{\sigma}_i^2 \equiv \hat{\mathbb{E}}\left[\hat{u}_i\left(\hat{\zeta}_i\right)^2\right]$ *is the sample variance of the idiosyncratic shocks.*

Proof. Using the market clearing condition, we have:

$$\sum_{j \neq i} S_{j,t} \left(\Delta q_{j,t} + \hat{\zeta}_j \Delta p_t \right) = \hat{\zeta}_S \Delta p_t - S_i \hat{u}_i \left(\hat{\zeta}_i \right).$$

Plug it into the sample moment condition (3.3) and rearrange, we have the sample moment conditions (3.5). □

Lemma 1 states that the optimal estimator can be equivalently implemented by regressing quantities on prices and adjusting for the bias—the sector's own impact on prices $\frac{1}{\hat{\zeta}_S} S_i \hat{\sigma}_i^2$. Notice that the bias disappears when the sector's own impact on prices is zero, i.e., when the sector is infinitesimal, or the market is perfectly elastic.[12] In addition to the OLS interpretation, Lemma 1 also offers an alternative, and sometimes more stable, algorithm for estimating the model.

3.4 Common Factors and the Robustness of Identification

Our identification method relies on the assumption that, after controlling for common factors, idiosyncratic shocks are orthogonal across sectors. The primary threat to identification is the presence of residual correlations in idiosyncratic shocks ($u_{i,t}$). In this section, we address this concern through multiple approaches and provide diagnostic tools to assess the robustness of our estimates.

When the econometricians fail to control for all common demand shocks, our estimates will be biased. However, the bias is proportional to the size of the residual comovement. As we prove in Appendix A.2, the biased estimate of the aggregate elasticity $\hat{\zeta}_S^b$ can be approximated by:

$$\hat{\zeta}_S^b \approx \zeta_S \sqrt{1 - \mathcal{R}^2} \tag{3.6}$$

where $\mathcal{R}^2$ represents the R-square of hidden common factors in price movements (excluding controlled common factors), i.e., $\mathcal{R}^2 = \frac{Var(\text{Hidden Factors})}{Var(\Delta p_t)}$. The term $1 - \mathcal{R}^2$ captures the share of price variance explained by true idiosyncratic shocks. Equation (3.6) shows that the downward bias in the estimated aggregate elasticity increases with the share of hidden common comovement.

[12] Appendix B.4 provides an illustration of the effect bias correction has on the simple OLS estimates for sector-level price elasticity estimates.

We address this concern through multiple layers of controls. First, we include a comprehensive set of observable factors that explain price movements, ranging from macroeconomic variables to market expectations about future yields. These observable factors collectively explain approximately 50% of the price variance.

To further capture potential unobserved common demand shocks, we employ a robust version of PCA to extract additional common factors from granular data sources, including foreign country flows, bank-level data, and SPF Treasury yield forecasts. Our baseline specification includes three principal components, with additional factors providing only marginal improvements in explanatory power. As shown in Appendix Table B.4, alternative specifications with more factors yield results nearly identical to our baseline findings.

The bias formula in Equation (3.6) suggests that the impact of residual comovement on our estimates is relatively modest. For instance, if hidden factors explain 25% of the residual variance ($\mathcal{R}^2 = 0.25$), our estimated elasticity would be biased downward by only about 13% ($\sqrt{1-0.25} \approx 0.87$). To generate a 50% bias in our aggregate estimates, hidden factors would need to explain 75% of the residual variance. Given our comprehensive set of controls and PCA-extracted factors, such a high level of uncontrolled common comovement seems unlikely.

For investor-specific elasticity estimates, there are also potential concerns about strategic behaviors. For example, fast-moving investors might front-run a large but slow-moving investor's positive demand shock. Such strategic interactions would violate Assumption 1 and bias our estimates. To address this concern, we implement a leave-one-out estimation approach, where we estimate the system by excluding one sector at a time to test the sensitivity of our results to particular sectors.

Additional Discussion

In Appendix A.1, we extend our approach to allow for time-varying elasticities and more flexible control variables. The appendix also offers the additional discussions of our method, including handling measurement errors (Appendix A.3),[13] and the relation to the standard GIV proposed by Gabaix and Koijen (2024) (Appendix A.4).

[13]With measurement errors, the estimates of the residual sector will be biased. In our implementation, we only incorporate moment conditions involving the household sector (the residual) with sectors that have reliable measurements, such as the Fed, supply, and banks. Appendix Table B.3 also presents estimation results that completely exclude the household sector from the set of moment conditions. These estimates closely align with our baseline specification, indicating that measurement error is not a significant concern.

4 The Price Elasticity of the Treasury Market

In this section, we present our findings on the price elasticity of the Treasury market. We first analyze the elasticity of aggregate demand for Treasury bonds. We then examine sector-specific price elasticities and factor loadings. Finally, to understand who provides liquidity to the Treasury market and how this has evolved over time, we investigate which sectors contribute most to the aggregate demand elasticity and how this has changed since the financial crisis.

Aggregate Price Elasticity The top row of Table 1 reports the aggregate price elasticity of the Treasury market. Our estimate for the aggregate market elasticity is 1.0. This implies that a macro multiplier of 1.0 (reciprocal of elasticity)—the parameter measures the impact of a demand shock on the aggregate market value of Treasury bonds. A unit macro multiplier implies that a 1% demand shock results in a 1% increase in the aggregate market value of Treasury bonds. In terms of yields, this translates to a 15 basis point decrease (given the duration of outstanding Treasury bonds is around 6.5 years).

Our macro multiplier estimate of 1 suggests that the U.S. Treasury market can more effectively absorb demand shocks compared to the U.S. equity market, which has a macro multiplier closer to 5 (Gabaix & Koijen, 2022), and the U.S. corporate bond market, which has a portfolio-level multiplier of 3.5 (Chaudhary et al., 2023). However, the Treasury market is less effective at absorbing demand shocks than the Euro Area countries bond markets, which have a macro multiplier of 0.3 (Koijen et al., 2017).

These differences in macro multipliers across asset classes are consistent with the principle that multipliers increase when outside assets are poor substitutes, which makes it harder for arbitrageurs to hedge risks when countering demand shocks (Chaudhary et al., 2023). Euro area country bonds have low macro multipliers because they are highly substitutable—for instance, Dutch bonds can effectively substitute for German bonds. In contrast, equities and corporate bonds have higher macro multipliers because they lack close substitutes that can replicate their return. The Treasury market's intermediate macro multiplier reflects its position between these two ends: it has better substitutes than equities and corporate bonds, such as investment grade corporate bonds and agency MBSs, but fewer good substitutes than Euro area country bonds.

Sector-specific price elasticities The aggregate elasticity estimate of 1.0 masks significant heterogeneity across different market participants. Table 1 reports the price elasticity

Table 1: **Average price elasticities**

Sector	$S(\%)$	ζ	ζ **Share (%)**
Aggregate		1.03	100.0
		(0.77, 1.3)	
Households	5.74	10.54	58.55
		(5.33, 15.76)	
RoW	44.45	0.42	17.8
		(0.23, 0.61)	
Fed	22.08	0.42	9.28
		(0.11, 0.74)	
Mutual Funds	6.75	0.6	3.95
		(0.13, 1.08)	
Insurance	2.59	1.08	2.7
		(0.76, 1.4)	
Banks	5.26	0.52	2.61
		(0.28, 0.76)	
Dealers	0.81	2.22	1.73
		(-6.45, 10.88)	
Other	11.78	-0.14	-1.62
		(-0.37, 0.08)	
ETF	1.18	-0.53	-0.6
		(-0.89, -0.17)	
Pension	5.42	-0.02	-0.13
		(-0.18, 0.13)	
Supply	100.0	0.06	5.74
		(-0.01, 0.13)	

Note: Table 1 reports the aggregate price elasticity, sector-specific price elasticity of demand ζ for the 10 investor categories in the sample, and the price elasticity of supply. The sample period is 2003Q4–2023Q4. The price elasticities are identified using the optimal GIV estimator developed in Section 2. Time-series averages are taken for sectors that assume to have different elasticities before and after 2009Q1 (the sectors include Federal Reserve, Rest of World and U.S. Banks). S corresponds to the size weight used in the estimation, defined as the average market share of each entity throughout the sample period. ζ share denotes the (size-weighted) fraction of aggregated elasticity accounted for by each sector. 95% confidence intervals are reported, with the standard errors given by Theorem 1.

of demand of each sector, and shows each sector's contribution to the aggregate elasticity. This contribution, labeled as "ζ share" in the table, is calculated as ζ share $\equiv \frac{\zeta_i \times S_i}{\zeta_S}$, where ζ_i is the sector's elasticity, S_i is its market share, and ζ_S is the aggregate elasticity. The contribution of a sector to the aggregate elasticity can be viewed as the extent to which a given sector helps provide liquidity to the overall Treasury market. Sectors with high contributions are very elastic and, hence, respond strongly to price changes by absorbing demand shocks. Or have large market share and, hence due to their size, are able to

absorb large demand shocks.

The household sector is the most price-elastic sector. In spite of being relatively small, their high price elasticity means that the sector accounts for 55% of the total liquidity provision in the market. As discussed in the data section, the household sector is a catch-all category that includes various investors not directly measured by the Financial Accounts, such as hedge funds, family offices, separately managed accounts for high net-worth individuals, and endowment funds of not-for-profit organizations. These sophisticated investors, operating with fewer regulatory constraints and substantial capital, can naturally serve as the most nimble liquidity providers in the Treasury market.

Examining other sectors, we find that foreign investors are less price-elastic than domestic investors. However, due to their substantial market share, foreign investors still rank as the second-largest liquidity providers after the household sector. The Federal Reserve demonstrates significant price elasticity in our estimates. As we elaborate in Section 5.1.2, our methodology controls for the Fed's scheduled purchases, meaning that our elasticity estimates capture market responses to unexpected policy decisions, such as the timing of initiating or terminating asset purchase programs. And as we will discuss, the Fed's role as a Treasury market liquidity provider has only really become significant since the financial crisis.

Security brokers and dealers contribute only 1.63% to the aggregate elasticity. This modest contribution reflects the fact that we are focusing on demand and supply forces at a quarterly horizon. While broker-dealers play a crucial role in intermediating daily trading volumes, they maintain relatively small net positions over quarterly horizons, resulting in them playing a minor role in our analysis. For instance, their average quarter-end net position represents less than 1% of total market value (see Appendix Figure B.6 for more details).

Exchange-traded funds (ETFs) and pension funds are among the least elastic sectors. This is consistent with the passive trading strategies and high use of implicit benchmarking in these sectors. Pension funds are well-known as buy-and-hold investors in the Treasury market, which aligns with our finding of their low price elasticity. Our findings are also consistent with Koijen et al. (2017), who find that pension funds have the lowest price elasticity in the European government bond market.

On the supply side, we estimate a weak positive elasticity that is statistically indistinguishable from zero. This result reflects the Treasury's commitment to a "regular and

predictable" debt management approach, whereby they avoid timing the market when issuing Treasury bonds. The Treasury typically announces its planned offering amounts of notes and bonds for the upcoming quarter, with minimal deviations from these announcements during normal periods (Cassidy & Mirani, 2024). Hence, after controlling for the preannounced supply schedules, there is little room for the supply to respond to price changes.

The price impact at longer horizons We find that demand and supply shocks have a persistent price impact lasting at least for a few quarters, similar to what Gabaix and Koijen (2022) found for the aggregate equity market. To formally examine how these demand shocks propagate over time, we employ a local projection approach following Jordà (2005),

$$\Delta p_t^{t+h} = \alpha_h + M_h \hat{u}_{S,t} + \boldsymbol{\lambda}_h^p \boldsymbol{\eta}_t + e_{t+h}, \tag{4.1}$$

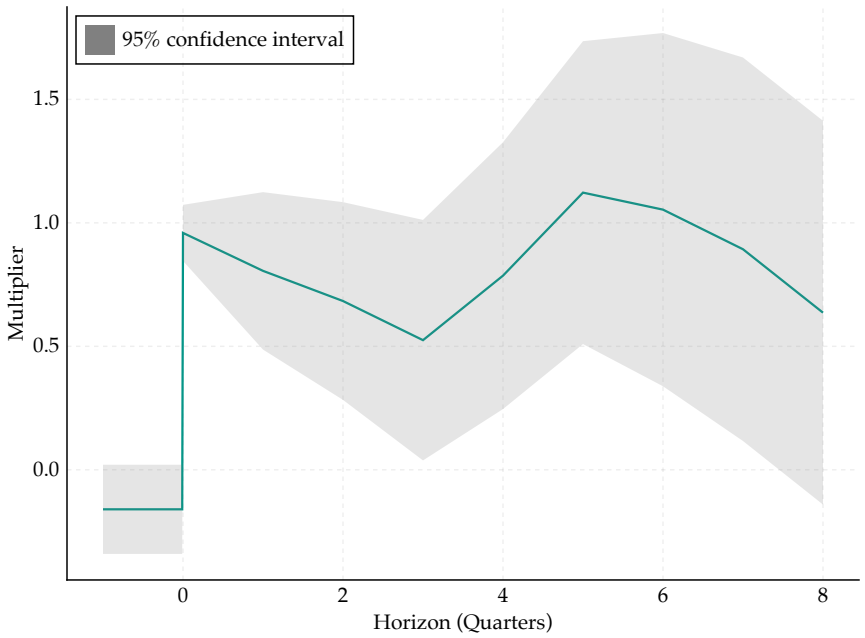
where $h = 0, 1, \ldots, 8$ quarters and Δp_t^{t+h} represents the cumulative price changes from quarter t to quarter $t + h$. As a placebo test, we also estimate the local projection using the price change from the previous quarter, Δp_{t-1}.

Figure 3 plots the cumulative price impact M_h of a one-percent demand shock with the 95% confidence intervals. The price change in the quarter prior to the shock $(h = -1)$ does not predict the demand shock in this quarter, consistent with demand shocks not being priced in advance. On impact, the price increases by 1%, consistent with our macro multiplier estimate. This price impact persists and remains statistically significant for up to 8 quarters. Beyond this horizon, statistical power is limited, preventing us from determining if and when the effect dissipates.

Robustness of elasticity estimates Our elasticity estimates are robust to a variety of alternative specifications and robustness checks.

Our identification strategy uses idiosyncratic shocks from other sectors to instrument for price in another sector's demand. This strategy works as long as idiosyncratic shocks across different sectors are independent of one another. A potential concern is that demand shocks may be correlated across sectors. To address this concern, we perform a leave-one-out analysis by sequentially excluding one sector at a time from our estimation procedure. While this approach reduces statistical power, if our identification assumption is valid, the estimated elasticities should be similar across the leave-one-out specifications. Table B.3 in the Appendix presents these results. The sector-level elasticity estimates re-

Figure 3: **Dynamic Price Impact of Demand and Supply Shocks**



Note: Figure 3 plots the impulse response function of Treasury price to demand and supply shocks. To get the impulse response function, we use the extracted size-weighted idiosyncratic demand and supply shocks $\hat{u}_{S,t}$ to estimate a local projection (Jordà, 2005) following (4.1). Homoskedastic standard errors are used to construct the 95% confidence interval.

main remarkably consistent across all leave-one-out specifications, suggesting that our identification strategy is robust to potential cross-sector correlations in demand shocks.

Table B.4 presents additional robustness checks, showing our elasticity estimates are relatively stable. First, to address the concern that we are not controlling for all relevant factors, we include seven unobserved common factors recovered from PCA—five from granular bank and foreign flows and two from yield curve forecasts. Second, we repeat our analysis on a longer sample extended back to the 1970s. To extend the sample, we use only Financial Account data, as country-level and bank-level holdings data are not available for this period. We find the elasticity estimates are similar for this longer, albeit less granular, sample. Third, we explore how our results are impacted by expanding our definition of Treasury bonds to include Treasury bills (Treasuries with maturity less than one year). Consistent with Treasury bills being more "cash-like" and having more close substitutes, we find that with this expanded definition, our elasticity estimates are twice as high, reaching 2.0.

4.1 Time-Varying Elasticities: Post-GFC Changes in Liquidity Provision

Leveraging the flexibility of our framework, we document a significant regime shift in Treasury market liquidity provision since the Great Financial Crisis (GFC). A sector's price elasticity of demand reflects its willingness to stand on the other side of the market when demand and supply shocks move Treasury prices. Most notably, since the GFC, we find that U.S. banks and foreign investors have become much less price-sensitive, while the Federal Reserve has emerged as a state-contingent liquidity provider, stepping in when Treasury prices fall too much.

Table 2 reports the price elasticities of foreign investors, U.S. banks, and the Fed before and after the GFC. Foreign investors and U.S. banks have become considerably less price elastic, with their elasticities declining by 47% and 51%, respectively, since the GFC. Meanwhile, the Fed, which was completely price inelastic prior to the financial crisis, now exhibits significant price elasticity.[14] This elasticity primarily reflects the Fed's interventions during crisis periods, highlighting its role as a state-contingent liquidity provider—willing to provide a backstop when Treasury prices fall too much.

The decline in price elasticity for U.S. banks likely reflects post-crisis constraints on their intermediation capacity (see Du, Tepper, & Verdelhan, 2018, for more discussion on implications for other markets). Specifically, non-risk-weighted regulatory constraints, such as supplementary leverage ratio requirements, have made it more costly for banks to expand their balance sheets for Treasury-related intermediation activities (Favara et al., 2024). Tighter risk-based regulations have strengthened banks' incentives to substitute loans for liquid Treasury holdings (Stulz, Taboada, & van Dijk, 2022). Additionally, during the post-COVID monetary tightening cycle, banks substantially increased the share of securities in their portfolios designated as "held-to-maturity," exploiting accounting rules to protect book capital from rising interest rates (Granja, Jiang, Matvos, Piskorski, & Seru, 2024). These factors collectively reduce banks' sensitivity to price movements in the Treasury market.

Overall, these regime shifts mark a substantial change in the market structure of liq-

[14]The Fed's elasticity before the financial crisis is estimated to be precisely zero because we assume all changes in the Fed's Treasury holdings outside of quantitative-easing regimes are anticipated and controlled as common factors. These changes typically result from open market operations to achieve the FOMC's interest rate targets. Alternative approaches—treating all changes as unanticipated or using an AR(1) process to control for expected changes—all yield near-zero elasticity estimates for the Fed in the pre-crisis period. See Appendix B.3 for more details.

Table 2: **Regime shifts for price elasticities of U.S. banks, foreigners, and the Fed, before and after 2009**

Sector	ζ	ζ **Share (%)**
Fed (03-08)	0.0	-
	-	
Fed (09-23)	0.57	12.53
	(0.32, 0.83)	
Rest of World (03-08)	0.76	30.38
	(0.48, 1.04)	
Rest of World (09-23)	0.3	13.39
	(0.15, 0.46)	
U.S. Banks (03-08)	0.84	3.98
	(0.47, 1.2)	
U.S. Banks (09-23)	0.41	2.13
	(0.21, 0.61)	

Note: Table 2 reports the estimated price elasticities of demand for U.S. banks, foreigners, and the Fed before and after the assumed regime shift date of 2009Q1. The model is estimated using data from 2003Q4 to 2023Q4. The price elasticities of demand are identified using the optimal GIV estimator developed in Section 3. 95% confidence intervals are reported, with the standard errors given by Theorem 1.

uidity provision in the Treasury market. Foreign investors, once dominant players, have significantly reduced their active participation, while the Federal Reserve has emerged as a crucial liquidity provider during periods of market stress. In Section 5, we examine this transformation further by decomposing observed yield fluctuations and quantifying the contributions of different sectors to Treasury market dynamics.

5 Yield Decomposition and Structural Changes

Having estimated price elasticities and factor sensitivities of different sectors, we now turn to quantifying their contributions to Treasury yield movements over time. We use the equilibrium pricing equation (2.3) to decompose observed Treasury yield fluctuations from two complementary perspectives. First, we analyze the contribution of each sector to yield changes, revealing which investors have been most influential in driving yields at different points in time. Second, we examine the contribution of common factors, showing which economic forces investors are responding to most strongly, and hence are driving Treasury yield fluctuations. Using the equilibrium pricing equation (2.3), we decompose Treasury yield fluctuations and study their drivers from two complementary

perspectives. First, we analyze the contribution of each sector to yield changes. The sectoral decomposition reveals which investors have been most influential in driving yields at any given point in time. Second, we analyze the contribution of common factors to yield changes. This tells us which factors investors are most strongly responding to, and hence driving Treasury yield fluctuations.

5.1 Decomposition of Gross Contribution by Sector

Sector i's contribution to Treasury price changes are given by the sum of the fixed effect, the response to common factors, and the idiosyncratic shocks, scaled by the market multiplier:

$$\Delta\hat{p}_{i,t} = \frac{1}{\hat{\zeta}_{S,r(t)}} S_i \left(\widehat{\overline{\Delta q}_i} + \hat{\boldsymbol{\lambda}}_{i,r(t)} \boldsymbol{\eta}_t + \hat{u}_{i,t} \right),$$

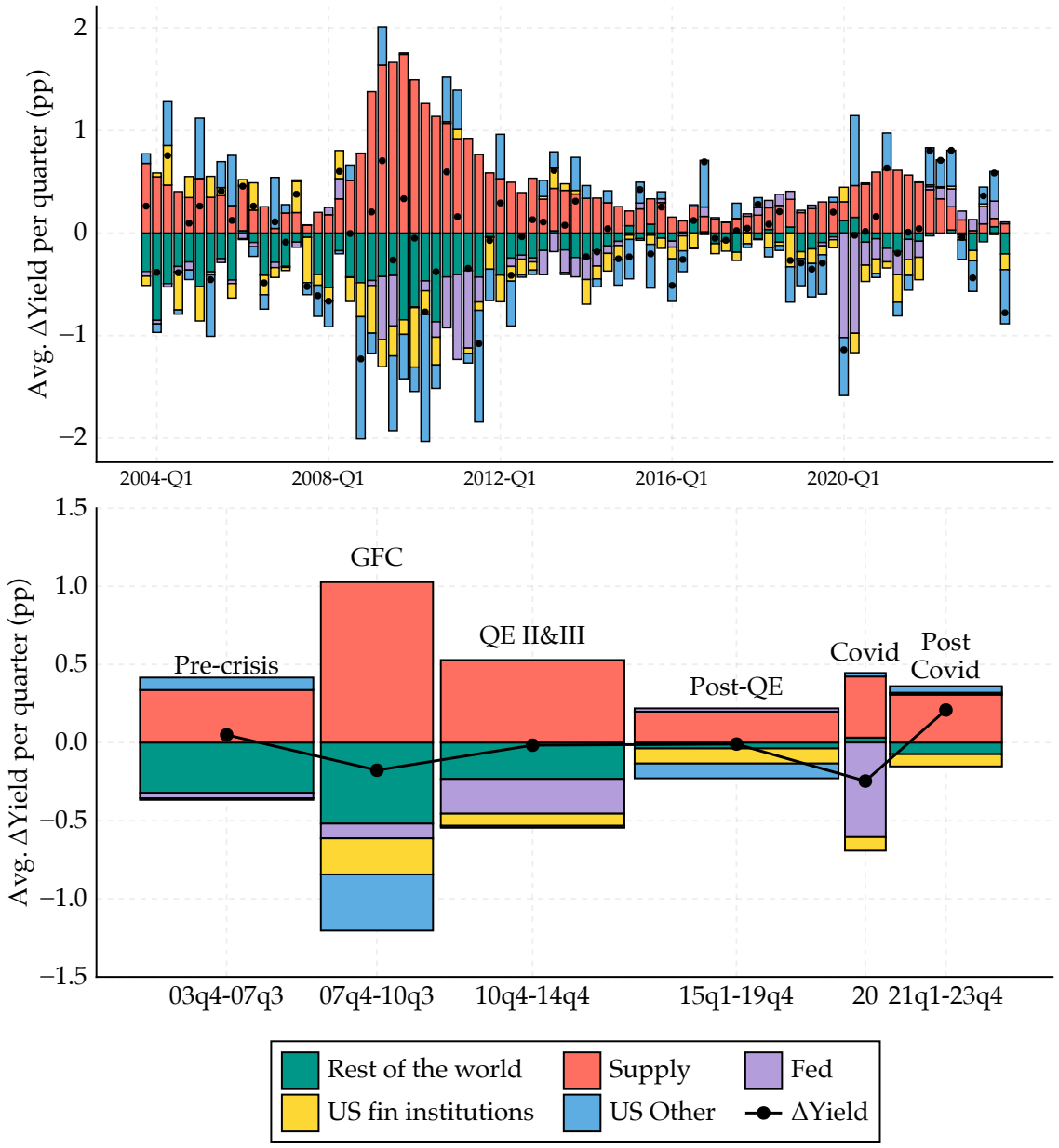
where hats denote estimated values.[15]

To clarify the economic insights from our decomposition, we consolidate sectors into five groups. We highlight: (1) major U.S. financial institutions (mutual funds, ETFs, insurance companies, pension funds, and banks), (2) foreign investors, (3) the Federal Reserve, and (4) Treasury supply from the Department of the Treasury. We also create a fifth group, "US Other," which captures remaining Treasury market participants, primarily households along with non-financial companies, state and local governments, and smaller financial firms (bank holding companies, credit unions, GSEs, and ABS issuers).[16]

Figure 4 presents our yield decomposition by sector. The upper panel shows quarterly contributions over time, while the lower panel aggregates these results into six distinct episodes, using quarterly averages, for better interpretability. Our analysis reveals two major shifts in Treasury market dynamics over the past two decades. First, foreign investors were the dominant force in pushing down Treasury yields from 2003 to 2010, contributing an average reduction of 33 basis points per quarter. However, their influence significantly diminished after 2010, as we will explore in Section 5.1.1. Second, the Federal Reserve emerged as a crucial market participant beginning in 2009, with its demand offsetting 42% of the upward yield pressure from expanded Treasury supply during the Quantitative Easing period. We examine this new role of the Fed in Section 5.1.2. Throughout this period, major U.S. financial institutions, including mutual funds and pension funds, had comparatively minor impact on Treasury yields.

[15] The idiosyncratic shock for each sector, $\hat{u}_{it}$, is backed out from the estimated linear system.
[16] Table B.1 provides the complete sector categorization details.

Figure 4: **Contribution to Treasury yield fluctuations by investor and issuer groups**



Note: Figure 4 reports our main yield decomposition exercise by attributing Treasury yield movement during our sample period to each broadly-defined investor and issuer groups. The top panel reports the decomposition quarter by quarter, and the bottom panel groups the quarterly numbers to 6 distinct episodes. We aggregate investor sectors reported in Financial Account (Z.1) to four investor categories and one issuer sector ("supply"), the exact mapping available in Appendix B.1. Group-specific contribution is backed out from the pricing equation (2.3), assuming that the market multiplier is fixed at the estimated value $\hat{\zeta}_S^{-1}$. We report average yield contribution per quarter in percentage points and the width of the bars in Panel (b) reflects the length of the corresponding episode.

5.1.1 The Evolving Influence of Foreign Investors

In the first decade of the 2000s, foreign investors channeled nearly 3 trillion USD into U.S. Treasuries, becoming a dominant force in the market. Current account surplus countries—including China, Japan, oil exporters, and European nations—built substantial Treasury holdings as they accumulated foreign reserves. This phenomenon sparked significant academic and policy debate about the impact of foreign investors on U.S. interest rates. Greenspan (2005) highlighted the "interest rate conundrum" where long-term rates remained low despite Fed rate hikes, most notably in 2006 when the Fed Funds rate exceeded the 10-year Treasury yield by 80 basis points. Similarly, Bernanke (2005) raised concerns about financial stability risks from persistently low long-term rates driven by this "global savings glut."[17] Our framework allows us to quantify the role different countries played in driving Treasury yield fluctuations. Hence, more systematically evaluate the impact of foreign investors.[18]

Figure 4 shows that foreign investors played a dominant role in driving Treasury yields before the Global Financial Crisis (GFC), but their influence has significantly diminished since then. Figure 5 provides a more detailed breakdown of Treasury yield changes by country and region. In the pre-crisis period, China, Europe, and Japan collectively accounted for 61% of the foreign sector's impact on yields. Consistent with the global savings glut hypothesis, these foreign investors reduced Treasury yields by 0.74 percentage points annually. China was particularly influential, depressing yields by a cumulative 1.7 percentage points over four years.

The aftermath of the financial crisis marked a significant shift in foreign investors' influence on the Treasury market. China's role diminished considerably, while European investors temporarily increased their presence during the Euro Area sovereign debt crisis.[19] Since then, foreign investors' have not put that much downward pressure on Treasury yields. In fact, during the initial phase of the COVID-19 pandemic, foreign investors actually sold Treasuries, contributing to a 34 basis point increase in yields.

[17] For additional discussion on this topic, see Caballero (2006) and Mendoza et al. (2009).

[18] Jiang, Richmond, and Zhang (2024) use a global demand system to examine the role of global savings in accounting for the evolution of U.S. net foreign asset positions. While we share similar decomposition methodology, our focus is on the Treasury price directly.

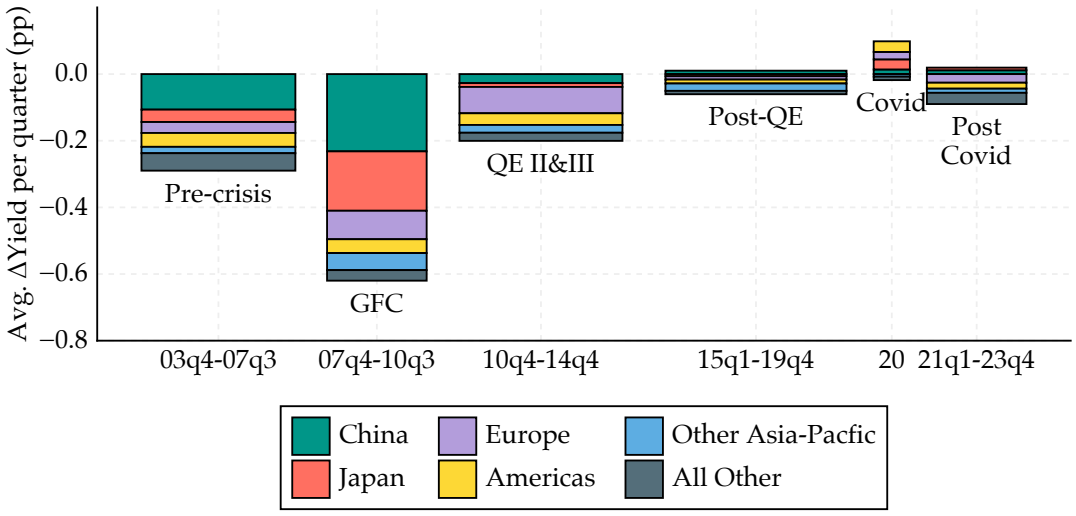
[19] Exchange rate concerns likely motivated Treasury purchases by China and Japan, both active currency intervention participants. The rapid Fed Funds rate cut during the Global Financial Crisis created appreciation pressure, while the unwinding of QE after 2014 led to depreciation pressure for China, prompting foreign reserve sales in 2015. However, these sales had minimal price impact compared to pre-crisis demand shocks.

Our findings on the evolving role of foreign investors aligns with findings by Du, Im, and Schreger (2018), who document a narrowing negative gap between long-term Treasury yields and currency-hedged G10 government yields after the financial crisis. Our analysis complements their work by providing a quantity-based perspective, demonstrating that foreign investors' compression of U.S. Treasury yields was primarily concentrated in the first decade of the 2000s. The finding is also consistent with previous studies documenting a smaller price impact of foreign official flows in and out of U.S. Treasuries after the financial crisis (Beltran, Kretchmer, Marquez, & Thomas, 2013).

The diminished role of foreign investors suggests that Treasury market disruptions would likely be limited if foreign investors sold Treasury holdings in response to geopolitical tensions. Since the financial crisis, the total supply of Treasuries has expanded substantially. This expansion has reduced foreign investors' share of the total Treasury market. For example, Figure B.8, panel (b) in the Appendix, shows that China's market share declined from its 2010 peak of 17.5 percent to just 4 percent by the end of 2023. This decline resulted from two factors: rapid Treasury issuance while China maintained constant holdings before 2020, and China's steady withdrawal from Treasuries since 2020.

Our framework allows us to quantitatively assess the potential market impact of foreign investor actions that have been the subject of significant policy concern. Consider a hypothetical scenario that has received considerable attention: China liquidating its entire U.S. Treasury holdings within a quarter. This scenario—reportedly proposed but rejected during the global financial crisis—has been characterized as China's economic "nuclear option" during trade disputes (Paulson, 2013; Sorkin, 2018). While we cannot assess the broader geopolitical implications, our estimated market multiplier provides a first-order approximation of the yield impact. Given our market multiplier of 0.99, a complete, unanticipated liquidation of China's Treasury holdings as of end-2023 would increase Treasury yields by approximately 60 basis points. For context, this impact falls within the normal range of quarterly yield fluctuations, as the standard deviation of quarterly Treasury yield changes from 2003Q4 to 2023Q4 is 45 basis points. The situation would have been far more severe had this scenario occurred in 2008, when China held nearly 20% of U.S. Treasuries. At that time, such a liquidation would have triggered a three percentage point spike in yields—a dramatic move that could have significantly amplified global financial instability during the crisis.

Figure 5: **Important foreign holders' contributions to yields, percentage points per year**



Note: Figure 5 decomposes the contribution of foreign investors to Treasury yield fluctuations further to the level of large countries and regions. We report average yield contribution per quarter in percentage points. The width of the bars reflects the length of the corresponding episode.

5.1.2 The Federal Reserve as a State-Contingent Liquidity Provider

While foreign investors' influence has waned, the Federal Reserve has emerged as a critical state-contingent liquidity provider in the Treasury market since the Global Financial Crisis (GFC). A comparison of the GFC and COVID-19 episodes reveals a striking evolution in the composition of market participants driving Treasury yields during periods of stress. During the GFC and its aftermath (07Q4–10Q3), yield compression stemmed from multiple sectors: foreign investors (53 basis points per quarter), U.S. households (36 basis points, labeled "US Other" in Figure 4), and major U.S. financial institutions (24 basis points). In contrast, during the COVID-19 pandemic in 2020, the Federal Reserve dominated market intervention, single-handedly reducing yields by 62 basis points per quarter through its purchases. At the same time, other sectors collectively contributed only a 2.5 basis point decline, with foreign investors and U.S. households actually exerting slight upward pressure on yields. Consistent with the Federal Reserve playing the role of a state-contingent liquidity provider.

Table 3 presents our estimates for Federal Reserve behavior since 2009. These estimates control for anticipated Fed purchases as a macro factor, with all results reflecting

deviations from the expected purchase path.[20]

Our analysis reveals the Fed is price elastic, initiating QE operations when Treasury markets experience downward demand pressures. This behavior aligns with the stated objectives of QE operations (Gagnon et al., 2011), which include Treasury market stabilization. The phrase "the smooth functioning of the Treasury market" appears frequently in FOMC minutes, underscoring this priority.[21]

The Fed's QE policies respond actively to market distress, as measured by the VIX index. We estimate that the Fed's intervention in Treasury markets during the height of the COVID-19 crisis reduced Treasury bond and note yields by 2 percentage points, effectively counterbalancing upward yield pressure primarily driven by supply expansion.[22]

Finally, we observe strong coordination between direct Treasury purchases and traditional monetary policy. When the Fed raises the federal funds rate or when inflation increases, it simultaneously reduces its Treasury purchases.

Table 3: **Treasury Demand of the Federal Reserve**

$Period$	$S(\%)$	ζ	$\epsilon^{VIX}_{(std.)}$	Δ **FFR**	$Inf.$
09-23	22.08	0.57	1.55	-9.4	-0.43
		(0.32, 0.83)	(0.74, 2.36)	(-12.39, -6.41)	(-1.55, 0.7)

Note: Table 3 reports a select set of estimated parameters related to the Federal Reserve's demand curve for U.S. Treasury notes and bonds. ζ refers to the price elasticity of demand. $\varepsilon^{VIX}_{(std.)}$ refers to the demand loading on a positive VIX shock, obtained by taking the residual from an AR(1) time-series regression of the VIX index. ΔFFR refers to quarterly changes in the Federal Funds rate, and $Inf.$ denotes the deviation of CPI inflation from the 2% per annum inflation target. 95% confidence intervals are reported, with the standard errors given by Theorem 2.

[20]The Fed typically announces purchases during FOMC meetings according to a pre-scheduled plan. Appendix B.3 details our methodology for constructing anticipated purchases and shows that deviations primarily occurred during the initial and concluding phases of QE operations, when the Fed had flexibility to respond to contemporaneous macroeconomic and financial conditions, including Treasury yields.

[21]For example, a 2020 New York Fed announcement stated: "The Desk stands ready to adjust the size and composition of its purchase operations as appropriate to support the smooth functioning of the Treasury market." Another contemporaneous announcement specified that "the Desk will conduct purchase...subject to reasonable prices."

[22]State-contingent purchases can further reduce Treasury yields through the insurance channel proposed by Haddad, Moreira, and Muir (2024): supporting bond prices during market stress provides additional safety and lowers bond risk premia. Haddad, Moreira, and Muir (2024) finds this insurance channel accounts for approximately 75% of QE's effect on yields.

5.2 Decomposition by Factors

While our sectoral decomposition provides valuable insights into which investors drive Treasury yield movements, it combines the effects of multiple demand shifters. To gain deeper understanding of the underlying economic forces, we now complement our analysis with a factor-based decomposition approach. We employ a two-step methodology: first decomposing yield changes according to the economic factors that shift demand curves (such as risk sentiment, inflation, and monetary policy), then identifying which sectors transmit these factor-driven pressures to market prices. This approach is similar to traditional reduced-form factor pricing models that regress prices on observed macroeconomic variables, as it reveals which factors most significantly drive Treasury yield fluctuations. However, our method has the additional advantage of identifying which sectors are most influential in transmitting specific economic forces to Treasury prices.

Formally, the contribution of the k-th factor to yield changes is given by:

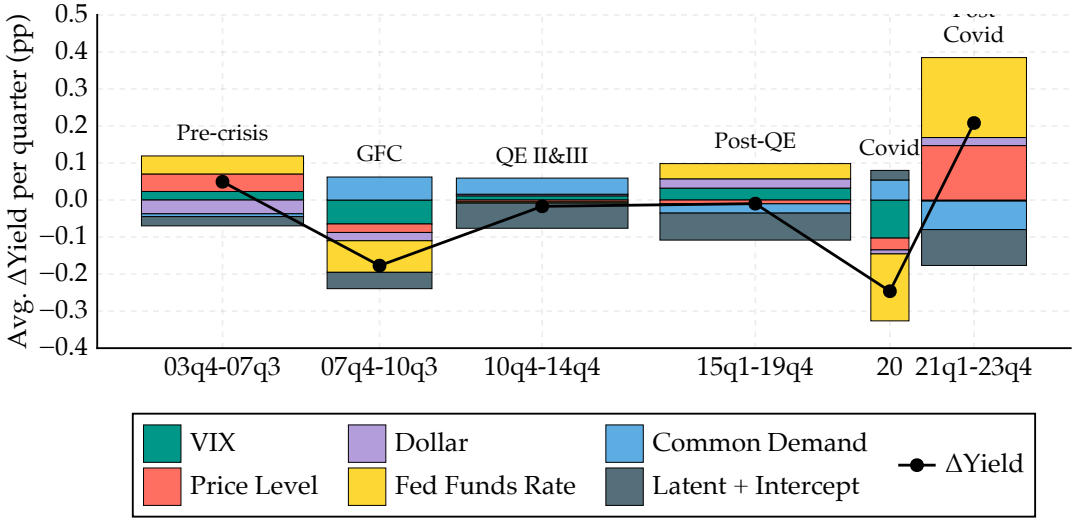
$$\Delta\hat{p}_{\eta(k),t} = \hat{\zeta}^{-1}_{S,r(t)}\hat{\boldsymbol{\lambda}}_{S,r(t)}\eta_t(k), \tag{5.1}$$

where $\hat{\boldsymbol{\lambda}}_{S,r(t)} = \sum_i S_i\hat{\boldsymbol{\lambda}}_{i,r(t)}$ represents the size-weighted average sensitivity to factor k across all sectors. The contribution from idiosyncratic shocks equals $\hat{\zeta}^{-1}_{S,r(t)}\hat{u}_{S,t}$, which our estimates indicate accounts for around 50% of the total variation in Treasury prices during our sample period.

Figure 6 illustrates the contribution of various factors to Treasury yield movements, expressed in quarterly averages (percentage points). We organize these factors into distinct categories, focusing on four key drivers: VIX changes (risk sentiment), inflation, U.S. dollar strength fluctuations, and Federal Funds rate adjustments. We group unobserved common demand factors, predictable Fed purchases, and previous-quarter net issuance under the label "common demand"—representing factors either widely known to market participants or capturing underlying patterns in investor demand across sectors. The decomposition includes intercepts to account for average price pressure from all sectors under "neutral" market conditions.[23]

[23]This decomposition interprets macro factors as deviations from neutral benchmark levels. Different benchmarks would redistribute contributions between macro factors and the intercept (which appears alongside sector-specific idiosyncratic components). We select economically meaningful benchmarks: sample means for most factors, zero for Fed funds rate changes, and 2 percent annual inflation for CPI. Thus, the intercept represents average price pressure under conditions of constant Fed funds rate, 2% inflation, and average values for other macro factors.

Figure 6: **Macro and idiosyncratic drivers of Treasury yields**



Note: Figure 6 reports our yield decomposition exercise attributing yield movements to common, macro factors, idiosyncratic shocks, and group-specific fixed effects. Factor-specific contribution is backed out from the pricing equation (5.1), assuming that the market multiplier is fixed at the estimated value $\hat{\zeta}_S^{-1}$. We report average yield contribution per quarter in percentage points and the width of the bars in Panel (b) reflects the length of the corresponding episode. The bars named "common demand" nest the influence of policy factors (announced Fed purchase and lagged net issuance), and the impact of three principal components extracted from granular Treasury holding data of U.S. banks and foreign investors. The width of the bars reflects the length of the corresponding episode.

Consistent with VIX being a barometer of global risk sentiment, its negative impact on yields is most pronounced during crisis periods. During the 2020 crisis, VIX surges led to a 48 basis point decline in Treasury yields, while during the financial crisis (07Q4-10Q3), they contributed to an 84 basis point cumulative decline. We further investigate which sectors flee to Treasuries during periods of elevated global risk in Section 6.

Conventional monetary policy also exhibits substantial time variation in its influence on longer-term yields. We estimate that despite the Fed's rapid rate hike of more than 4 percentage points over two years, the cumulative pass-through of the short rate on the yields on Treasury bonds and notes is 78 basis points, again illustrating the interest rate "conundrum" faced by the Fed (Greenspan, 2005). During the two crisis episodes, the Fed's interest rate cut lowers yields by 96 and 52 basis points respectively on a cumulative basis. The recent tightening cycle that began in early 2022 raises Treasury yields by a total of 1.8 percentage points.

Hanson and Stein (2015) argue that monetary policy's effect on long-term rates con-

tradicts sticky-price models, proposing instead a channel through demand pressures induced by reach-for-yield motives. Our framework allows us to identify which sectors transmit short rate changes to medium-and-long term yields. Table B.5 in the Appendix reports the full coefficients of factor loadings by sectors. Almost all sectors negatively load on the Fed funds rate, indicating increased demand for Treasury notes and bonds when the short rate decreases and term premia increase. Notably, for a 1% Fed funds rate increase, banks' demand for Treasury notes and bonds decreases significantly by 3.63% ($p < 0.05$). This aligns with research on the deposit channel of monetary policy (Drechsler, Savov, & Schnabl, 2017): as the Fed Funds rate rises, banks widen deposit spreads, causing deposit outflows and corresponding reductions in Treasury holdings.

Consistent with the asset-liability management practices of insurance companies and pension funds (ICPFs), we find their demand for long-term bonds increases when the Fed funds rate rises. ICPF liabilities have a particularly long duration, which exposes them to interest rate risks. To hedge this risk, ICPFs purchase long-maturity bonds. However, available bonds typically have a shorter duration than their liabilities. Hence, ICPFs rely on dynamic trading strategies, which require them to take a leveraged position in bonds to synthetically match the duration of liabilities (Domanski, Shin, & Sushko, 2017; Li, 2024). When Fed funds rise, holding long-term yields fixed, this causes the value of assets to fall more in value than liabilities, requiring ICPFs to purchase more long-term bonds to ensure they are still duration-matched, resulting in a positive loading on the Fed funds rate.

Inflation remained a dormant force in the Treasury market for most of our sample period. However, following the COVID-19 pandemic, global fiscal and monetary stimulus combined with supply-chain pressures pushed inflation to levels not seen since the 1980s. Our estimates indicate that inflation alone pushed yields up by 1.6 percentage points in the three years since 2021. Among sectors, households show the greatest sensitivity to inflation, reducing Treasury holdings by 16% for each percentage point increase in inflation. This finding supports evidence from Nagel and Yan (2022), who demonstrate that households pay attention to inflation news and respond by withdrawing from nominal Treasury-related investments.[24]

[24]The Financial Accounts data do not distinguish between nominal Treasury securities and inflation-indexed Treasury bonds (TIPS), limiting our inflation hedging analysis to a high level. However, the TIPS market represents less than 10% of all marketable Treasury debt as of 2024 and was even smaller earlier in our sample. Therefore, we primarily attribute household flows to nominal bonds and notes.

6 Treasury Investors and "Flight to Safety"

In our final exercise, we use our estimated price elasticities, factor loadings, and decomposition to investigate the drivers of "flight to safety" in the Treasury market—the phenomenon where yields decline as global risk sentiment increases.

Models generating "flight-to-safety" yield dynamics typically assume that foreign investors exhibit countercyclical demand for U.S. Treasuries, meaning these assets become more valuable to them during periods of heightened global risk (Jiang et al., 2021; Kekre & Lenel, 2024, among others). Despite the theoretical importance of this assumption in flight-to-safety models, its empirical validity has remained largely unexamined. This warrants systematic analysis, especially given evidence that challenges this conventional wisdom. For instance, during the COVID-19 pandemic in March 2020, foreign investors actually sold off Treasuries rather than increasing their holdings (He et al., 2022; Vissing-Jorgensen, 2021; Weiss, 2022).

Our estimated model allows us to assess the extent to which foreign investors drive flight-to-safety dynamics. We analyze the estimated flow loadings on quarterly VIX index changes for foreign investors. In the data, Treasury yields and the VIX index exhibit strong negative comovement, making the VIX an effective indicator of investors' tendency to seek safe assets during periods of heightened risk.

Table 4 presents both the size-weighted aggregate VIX loading and sector-specific loadings for selected investors, with the complete set of investor groups reported in Table B.5 in the Appendix. Our findings show that a one standard deviation increase in the VIX index generates a 0.75 percent inflow into the Treasury market. Notably, households exhibit the strongest "flight-to-safety" behavior, increasing their Treasury demand by 16 percent. In contrast, foreign investors show no statistically significant sensitivity to VIX changes. In fact, their point estimate is negative, suggesting that foreign investors tend to reduce their U.S. Treasury holdings during risk-off episodes rather than increase them.

Our finding that foreign Treasury demand has a negative loading on VIX is at odds with the standard assumption that foreign investors have stronger countercyclical demand for Treasuries. We further verify our findings using a more reduced-form approach to ensure our conclusion is not driven by our model's specification. In Figure 7, we plot foreign inflows *net of Treasury issuance* (normalized by market size) against domestic flows over the entire sample period (panel (a)) and observe a stark difference: when VIX is high, foreign investors tend to purchase fewer Treasuries—or even sell them—compared

Table 4: **Sensitivities to global risk sentiments for selected sectors**

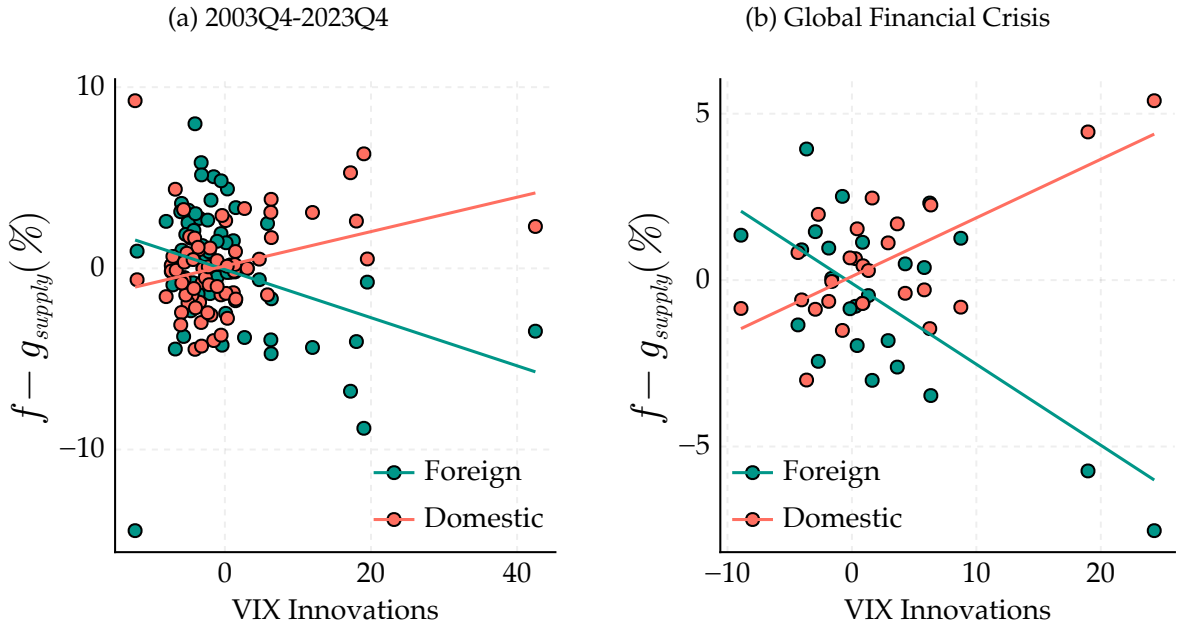
Sector	$S(\%)$	$VIX_{(std.)}$	$VIX_{(std.)}$ **Share (%)**
Aggregate (09-)		0.75	100.0
		(0.0, 1.49)	
Households	5.74	16.12	124.11
		(6.12, 26.13)	
Fed (09-)	22.08	1.55	45.94
		(0.74, 2.36)	
Rest of World	44.45	-0.2	-11.69
		(-0.87, 0.48)	
Supply	100.0	-0.19	-25.02
		(-0.4, 0.02)	
Mutual Funds	6.75	-1.94	-17.6
		(-3.52, -0.37)	

Note: Table 4 reports the estimated responsiveness to a rise in the VIX index for a seleted set of sectors in the data. The sample period is 2003Q4–2023Q4. The loadings are identified using the optimal GIV estimator developed in Section 2. S corresponds to the size weight used in the estimation, defined as the average market share of each entity throughout the sample period. $\varepsilon^{VIX}_{(std.)}$, the regressor of interest, is obtained by running a AR(1) time-series regression on the VIX index and taking the residual. $\varepsilon^{VIX}_{(std.)}$ share denotes the (size-weighted) fraction of aggregated VIX loading accounted for by each sector. 95% confidence intervals are reported, with the standard errors given by Theorem 2.

to domestic investors. This relationship is not merely a recent phenomenon since the pandemic; it was also evident at monthly frequency during the Global Financial Crisis. This pattern contradicts the notion that foreign investors have stronger countercyclical demand for Treasuries, but aligns with Fu (2023), who document that foreign investors generally withdraw capital during economic downturns.

We note that simple correlation or direct regression coefficient between flow and VIX does not capture an investor's true responsiveness of Treasury *demand* to rising global risk sentiment but only the relative tendency. Only through an equilibrium model are we able to disentangle the endogenous demand response from the observed equilibrium holdings. Hence, this finding underscores the importance of accounting for endogenous demand and supply interaction when discussing phenomena related to international capital flows.

Figure 7: **Foreign flows (net of issuance) and global risk indicators**



Note: Figure 7 illustrates the importance of accounting for equilibrium interactions among investors and issuers to properly estimate the sensitivity of Treasury demand to shift in global risk sentiments, proxied by VIX innovations. In both panels, we plot foreign (green) and U.S. domestic (red) inflow to Treasury notes and bonds f (% of total holdings in the previous quarter), net of total issuance g (also expressed as % of total market value of outstanding issuance the previous quarter). Panel (a) plots all observations throughout the sample period. Panel (b) focuses on the Global Financial Crisis episode at the monthly frequency (2007/12-2009/12).

7 Conclusion

This paper introduces a novel empirical framework to understanding how demand and supply forces drive asset price fluctuations. Methodologically, our estimation approach helps flexibly and efficiently identify heterogeneous price and factor elasticities and precisely quantify the contribution of various market participants to asset price movements. Our optimal GIV estimator based on granularity can be easily applied to other markets, and will be particularly powerful in the case of concentrated markets where demand shocks play a larger role in driving market prices.

When applied to the U.S. Treasury market, our method offers novel answers to a series of important questions. We provide the first direct macro elasticity estimate of the market. We demonstrate significant structural shifts in liquidity provision marked by the global financial crisis, featuring the retreat of foreign investors and U.S. banks and the rising importance of the Federal Reserve. We also show that the "flight-to-Treasury"

behavior of foreign investors during global downturns – taken as a fact in standard narratives – is not supported in the data. While our model is intended to provide a high-level characterization of the market dynamics, our estimate serves as a useful benchmark to guide future research to delve deeper into the underlying mechanisms.

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A Methodological Appendix

A.1 General Framework

Here we introduce the more flexible model. The general model is specified as follows:

$$\left.\begin{array}{rl} q_{i,t} & = -p_t \times \mathbf{C}'_{i,t}\boldsymbol{\zeta} + \mathbf{X}'_{i,t}\boldsymbol{\beta} + u_{i,t}, \\ 0 & = \sum_i S_{i,t} q_{i,t} \end{array}\right\} \Longrightarrow p_t = \frac{1}{\mathbf{C}'_{S,t}\boldsymbol{\zeta}}\left[\mathbf{X}'_{S,t}\boldsymbol{\beta} + u_{S,t}\right],$$

which allows for the following flexibility:

- The elasticity is parameterized by the matrix $\mathbf{C}_{i,t}$, which can be entity-specific and time-varying;
- The control variable $\mathbf{X}_{i,t}$ can also also be entity&time-specific;
- The size vector $S_{i,t}$ is also allowed to be time-varying; we also do not require it to sum to 1.

The simple model can be recovered from the general specification by setting $\mathbf{C}_{i,t}$ to be the entity fixed effects, and $\mathbf{X}_{\mathbf{i,t}}$ to be the interaction of entity fixed effects with the aggregate factors $\boldsymbol{\eta}_t$.

The moment conditions used to identify the elasticity vector $\boldsymbol{\zeta}$ remain the same as before, only it is now conditional on all other exogenous variables $(\boldsymbol{\eta}_t, \mathrm{C}_t, \mathrm{S}_t)$:

$$\mathbb{E}\left[u_{i,t}u_{j,t} \mid \mathbf{X}_t, \mathbf{C}_t, \mathbf{S}_t\right] = 0. \tag{A.1}$$

We again follow the three-step procedures outlined in B.2 to strip away the influence of control variables $\mathbf{X}_{i,t}$, and then form the optimal GIV estimator for $\boldsymbol{\zeta}$ using the residuals $q^{\varepsilon}_{i,t}$ and p^{ε}_t. We provide the optimal GIV estimator and its asymptotic properties below, and refer readers to Appendix A for the derivation.

Definition 2. Let $\boldsymbol{\psi}_t(\mathbf{z})$ be a vector of length $\frac{N(N-1)}{2}$ with subscript ij $(i \neq j)$ denote the row corresponding the entity pair (i, j) :

$$\psi_{ij,t}(\mathbf{z}) \equiv \hat{u}_{it}(\mathbf{z})\,\hat{u}_{jt}(\mathbf{z}) \equiv \left(q^{\varepsilon}_{i,t} + p^{\varepsilon}_t \mathbf{C}'_{i,t}\mathbf{z}\right)\left(q^{\varepsilon}_{j,t} + p^{\varepsilon}_t \mathbf{C}'_{j,t}\mathbf{z}\right).$$

Denote $\mathbf{V}^{\psi} \equiv \mathbb{E}\left[\boldsymbol{\psi}_t(\boldsymbol{\zeta})\boldsymbol{\psi}_t(\boldsymbol{\zeta})'\right] = Diag\left(\sigma_1^2\sigma_2^2, \sigma_1^2\sigma_3^2, \ldots, \sigma_{N-1}^2\sigma_N^2\right)$. Denote $\hat{\mathbf{W}}_t^*(\mathbf{z})$ as weighting matrix of the size $\frac{N(N-1)}{2} \times N_\zeta$ such that

$$\hat{\mathbf{W}}_{ij,k,t}^*(\mathbf{z}) = \frac{1}{\mathbf{C}_{S,t}'\mathbf{z}}\left(\frac{S_{jt}C_{it,k}}{\hat{\sigma}_i^2(\mathbf{z})} + \frac{S_{it}C_{jt,k}}{\hat{\sigma}_j^2(\mathbf{z})}\right),$$

where $\hat{\sigma}_i^2(\mathbf{z}) \equiv \hat{\mathbb{E}}\left[\hat{u}_{it}(\mathbf{z})^2\right]$. The optimal GIV estimator $\hat{\boldsymbol{\zeta}}$ for the general model solves the following sample moment conditions:

$$\hat{\mathbb{E}}\left[\hat{\mathbf{W}}_t^*\left(\hat{\boldsymbol{\zeta}}\right)'\boldsymbol{\psi}_t\left(\hat{\boldsymbol{\zeta}}\right)\right] = \mathbf{0}.$$

Similar to the simple model, we show the optimal GIV estimator in this case is also asymptotically efficient:

Theorem 2 (Asymptotic efficiency in the general model)**.** *Given the moment conditions (A.1), Under regularity conditions*[25]*, the optimal GIV estimator $\hat{\boldsymbol{\zeta}}$ is consistent and asymptotically normal:*

$$\sqrt{T}\left(\hat{\boldsymbol{\zeta}} - \boldsymbol{\zeta}\right) \xrightarrow{d} \mathcal{N}\left(0, \mathbf{V}^{\zeta}\right),$$

for $T \to \infty$, where

$$\mathbf{V}^{\zeta} = \left(\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{V}^{\psi}\mathbf{W}_t^*\right]\right)^{-1}.$$

Moreover, $\mathbf{V}^{\zeta}$ achieves the semi-parametric efficiency bound.

Proof. See Appendix A.6. □

A.2 The "Missing Intercept" Problem

Consider the case with a single factor, say monetary policy shocks. In this case, the direct, OLS estimate of asset demand loading on monetary shocks, λ_i^q, is given by:

$$\lambda_i^q \equiv \frac{\mathbb{E}\left[q_{i,t}\eta_t\right]}{\mathbb{E}\left[\eta_t^2\right]} = \frac{\mathbb{E}\left[\left(-\zeta_i p_t + \lambda_i\eta_t\right)\eta_t\right]}{\mathbb{E}\left[\eta_t^2\right]} = \lambda_i - \frac{\zeta_i}{\zeta_S}\lambda_S. \tag{A.2}$$

This equation makes it clear that the estimated coefficient will be downward biased with the bias given by the market average loading multiplied by entity i's price elasticity relative to the market. Hence, observing asset sales from an investor after monetary tightening ($\lambda_i^q < 0$) does not necessarily imply that their demand shifts downwards after surprise

[25] See Appendix A.6 for the exact conditions.

monetary policy tightening. If all price elasticities have the same sign, we can only infer their demand is lower than than the market average ($\lambda_i < \lambda_S$). Nevertheless, without knowing the price elasticities and the aggregate loading, we cannot determine the sign of the true demand loading λ_i. This issue reflects the "missing intercept" problem commonly faced in macroeconomics: when making inference using micro data, the general equilibrium effects are differenced out in the cross-section. Here the equilibrium asset price is the intercept that is omitted from the analysis.

A.3 Measurement Errors

The quantity data can be noisy in real world applications. The quantity observed by the econometrician may be contaminated by the additional measurement errors:

$$\tilde{q}_{i,t} = q_{i,t} + \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ only enters the observed $\tilde{q}_{i,t}$ but not the real $q_{i,t}$ and hence not the pricing equation (2.3).

If the measurement errors are *classic*, i.e., it is independent with prices, common factors and each other, then the optimal GIV estimator is still consistent, as the moment conditions in (3.2) still holds with additional orthogonal terms $\varepsilon_{i,t}$. The size-weighting scheme, however, will no longer be optimal except for the special case where $var\left(\varepsilon_{i,t}\right) \propto var(u_{i,t})$.

Nevertheless, the existence of a residual sector may break the consistency of the estimator under classic measurement errors. A residual sector is a sector that is not directly observed in the data, but backed out from the market clearing condition. In real world applications, we typically do not observe the direct report of the holdings and flows from every market participant. For example, the household sector in the Flow of Funds data is a residual sector imputed using market clearing.

After imposing market clearing, measurement errors in the observed data will negatively enter the quantity for the residual sector r:

$$\tilde{q}_{r,t} \equiv -\frac{1}{S_r}\sum_{i \neq r} S_i \tilde{q}_{i,t} = q_{r,t} - \frac{1}{S_r}\sum_{i \neq r} S_i \varepsilon_{i,t}.$$

In this case, moment conditions between the residual sector r and other sectors with mea-

surement errors may no longer hold, as the measurement errors lead to a negative covariance:

$$\mathbb{E}\left[\left(u_{r,t}-\frac{1}{S_r}\sum_{i\neq r}S_i\varepsilon_{i,t}\right)(u_{i,t}+\varepsilon_{i,t})\right]=-\frac{S_i}{S_r}\sigma^2_{i,\varepsilon}.$$

If one is not interested in the aggregate market elasticity, one can simply exclude the residual sector form the estimation. If there exist investors free from measurement errors ($\sigma_{i,\varepsilon}=0$), then the elasticity for the residual sector can also be consistently estimated by only including sectors without measurement errors.

A.4 Comparison with the Standard GIV

The size-weighting cheme proposed above may look reminiscent to readers who are familiar with the original GIV method proposed in the seminal paper of Gabaix and Koijen (2024). In this section we discuss the relationship of our approach to the method introduced in Gabaix and Koijen (2024), hereafter referred to as the standard GIV. This section can be skipped without compromising the understanding of our results in the following sections.

On top of the assumptions above, the standard GIV further imposes homogeneity in elasticities across entities.[26] To closely compare two estimators, we also consider the case with homogeneous elasticity so that $\zeta_i \equiv \zeta$, and we also consider the case where the size vector sums to 1, $\sum_i S_i = 1$.

With homogeneity, the optimal GIV estimator pools the sample moment conditions (3.3) across i weighted by the inverse of residual variance $(\sigma_i^2)^{-1}$ (see Section A.1), so that the optimal GIV estimator ζ^{OGIV} corresponds to the following moment conditions in population:

$$\sum_i \frac{(\sigma_i^2)^{-1}}{\Sigma_i(\sigma_i^2)^{-1}}\mathbb{E}\left[\left(q_{i,t}+\zeta^{OGIV}p_t\right)\sum_{j\neq i}S_j\left(q_{j,t}+\zeta^{OGIV}p_t\right)\right]=0$$

Denote the $\mathbf{\Sigma}_u = diag\left(\sigma_1^2,\sigma_2^2,\ldots,\sigma_N^2\right)$ as the covariance matrix of the residual variance, and $\mathbf{E}_i \equiv \frac{(\sigma_i^2)^{-1}}{tr(\mathbf{\Sigma}_u^{-1})}$ as the weights using the inverse of the residual volatility, we can

[26] Gabaix and Koijen (2024) also offer a method to handle heterogeneity in the online appendix, which is further developed by Chodorow-Reich et al. (2024). Here the standard GIV refers to the case with homogeneity introduced in the main text of Gabaix and Koijen (2024).

consolidate the corresponding moment conditions above in the matrix form:

$$\mathbf{E}'\mathbb{E}\left[\left(\mathbf{q}_t+\boldsymbol{\iota}\zeta^{OGIV}p_t\right)\left(\mathbf{q}_t+\boldsymbol{\iota}\zeta^{OGIV}p_t\right)'\right]\mathbf{S}=\mathbf{E}'\boldsymbol{\Sigma}_u\mathbf{S}=\frac{1}{tr(\boldsymbol{\Sigma}_u^{-1})}. \qquad \text{(Optimal-GIV)}$$

Notice that this is a quadratic equation in ζ^{OGIV} and has to be solved nonlinearly.

The key insight in the standard GIV is that, with homogeneous elasticities, cross-sectional demeaning can eliminate the endogenous term ζp_t. Mathematically, for any vector that sums to 1, $\mathbf{X}'\boldsymbol{\iota}=1$, we also have $\mathbf{E}'\boldsymbol{\Sigma}_u\mathbf{X}=\frac{1}{tr(\boldsymbol{\Sigma}_u^{-1})}$, so by taking the difference of these two equations, we have:

$$\mathbf{E}'\mathbb{E}\left[\left(\mathbf{q}_t+\boldsymbol{\iota}\zeta^{SGIV}p_t\right)\left(\mathbf{q}_t+\boldsymbol{\iota}\zeta^{SGIV}p_t\right)'\right](\mathbf{S}-\mathbf{X})=0, \qquad \text{(Standard-GIV)}$$

where $\mathbf{S}-\mathbf{X}$ essentially demeans $\mathbf{q}_t$ in the cross section. Move weighting vectors into the expectation operator, this weighting scheme can be further expressed as in terms of weighted average of q:

$$\mathbb{E}\left[\left(q_{E,t}+\zeta^{SGIV}p_t\right)\left(q_{S,t}-q_{X,t}\right)\right]=0.$$

Importantly, the term ζp_t drops out from the second term in the expectation due to differencing. As it is linear in ζ, it now be implemented with an IV regression of precision-weighted quantity $(q_{E,t})$ on p_t, using $q_{S,t}-q_{X,t}$ as the instrument. Gabaix and Koijen (2024) further show that within this class of the linear estimators, setting $\mathbf{X}=\mathbf{E}$ achieves the highest statistical power, and hence the recommended instrument is the size-minus-precision weighted q.

At first glance, the mathematical difference between the standard GIV and the optimal GIV in the simplest case is merely whether to demean $q_{i,t}$ in the cross section. This subtle difference nevertheless has an important implication on the statistical power in a sample where the distribution of the contribution to price changes across entities does not exhibit a large fat tail.

To see the power comparison, consider a simpler case with homoskedasticity, i.e., $\sigma_i\equiv\sigma$. In this case, the asymptotic variance of the optimal GIV estimator has a simple

expression: [27]

$$\sqrt{T}\left(\hat{\zeta}^{OGIV}-\zeta\right)\xrightarrow{d}\mathcal{N}\left(0,\mathbf{V}_{\zeta}^{OGIV}=\frac{\zeta^2}{(N-2)\sum_i S_i^2+1}\right),$$

while the standard GIV converges to a different limiting distribution: [28]

$$\sqrt{T}\left(\hat{\zeta}^{SGIV}-\zeta\right)\xrightarrow{d}\mathcal{N}\left(0,\mathbf{V}_{\zeta}^{SGIV}=\frac{\zeta^2}{N\sum_i S_i^2-1}\right).$$

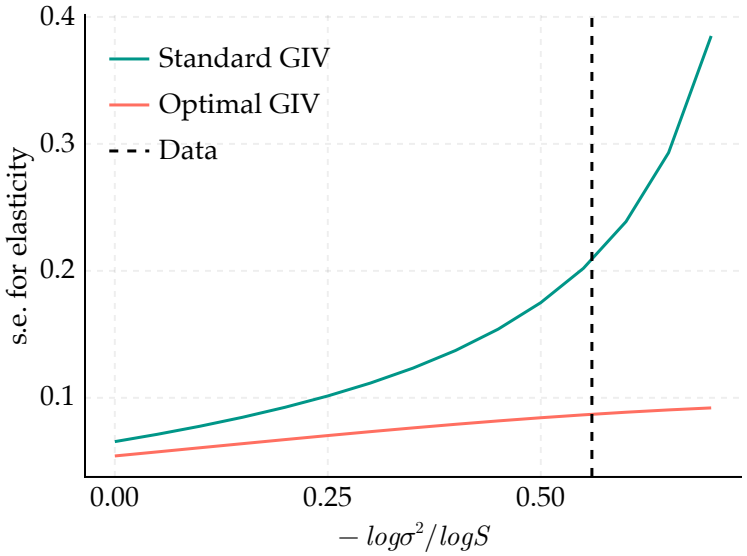
We can show that $\mathbf{V}_{\zeta}^{OGIV} > \mathbf{V}_{\zeta}^{SGIV}$. More importantly, the crucial difference is that the standard GIV relies on the fat-tail distribution in S_i for statistical power, while the optimal GIV does not. This is because when sizes are equally distributed ($S_i = \frac{1}{N}$), the size weighting and precision weighting (which is equal weighting in the case of homoskedasticity) coincides, so the standard GIV's instrument has zero variation after demeaning. This is not the case in the optimal GIV, whose statistical power still grows at the rate of $\sqrt{T}$.

This power comparison is not only theoretical but is also relevant practically. While fat-tail distribution in sizes is prevalent in real-world data, the residual volatility typically shrinks as an entity becomes larger. As shown in the expressions in (A.21), what matters for the statistical power is not only the size distribution but the the distribution of each entity's contribution to price volatility, i.e., the size-weighted volatility, $S_i^2\sigma_i^2$. To see that, consider the case where the size has a fat tail distribution but the residual volatility is inversely proportional to the size, $\sigma_i \propto \frac{1}{S_i}$. In this case, the size vector again coincide with the precision weighting, and there is no variation in the size-minus-precision instruments.

Figure A.1 compares the statistical power of the standard GIV in Gabaix and Koijen (2024) vs. the optimal GIV in simulation. We simulate the model mirroring the Treasury market in the flow of fund data. We assume there are 12 sectors with a homogeneous elasticity of 1, and the supply is inelastic. The size distribution is calibrated with the concentration in the Financial Accounts data, and we vary the rate at which volatility decreases as the size of a sector increases. Other model parameters are reported in the note accompanyiing Figure A.1. As the volatility decreases, the precision of standard GIV decays rapidly, while only mildly for the optimal GIV. When the volatility-size ratio matches that in the Financial Accounts data, the optimal GIV is twice as powerful as the standard GIV.

[27] See the Appendix A.6 for the derivation.
[28] See Gabaix and Koijen (2024) for the derivation.

Figure A.1: **Statistical power comparison: standard GIV vs. optimal GIV**



Note: Figure A.1 compares the statistical power of the standard GIV in Gabaix and Koijen (2024) vs. the optimal GIV in simulation. Simulation parameters: number of sectors $N = 12$, $T = 80$ quarters, no common factors, the excess HHI in the size distribution, $h \equiv \sqrt{\sum_i S_i^2 - \frac{1}{N}} = 0.5$, elasticity $\zeta = 1.0$, and the level of the shock volatility is calibrated so that the $\sigma_p^2 = 2.5\%$.

A.5 Bias Analysis

Consider the baseline model after residualizing against common factors. The econometrician believes the demand shocks $u_{i,t}$ are uncorrelated:

$$\Delta q_{i,t} = -\zeta_i \Delta p_t + u_{i,t}, \tag{A.3}$$

$$\Delta p_t = \frac{1}{\zeta_S} u_{S,t}. \tag{A.4}$$

Here, as a shorthand, we use the S subscript to denote the size-weighted sum, i.e., $\zeta_S = \sum_i S_i \zeta_i$ and $u_{S,t} = \sum_i S_i u_{i,t}$.

However, there is in fact a remaining common demand shock η_t in the demand shock

$u_{i,t}$ that the econometrician fails to recognize. The true model is in fact:

$$\Delta q_{i,t} = -\zeta_i \Delta p_t + \lambda_i \eta_t + \epsilon_{i,t}, \tag{A.5}$$

$$\Delta p_t = \frac{1}{\zeta_S} \left(\lambda_S \eta_t + \epsilon_{S,t} \right), \tag{A.6}$$

Failing to control for the common factor η_t, the econometrician specifies the following sample moment conditions and estimates the elasticities using the optimal GIV estimator:

$$\hat{\mathbb{E}}[\left(\Delta q_{i,t} + \hat{\zeta}_i^b \Delta p_t\right) \left(\Delta q_{j,t} + \hat{\zeta}_j^b \Delta p_t\right)] = 0, \tag{A.7}$$

We can show that the estimated biased aggregate elasticity $\hat{\zeta}_S^b$ converges to $\zeta_S^b = \sum_i S_i \zeta_i^b$, which is approximately:

$$\zeta_S^b \approx \zeta_S \sqrt{1 - \mathcal{R}^2}, \quad \mathcal{R}^2 \equiv \frac{var(\lambda_S \eta_t)}{\zeta_S^2 var(p_t)} = \frac{\lambda_S^2 \sigma_\eta^2}{\lambda_S^2 \sigma_\eta^2 + \sum_i S_i^2 \sigma_{\epsilon,i}^2} \tag{A.8}$$

where $\mathcal{R}^2$ is the share of the hidden factor in the total variance of the (residualized) price. Equation (A.8) states that if the econometrician fails to recognize the common factor, there would be a downward bias in the estimated aggregate elasticity, and the bias is increasing in the share of the unobserved comovement. The precise statement on the approximation and the proof are given in Proposition A.1 below.

To illustrate the magnitude of the bias, in the figure below we take our estimated aggregate elasticity $\hat{\zeta}_S = 1$, and plot the true aggregate elasticity ζ_S assuming we had missed out comovement in the residuals that explains $\mathcal{R}^2$ of the residual variance. It shows that for a medium level of residual comovement, the potential bias is quite small. In order for our estimates to be off by 100%, 75% of the residual variance in the demand shocks has to be explained by common factors. It seems unlikely to us that there exists such a strong hidden common factor that is not observable and cannot be picked up by PCA.

Proposition and Proof

Under the homogeneous case (homoskedasticity $\sigma_i = \sigma$, equal sizes $S_i = \frac{1}{N}$, and same loadings $\lambda_i = \lambda_S$), Equation (A.8) is exact. When the size distribution is unequal, the residual from the approximation vanishes as N goes to infinity. More precisely, we have

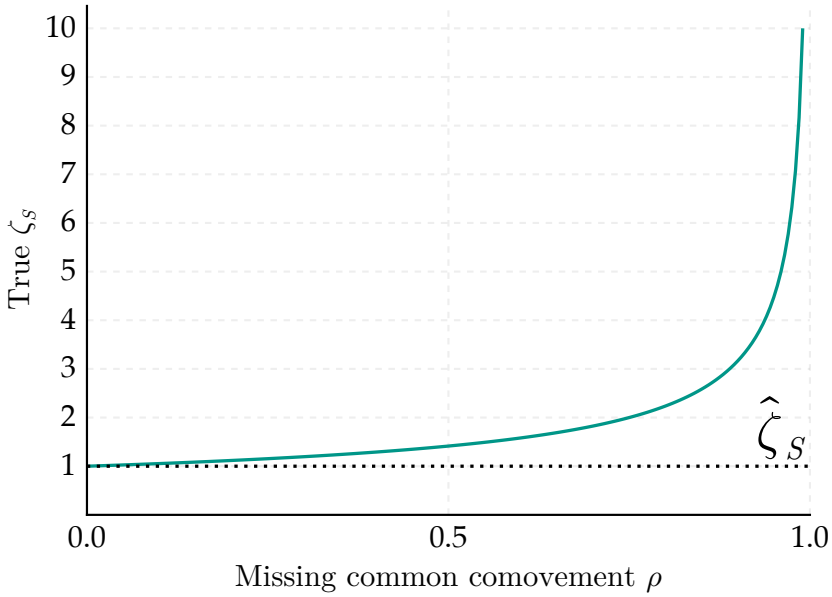


Figure A.2: Relationship between the true aggregate elasticity ζ_S and the share of hidden comovement $\mathcal{R}^2$. The horizontal dotted line represents the estimated aggregate elasticity $\hat{\zeta}_S = 1$. The curve shows the implied true aggregate elasticity for different values of $\mathcal{R}^2$.

the following proposition:

Proposition A.1. *Consider a sequence of models specified in (A.5) and (A.6) indexed by N, where $\mathcal{R}^2_N = \frac{\lambda^2_{S,N}\sigma^2_{\eta,N}}{\lambda^2_{S,N}\sigma^2_{\eta,N}+\sum_i S^2_{i,N}\sigma^2_{\epsilon,i}}$ converges to a constant $\mathcal{R}^2$ as N goes to infinity. The bias of the misspecified aggregate elasticity converges to:*

$$\lim_{N\to\infty} \frac{\zeta^b_{S,N}}{\zeta_{S,N}} = \sqrt{1-\mathcal{R}^2} \tag{A.9}$$

Proof. For notational ease, we drop the N subscript. Define $u_{i,t} \equiv \Delta q_{i,t} + \zeta_i \Delta p_t$ as the misspecified residuals. Using the true model in (A.5), it can be expressed as:

$$u_{i,t} = \left(-\left(\zeta_i - \zeta^b_i\right)\Delta p_t + \lambda_i \eta_t + \epsilon_{i,t}\right) \tag{A.10}$$

Plugging in Equation (A.6) into the misspecified residual, and denoting $b_i \equiv \frac{\zeta_i - \zeta^b_i}{\zeta_S}$, we have:

$$u_{i,t} = (\lambda_i - \lambda_S b_i)\,\eta_t - b_i \epsilon_{S,t} + \epsilon_{i,t} \tag{A.11}$$

$$\mathbb{E}\left[u_{i,t}u_{j,t}\right] = (\lambda_i - \lambda_S b_i)\,(\lambda_j - \lambda_S b_j)\,\sigma_\eta^2 + b_i b_j \sigma_S^2 - b_i S_j \sigma_j^2 - b_j S_i \sigma_i^2$$

where $\sigma_\eta^2 = \mathbb{E}\left[\eta_t^2\right]$, $\sigma_i^2 = \mathbb{E}\left[\epsilon_{i,t}^2\right]$, and $\sigma_S^2 = \sum_i S_i^2 \sigma_{\epsilon,i}^2$ is the size-weighted variance of the residuals.

The optimal GIV estimator solves:

$$\mathbb{E}\left[u_{i,t} \sum_{j \neq i} S_j u_{j,t}\right] = 0 \tag{A.12}$$

Using $\sum_{j\neq i} S_j b_j = b_S - S_i b_i$, $\sum_{j\neq i} S_j \lambda_j = \lambda_S - S_i \lambda_i$, and $\sum_{j\neq i} S_j \sigma_j^2 = \sigma_S^2 - S_i \sigma_{\epsilon,i}^2$, the moment condition above can be rewritten as a quadratic equation in b_i:

$$\begin{aligned} S_i\left(\sigma_S^2 + \lambda_S^2 \sigma_\eta^2\right) b_i^2 - \left[2S_i^2 \sigma_{\epsilon,i}^2 + S_i \lambda_S \lambda_i \sigma_\eta^2 + (b_S - 1)\left(\sigma_S^2 + \lambda_S^2 \sigma_\eta^2\right)\right] b_i \\ + \left[S_i b_S \sigma_{\epsilon,i}^2 + S_i \lambda_i^2 \sigma_\eta^2 - (1 - b_S)\,\lambda_S \lambda_i \sigma_\eta^2\right] = 0. \end{aligned} \tag{A.13}$$

We have N quadratic equations in b_i and $b_S = \sum_i S_i b_i$ as the fixed point of this system.

Focusing on the bias in the aggregate elasticity b_S, we take the size-weighted summation across all i:

$$\begin{aligned} (\sigma_S^2 + \lambda_S^2 \sigma_\eta^2)\left[\sum_i S_i^2 b_i^2 - b_S(b_S - 1)\right] - 2\sum_i S_i^3 \sigma_i^2 b_i - 2\lambda_S \sigma_\eta^2 \sum_i S_i^2 \lambda_i b_i \\ + b_S \sum_i S_i^2 \sigma_i^2 + \sigma_\eta^2 \sum_i S_i^2 \lambda_i^2 - (1 - b_S)\sigma_\eta^2 \lambda_S^2 = 0 \end{aligned} \tag{A.14}$$

Under homogeneity, we can use $b_i = b_S$ and solve for b_S:

$$b_S = 1 - \frac{\lambda_S^2 \sigma_\eta^2}{\sigma_S^2 + \lambda_S^2 \sigma_\eta^2}.$$

To derive an approximate solution when homogeneity does not hold, we consider the

rate of convergence of each term as $N \to \infty$. Using the big O notation to indicate the same rate of convergence, and little o to indicate a faster rate of convergence, we can determine the rate of convergence of each term: $\sigma_\eta^2 = O(\sigma_S^2), (\sigma_S^2 + \sigma_\eta^2)\sum_i S_i^2 b_i^2 = o(\sigma_S^2), \sum S_i^3 \sigma_i^2 b_i = o(\sigma_S^2), \sigma_\eta^2 \sum S_i^2 b_i = o(\sigma_S^2), \sigma_\eta^2 \sum_i S_i^2 \lambda_i^2 = o(\sigma_S^2)$. Hence the equation above can be simplified as:

$$\underbrace{(\sigma_S^2 + \lambda_S^2\sigma_\eta^2)b_S^2 - 2(\sigma_S^2 + \lambda_S^2\sigma_\eta^2)b_S + \lambda_S^2\sigma_\eta^2}_{F(b_S)} + o(\sigma_S^2) = 0 \tag{A.15}$$

□

The leading term $F(b_S)$ has a root smaller than one at $b_S^* = 1 - \frac{\lambda_S^2\sigma_\eta^2}{\sigma_S^2 + \lambda_S^2\sigma_\eta^2}$. We also have $F'(b_S^*) = \lambda_S^2\sigma_\eta^2$. Using Taylor expansion around b_S^*, we have:

$$b_S = b_S^* - \frac{o(\sigma_S^2)}{\lambda_S^2\sigma_\eta^2} + o(\sigma_S^2) = b_S^* + o(1)$$

Expressing b_S in terms of ζ_S^b and ζ_S, we have:

$$\zeta_S^b = \zeta_S\sqrt{(1 - \mathcal{R}^2)} + o\left(1\right)$$

A.6 Proof

We prove the properties of the optimal GIV estimator for the general framework introduced in (A.1), restated here:

$$\left.\begin{array}{rl} q_{i,t} & = -p_t \times \mathbf{C}_{i,t}'\boldsymbol{\zeta} + \mathbf{X}_{i,t}'\boldsymbol{\beta} + u_{i,t}, \\ 0 & = \sum_i S_{i,t} q_{i,t} \end{array}\right\} \implies p_t = \frac{1}{\mathbf{C}_{S,t}'\boldsymbol{\zeta}}\left[\mathbf{X}_{S,t}'\boldsymbol{\beta} + u_{S,t}\right], \tag{A.16}$$

where $\mathbf{C}_{i,t}$ and $\mathbf{X}_{i,t}$ are matrices of exogenous variables that can be individual-specific and time-varying, and $\boldsymbol{\zeta}$ and $\boldsymbol{\beta}$ are vectors of constant coefficients to be estimated. Recall that we use the S subscript to denote size weighted summation, i.e., $\mathbf{X}_{S,t} = \sum_i S_{i,t}\mathbf{X}_{i,t}$. We denote the length of $\boldsymbol{\zeta}$ as N_ζ and the length of $\boldsymbol{\beta}$ as N_β. For convenience, I also define $\zeta_{S,t} = \mathbf{C}_{S,t}'\boldsymbol{\zeta}$ as the aggregate elasticity, and $M_t = \frac{1}{\zeta_{S,t}}$ the "multiplier", namely, the change in p_t in response to a one-unit change in quantity.

We formally state the assumptions needed for the optimal GIV estimator:

Assumption A.1 (Full model)**.**

1. The model is specified as in (A.16), with $\mathbf{S}_t > 0$ and $\mathbf{C}'_{S,t}\boldsymbol{\zeta} \neq 0$ with probability 1.
2. For each entity i, $u_{i,t}$ is i.i.d. with $\mathbb{E}\left[u_{i,t} \mid \mathrm{C}_t, \mathrm{S}_t, \mathbf{X}_t\right] = 0$ and $\mathbb{E}\left[u_{i,t}^2 \mid \mathrm{C}_t, \mathrm{S}_t, \mathbf{X}_t\right] = \sigma_i^2 > 0$.
3. For any $i \neq j$, $u_{i,t}$ is independent to $u_{j,t}$ conditional on $(\mathrm{C}_t, \mathrm{S}_t, \mathbf{X}_t)$.
4. $\mathbb{E}\left[\mathbf{X}_{i,t}\mathbf{X}'_{i,t}\right]$ are non-singular.
5. The parameter space for $(\boldsymbol{\zeta}, \boldsymbol{\beta})$ is compact and the true parameter is in the interior of the parameter space.

Notice that we do *not* require the size vector S_i sums to 1. The only assumption we impose on the sizes are positive. This is not a restriction as one can always simply swap the sign of $q_{i,t}$ and $S_{i,t}$ to satisfy the assumption. For example, the supply can be specified as a sector with size 1 and a higher supply enters as a negative $q_{i,t}$, so that their elasticity has the same sign as other sectors.

We first proceed without the exogenous variables $\mathbf{X}_{i,t}$. As we show in A.8, all results describe here go through with common factors.

A.7 Proof of Optimal GIV Estimator

For ease of reading, we reintroduce the definition of optimal GIV estimator here.

Let $\boldsymbol{\psi}_t(\mathbf{z})$ be a vector of length $\frac{N(N-1)}{2}$ with subscript ij $(i \neq j)$ denote the row corresponding the entity pair (i, j) :

$$\psi_{ij,t}(\mathbf{z}) \equiv \hat{u}_{it}(\mathbf{z})\,\hat{u}_{jt}(\mathbf{z}) \equiv \left(q_{i,t} + p_t\mathbf{C}'_{i,t}\mathbf{z}\right)\left(q_{j,t} + p_t\mathbf{C}'_{j,t}\mathbf{z}\right).$$

We have the conditional moment conditions:

$$\begin{aligned}\mathbb{E}\left[\psi_{ij,t}(\boldsymbol{\zeta}) \mid \mathrm{C}_t, \mathrm{S}_t\right] &= \mathbb{E}\left[\left(q_{i,t} + p_t\mathbf{C}'_{i,t}\boldsymbol{\zeta}\right)\left(q_{j,t} + p_t\mathbf{C}'_{j,t}\boldsymbol{\zeta}\right) \mid \mathbf{C}_t, \mathbf{S}_t\right] \\ &= \mathbb{E}\left[u_{i,t}u_{j,t} \mid \mathbf{C}_t, \mathbf{S}_t\right] = 0.\end{aligned}$$

Denote $\mathbf{V}^{\psi} \equiv \mathbb{E}\left[\boldsymbol{\psi}_t(\boldsymbol{\zeta})\,\boldsymbol{\psi}_t(\boldsymbol{\zeta})'\right] = Diag\left(\sigma_1^2\sigma_2^2, \sigma_1^2\sigma_3^2, \ldots, \sigma_{N-1}^2\sigma_N^2\right)$. Also denote $\hat{\mathbf{W}}_t^*(z)$

as a weighting matrix of the size $\frac{N(N-1)}{2} \times N_\zeta$, whose entry corresponding to the row ψ_{ij} and the column ζ_k is given as:

$$\hat{W}^*_{ij,k,t}(\mathbf{z}) = \frac{1}{\mathbf{C}'_{S,t}\mathbf{z}} \left(\frac{S_{jt}C_{it,k}}{\sigma_i^2} + \frac{S_{it}C_{jt,k}}{\sigma_j^2} \right) \tag{A.17}$$

Definition. The optimal GIV estimator $\hat{\boldsymbol{\zeta}}$ solves:

$$\mathbf{b}_T^{W^*}\left(\hat{\boldsymbol{\zeta}}\right) \equiv \frac{1}{T}\sum_t W_t^*\left(\hat{\boldsymbol{\zeta}}\right)' \boldsymbol{\psi}_t\left(\hat{\boldsymbol{\zeta}}\right) = 0.$$

To understand how this is derived, we define the Jacobian matrix of $\boldsymbol{\psi}_t(\mathbf{z})$ evaluated at the true parameter, $\mathbf{D}_t = \frac{\partial \boldsymbol{\psi}_t(\mathbf{z})}{\partial z} \mid_{z=\zeta}$. Its entry is given as:

$$D_{ij,t} = u_{jt}p_t C_{it,k} + u_{it}p_t C_{jt,k},$$

and then the optimal weighting matrix is given as:

$$\mathbf{W}_t^* = \left(\mathbf{V}^\psi\right)^{-1} \mathbb{E}\left[\mathbf{D}_t \mid \mathbf{C}_t, \mathbf{S}_t\right],$$

where we use the knowledge that $\mathbb{E}\left[u_{jt}p_t \mid \mathbf{C}_t, \mathbf{S}_t\right] = \frac{1}{\mathbf{C}'_{S,t}\boldsymbol{\zeta}} S_{jt}\sigma_j^2$.

With a complicated functional form, the weighting matrix has a very intuitive interpretation. Consider the simple case described in the main text, where each investor has its own time-invariant elasticity and size, namely, $S_{jt} = S_j$ and $C_{it,k} = \begin{cases} 1 & i = k \\ 0 & i \neq k \end{cases}$. In this case, the optimal GIV estimator solves:

$$\frac{1}{T}\sum_t \hat{u}_{it}\left(\hat{\boldsymbol{\zeta}}\right) \underbrace{\sum_{j \neq i} S_j \hat{u}_{jt}\left(\hat{\boldsymbol{\zeta}}\right)}_{\hat{u}_{S(-i),t}\left(\hat{\boldsymbol{\zeta}}\right)} = 0 \quad \forall i.$$

That is, the optimal GIV estimator simply weigh different sectors using their sizes. If we further assume a homogeneous elasticity across all entities, the optimal GIV estimator further weigh entities sharing the same elasticity using their respective volatility, in the

same spirit as the generalized least square (GLS) estimator.

$$\frac{1}{T}\sum_t\sum_i \frac{1}{\sigma_i^2}\hat{u}_{it}\left(\hat{\boldsymbol{\zeta}}\right)\hat{u}_{S(-i),t}\left(\hat{\boldsymbol{\zeta}}\right)=0.$$

We make one additional assumption on the weighting matrices to ensure the estimator is well-behaved.

Assumption A.2. $\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{W}_t^*\right]$ *is non-singular.* $\mathbb{E}\left[\mathbf{W}_t^{*\prime}\boldsymbol{\psi}_t\left(\boldsymbol{\zeta}\right)\right]=0$ *if and only if* $\mathbf{z}=\boldsymbol{\zeta}$.

In many cases, the second part of the assumption is actually redundant and directly follows from the first part. For example, when size weights and $\mathbf{C}_{i,t}$ are constant across time, or $\mathbf{C}_{i,t}$ are non-negative with probability 1 (such as dummy variables), non-singular conditions in $\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{W}_t^*\right]$ automatically implies the unique identification. The additional assumption is only needed when we have nonrestrictive loading factors $\mathbf{C}_{i,t}$. To see this, consider another candidate $\tilde{\boldsymbol{\zeta}}\equiv\boldsymbol{\zeta}+\Delta\boldsymbol{\zeta}$. We have:

$$\begin{aligned}
\mathbb{E}\left[\mathbf{W}_t^{*\prime}\boldsymbol{\psi}_t\left(\tilde{\boldsymbol{\zeta}}\right)\right]&=\mathbf{0}\\
&=\mathbb{E}\left[M_t\sum_{i\neq j}\left(\frac{S_{jt}\mathbf{C}_{it}}{\sigma_i^2}+\frac{S_{it}\mathbf{C}_{jt}}{\sigma_j^2}\right)\left(u_{i,t}+p_t\mathbf{C}_{i,t}^{\prime}\Delta\boldsymbol{\zeta}\right)\left(u_{j,t}+p_t\mathbf{C}_{j,t}^{\prime}\Delta\boldsymbol{\zeta}\right)\right]\\
&=\mathbb{E}\left[M_t\sum_{i\neq j}\left(\frac{S_{jt}\mathbf{C}_{it}}{\sigma_i^2}+\frac{S_{it}\mathbf{C}_{jt}}{\sigma_j^2}\right)\left(M_t\left(S_{jt}\sigma_j^2\mathbf{C}_{i,t}^{\prime}+S_{it}\sigma_i^2\mathbf{C}_{j,t}^{\prime}\right)\Delta\boldsymbol{\zeta}+\sigma_p^2\Delta\boldsymbol{\zeta}^{\prime}\mathbf{C}_{i,t}\mathbf{C}_{j,t}^{\prime}\Delta\boldsymbol{\zeta}\right)\right]\\
&=\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{V}^{\psi}\mathbf{W}_t^{*\prime}\right]\Delta\boldsymbol{\zeta}+\mathbb{E}\left[\sigma_p^2M_t\sum_{i\neq j}\left(\frac{S_{jt}\mathbf{C}_{it}}{\sigma_i^2}+\frac{S_{it}\mathbf{C}_{jt}}{\sigma_j^2}\right)\left(\Delta\boldsymbol{\zeta}^{\prime}\mathbf{C}_{i,t}\mathbf{C}_{j,t}^{\prime}\Delta\boldsymbol{\zeta}\right)\right].
\end{aligned}$$

With non-negative $\mathbf{C}_{it}$ and non-singular $\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{W}_t^*\right]$, the only solution to the equation above is $\Delta\boldsymbol{\zeta}=\mathbf{0}$. However, with unrestricted $\mathbf{C}_{i,t}$ potentially multiple roots can arise from this equation. One needs to verify the uniqueness of solution when complicated loading factors are used.

With this definition, we prove Theorem 2, restated below.

Theorem (Asymptotic efficiency in the general model)**.** *Given the moment conditions (A.1), under Assumption A.1 and Assumption A.2, the optimal GIV estimator* $\hat{\boldsymbol{\zeta}}$ *is consistent and asymptotically normal:*

$$\sqrt{T}\left(\hat{\boldsymbol{\zeta}}-\boldsymbol{\zeta}\right)\xrightarrow{d}\mathcal{N}\left(0,\mathbf{V}^{\zeta}\right),$$

for $T \to \infty$, where

$$\mathbf{V}^{\zeta} = \left(\mathbb{E}\left[\boldsymbol{W}_t^{*\prime}\mathbf{V}^{\psi}\boldsymbol{W}_t^{*}\right]\right)^{-1}.$$

Moreover, $\mathbf{V}^{\zeta}$ achieves the semi-parametric efficiency bound.

Proof. The consistency of the estimator directly follows the standard GMM argument.

To prove optimality, we first derive the asymptotic variance for an estimator $\hat{\zeta}^W$ with a generic weighting matrix that solves:

$$\mathbf{b}_T^W\left(\hat{\boldsymbol{\zeta}}^W\right) \equiv \frac{1}{T}\sum_t W_t\left(\hat{\boldsymbol{\zeta}}^W\right)'\boldsymbol{\psi}_t\left(\hat{\boldsymbol{\zeta}}^W\right) = 0. \tag{A.18}$$

The weighting scheme W_t can be a function of the given estimates and observed variables $(\mathrm{C}_t, \mathrm{S}_t)$. Denote $\mathbf{D}_t^W = \frac{\partial \mathbf{W}_t(\mathbf{z})'\boldsymbol{\psi}_t(\mathbf{z})}{\partial \mathbf{z}}\,|_{z=\zeta}$, we have

$$\mathbf{V}_{\zeta}^W = \mathbb{E}\left[\mathbf{D}_t^{W\prime}\right]^{-1}\mathbb{E}\left[\mathbf{W}_t'\boldsymbol{\psi}_t\left(\boldsymbol{\zeta}\right)\boldsymbol{\psi}_t\left(\boldsymbol{\zeta}\right)'\mathbf{W}_t\right]\mathbb{E}\left[\mathbf{D}_t^W\right]^{-1} \tag{A.19}$$

$$= \mathbb{E}\left[\mathbf{D}_t'\mathbf{W}_t\right]^{-1}\mathbb{E}\left[\mathbf{W}_t'\mathbf{V}^{\psi}\mathbf{W}_t\right]\mathbb{E}\left[\mathbf{D}_t\mathbf{W}_t'\right]^{-1} \tag{A.20}$$

where the second equation uses $\mathbb{E}\left[\mathbf{D}_t^W\right] = \mathbb{E}\left[\frac{\partial \mathbf{W}_t(\mathbf{z})'}{\partial \mathbf{z}}\boldsymbol{\psi}_t\left(\boldsymbol{\zeta}\right) + \mathbf{W}_t'\frac{\partial \boldsymbol{\psi}_t(\mathbf{z})}{\partial z}\right]\,|_{z=\zeta} = \mathbb{E}\left[\mathbf{W}_t'\mathbf{D}_t\right]$. Plug in $\mathbf{W}^* = \left(\mathbf{V}^{\psi}\right)^{-1}\mathbb{E}\left[\mathbf{D}_t \mid \mathbf{C}_t, \mathbf{S}_t\right]$, we have: we have

$$\mathbf{V}_{\zeta}^{W^*} = \left(\mathbb{E}\left[\mathbf{D}_t'\left(\mathbf{V}^{\psi}\right)^{-1}\mathbf{D}_t\right]\right)^{-1} = \left(\mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{V}^{\psi}\mathbf{W}_t^{*}\right]\right)^{-1}. \tag{A.21}$$

One can verify that (A.21) is also the semi-parametric efficiency bound shown by Chamberlain (1987). To see it more straightforwardly, we can show that for any $\mathbf{W}_t \neq \mathbf{W}_t^*$, $\Delta \equiv \mathbf{V}_{\zeta}^W - \mathbf{V}_{\zeta}^{W^*}$ is positive definite. The proof for the optimality generally follows the strategy of optimal instrument in conditional models, surveyed in Newey (1993).

$$\boldsymbol{\Delta} \equiv \mathbb{E}\left[\mathbf{D}_t'\left(\mathbf{V}^{\psi}\right)^{-1}\mathbf{D}_t\right] - \mathbb{E}\left[\mathbf{D}_t'\mathbf{W}_t\right]\mathbb{E}\left[\mathbf{W}_t'\mathbf{V}^{\psi}\mathbf{W}_t\right]^{-1}\mathbb{E}\left[\mathbf{W}_t'\mathbf{D}_t\right].$$

Given $\mathbf{V}^{\psi}$ is a positive definite diagonal matrix, it is convenient to factor $\mathbf{V}^{\psi}$ into $\mathbf{D}_t$ and $\mathbf{W_t}$ by defining:

$$\tilde{\mathbf{D}}_t = \left(\mathbf{V}^{\psi}\right)^{-\frac{1}{2}}\mathbf{D}_t$$

$$\tilde{\mathbf{W}}_t = \left(\mathbf{V}^{\psi}\right)^{\frac{1}{2}}\mathbf{W}_t.$$

Define $\mathbf{G}_t = \begin{bmatrix} \tilde{\mathbf{D}}_t' \\ \tilde{\mathbf{W}}_t' \end{bmatrix}$, and $\mathbf{H}' = \begin{bmatrix} \mathbf{I} & -\mathbb{E}\left[\tilde{\mathbf{D}}_t'\tilde{\mathbf{W}}_t\right]\mathbb{E}\left[\tilde{\mathbf{W}}_t'\tilde{\mathbf{W}}_t\right] \end{bmatrix}$, we can show:

$$\boldsymbol{\Delta} = \mathbf{H}'\mathbb{E}\left[\mathbf{G}_t\mathbf{G}_t'\right]\mathbf{H}.$$

Clearly, $\gtrless$ is positive semi-definite. $\boldsymbol{\Delta} = 0$ when $\tilde{\mathbf{W}}_t = \mathbb{E}\left[\tilde{\mathbf{D}}_t \mid \mathbf{C}_t, \mathbf{S}_t\right]$, or $\mathbf{W}_t = \left(\mathbf{V}^{\psi}\right)^{-1}\mathbb{E}\left[\mathbf{D}_t \mid \mathbf{C}_t, \mathbf{S}_t\right]$. □

A.8 Asymptotic Properties when Common Factors are Included

With common factors, we proceed with the following steps.

0. (If needed: Use PCA to extract unobserved common factors from granular data)
1. Regress $q_{i,t}$ and $p_t\mathbf{C}_{i,t}'$ on $\mathbf{X}_{i,t}$ to estimate $\hat{\boldsymbol{\beta}}^{q}$ and $\hat{\boldsymbol{\beta}}^{pC}$.
2. Take the residual from the first step, $q_{i,t}^{\varepsilon} \equiv q_{i,t} - \mathbf{X}_{i,t}'\hat{\boldsymbol{\beta}}^{q}$ and $\mathbf{pC}_{i,t}^{\varepsilon\prime} = p_t\mathbf{C}_{it}' - \mathbf{X}_{i,t}'\hat{\boldsymbol{\beta}}^{pC}$, and form the moment conditions:

$$\psi_{ijt}^{\varepsilon}(\mathbf{z}) \equiv \hat{u}_{it}^{\varepsilon}(\mathbf{z})\,\hat{u}_{jt}^{\varepsilon}(\mathbf{z}) \equiv \left(q_{i,t}^{\varepsilon} + \mathbf{pC}_{i,t}^{\varepsilon\prime}\mathbf{z}\right)\left(q_{j,t}^{\varepsilon} + p\mathbf{C}_{j,t}^{\varepsilon\prime}\mathbf{z}\right).$$

   Proceed with the optimal weighting matrix defined in (A.17) to estimate $\hat{\zeta}$.
3. Form the estimator for $\boldsymbol{\beta}$ as:

$$\hat{\boldsymbol{\beta}} = \hat{\boldsymbol{\beta}}^{q} + \hat{\boldsymbol{\beta}}^{pC}\hat{\boldsymbol{\zeta}}.$$

The following proposition shows the asymptotic variance of $\hat{\boldsymbol{\zeta}}$ and $\hat{\boldsymbol{\beta}}$.

Proposition A.2. *The asymptotic variance formula for $\hat{\boldsymbol{\zeta}}$ given by (A.21) still holds with common factors. $\hat{\boldsymbol{\beta}}$ is a consistent estimator for $\boldsymbol{\beta}$, and its asymptotic variance for $\hat{\boldsymbol{\beta}}$ is given as:*

$$Var(\hat{\boldsymbol{\beta}}) = \frac{1}{T}\left[Var^{OLS}(\hat{\boldsymbol{\beta}}) + \boldsymbol{\beta}^{pC}Var(\hat{\boldsymbol{\zeta}})\boldsymbol{\beta}^{pC\prime}\right] \tag{A.22}$$

$$Var^{OLS}\left(\hat{\boldsymbol{\beta}}\right) = \left(\sum_i \mathbb{E}\left[\mathbf{X}_{i,t}\mathbf{X}_{i,t}'\right]\right)^{-1}\left(\sum_i \mathbb{E}\left[\mathbf{X}_{i,t}\mathbf{X}_{i,t}'\right]\sigma_i^2\right)\left(\sum_i \mathbb{E}\left[\mathbf{X}_{i,t}\mathbf{X}_{i,t}'\right]\right)^{-1} \tag{A.23}$$

Proof. The proof follows Newey and McFadden (1994). The two-step estimator can be

formulated as a joint GMM estimator that solves:

$$\frac{1}{T}\sum_t \mathbf{g}_t\left(\mathbf{b},\mathbf{z}\right) \equiv \frac{1}{T}\sum_t \left[\begin{array}{c} \mathbf{g}_t^{OLS}\left(\mathbf{b}\right) \\ \mathbf{W}_t^{*\prime}\boldsymbol{\psi}_t(\mathbf{b},\mathbf{z}) \end{array}\right] = 0$$

where $\mathbf{g}^{OLS}\left(\mathbf{b}\right)$ is the moment condition for the first step of to identify $(\boldsymbol{\beta}^q, \boldsymbol{\beta}^{pC})$, and the second block is optimal GIV moment conditions, taken OLS coefficients as given. As the coefficients are just-identified, the solutions to the GMM estimation are identical to the two-step estimator, and hence we can utilize properties of the GMM estimator to study the asymptotic behaviors. Use $\boldsymbol{\theta}$ to denote the vector of $(\boldsymbol{\beta},\boldsymbol{\zeta})$ and $\hat{\boldsymbol{\theta}}$ the corresponding estimator, we have:

$$\begin{aligned}\sqrt{T}\left(\hat{\boldsymbol{\theta}}-\boldsymbol{\theta}\right) &\xrightarrow{d}\mathcal{N}\left(\mathbf{0},\left(\mathbf{D}^{g\prime}\right)^{-1}\left(\mathbf{V}^g\right)\left(\mathbf{D}^g\right)^{-1}\right)\\ \mathbf{D}^g &= \mathbb{E}\left[\frac{\partial \mathbf{g}_t\left(\boldsymbol{\theta}\right)}{\partial \boldsymbol{\theta}}\right]\\ \mathbf{V}^g &= \mathbb{E}\left[\mathbf{g}_t\left(\boldsymbol{\theta}\right)\mathbf{g}_t\left(\boldsymbol{\theta}\right)^{\prime}\right].\end{aligned}$$

A crucial feature of these matrices is that they are block-diagonal:

$$\begin{aligned}\mathbf{D}^g &= \left[\begin{array}{cc} \frac{\partial \mathbf{g}_t^{OLS}(\mathbf{b})}{\partial \mathbf{b}}\mid_{\mathbf{b}=\boldsymbol{\beta}} & \\ & \mathbb{E}\left[\mathbf{W}_t^{*\prime}\mathbf{D}_t\right] \end{array}\right]\\ \mathbf{V}^g &= \left[\begin{array}{cc} \mathbf{V}^{OLS} & \mathbf{0} \\ \mathbf{0} & \mathbf{W}^{*\prime}\mathbf{V}^{\psi}\mathbf{W}^{*} \end{array}\right].\end{aligned}$$

To see $\mathbf{D}^g$ is diagonal, notice that the estimate for $\boldsymbol{\zeta}$ does not enter the moment conditions for the OLS step by the two-step nature, and

$$\mathbb{E}\left[\frac{\partial \psi_{ij,t}\left(\boldsymbol{b},\boldsymbol{\zeta}\right)}{\partial \mathbf{b}}\mid_{\mathbf{b}=\boldsymbol{\beta}}\right] = \mathbb{E}\left[\frac{\partial\left(u_{it}-\mathbf{X}_{it}^{\prime}\left(\mathbf{b}-\boldsymbol{\beta}\right)\right)\left(u_{jt}-\mathbf{X}_{jt}^{\prime}\left(\mathbf{b}-\boldsymbol{\beta}\right)\right)}{\partial \mathbf{b}}\mid_{\mathbf{b}=\boldsymbol{\beta}}\right] = \mathbf{0}.$$

$\mathbf{V}^g$ being diagonal is a result that the error term in $\mathbf{g}_t^{OLS}$ is linear in u_{it}, while the error terms of $\boldsymbol{\psi}_t$ are quadratic $u_{it}u_{jt}$, so any linear combination between them have a covariance of zero.

Due to the block-diagonal structure in $\mathbf{D}^g$ and $\mathbf{V}^g$, the asymptotic variance of $\hat{\boldsymbol{\zeta}}$ is not affected by the first step estimation.

To further derive the asymptotic variance of $\hat{\boldsymbol{\beta}}$, we use the Delta method:

$$Var(\hat{\boldsymbol{\beta}}) = \begin{bmatrix} \mathbf{I} & \boldsymbol{\zeta}' \end{bmatrix} Var(\begin{bmatrix} \hat{\boldsymbol{\beta}}^{q} & \hat{\boldsymbol{\beta}}^{pC} \end{bmatrix}) \begin{bmatrix} \mathbf{I} & \boldsymbol{\zeta}' \end{bmatrix}' + \boldsymbol{\beta}^{pC} Var(\hat{\boldsymbol{\zeta}}) \boldsymbol{\beta}^{pC\prime}$$

where the first part is equivalent to asymptotic variance of the OLS estimator of regressing $q_{i,t} + p_t \mathbf{C}'_{i,t} \boldsymbol{\zeta}$ on $\mathbf{X}_{i,t}$, which is given in (A.23). □

A.9 When only a subset of sectors are observed

Consider the case where only a subset of sectors are observed. In this case,

$$\left.\begin{array}{rl} q_{i,t} & = -p_t \times \mathbf{C}'_{i,t}\boldsymbol{\zeta} + \mathbf{X}'_{i,t}\boldsymbol{\beta} + u_{i,t}, \\ q_{i,t}^{unobs} & = -\zeta_t^{unobs} p_t + \epsilon_t \\ 0 & = \sum_i S_{i,t} q_{i,t} + q_t^{unobs} \end{array}\right\} \implies \quad p_t = M_t \left[\mathbf{X}'_{S,t}\boldsymbol{\beta} + u_{S,t} + \epsilon_t\right], \tag{A.24}$$

where $M_t = \left(\mathbf{C}'_{S,t}\boldsymbol{\zeta} + \zeta_t^{unobs}\right)^{-1}$ is the inverse of the sum of the observed and unobserved sectors' demand elasticities. In this case, whether we can correctly identify the elasticity depends on the covariance structure of the error terms.

Consistency Notice that to identify ζ_i for observed sectors, the original moment conditions $\mathbb{E}\left[u_{i,t}u_{j,t}\right] = 0$ suffice, even if $u_{i,t}$ can be correlated with the unobserved sector's error term $\epsilon_{i,t}$. Using the language of the IV interpretation, the IV is valid regardless how the instruments affect the endogenous variable p_t, as long as the instruments affect the outcome variable $q_{i,t}$ only through the p_t.

The aggregate elasticity, or the multiplier M_t, cannot be identified simply by $\mathbf{C}'_{S,t}\boldsymbol{\zeta}$, due to the elasticity provision of the unobserved sector. Instead, we can recover M_t by regressing p_t on $u_{S,t}$, under the assumption that $\mathbb{E}\left[u_{i,t}\epsilon_t\right] = 0$. This assumption is justifiable: Notice that ϵ_t essentially is an unobserved common factor, so if $u_{i,t}$ loads on η_t, in principle it can be recovered techniques of factor extractions such as PCA.[29]

B Empirical Appendix

B.1 More on the Data

Financial Accounts data The main dataset we use for Treasury bonds and notes holdings comes from Table FU.210 and L.210 of Federal Reserve's Z.1 release.[30] We use seasonally unadjusted transactions and holdings of Treasury notes and bonds (labelled as "other Treasury securities") whenever possible. Not all sectors in the Z.1 release separately report holdings of bills, notes and bonds. Those that do not report this breakdown

[29] Alternatively, we can also assume the observed sectors are representative of the unobserved sectors, and hence we can impute the ζ_t^{unobs} using the observed sectors' $\mathbf{C}'_{i,t}\boldsymbol{\zeta}$.

[30] https://www.federalreserve.gov/apps/fof/FOFTables.aspx

are typically small holders and are lumped into the "other" category for estimation. There are, however, a number of large sectors with no information on notes and bonds holdings directly available, including the household sector (residual), pension funds and ETFs. In these cases, we assume that their holdings are entirely in Treasury notes and bonds.

Country-level foreign holdings and bank-level holdings We use information from the Treasury International Capital system (TIC) to compile country-level holdings of long-term (bonds and notes) and short-term (bills) Treasury securities by foreign investors. For short-term holdings, we source information included in the banking liabilities survey that starts from February 2003. For notes and bonds, we resort to the benchmark-consistent estimates put together by Bertaut and Judson (2022), Bertaut and Judson (2014), and Bertaut and Tryon (2007). Gaps in the series are present from 2011Q3 to 2011Q4, when the TIC survey methodology is in transition. We use the SLT1D table to fill in the blanks.

For individual U.S. bank holdings of Treasury notes and bonds, we use data from FFIEC 031/041/051 filings, also known as the Call Reports. We download the raw data from WRDS and take several steps to clean the dataset. First, as WRDS data may contain FFIEC 002 filers (foreign branches), we identify and drop all foreign branches in the data using the relationship files from the NIC information system. Then, we largely follow the methodology of Financial Accounts to extract information on Treasury holdings. Quarterly transaction figures are computed by summing up three variables: RCON0211, RCON1286 and RCON3531 and taking the first difference. The market value of holdings are the sum of three variables: RCON0213, RCON1287 and RCON3531.[31] To get the breakdown between bills and other securities, we use an imputation method similar to Jansen et al. (2024). With information on the residual maturity breakdown of Treasury and agency securities (RCONA549 to RCONA554, excluding trading assets,) we compute total holdings of Treasury and agency securities and impute notes and bonds holdings assuming that the share between bills and notes and bonds are stable across the residual maturity bucket, and the data in the residual maturity buckets above one year can well approximate notes and bonds holdings.

A challenge of working with country- and bank-level holdings is that our estimation

[31]Only large banks (FFIEC 031 filers) report information on Treasury securities held as trading assets (RCON3531) and only fair values are reported. For Treasuries held as trading assets after 2018Q1, RCON3531 is very sparsely populated. We use RCFD3531 net of foreign office holdings as the substitute. Unlike the financial account, who assumes that U.S. Treasuries comprise 3% of the total trading book of foreign offices, we use historical realized values of RCFD3531 and RCON3531 to make the adjustment. Eventually, only two banks' RCFD3531 numbers need to be adjusted. For all other banks, we direct use RCFD3531 to impute missing RCON3531 numbers.

algorithm requires a balanced panel. A country or bank must consistently hold non-zero amount of Treasury securities throughout our sample period to be included individually in the data. Otherwise, they will be swept into an entity labelled "all other countries" (TIC) or "all other banks" (call report), which aggregate Treasury notes and bonds holdings of all country or bank entities that do not always hold Treasuries during the sample period. By 2023, individual bank holding and country holding cover 80% and 90% of the total holdings reported in the Z.1 release, respectively.[32]

Discrepancy The fact that not all investor sectors report Treasury notes and bonds holdings and the lack of direct estimates of notes and bonds holdings and transactions from the call report data would introduce valuation and coverage discrepancies (see Figure B.5). We sweep the discrepancy component into the household sector (the residual sector in the Z.1 methodology) in our baseline estimation.

Observed common factors Our baseline estimation makes use of the following observed macro factors: the CBOE SP500 implied volatility index (VIX, FRED ticker VIXCLS), the effective Federal Funds rate (FRED ticker FEDFUNDS), CPI (FRED ticker CPIAUCSL), and the nominal broad dollar index (splicing goods trade-weighted dollar index and goods-and-service trade-weighted dollar index, FRED tickers DTWEXBGS and DTWEXB).

Sector classification and aggregation Table B.1 reports our aggregation of Financial Account sectors to categories for GMM estimation and for yield decomposition. For italicized sectors (U.S.-chartered banks and foreign investors), we use call report and TIC data to break down sector aggregates into individual bank/country holdings.

B.2 Identification of Factor Loadings $\boldsymbol{\lambda}_i$

For many research questions, researchers are not interested in the elasticities *per se*, but more in the loadings on the common factors by different entities λ_i. For example, a researcher may want to understand the heterogeneous responses of asset demand to mon-

[32]More specifically, we require countries to hold non-zero Treasury bonds and notes throughout from 2003Q1 to be included individually, and banks to have a non-zero position starting from 2001Q4 to be included. As countries and banks with consistently positive holdings tend to be large, our country- and bank-level holding is highly representative of the entire market. For flows, the correlation between individual bank aggregates and the Financial Accounts aggregates is 92%, and for the TIC data, the correlation is 93%.

etary policy shocks. We first deal with the case where factors are observable, and then discuss the strategies when there exist unobserved common factors.

To recover the factor loadings, we follow the three-step approach:

1. We regress p_t and $q_{i,t}$ on $\boldsymbol{\eta}_t$ to obtain the residual p_t^{ε} and $q_{i,t}^{\varepsilon}$, and we also denote the coefficients as $\hat{\boldsymbol{\lambda}}_i^q$ and $\hat{\boldsymbol{\lambda}}_i^p$;

2. We estimate elasticities $\boldsymbol{\zeta}$ using residuals p_t^{ε} and $q_{i,t}^{\varepsilon}$ as discussed in Section 3.3;

3. We then construct the estimators for $\boldsymbol{\lambda}_i$ as:

$$\hat{\boldsymbol{\lambda}}_i = \hat{\boldsymbol{\lambda}}_i^q + \hat{\zeta}_i \hat{\boldsymbol{\lambda}}^p.$$

In Appendix A.8, we discuss the asymptotic properties of this three-step procedure. Despite the multi-step feature of this estimation method, no adjustment is needed for the asymptotic variance for $\hat{\zeta}$. We also derive the asymptotic variance for loading estimators $\hat{\lambda}_i$ in the Appendix.

Unobserved common factors Failing to control for common factors will lead to a violation of Assumption 1. In particular, some common factors may not be observed directly by econometrician. To avoid common factors contaminating the identification, one idea is to use principal component analysis (PCA) to extract unobserved common factors, and use the residuals to identify the elasticities.

One potential complication is that, as pointed out by Qian (2024), with unobserved common factors and fully flexible elasticity specifications, ζ is not uniquely identified. The key intuition is that the price itself is essentially another (endogenous) factor, and alternative values of the price elasticity, combined with appropriate values of loadings on the unobserved common factors could also fit the data.

We offer two solutions to this issue, one nonparametric and the other parametric. First, suppose we observe a sector of similar entities. If within the sector the elasticity is homogeneous, then we can demean entities within this sector period by period to remove the influence of p_t. Then we can use PCA to extract the unobserved common factors from the demeaned data. This is the nonparametric approach. Second, we can alternatively

parameterize the factor loadings as a linear function of characteristics of each entity, i.e.,

$$\boldsymbol{\lambda}_{i,t}\boldsymbol{\eta}_t = \boldsymbol{X}'_{i,t}\dot{\boldsymbol{\lambda}}\boldsymbol{\eta}_t,$$

in which case the factors can be controlled for using characteristics with time-specific coefficients.

B.3 Predictability of Policy Sectors

B.3.1 The Federal Reserve

Historically, the New York Fed's Open Market Trading Desk (the Desk) used outright purchases or sales of Treasury securities as a tool to manage the supply of bank reserves to maintain conditions consistent with the Federal funds target rate set by the FOMC. Hence, small Treasury market flows were present in the NY Fed's System Open Market Account (SOMA) before 2008. The nature of these flows changed drastically during the Global Financial Crisis. Since 2009 to 2024, the Fed conducted 4 rounds of large-scale asset purchases including Treasuries and GSE debt, commonly known as Quantitative Easings (QEs), which significantly enlarged the SOMA portfolio in long-term Treasury securities.

Once activated, the scale of the QE operations can be predicted. At the start of each round of QEs, The Federal Open Market Committee (FOMC) typically announces the total amount and the pace of the purchases to provide forward guidance to market participants. Closely following the instructions of the FOMC, the Desk at the New York Fed issues detailed schedule for future purchases typically at a biweekly frequency. As the operations are prescheduled, they generally do not respond to the contemporaneous market development.[33]

To control for the scheduled Fed purchases, we construct a sequence of anticipated purchases by the Fed in each quarter. Outside of QE regimes, we treat all purchases as anticipated; during QE regimes, we construct the anticipated purchases based on the FOMC announcement of the Fed in the last quarter. For example, in March 18, 2009, the FOMC announced it would purchase up to $300 billion of longer-term Treasury securities over the next six months. The scheduled purchase by the Fed in Q2-3 would be $150

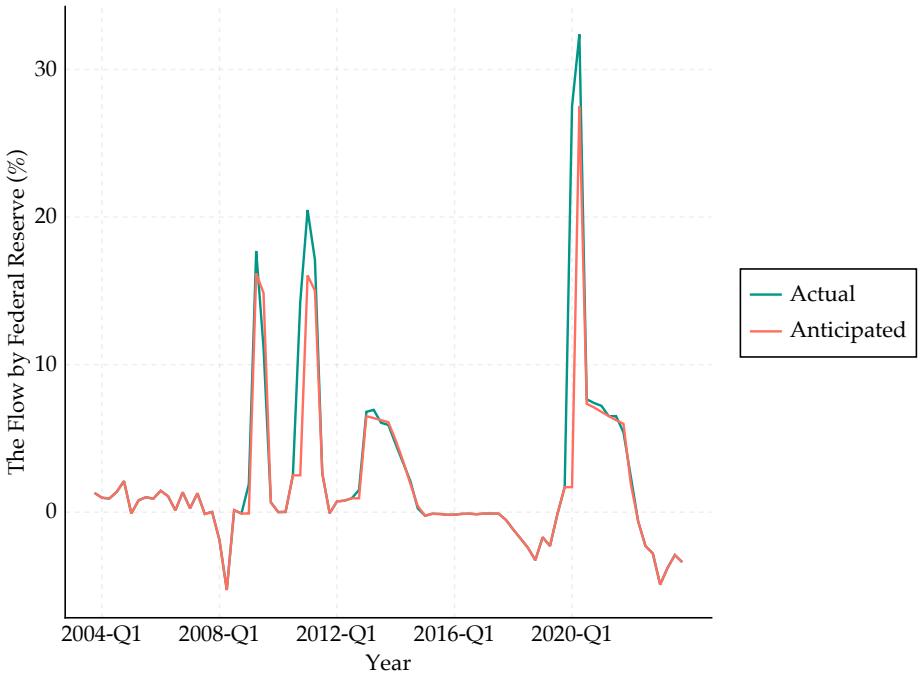
[33]One exception is the initial stage of the QE in response to the COVID pandemic. Due to the extremity of the macroeconomic and financial conditions, the FOMC announced that it "will continue to purchase Treasury securities and agency mortgage-backed securities in the amounts needed to support smooth market functioning and effective transmission of monetary policy to broader financial conditions", without specifying the duration and the total amount.

billion each, until further policy changes by the FOMC.

Table B.2 reports the anticipated purchases versus the actual purchases of the Fed during active QE periods. When the QE is not pre-scheduled in that quarter (typically at the start of the QEs), we use lagged purchases by the Fed from the previous quarter as the expected purchase.[34] As investors may use more information than the FOMC announcements alone, we lean towards conservative when setting the anticipated purchases. For example, during the exit of the QE3, even though the FOMC announcement of reducing purchases are not pre-scheduled in earlier quarters, as it follows a predictable patterns and well-anticipated by investors, we consider these changes are "scheduled". Outside of the QE periods, we treat all realized, contemporaneous purchases as anticipated, as they are either due to rollovers of maturing Treasuries or reserve management purposes. As the scale of these outright purchases are small, alternative treatments have little effects on our results. Figure B.1 plots the path of the Fed's flows together with the one-quarter-ahead anticipated path sequence. As shown in the plot, for most quarters, the realized purchases closely track the anticipated purchases. The major deviations occur on the entry and exit of the QE programs. Our estimates for the Fed's sensitivity to prices and to macro factors mainly reflect the policy consideration during episodes in which Fed deviates from the anticipated schedule.

[34] Alternatively, we can also estimate an AR process of the Fed purchase outside of QE and use that as predictor. The results are not sensitive to the treatment as the deviation of the QE purchase from the regular outright operations are an order of magnitude larger.

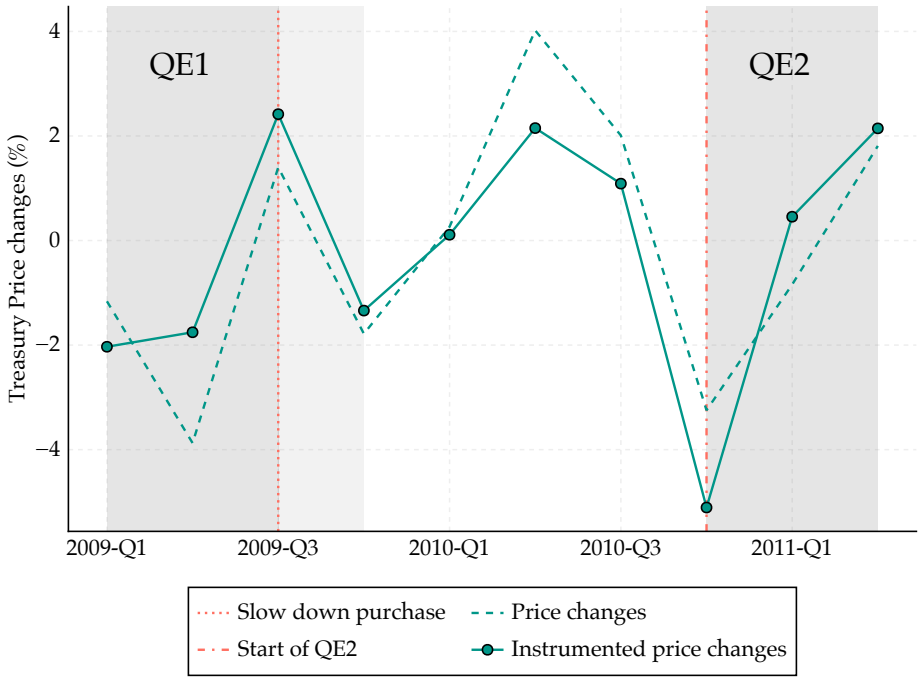
Figure B.1: **Case Study: QE Entry and Exit between 2009-2010**



Note: Figure B.1 plots the actual purchases (normalized by total Fed holdings) of U.S. Treasury notes and bonds against the constructed one-quarter-ahead anticipated Fed purchase measure in green. The anticipated path is generated by combining the actual Fed purchase path before 2009 with the pre-announced purchase schedule by the New York Fed starting from the beginning of the QE operation.

As a further illustration, in Figure B.2 we focus on the end of the QE1 in 2009Q3 and the start of QE2 in 2010Q4. The original schedule for the first round of Treasury purchases ends at 2009Q3. In that quarter, the FOMC meetings decided to change the schedule and slow down the purchase and extend to Q4 in order to "promote a smooth transition in markets as these purchases of Treasury securities are completed". This results in a negative deviation from the anticipated path. In the figure, we plot the path of the price changes of the Treasury notes and bonds (the dash line), and the price change predicted using other sectors' demand shocks (the solid line). As shown in the price path, the quarter in which they decided to slow down the purchase is the one with the largest Treasury price appreciation in the entire QE1 episode. Similarly, the start of the QE2 also coincides with the quarter that saw the largest Treasury price depreciation.

Figure B.2: **Case Study: QE Entry and Exit between 2009-2010**



Note: Figure B.2 traces Treasury price changes from 2009 to 2011, covering the end of QE1 and the start of QE2. The path of actual Treasury price changes (dashed line) is plotted against the instrumented price changes, predicted using the size-weighted granular shocks extracted from the GMM estimation.

B.4 Case Study: Household and Mutual Fund Sectors

Figure B.3 provides an illustration of our sector-specific estimates against the reduced-form OLS estimates. For the household sector and the mutual fund sector, we plot their "demand curves". We residualize sector inflow into Treasuries against common factors and plot it on the x-axis. The y-axis represents two notions of Treasury price changes. Using green circle markers, we plot the observed price changes, also residualized against the common factors. OLS estimation would thus imply that that the household sector is completely inelastic, while mutual funds have a slight downward-sloping demand curve. Simultaneity, however, renders OLS estimators biased in this context: When sectors are granular and demand is downward-sloping, a higher asset price reduces demand, but the reduced demand will counteract the price.

In orange, we plot the flows against the predicted price changes from idiosyncratic shocks from other sectors that we extract from our estimation. As discussed in the IV

interpretation of in Section 2, the slopes of the orange lines correspond exactly to the (reciprocal of) the elasticity coefficients reported in Table 1.[35] Using the instrumented price changes reveals that the household sector is in fact highly elastic. Mutual funds are also slightly more elastic than what the simple correlation suggests.

The bias-corrected OLS interpretation of our optimal GIV estimator (see Lemma 1) helps interpret these differences. Though the mutual fund sector and the household sector are comparable in terms of sizes, the household sector has much more volatile idiosyncratic shocks than the mutual fund sector, a pattern that is also visible from the volatility of the raw flows. The optimal GIV estimator recognizes that and make larger correction for the household sector than for mutual funds.

B.5 Robustness of Elasticity Estimation

Table B.5 reports the full set of estimated parameters from the baseline specification. Table B.4 demonstrates the robustness of our price elasticity estimation to alternative samples, controls, or dependent variables. Table B.3 shows that our finding remains robust if we remove any sector from the construction of moment conditions and reestimate the model.

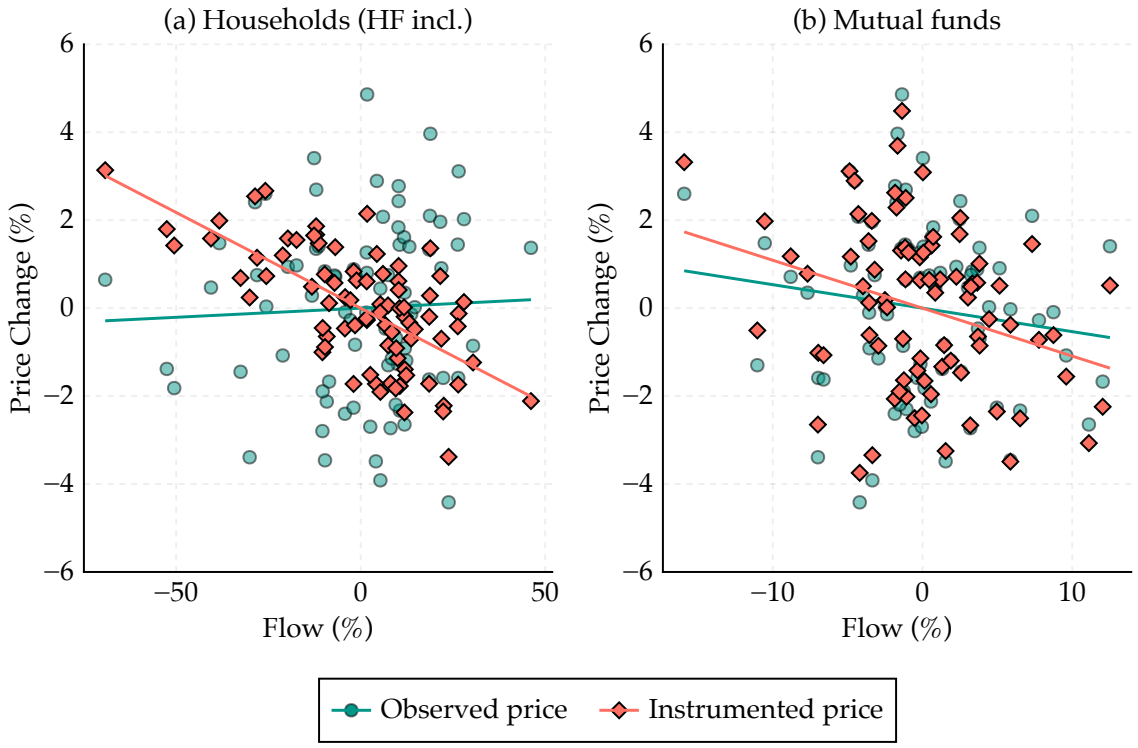
B.6 Comparing Multipliers Estimates Across the Literature

In this section, we compare our Treasury macro multiplier estimates with those from the literature. The focus on estimating multiplier parameters—the percentage change in prices to a percentage change in demand as a share of outstanding Treasury securities—is a recent development. However, the literature has long studied the price impact of demand shocks arising from foreign FX interventions, quantitative easing, Treasury repurchase operations, and other policy interventions. By making a few assumptions about the implied size of the quantity changes, we can map these price impact estimates from the literature to multipliers. While these mappings are not perfect, they provide a useful benchmark for our estimates.

Figure B.4 compares our Treasury macro multiplier estimates with those from the literature. The y-axis shows the macro multiplier—defined as the percentage change in prices relative to the percentage change in demand as a share of outstanding Treasury

[35] To further ensure the exclusion restriction is respected, we can exclude all moment conditions involving the target sectors (households/mutual funds) when extracting idiosyncratic shocks for other sectors. In this way, those extracted idiosyncratic shocks are completely unrelated to the target sectors except through the price. This is corresponding to the leave-one-out estimator reported in Appendix Table B.3.

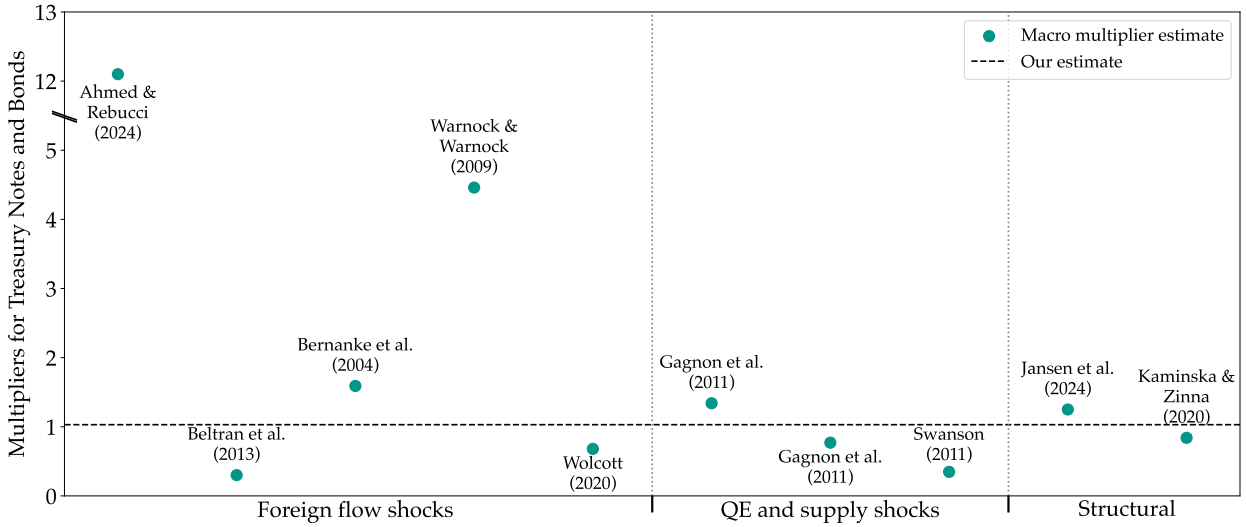
Figure B.3: **Optimal GIV vs. OLS: Two examples**



Note: Figure B.3 compares the estimated price elasticities of demand using our identification approach to the OLS estimates, using the household sector and the mutual fund sector as case studies. In both panels, the green dots relate the sector inflow to U.S. Treasury notes and bonds to observed quarterly changes in the Treasury price, both residualized against the common factors included in our baseline specification. For the red dots, the y-axis plots the predicted price changes using size-weighted idiosyncratic shocks (excluding the sector of interest) estimated from the GMM procedure.

securities. The x-axis groups estimates by the different types of demand shocks and methodologies they used to measure price impact. These include foreign flow shocks, quantitative easing (QE) and supply shocks, and structural methods that estimate Vayanos and Vila (2021)-style models to derive macro multipliers. The details of this mapping are discussed below. With the exception of a couple of outliers, our estimates of around 1 is in line with the macro multiplier estimates implied by the literature.

Figure B.4: **Comparing Multipliers Estimates Across the Literature**



Note: Figure B.4 compares our Treasury macro multiplier estimates with those from the literature. When the paper directly estimates macro multipliers, we present them. When paper only estimate the price impact, we map them to multipliers by making a few assumptions about the implied size of the quantity changes.

Below we outline how we map each papers estimates to multipliers.

Bernanke, Reinhart, and Sack (2004) examine how 10-year Treasury yields respond to Japanese Ministry of Finance interventions in the foreign exchange market between 2000 and 2004. Specifically, they study three-day windows around these interventions and find that a $1 billion purchase of dollars (subsequently invested in Treasuries) reduces the 10-year yield by 0.66 basis points. To express this result as a macro multiplier, we proceed in two steps. First,we scale their semi-elasticity to a 1% demand shock (as a share of outstanding). The average amount of Treasury notes and bonds outstanding during the sample period was $2.4 trillion. Thus, a 1% demand shock corresponds to a $24 billion purchase. Since a $1 billion purchase lowers yields by 0.66 basis points, a 1% demand shock lowers yields by $0.66 \times 24 = 15.8$ basis points. Second, we now map this semi-elasticity to a price multiplier. We multiply the yield change by the duration of a 10-year bond (assumed to be 10), we find that a 1% demand shock increases Treasury prices by 1.58%. Thus, the implied macro multiplier is 1.58. This analysis assumes that all foreign purchases were unexpected, and hence likely overestimates the size of the demand shock and underestimates the size of the multiplier.

Warnock and Warnock (2009) regress monthly 10-year yields on official inflows (as

a share of lagged GDP) from 1984–2005. Their estimate implies a 1% flow shock (of GDP) lowers yields by 25 basis points. Since Treasuries averaged 56% of GDP, a 1% demand shock (of outstanding) is $1/0.56 \approx 1.8\%$ of GDP, so yields fall by $25/0.56 \approx 44.6$ basis points. With a 10-year duration, this is a 4.46% price change, so the implied macro multiplier is 4.46. This likely overstates the shock, as it treats all 12 months of flows as unexpected.

Beltran et al. (2013) use instruments (Japanese FX interventions, oil shocks, Chinese balance-of-payments surprises) to estimate the effect of official foreign purchases on the five-year term premium (1994–2007). A 1% demand shock (of outstanding) lowers the five-year term premium by 5 basis points. With a five-year duration, this is a 0.25% price increase, so the macro multiplier is 0.25.

Wolcott (2020) estimate a VAR with macro variables, foreign flows, and yields, imposing no-arbitrage. Using Cholesky identification, they find a one-standard-deviation foreign flow shock (0.3% of outstanding) lowers the five-year yield by 2 basis points. Scaling to a 1% shock gives a 6.7 basis point yield effect; with a five-year duration, the macro multiplier is 0.68.

Ahmed and Rebucci (2021) identify exogenous foreign official flow shocks via heteroskedasticity in a structural VAR. An unexpected $100 billion purchase (1.03% of the $9.7 trillion average stock) lowers the 10-year yield by 125 basis points. Scaling to a 1% shock gives a 121 basis point yield move; with a 10-year duration, this is a 12.1% price increase, so the macro multiplier is 12.1.

Gagnon et al. (2011) provide two estimates. First, an event study of QE1 announcements (2008–2009) finds that eight windows lowered the 10-year yield by 91 basis points. If the full $300 billion (6.8% of the $4.41 trillion stock) was a surprise revealed in these eight windows, this is a 13.4 basis point yield effect per 1% shock; with a 10-year duration, the multiplier is 1.34. Second, a monthly regression of yields on supply (assumed exogenous) finds a 1% increase in supply-to-GDP raises the term premium by 4.4 basis points. With average debt/GDP of 57%, this is 7.7 basis points per 1% shock (of outstanding); with a 10-year duration, the multiplier is 0.77.

Swanson (2011) uses the Kennedy administration's Operation Twist announcements (1961–1962) as exogenous shocks. The first four announcements lowered the 10-year yield by 16 basis points, with purchases equal to 4.6% of outstanding. Thus, a 1% shock moves yields by 3.5 basis points; with a 10-year duration, the price change is 0.35%, so the mul-

tiplier is 0.35.

Kaminska and Zinna (2020) estimate the Vayanos–Villa preferred-habitat model via Bayesian MCMC and simulate the three LSAP waves. The implied multipliers are $M_1 = 0.76$, $M_2 = 1.32$, and $M_3 = 0.45$, with an average of 0.84.

Jansen et al. (2024) estimate investor demand (pension funds, mutual funds, insurance companies, etc.) for short-, medium-, and long-term Treasuries, and embed these in a Vayanos and Vila (2021)-style model, treating broker-dealers and hedge funds as arbitrageurs. They estimate a macro multiplier of 1.25 for a permanent 1% demand shock (focusing on medium- and long-term Treasuries for comparability). We focus on their permanent demand shock, as our analysis also considers permanent changes in holdings.

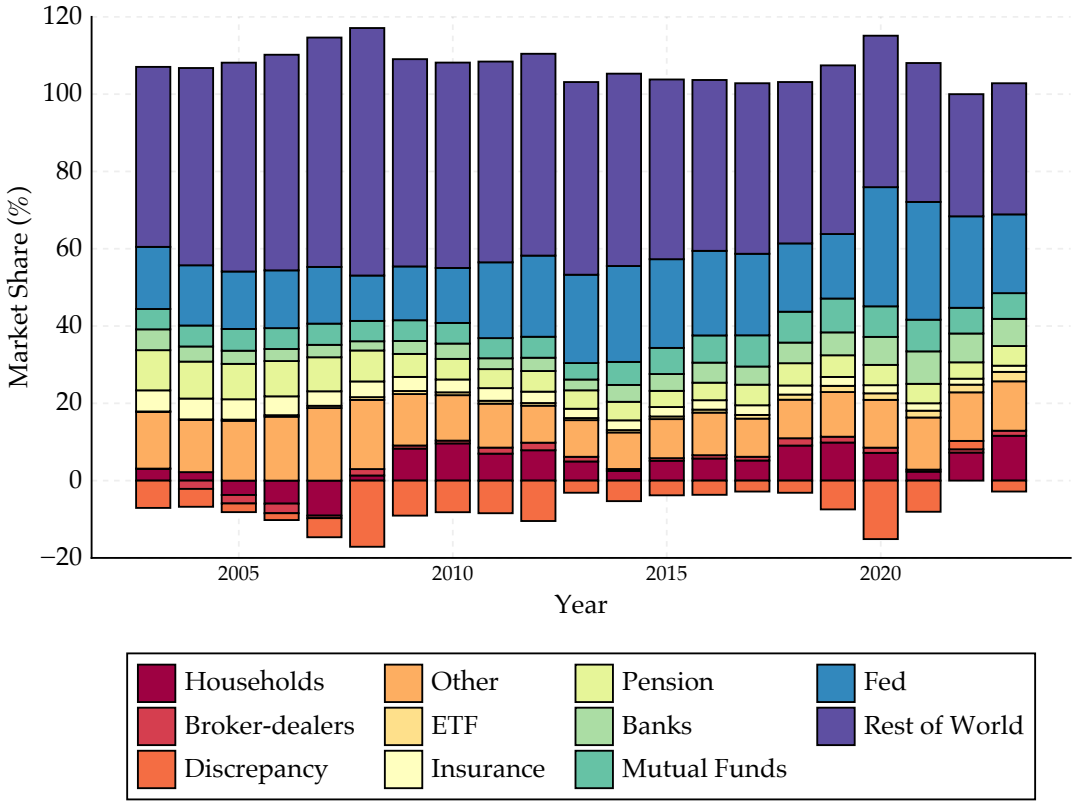
A few notable papers examine the effects of exogenous quantity changes in the Treasury market, though their results are not directly comparable to ours.

For example, Krishnamurthy and Vissing-Jorgensen (2012) study how Treasury supply affects the convenience yield. They find that, between 1969 and 2008, a 1% increase in the debt-to-GDP ratio reduces the convenience yield by 0.87 basis points (measured using 10-year yields). Adjusting for the average debt-to-GDP ratio during this period and for duration, this implies a multiplier of 0.18. This smaller multiplier reflects two key differences: their dependent variable is the convenience yield (not the level of yields), and their analysis is conducted at an annual frequency (rather than quarterly). When we estimate the impact of our demand shocks on the convenience yield at an annual frequency, we obtain a similar estimate.

Similarly, Greenwood, Hanson, and Stein (2015) show that short-term debt yields rise when Treasury bill supply increases, consistent with a downward-sloping demand curve for T-bills. However, their object of interest differs from ours: they focus on the effect of Treasury bill supply on short-term debt yields, while we study the effect of demand on Treasury Notes and Bonds yields (long-term debt).

B.7 Additional Tables and Figures

Figure B.5: **Investor composition of U.S. Treasury notes and bonds**



Note: Figure B.5 plots the investor base of U.S. Treasury notes and bonds. We organized the holders of the U.S. Treasury identified in the Financial Account data into 10 sectors based on the classification reported in Section B.1 in the Appendix. Our procedure for calculating Treasury notes and bonds holdings from raw Financial Account data introduces a "discrepancy" component due to valuation differences and imputed holdings for sectors that do not separately report bill holdings. The market share plotted refers to each sector's market value of holdings as % of the total market value of the Treasury notes and bonds outstanding.

Table B.1: **Mapping from Sectors to Groups**

Sector	**Category (estimation)**	**Category (decomposition)**
Banks in U.S.-affiliated areas	Banks	US Financial Institution
Foreign banking offices in the U.S.	Banks	US Financial Institution
U.S.-chartered depository institutions	Banks	US Financial Institution
Exchange-traded funds	ETF	US Financial Institution
Monetary authority	Fed	Fed
Households and nonprofit organizations	Households	US Other
Property-casualty insurance companies	Insurance	US Financial Institution
Life insurance companies	Insurance	US Financial Institution
Money market funds	Other	US Financial Institution
Closed-end funds	Mutual Funds	US Financial Institution
Mutual funds	Mutual Funds	US Financial Institution
Nonfinancial corporate business	Other	US Other
Nonfinancial noncorporate business	Other	US Other
State and local governments	Other	US Other
Government-sponsored enterprises	Other	US Other
Credit unions	Other	US Other
Other financial business	Other	US Other
Issuers of asset-backed securities	Other	US Other
Holding companies	Other	US Other
State and local government employee defined benefit retirement funds	Pension	US Financial Institution
Federal government defined contribution retirement funds	Pension	US Financial Institution
Federal government defined benefit retirement funds	Pension	US Financial Institution
Private defined contribution pension funds	Pension	US Financial Institution
Private defined benefit pension funds	Pension	US Financial Institution
Rest of the world	Rest of World	Rest of World
Security brokers and dealers	Security brokers and dealers	US Financial Institution
Supply	Supply	Supply

Table B.2: The scheduled and actual purchases during QEs

	Anticipated ($ billions)	Actual ($ billions)	Remarks
2009-Q1		16	QE1 for Treasuries started (link)
2009-Q2	150	164	
2009-Q3	150	113	The FOMC decided to slow down the purchase (link)
2009-Q4	7	7	
2010-Q4		210	QE2 started (link)
2011-Q1	250	319	
2011-Q2	245	279	
2013-Q1	135	141	The FOMC announced in 2012-Q2 to QE3 (link)
2013-Q2	135	147	
2013-Q3	135	131	
2013-Q4	135	131	
2014-Q1	110	104	
2014-Q2	80	77	
2014-Q3	45	49	
2014-Q4	10	6	
2020-Q1		863	COVID-19 (link)
2020-Q2	863	1034	Total purchases not scheduled, use lagged purchases
2020-Q3	240	250	
2020-Q4	240	250	
2021-Q1	240	254	
2021-Q2	240	240	
2021-Q3	240	250	
2021-Q4	240	217	
2022-Q1	80	100	

Table B.3: **Price elasticity by sector: Leave-one-out Estimation**

Sector	Baseline	Other	Households	Pension	Insurance	Funds	ETF	Dealers	Fed	Banks	RoW	Supply
Aggregate	1.03	1.08	0.59	1.2	1.32	1.42	1.27	1.22	1.08	1.25	1.29	1.64
	(0.77, 1.3)	(0.78, 1.38)	(0.48, 0.69)	(0.84, 1.55)	(0.86, 1.77)	(0.82, 2.03)	(0.87, 1.68)	(0.79, 1.65)	(0.77, 1.39)	(0.84, 1.66)	(0.43, 2.16)	(0.72, 2.57)
Other	-0.14		-0.02	0.49	0.48	0.44	0.49	0.58	0.59	0.53	0.44	0.51
	(-0.37, 0.08)		(-0.2, 0.15)	(0.25, 0.73)	(0.23, 0.72)	(0.2, 0.69)	(0.24, 0.74)	(0.33, 0.83)	(0.36, 0.82)	(0.28, 0.77)	(0.2, 0.68)	(0.25, 0.77)
Households	10.54	11.42		13.32	16.05	19.07	14.81	14.35	12.24	14.81	19.29	23.04
	(5.33, 15.76)	(5.36, 17.48)		(6.07, 20.58)	(6.77, 25.33)	(6.93, 31.21)	(6.45, 23.16)	(5.74, 22.96)	(5.9, 18.59)	(6.4, 23.22)	(1.72, 36.87)	(5.13, 40.94)
Pension	-0.02	0.02	0.03		0.06	0.07	0.06	0.07	0.09	0.06	0.08	0.05
	(-0.18, 0.13)	(-0.15, 0.18)	(-0.09, 0.16)		(-0.11, 0.23)	(-0.1, 0.24)	(-0.11, 0.23)	(-0.1, 0.25)	(-0.07, 0.25)	(-0.11, 0.23)	(-0.08, 0.24)	(-0.13, 0.23)
Insurance	1.08	0.27	0.71	0.27		0.24	0.26	0.16	0.22	0.23	0.25	0.14
	(0.76, 1.4)	(-0.03, 0.57)	(0.47, 0.95)	(-0.04, 0.59)		(-0.07, 0.56)	(-0.06, 0.57)	(-0.16, 0.48)	(-0.07, 0.52)	(-0.08, 0.54)	(-0.06, 0.55)	(-0.19, 0.47)
Mutual Funds	0.6	0.53	0.95	0.57	0.54		0.55	0.43	0.42	0.62	0.58	0.42
	(0.13, 1.08)	(0.05, 1.02)	(0.57, 1.34)	(0.07, 1.08)	(0.03, 1.06)		(0.03, 1.07)	(-0.09, 0.95)	(-0.05, 0.9)	(0.11, 1.13)	(0.07, 1.1)	(-0.12, 0.96)
ETF	-0.53	-0.37	-0.41	-0.34	-0.36	-0.35		-0.29	-0.31	-0.33	-0.4	-0.39
	(-0.89, -0.17)	(-0.74, 0.0)	(-0.69, -0.12)	(-0.72, 0.05)	(-0.75, 0.03)	(-0.74, 0.04)		(-0.68, 0.11)	(-0.67, 0.05)	(-0.72, 0.06)	(-0.77, -0.03)	(-0.8, 0.02)
Dealers	2.22	4.68	-6.58	0.84	-0.07	-1.12	0.56		2.49	0.97	-0.46	-2.7
	(-6.45, 10.88)	(-4.53, 13.89)	(-13.52, 0.35)	(-8.47, 10.14)	(-9.51, 9.37)	(-10.61, 8.38)	(-8.92, 10.04)		(-6.4, 11.39)	(-8.43, 10.38)	(-10.87, 9.95)	(-12.88, 7.49)
Fed	0.42	0.47	0.1	0.38	0.35	0.29	0.37	0.42		0.36	0.31	0.35
	(0.11, 0.74)	(0.14, 0.8)	(-0.15, 0.35)	(0.05, 0.71)	(0.02, 0.68)	(-0.03, 0.62)	(0.04, 0.71)	(0.08, 0.76)		(0.03, 0.69)	(-0.01, 0.64)	(0.0, 0.7)
Banks	0.52	0.6	0.11	0.56	0.54	0.54	0.55	0.72	0.55		0.54	0.6
	(0.28, 0.76)	(0.35, 0.85)	(-0.09, 0.3)	(0.3, 0.81)	(0.28, 0.8)	(0.28, 0.8)	(0.29, 0.81)	(0.46, 0.99)	(0.31, 0.8)		(0.3, 0.79)	(0.33, 0.87)
RoW	0.42	0.35	0.73	0.4	0.39	0.39	0.39	0.34	0.37	0.39		0.32
	(0.23, 0.61)	(0.16, 0.55)	(0.58, 0.88)	(0.2, 0.6)	(0.18, 0.59)	(0.18, 0.6)	(0.18, 0.6)	(0.13, 0.55)	(0.18, 0.57)	(0.19, 0.59)		(0.1, 0.55)
Supply	0.06	0.05	0.21	0.03	0.03	0.01	0.03	0.02	0.06	0.03	-0.0	
	(-0.01, 0.13)	(-0.02, 0.13)	(0.13, 0.29)	(-0.04, 0.11)	(-0.05, 0.1)	(-0.06, 0.09)	(-0.04, 0.11)	(-0.06, 0.09)	(-0.01, 0.13)	(-0.05, 0.1)	(-0.08, 0.08)	

Note: Table B.3 reports the estimate sector-specific and aggregate price elasticities in our "leave-one-out" checks. For each sector, we estimate the model by removing the sector from the construction of the moment conditions report the estimated elasticities of other sectors. 95% confidence intervals are report based on standard errors derived in Theorem 2.

Table B.4: **Price elasticity by sector: Alternative Specifications**

Sector	Baseline	More factors	1970-2023	Including Bills
Aggregate	1.04	1.08	1.3	2.09
	(0.81, 1.27)	(0.83, 1.34)	(1.11, 1.5)	(1.26, 2.91)
Other	-0.24	-0.11	0.19	0.56
	(-0.46, -0.01)	(-0.34, 0.11)	(0.02, 0.36)	(0.26, 0.87)
Households	10.07	11.09	10.5	4.34
	(5.26, 14.88)	(5.71, 16.46)	(7.29, 13.7)	(0.78, 7.9)
Pension	0.2	0.2	-0.23	0.17
	(0.04, 0.36)	(0.04, 0.36)	(-0.39, -0.07)	(-0.07, 0.4)
Insurance	0.51	0.38	-0.67	-0.01
	(0.21, 0.81)	(0.09, 0.66)	(-0.93, -0.41)	(-0.51, 0.49)
Mutual Funds	0.58	0.51	0.47	0.55
	(0.11, 1.05)	(0.03, 1.0)	(0.23, 0.72)	(-0.11, 1.21)
ETF	-0.1	-0.2	0.23	-0.33
	(-0.46, 0.26)	(-0.56, 0.17)	(0.04, 0.42)	(-0.83, 0.17)
Dealers	7.42	7.94	-1.47	1.11
	(-1.49, 16.32)	(-1.22, 17.1)	(-8.37, 5.43)	(-10.11, 12.33)
Fed	0.44	0.49	0.03	0.24
	(0.15, 0.72)	(0.2, 0.79)	(-0.06, 0.13)	(-0.13, 0.6)
Banks	0.53	0.43	1.0	0.63
	(0.35, 0.7)	(0.26, 0.6)	(0.51, 1.49)	(0.42, 0.85)
RoW	0.44	0.39	0.39	0.57
	(0.3, 0.58)	(0.25, 0.53)	(0.27, 0.52)	(0.36, 0.79)
Supply	0.05	0.04	0.26	1.33
	(-0.02, 0.12)	(-0.03, 0.11)	(0.18, 0.33)	(0.32, 2.34)
MMF				2.4
				(0.33, 4.47)

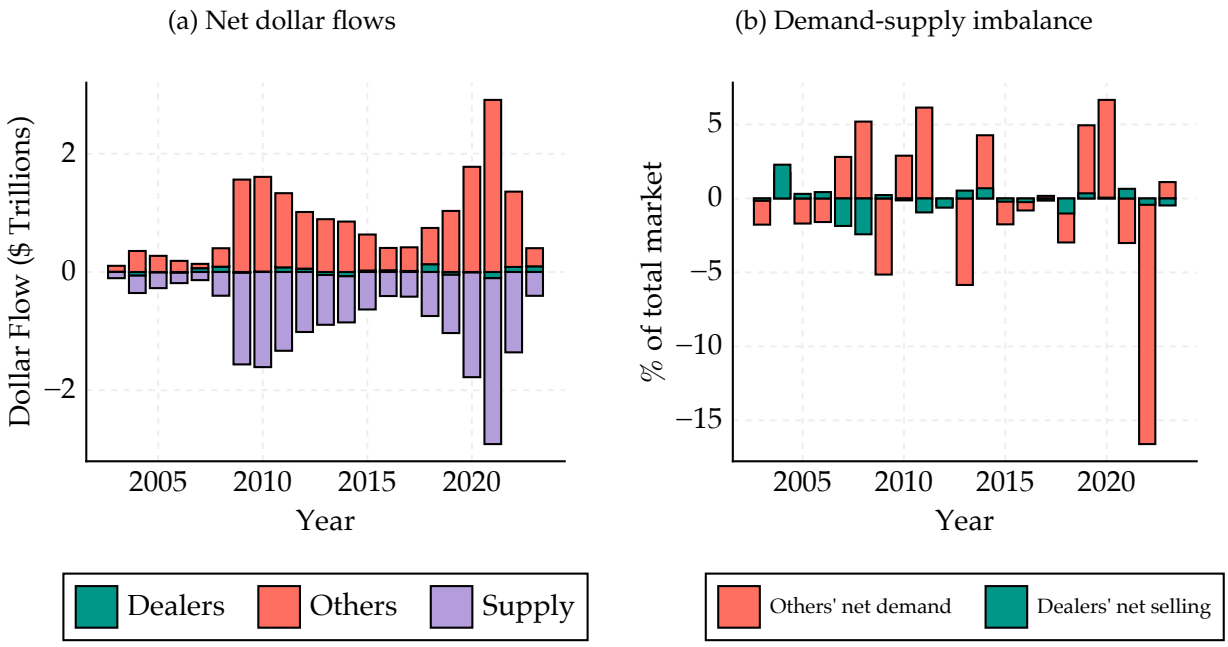
Note: Table B.4 demonstrates the robustness of our price elasticity estimation by augmenting the model with 5 estimated principal components from granular Treasury holding data for U.S. banks and foreign investors and two factors from forecasts on one-year and ten-year yield changes (column 2), by extending the sample period to 1970–2023 and estimating the model only on Financial Account data (column 3), and by including Treasury bills in the estimation (column 4). 95% confidence intervals are report based on standard errors derived in Theorem 2.

Table B.5: **Baseline Estimates: Full Table**

Sector	$S(\%)$	ζ	$\epsilon^{VIX}_{(std.)}$	Δ **FFR**	$Inf.$	$\epsilon^{USD}_{(std.)}$	**Lagged** f_{supply}	**Fed schedule**
Aggregate		1.03	0.66	-2.89	-1.2	-0.6	0.13	-0.15
		(0.77, 1.3)	(-0.16, 1.48)	(-4.99, -0.79)	(-2.05, -0.35)	(-1.34, 0.14)	(-0.55, 0.81)	(-1.07, 0.76)
Supply	100.0	0.06	-0.19	-0.42	0.09	0.07	1.87	-0.09
		(-0.01, 0.13)	(-0.4, 0.02)	(-1.0, 0.15)	(-0.14, 0.32)	(-0.13, 0.27)	(1.7, 2.04)	(-0.27, 0.1)
RoW	44.45	0.42	-0.2	0.41	-0.3	-0.4	-2.26	-0.98
		(0.23, 0.61)	(-0.87, 0.48)	(-1.45, 2.27)	(-1.03, 0.43)	(-1.04, 0.25)	(-2.81, -1.7)	(-1.6, -0.36)
Fed	22.08	0.42	1.15	-6.96	-0.32	-0.29	0.51	5.74
		(0.11, 0.74)	(-0.34, 2.64)	(-10.16, -3.77)	(-1.67, 1.04)	(-1.47, 0.89)	(-0.77, 1.8)	(3.42, 8.05)
Other	11.78	-0.14	-2.07	-3.57	1.72	1.77	-0.59	1.19
		(-0.37, 0.08)	(-3.19, -0.96)	(-6.63, -0.52)	(0.51, 2.92)	(0.72, 2.83)	(-1.51, 0.32)	(0.17, 2.22)
Mutual Funds	6.75	0.6	-1.94	-0.34	-0.06	0.44	-2.17	-0.86
		(0.13, 1.08)	(-3.52, -0.37)	(-4.66, 3.97)	(-1.78, 1.66)	(-1.04, 1.93)	(-3.45, -0.9)	(-2.29, 0.56)
Households	5.74	10.54	16.12	-12.36	-17.47	-9.6	-9.49	-17.23
		(5.33, 15.76)	(6.12, 26.13)	(-39.76, 15.04)	(-28.79, -6.15)	(-18.97, -0.23)	(-17.17, -1.81)	(-25.81, -8.64)
Pension	5.42	-0.02	-0.39	2.85	-0.49	-0.85	-0.97	-0.77
		(-0.18, 0.13)	(-1.4, 0.62)	(0.07, 5.62)	(-1.58, 0.61)	(-1.8, 0.11)	(-1.8, -0.13)	(-1.7, 0.16)
Banks	5.26	0.52	-0.28	-0.61	0.74	1.15	-1.0	1.93
		(0.28, 0.76)	(-1.84, 1.28)	(-4.93, 3.7)	(-0.94, 2.42)	(-0.35, 2.65)	(-2.31, 0.3)	(0.48, 3.39)
Insurance	2.59	1.08	0.66	4.42	-1.13	-1.13	-2.57	-1.18
		(0.76, 1.4)	(-0.4, 1.72)	(1.53, 7.32)	(-2.29, 0.02)	(-2.12, -0.13)	(-3.43, -1.72)	(-2.14, -0.23)
ETF	1.18	-0.53	1.36	1.96	1.87	1.01	0.02	-0.16
		(-0.89, -0.17)	(0.19, 2.54)	(-1.25, 5.18)	(0.59, 3.15)	(-0.1, 2.12)	(-0.93, 0.97)	(-1.22, 0.9)
Dealers	0.81	2.22	16.03	-27.13	-35.9	-14.08	10.08	-2.62
		(-6.45, 10.88)	(-9.71, 41.77)	(-97.64, 43.38)	(-64.14, -7.67)	(-38.29, 10.13)	(-10.66, 30.82)	(-25.78, 20.53)

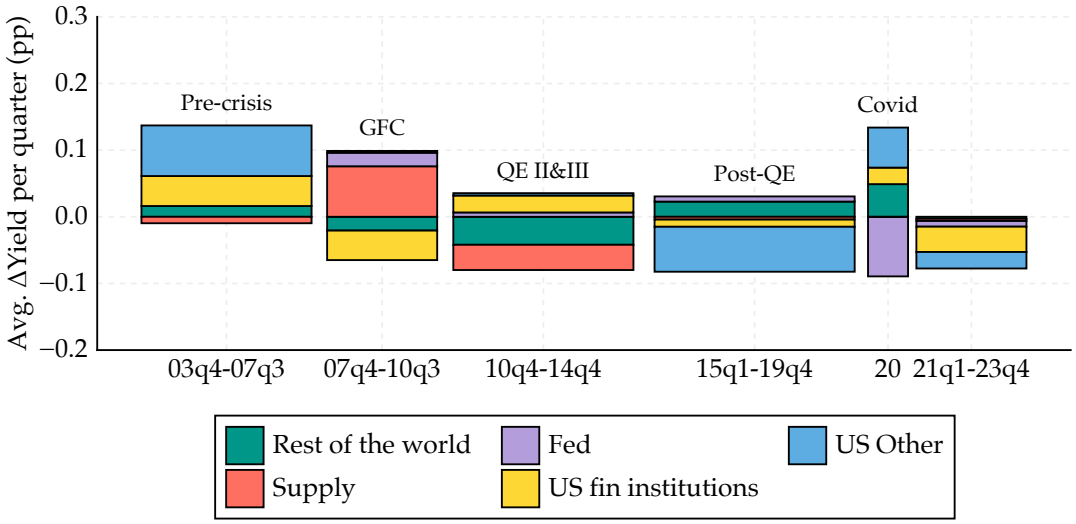
Note: Table B.5 reports the full set of estimated parameters and their associated 95% confidence intervals. ζ denotes price elasticities. S corresponds to the size weight used in the estimation, defined as the average market share of each entity throughout the sample period. Time-series averages are taken for sectors that assume to have different price elasticities before and after 2009Q1 (the sectors include Federal Reserve, Rest of World and U.S. Banks). $\varepsilon^{VIX}_{(std.)}$ and $\varepsilon^{USD}_{(std.)}$ refer to the demand loading on a positive VIX shock and USD index shock respective, obtained by taking the residual from AR(1) time-series regressions. ΔFFR refers to quarterly changes in the Federal Funds rate, and $Inf.$ denotes the deviation of CPI inflation from the 2% per annum inflation target. 95% confidence intervals are reported, with the standard errors given by Theorem 2.

Figure B.6: **The role of security broker-dealers**



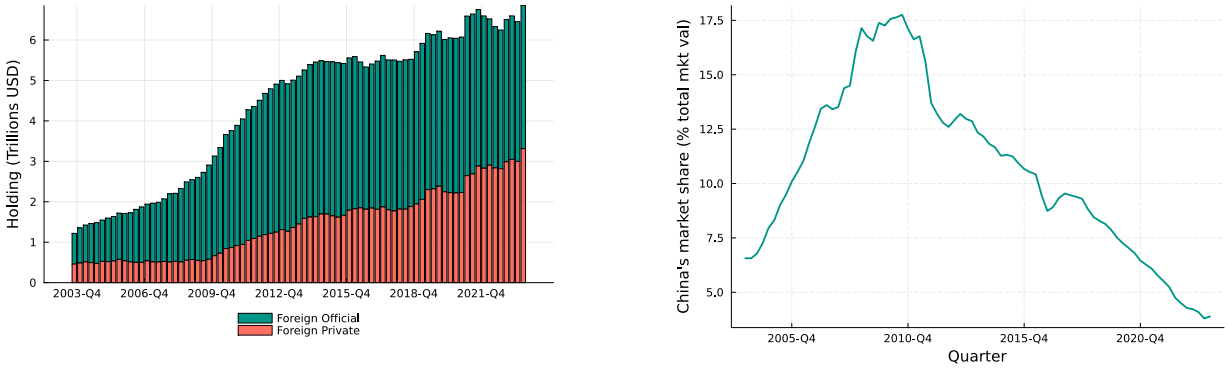
Note: Figure B.6 examines the role of security broker-dealers in affecting U.S. Treasury yields at low frequency. In Panel (a), we compare net annual flow into the Treasury market due to broker-dealers (in green) with those of other holders and the net issuance. In Panel (b), we plot a measure of demand-supply imbalance and the broker-dealers' degree of accommodation. For all sectors except the broker-dealers, the red bars aggregate the demand/supply curve shifts due to common factors and idiosyncratic shocks, $q_{it} + \zeta_{ir(t)} p_t$ to the annual frequency. The green bar, on the other hand, plots the annual total selling due to the broker-dealers. Bars pointing to the same direction indicates that dealers are accommodating the demand-supply imbalance of other sectors, by either selling when others increase demand, or buying when others sell.

Figure B.7: **Sectoral decomposition of latent demand and supply shocks**



Note: Figure B.7 further breaks down the contribution of latent demand and supply shocks (plotted in Figure 6) to the investor group level. We report average yield contribution per quarter in percentage points. The width of the bars reflects the length of the corresponding episode.

Figure B.8: **Foreign holdings of Treasury notes and bonds: Official holdings and China**



(a) Official vs. Private investors (level)

(b) China's share (% total market value)

Note: Figure B.8 provides additional context for understanding the influence of foreign demand on U.S. Treasury yields. Panel (a) plots the evolution of private and official holding of U.S. Treasury notes and bonds. Panel (b) specializes to China and plot its market share evolution over the sample period.