

# How Return Differentials Shape the U.S. Current Account: Evidence from a Sign-Restricted SVAR

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## **Abstract**

This paper reexamines the role of U.S. return differentials—the excess yield earned on external assets relative to liabilities—in sustaining the U.S. current account. I show that these differentials have provided nearly \$9 trillion in cumulative support since 1999, driven primarily by direct-investment returns but with a growing contribution from portfolio-investment yields since the global financial crisis. Decomposing the sources of this advantage reveals that equity profitability underpins most of the positive differentials, while debt liabilities systematically depress them. Via a sign-restricted structural VAR (SR-SVAR) I provide evidence that shocks in both direct investment (DI) return differentials and portfolio investment (PI) return differentials generate persistent shifts in the current account mainly through income and risk-premium channels. The evidence highlights the centrality of return differentials to U.S. external adjustment and underscores the evolving tension between the country’s “exorbitant privilege” and its “exorbitant duty” as issuer of the global reserve asset in a scenario of deepening negative external position and faltering credibility.

# 1 INTRODUCTION

Return differentials—the excess yield the United States earns on its external assets relative to what it pays on its external liabilities—are a central but contested ingredient of U.S. external adjustment. They are invoked to explain why the United States has been able to run sizeable current-account (CA) deficits while still recording a persistently positive net primary-income balance and only gradual changes in its net international investment position (NIIP). In this paper, I ask a simple question: to what extent, and through which channels, do return differentials—especially those associated with direct investment (DI) and portfolio investment (PI)—move the U.S. current account?

The motivation is the well-known structural transformations post-1970s shift in the U.S. external balance sheet. Since the early 1980s the current account (CA) has often been negative and the net international investment position (NIIP) increasingly so, yet income from U.S. foreign assets has exceeded payments on foreign holdings of U.S. assets for most of the period. Two episodes sharpen this contrast: during the global financial crisis and again around Covid-19, swings in global risk and dollar conditions left quantity positions large and volatile, while the U.S. primary-income surplus proved resilient. This juxtaposition suggests that return differentials—excess yields on U.S. external assets relative to liabilities—are a key channel linking valuation and income flows to the external balance (Gourinchas and Rey, 2007).

Recently, the external environment facing the United States has changed in ways that make these return wedges even more salient. The post-zero-lower-bound normalization, the 2021–2022 inflation surge, and the repricing of term premia have pushed long-maturity U.S. interest rates higher, raising debt-service costs and testing perceptions of fiscal credibility. At the same time, a more contested global order raises questions about the durability of the U.S. “safety premium” and the dollar’s ancillary advantages (see Rogoff, 2025). In this setting, quantifying how much—and through which channels across direct investment (DI) and portfolio investment (PI)—return differentials move the U.S. current account is not only an accounting exercise but a test of how external privileges interact with higher real rates and evolving global demand for U.S. assets.

The paper makes three main contributions. First, using a simple counterfactual exercise, it estimates the cumulative effect of return differentials on the U.S. current account at roughly \$9 trillion (2015 USD) between 1999 and 2024. More than two-thirds of this cumulative support stems from direct-investment returns, although the share of portfolio-investment differentials has grown since the global financial crisis. This quantitative accounting demonstrates that the U.S. advantage in external earnings remains large and persistent, despite successive episodes of global stress.

Second, the decomposition of yield differentials reveals that equity assets have been the main drivers of the U.S. return advantage, while debt instruments have acted as a drag. Within equity, the *return effect*—higher profitability within categories rather than a more favorable composition—dominates and explains most of the aggregate

differential, especially on the DI side. In contrast, debt, particularly in the PI segment, depresses overall U.S. returns, with its negative contribution arising mainly from composition rather than pricing. In DI, the negative role of debt reflects within-class return effects, whereas in PI, it reflects the U.S. tendency to issue large volumes of safe, low-yield debt to global investors.

Third, the structural analysis quantifies how these return-differential shocks propagate through the U.S. external accounts. Using a VARX baseline and a sign-restricted SVAR, the results show that DI shocks—interpreted as equity-profitability disturbances—generate delayed but sustained effects on the current account through the income and valuation channels. PI shocks—interpreted as valuation-yield disturbances—act through the FX and risk-premium channels, producing rapid but short-lived movements dominated by financial-market conditions. In both cases, the estimated responses of the current account exhibit cyclical reversals consistent with the adjustment of global portfolios and the risk cycle. The historical decomposition confirms that DI and PI shocks together explain a sizable share of current-account fluctuations, especially around the GFC and Covid episodes.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature, situating the debate on return differentials within the broader discussions of U.S. external privilege, global imbalances, and international financial hierarchy. Section 3 provides an overview of return differentials, including their measurement, empirical patterns, and decomposition into composition and return effects, with attention to the relative roles of direct and portfolio investment. Section 4 describes the data sources and construction of the quarterly series on return differentials and control variables. Section 5 outlines the econometric framework, including the VARX specification, identification strategy, and sign-restricted SVAR design. Section 6 presents the empirical results: baseline VARX responses, structural evidence from SR-SVARs, forecast-error variance decompositions, and historical decompositions. Section 7 concludes by synthesizing the contributions, discussing implications for the U.S. external position and global financial hierarchy, and suggesting avenues for further research.

## 2 RELATED LITERATURE

The modern debate on U.S. external privilege sits at the intersection of international macroeconomics and international political economy. On one side, the “exorbitant privilege” view emphasizes that issuing the reserve currency confers structural advantages—deep, liquid markets; policy space; and the capacity to finance deficits at favorable terms—producing systematically higher returns on U.S. external assets than on its liabilities (Gourinchas and Rey, 2007). On the other, classic “key currency” (Williams, 1934) and hegemonic-stability (Waltz, 2018, Gilpin, 1971, Kindleberger, 1986) traditions stress that leadership entails obligations: supplying global liquidity, stabilizing markets in crises, and underwriting open-system public goods. In this framing, U.S. privilege coexists with “duties” that can be costly in stress episodes.

Return-differential (RD) debates are one leg of this broader dispute. In the early–mid 2000s, a quasi-consensus formed that the United States did enjoy a positive return wedge. The government’s own assessment acknowledged it (ERP, 2003), and independent analyses echoed the point (e.g. Godley, 2003, Hung and Mascaro, 2004). The question gained salience as China’s WTO accession and export surge widened U.S. trade deficits and compressed some traditional comparative advantages. RD therefore offered a compelling channel through which the United States could sustain external imbalance while cushioning net investment income.

By the mid-2000s, two positions crystallized. The “exorbitant privilege” camp (Gourinchas and Rey, 2007) documented persistent excess returns—especially linked to equity-like claims—and argued they materially support the U.S. external position via valuation and income effects. A challenger camp questioned either the measurement or the magnitude. Curcuru et al., 2008 showed that mixing revised positions with unrevised flows overstated portfolio gaps and, using consistent data and a breakdown of RD into composition (class weights) and return (with class) effects, found modest composition effects and limited within-class premia, with timing/trading effects doing more work. Also against the existence of systemic RD, Gros, 2006 argued the “black hole” is largely an accounting artifact that deflates true excess returns, while Hausmann and Sturzenegger, 2006 reframed the income surplus as “dark matter,” that is, unmeasured intangibles that, if capitalized, would turn the puzzle from abnormal returns into missing wealth.

In the 2010s, RD debates partly gave way to those on the macro challenges of the post-GFC environment, such as zero lower bound (L. Summers, 2013, L. H. Summers, 2016) and social, economic, and demographic structural changes (Gordon, 2017) leading to secular stagnation. Also contributing to place RD behind the scenes of academic and policy concerns, several U.S. external-balance margins improved: the maturing shale revolution, rising services surpluses, and a durable primary-income surplus partly offset a still-negative current account. In this context, RD remained relevant but less front-and-center than crisis management and the slow-growth policy debate.

Two developments nonetheless pushed the RD research agenda forward. First, Ali, 2016 used industry-level data to show that DI-linked excess returns may exceed what macro aggregates imply. Second, Gourinchas and Rey, 2022 synthesized privilege with “exorbitant duty,” embedding U.S. external returns and valuation into the global financial cycle: the U.S. is long risky and short safe, earning premia in tranquil times yet absorbing stress when global risk reprices.

Most recently, a global perspective has broadened the lens. Akyüz, 2021 highlights that many emerging economies face the mirror image—low-yielding assets and high-yielding liabilities. Mayer, 2021 and Nievas and Sodano, 2024 document the cross-country distribution of return differentials over long horizons. These studies show that RD is not solely a U.S. phenomenon but part of a broader hierarchy of international balance sheets, with significant incidence on developing and emerging economies and a recent shift from a uniquely U.S. privilege toward a wider “rich-world privilege.”

### 3 RETURN DIFFERENTIALS — AN OVERVIEW

Return differentials (RD) are the yield gap between U.S. external assets and liabilities. Let  $r_t^A$  and  $r_t^L$  be the aggregate yields on assets and liabilities in period  $t$ , each measured as income over the lagged position (annualized for quarterly data):

$$r_t^A = \lambda \frac{I_t^A}{P_{t-1}^A}, \quad r_t^L = \lambda \frac{I_t^L}{P_{t-1}^L},$$

where  $I_t^A$  ( $I_t^L$ ) is investment income on assets (liabilities),  $P_{t-1}^A$  ( $P_{t-1}^L$ ) is the beginning-of-period stock of external assets (liabilities), and  $\lambda = 4$  for quarterly data ( $\lambda = 1$  for annual). The return differential is

$$RD_t = r_t^A - r_t^L.$$

Three facts stand out (see Figure 3.1). First, the DI return differential is persistently and substantially positive—roughly 0.8–1.2 pp through most of the sample—with a temporary post-GFC spike above  $1\frac{1}{2}$  pp. Second, the PI return differential, while smaller than DI, rises meaningfully after the GFC: from near zero pre-2009 to systematically positive levels in the 2010s (about 0.1–0.3 pp), with clear cyclicity around risk episodes (compression in 2020 and rebound thereafter). Third, the total RD remains positive and trends up through the 2010s, dips during the Covid shock, and then recovers. These dynamics motivate identifying separate DI- and PI-driven RD shocks and lead us to expect stronger, more persistent current-account effects from DI innovations, with PI playing a thinner but growing role.<sup>1</sup>

I then estimate the cumulative dollar impact of RD on the US current account (Figure 3.2). To do so, I use a counterfactual argument that assumes both yield on asset and yield on liabilities to be equal ( $RD = 0$ ). I assume a midpoint yield (the average between assets and liabilities) for total, DI, and PI, deflate each flow to 2015 USD using CPI rebased to 2015=100, and calculate the difference from 1999 to 2024. This procedure converts yield gaps into the cumulative contribution of RD to net primary income—and hence to the current account—in real terms.

Figure 3.2 shows a large and steady build-up: the real cumulative impact exceeds roughly \$9 trillion (2015 USD) by 2024. Compositionally, DI accounts for the bulk of the total by the end of the sample, while PI is modestly negative in the mid-2000s, turns positive after the GFC, and contributes an increasingly meaningful share through the 2010s–2020s. Shaded windows (2008–2012; 2020–2021) highlight that the upward drift persists despite crisis episodes, consistent with persistently higher returns on U.S. external assets—especially DI—relative to liabilities.

<sup>1</sup>Appendix A.1 documents the evolution of U.S. NIIP, DI, and PI balance sheets since 2006.

Return differentials: total, portfolio (PI), and direct investment (DI)  
 Quarterly, 2006Q1–2025Q1 (pp); shaded GFC/Covid

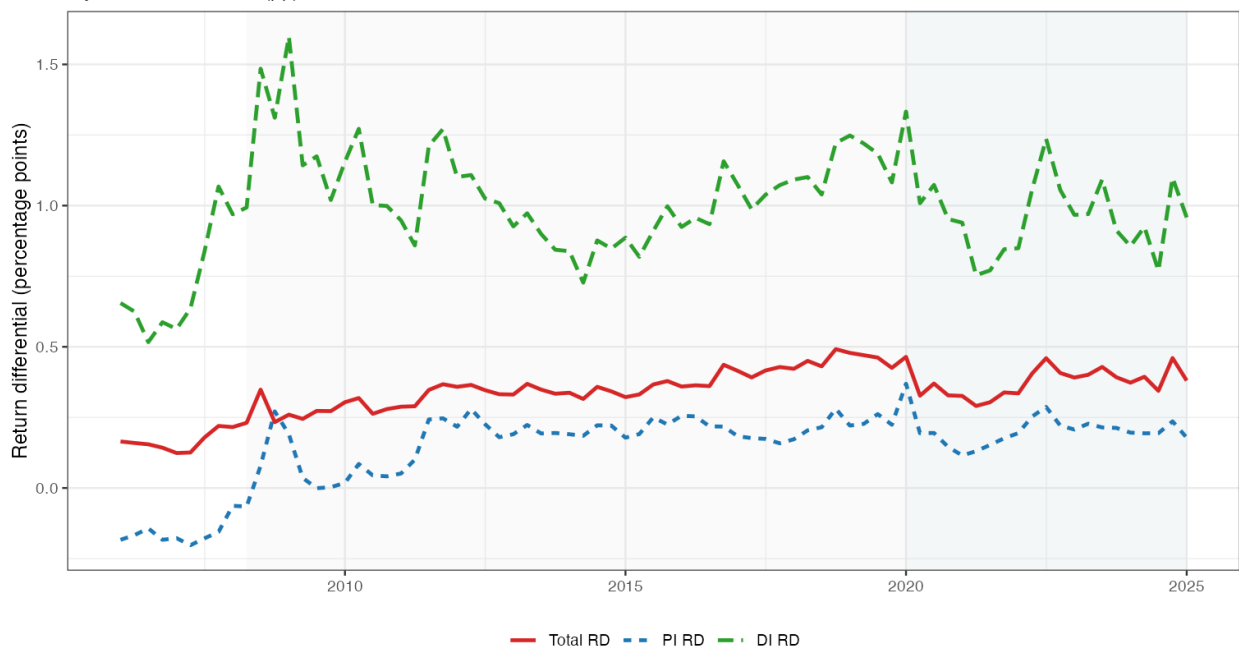


Figure 3.1: Return differentials: total, portfolio (PI), and direct investment (DI). Quarterly, 2006Q1–2025Q1 (percentage points). Shaded areas denote GFC (gray) and Covid (blue).

Cumulative dollar impact of return differentials (2015 USD), midpoint counterfactual  
Annual 1999–2024. DI and PI components; total shown in black. Shaded: 2008–2012, 2020–2021.

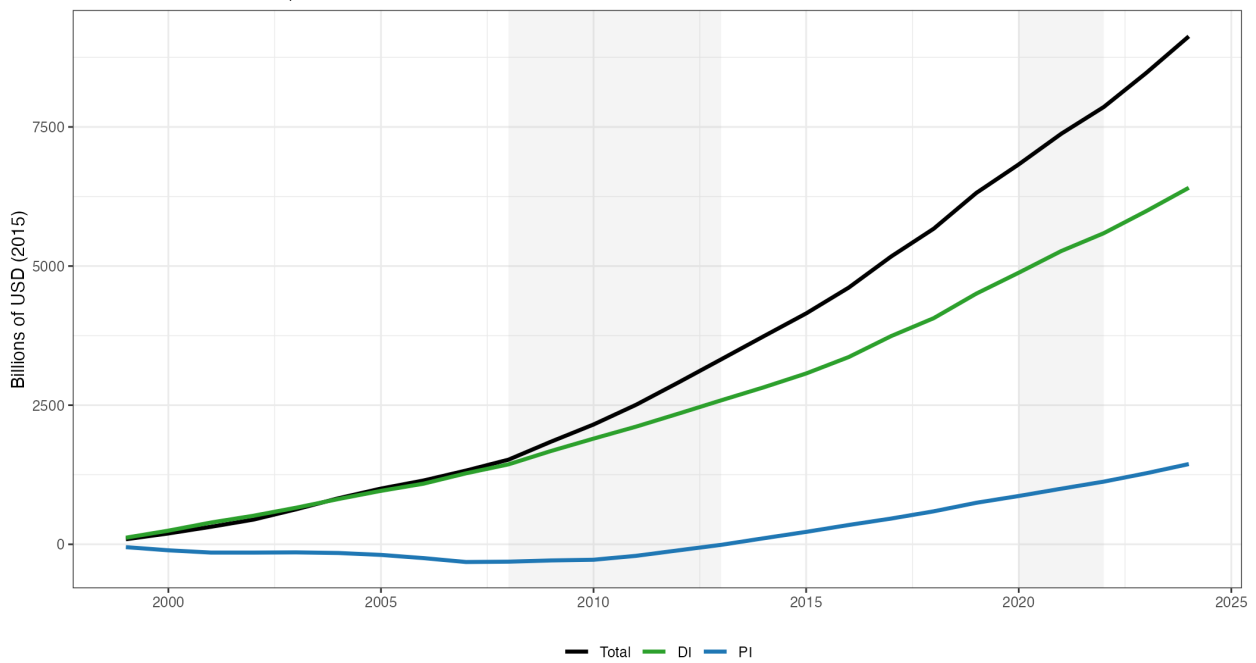


Figure 3.2: Cumulative dollar impact of return differentials on the U.S. current account, 1999–2024, in 2015 USD. Black = total; green = direct investment (DI); blue = portfolio investment (PI). Annual flows use the midpoint counterfactual  $RD_t \times \frac{A_t + L_t}{2}$ , deflated by CPI (2015=100) before cumulation. Shaded bands: 2008–2012 (GFC/Euro) and 2020–2021 (Covid).

To understand how and to what extent each asset class impacts overall U.S. RD, I decompose the annual external yield differential into composition and return effects following the portfolio-accounting approach in Curcuro et al., 2010 and Curcuro et al., 2013. Let us break US holdings into five broad classes, direct investment (DI) equity, DI debt, portfolio investment (PI) equity, PI debt, other investment (OI). For each class (represented by  $c$ ), define asset and liability yields  $r_{c,t}^A$  and  $r_{c,t}^L$  as investment income over lagged positions (annualized), and portfolio shares  $w_{c,t}^A$  and  $w_{c,t}^L$  as the class's lagged position divided by the side's total (shares sum to one on each side). The aggregate differential

$$\Delta r_t = \sum_c w_{c,t}^A r_{c,t}^A - \sum_c w_{c,t}^L r_{c,t}^L$$

can be written as

$$\Delta r_t = \underbrace{\sum_c (w_{c,t}^A - w_{c,t}^L) \bar{r}_{c,t}}_{\text{Composition effect}} + \underbrace{\sum_c \bar{w}_{c,t} (r_{c,t}^A - r_{c,t}^L)}_{\text{Return effect}}, \quad \bar{r}_{c,t} \equiv \frac{1}{2}(r_{c,t}^A + r_{c,t}^L), \quad \bar{w}_{c,t} \equiv \frac{1}{2}(w_{c,t}^A + w_{c,t}^L).$$

With this, I can determine whether RD derives from the U.S. holding more of the high-yield categories (composition effect) or from higher earnings within each category (return effect).<sup>2</sup>

Figure 3.3 shows that at the whole portfolio level, the blue bars (return effect) account for nearly all of the positive yield differential over 1999–2024. The red bars (composition effect) are small on average and often negative before the GFC, turn mildly positive around 2009–2012, and remain close to zero thereafter. The black line (total) sits in the 1–2 pp range through most of the 2010s, dips around Covid, and then recovers. This indicates that the U.S. advantage is predominantly a within-category pricing phenomenon rather than the result of an especially high-yield portfolio mix.

Figure 3.4 stacks, for each class, the composition effect (difference in asset–liability weights evaluated at mid-returns, red) and the return effect (within-class yield gap evaluated at mid-weights, blue); the black line is the category's total contribution in percentage points. DI equity lifts the aggregate most. The return effect is large and persistent (1.0–1.3 pp most years) and even ticked up in the 2010s. By contrast, the composition effect was strongly positive pre-GFC (roughly 0.4–0.7 pp) but drifted down thereafter (closer to 0.2–0.4 pp by the early-2020s). This points to a gradual rise in the liability share of DI equity—diluting the U.S. “long-equity” tilt—partly offset by a resilient (and at times stronger) DI return advantage. The total stays high (black line 1.3–2.0 pp), dips around 2020, and recovers. DI debt sees a clear upward trend from negative to roughly neutral. The composition term is negative pre-2007 (–0.10 to –0.15 pp), reflecting a liability-heavy DI-debt mix, but trends toward zero after 2010 and is near-neutral by 2022–24. The return effect is small, slightly positive (a few basis points). Net, DI debt moves from a consistent

<sup>2</sup>All quantities are computed from BEA ITA/IIP income and positions; derivatives are excluded and reserves enter OI on the asset side as noted in the data appendix.



U.S. external yield differential: composition vs. return effects  
Annual, 1999–2024. Bars: Composition + Return (pp). Black line: total yield differential.

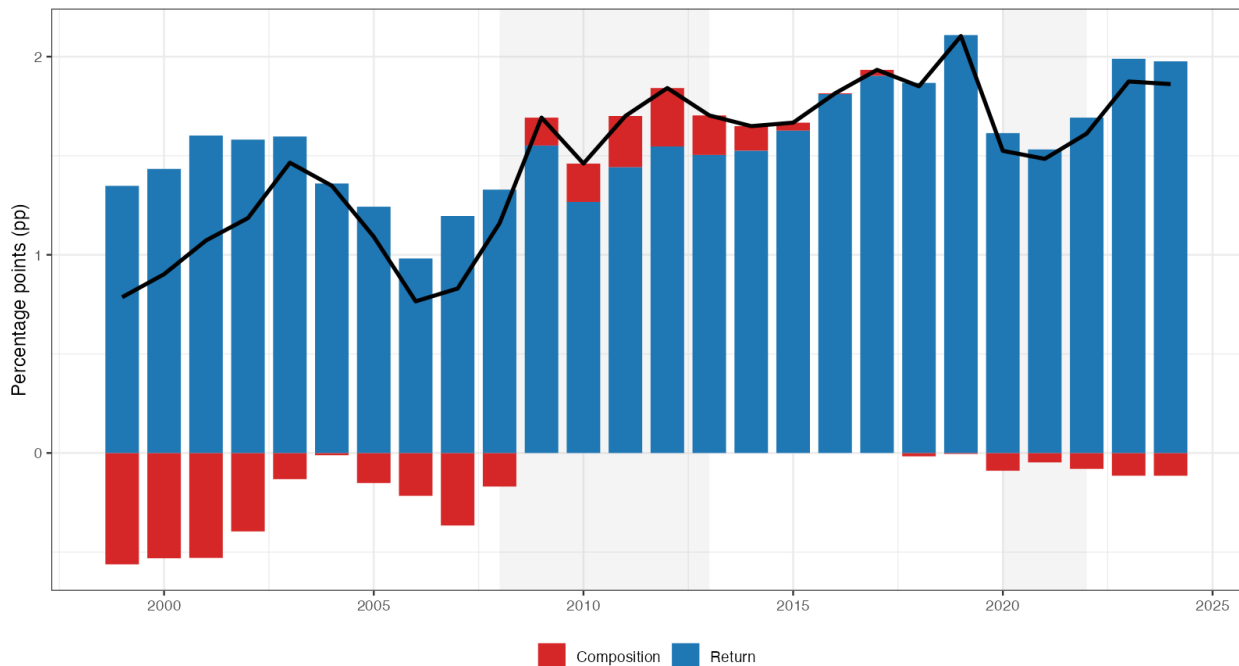


Figure 3.3: U.S. external yield differential: composition vs. return effects (annual, 1999–2024). Bars stack the composition (red) and return (blue) contributions in percentage points; the black line is the total yield differential. Shaded bands indicate 2008–2012 (GFC/Euro) and 2020–2021 (Covid).

negative contribution in the 2000s to “approximately zero” in recent years.

As for PI equity, over the period of analysis, the composition effect rises from 0.10–0.15 pp pre-GFC to 0.25–0.35 pp by the late-2010s, and the return effect climbs from 0.10 pp to 0.25–0.30 pp. The total contribution increases steadily (peaking around 0.6–0.7 pp), is briefly compressed in 2020, then re-establishes at a high level. This mirrors the secular deepening of outward and inward equity portfolios and a modest—but persistent—U.S. equity-return edge. Similar to DI debt, PI debt also sees a positive trend led by the composition effect. It is strongly negative in the early 2000s (–1.0 pp or worse), consistent with the U.S. issuing a lot of safe debt to the rest of the world; it improves materially over time, hovering around –0.3 to –0.5 pp by 2024. The return effect is small and only slightly positive. The total contribution stays negative throughout, but the drag shrinks meaningfully after 2010.

Putting it together, two broad shifts line up with your observations: (i) in the debt classes (especially PI debt, but also DI debt) the composition effect moves from clearly negative in the 2000s toward less negative/slightly-positive in the 2010s; (ii) in equity classes, DI equity’s composition advantage eases over time—partly offset by a stronger return effect—whereas PI equity sees both composition and return effects trend up. Summed at the aggregate, this is why the blue bars dominate in Figure 3.3: the U.S. advantage is primarily a within-category pricing/return phenomenon driven by equity (DI most of all), while the long-standing composition drag from debt has moderated but not disappeared.

Yield differential by category: composition vs return contributions  
Annual, 1999–2024. Bars = Composition + Return (pp) within category; black line = category total.

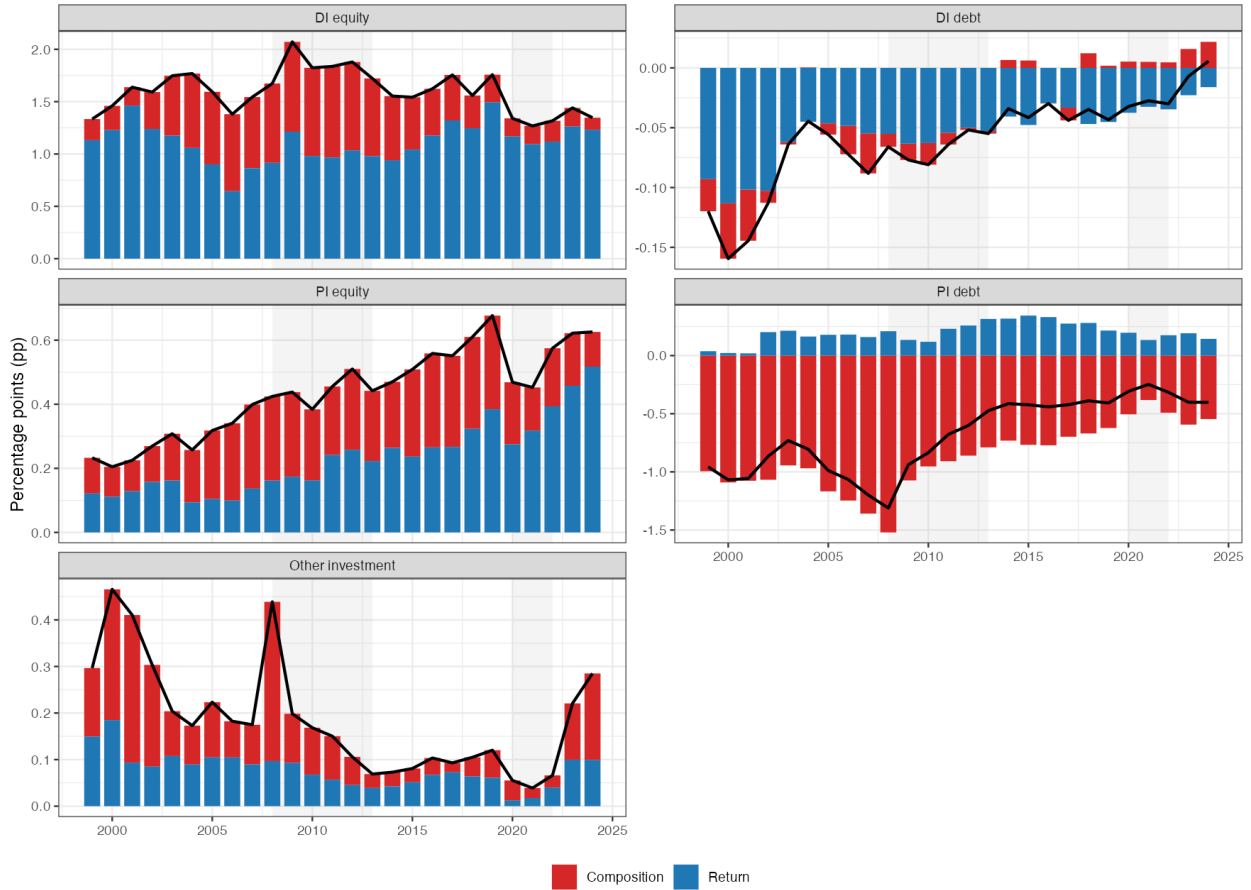


Figure 3.4: Yield differential by category: composition vs. return contributions (annual, 1999–2024). Panels show DI equity, DI debt, PI equity, PI debt, and other investment. In each panel, bars stack composition (red) and return (blue) in percentage points; the black line is the category's total contribution. Shaded bands indicate 2008–2012 (GFC/Euro) and 2020–2021 (Covid).

## 4 DATA

The core dataset is quarterly, 2006Q1–2025Q1, and combines BEA International Transactions Accounts (ITA) and International Investment Position (IIP) with standard macro-financial controls. The dependent variable is the current account as a share of GDP (CA/GDP, CAGDP). Control variables are U.S. real GDP growth ( $g$ ), rest-of-world growth ( $g\_star$ ), the broad real effective exchange rate (REER), the federal funds rate (FFR), the VIX (VIX), and two crisis dummies (GFC, Covid). Exact series definitions for  $g\_star$  and REER are documented in the Appendix.

**RETURN DIFFERENTIALS.** Category yields are defined as income divided by the beginning-of-period (lagged) position (annualized where needed), and the aggregate return differential as the asset-weighted average yield minus

the liability-weighted average yield:

$$r_t^{\text{diff}} \equiv r_t^A - r_t^L, \quad r_t^A = \frac{\text{Income on assets}_t}{\text{Assets}_{t-1}}, \quad r_t^L = \frac{\text{Income on liabilities}_t}{\text{Liabilities}_{t-1}}.$$

I report a total differential (`r_diff`) and differentials for direct investment (DI; `r_diff_DI`) and portfolio investment (PI; `r_diff_PI`). Returns are stored as fractions in the code and multiplied by 100 when presented (`r_diff_pp`, etc.).

GFC and Covid are quarterly dummies included as exogenous controls and represent the two major shocks in the Global economy. Exact date ranges are listed in the Appendix.

I parse quarters from the raw spreadsheets, restrict to 2006Q1–2025Q1, coerce numeric types, and keep return measures in percentages only for presentation.

## 5 METHODS

### 5.1 IDENTIFICATION

I study how return-differential shocks move the U.S. current account. The design of the VARX model is

$$\mathbf{y}_t = \begin{bmatrix} \text{CAGDP}_t \\ g_t \\ g_t^* \\ \text{REER}_t \\ \text{FFR}_t \\ \text{VIX}_t \\ r_t \end{bmatrix}, \quad \mathbf{x}_t = \begin{bmatrix} \text{GFC}_t \\ \text{Covid}_t \end{bmatrix},$$

where  $\mathbf{y}_t$  is the endogenous block and  $\mathbf{x}_t$  the exogenous block. CAGDP is the current account (share of GDP),  $g$  and  $g^*$  are U.S. and rest-of-world real growth, REER is the real effective exchange rate (higher = real appreciation of the dollar), FFR is the policy rate,  $VIX$  is the Chicago Board Options Exchange's (CBOE) volatility index, and  $r$  is the (total) external return differential in percentage points.<sup>3</sup> The exogenous block includes two crisis indicators for control.

Pre-estimation diagnostics follow a standard sequence and motivate all modeling choices. First, unit-root tests (ADF, PP, KPSS) indicate near-integration in several series (CAGDP, REER, FFR, and the return differential) and stationarity in foreign growth, so the VAR with exogenous controls is estimated in levels to preserve long-run comovements

<sup>3</sup>Section 4 details construction;  $r$  is income over lagged positions.

while relying on bootstrap inference for impulse responses. Second, lag length is chosen by information criteria with a pragmatic baseline of  $p = 2$  (balancing AIC/HQ/FPE vs. SC/BIC), and this choice is validated ex post by stability checks (all companion-matrix roots strictly inside the unit circle). Third, residual autocorrelation is assessed with Breusch–Godfrey LM and Portmanteau tests, which the system passes at conventional horizons; robustness to nearby lags is reported. Fourth, residual normality and ARCH–LM tests reveal non-Gaussianity and conditional heteroskedasticity concentrated in the growth and current-account blocks, reinforcing the use of bootstrap inference. Fifth, structural-stability diagnostics (Quandt–Andrews and Bai–Perron) point to breaks mainly around global-shock windows in the growth block, consistent with the inclusion of GFC and Covid dummies. Finally, Granger-causality checks confirm that return differentials have predictive content for the current account. The complete diagnostics are presented in Section 6.2.

Our baseline reduced-form model is thus a *VARX in levels with lag order  $p = 2$* :

$$\mathbf{y}_t = \mathbf{c} + A_1 \mathbf{y}_{t-1} + A_2 \mathbf{y}_{t-2} + \mathbf{B} \mathbf{x}_t + \mathbf{u}_t, \quad \mathbf{u}_t \sim (\mathbf{0}, \Sigma_u). \quad (5.1)$$

I report generalized (Pesaran–Shin) impulse responses and forecast-error variance decompositions from the VARX in levels, computed with bootstrap confidence bands and invariant to variable ordering. For transparency, I scale shocks so that the impulse in  $r_{\text{diff}}$  (and, where appropriate, FFR and REER) corresponds to a one–percentage-point increase on impact; ordering-robust Cholesky responses are provided in the appendix. Structural interpretation is reserved for the sign-restricted SVAR reported below.

To move from reduced-form to structural interpretation, I estimate sign-restricted SVARs that discipline the contemporaneous interactions among return differentials, monetary policy, VIX, and the exchange rate. Recursive orderings are ill-suited given likely correlations across these shocks; sign restrictions impose only minimal structure—directional responses consistent with theory—while leaving dynamics to be data-driven. Three variants are considered: (i) a DI model, identifying shocks to the direct-investment return differential; (ii) a PI model, isolating portfolio-investment shocks; and (iii) a joint model including DI, PI, VIX, and REER shocks, which serves as the baseline. Structural shocks are scaled to a +1 pp move in their own variable, with inference based on identification bands. For each model, I report impulse-response functions, forecast-error variance decompositions, and historical decompositions to quantify the contribution of return-differential shocks to U.S. current-account fluctuations.

## 6 RESULTS

### 6.1 ROADMAP

I estimate a quarterly VAR with exogenous controls (VARX) in levels on 2006Q1–2025Q1 U.S. data. The endogenous block is (CAGDP,  $g^*$ ,  $g$ , FFR, REER,  $r_{\text{diff}}$ ); exogenous controls are (VIX, GFC, Covid).

**SHOCK NORMALIZATION (DROP-IN).** Throughout the paper, each identified shock is rescaled so that the impact response of its own variable equals +1 unit. Formally, if  $\Theta_h$  denotes the (orthogonalized or sign-restricted) impulse-response matrices and  $i_j$  indexes the “own” variable of shock  $j$ , I report

$$\tilde{\Theta}_h(:, j) = \frac{\Theta_h(:, j)}{\Theta_0(i_j, j)} \quad (h = 0, 1, \dots),$$

so that  $\tilde{\Theta}_0(i_j, j) = 1$ . For return and rate variables— $r_{\text{diff}}$ ,  $r_{\text{diff,DI}}$ ,  $r_{\text{diff,PI}}$ , and FFR—“+1 unit” corresponds to a +1 percentage point move on impact. For REER, “+1 unit” means a +1% appreciation when REER is in logs (or +1 index point when it is in levels). This is a scale convention only: forecast-error variance decompositions are invariant to it, while the magnitudes of other variables’ IRFs scale accordingly. Inference uses (i) bootstrap confidence bands for reduced-form IRFs and (ii) identification bands for sign-restricted SVARs. Unit-root behavior in several variables, stability of the estimated VARX, and non-Gaussian/heteroskedastic residuals (notably in  $g$ ,  $g^*$ , and CAGDP) motivate the levels specification with bootstrap inference. Full diagnostics and lag choice ( $p=2$ ) are in Appendix B.

### 6.2 DIAGNOSTICS

**UNIT ROOT TESTS** The unit-root evidence in able B.3 follows a familiar macro pattern. For CAGDP, REER, the federal funds rate (FFR), and the total return differential  $r_{\text{diff}}$ , ADF, and PP tests fail to reject a unit root in levels but reject strongly after first differencing, while KPSS rejects level (and, where tested, trend) stationarity. The above variables are thus  $I(1)$ . Foreign growth  $g^*$  is stationary across all tests ( $I(0)$ ). U.S. growth  $g$  is borderline—mixed ADF/PP outcomes in levels with KPSS not rejecting stationarity—so I treat  $g$  as  $I(0)$  and verify robustness using differences. This mixture of near-integrated ratios/rates and stationary growth rates motivates estimating the VAR with exogenous controls in levels, which preserves potential long-run comovements that differencing would remove and is consistent for impulse responses in large samples.

**LAG-LENGTH TESTS** To decide on the lag dimension of the VARX model, I proceed with standard lag-length tests. Table B.1 shows that AIC, HQ, and FPE select the maximal lag ( $\hat{p} = 8$ ) in our search window, while SC/BIC selects a parsimonious model ( $\hat{p} = 1$ ). Because AIC/HQ penalize complexity more weakly than SC, they often drift upward in

small-to-moderate samples when dynamics are rich. Given our sample size (quarterly 2006Q1–2025Q1) and six endogenous variables plus exogenous controls, I adopt  $p = 2$  as a compromise: it is much less parameter-intensive than  $p = 8$  yet captures the short-run dynamics that  $p = 1$  misses.

**VAR STABILITY/ROOT OF CHARACTERISTIC POLYNOMIAL** Table B.4 shows that both the  $p = 1$  and  $p = 2$  specifications are dynamically stable: all companion-matrix eigenvalues lie strictly inside the unit circle (no moduli  $\geq 1$ ). The baseline  $p = 2$  model provides a slightly larger cushion from the unit-root boundary (largest modulus  $\approx 0.951$  versus  $\approx 0.984$  for  $p = 1$ ), implying shocks are persistent but mean-reverting. This validates the use of orthogonalized IRFs and FEVDs from the levels VAR and supports our choice of  $p = 2$  as the primary specification, while retaining  $p = 1$  as a useful robustness check.

**RESIDUAL AUTOCORRELATION** Table B.5 shows Breusch–Godfrey LM tests run equation by equation. The  $g$  and  $g^*$  equations reject the null of no serial correlation across all horizons ( $h=4, 8, 12$ ,  $p < 0.01$ ), while the CAGDP, REER, FFR, and  $r_{\text{diff}}$  equations do not exhibit significant autocorrelation at conventional levels. Panel B aggregates system-wide diagnostics. At moderate horizons the system Portmanteau tests can be tight (e.g., adjusted  $Q(8)$ ,  $p=0.045$ ), but at  $h=12$  both the Breusch–Godfrey LM ( $p=0.265$ ) and the asymptotic Portmanteau ( $p=0.542$ ) fail to reject serial independence, indicating that the VARX( $p=2$ ) passes the global serial correlation checks at the longest commonly used horizon. Taken together, these results suggest that while some autocorrelation persists in the GDP growth blocks ( $g, g^*$ ), the overall system is adequately whitened for inference; as a robustness step, I will (i) report IRFs with bootstrap bands (already implemented) and (ii) probe  $p=3$ – $4$  in an appendix to verify that our main results for CAGDP are not sensitive to additional lags.

**RESIDUAL NORMALITY AND HETEROSKEDASTICITY OF VARX INNOVATIONS** Residual diagnostics reveal that some equations (returns, interest rate, and REER) produce innovations that are close to Gaussian, while growth and current account residuals exhibit clear departures due to fat tails and skewness. This pattern is common in macro VARs: shocks to real activity and external balances are crisis-prone and non-Gaussian. To account for this, all inference in this paper relies on bootstrap methods, which remain valid under such departures from normality. In addition to non-normality, residuals were also tested for heteroskedasticity using ARCH–LM procedures. Results, reported in , show that the same variables identified as non-Gaussian—namely  $g$ ,  $g^*$ , and CAGDP—also exhibit conditional heteroskedasticity, while FFR, REER, and the return differential do not. This reinforces the interpretation that volatility clustering and fat-tailed shocks are intrinsic features of the growth and external balance series in this system. The joint diagnostics further justify the use of bootstrap inference in the VARX analysis, ensuring that confidence intervals properly reflect the non-normal, time-varying nature of the innovations.

**STRUCTURAL STABILITY** I assess structural stability of the VARX( $p = 2$ ) system using the Quandt–Andrews family of coefficient tests (supF, aveF, expF) and Bai–Perron tests for breaks in residual variance. The results are reported in Table B.9. For the return differential ( $r\_diff^{pp}$ ), the average F-test rejects stability at the 5% level whereas the supF statistic is only marginally significant (10%), indicating moderate but diffuse coefficient drift rather than a single sharp break. Foreign growth ( $g^*$ ) displays decisive instability: all three coefficient tests strongly reject ( $p < 0.001$ ) and two variance breaks are identified at 2019Q3 and 2022Q2, spanning the COVID shock and its aftermath. Domestic growth ( $g$ ) also rejects coefficient stability at conventional levels, although no variance break is detected. By contrast, the federal funds rate (FFR) and the real effective exchange rate (REER) show no evidence of variance breaks and do not exhibit sharp coefficient instability. Finally, CAGDP features one variance break around 2021Q4 but no sharp coefficient instability. Taken together, instability concentrates in the growth block (external and domestic) and, to a lesser extent, in CAGDP's volatility. This pattern aligns with the residual diagnostics: periods of elevated global and domestic macro uncertainty manifest as both non-Gaussian innovations and time-varying volatility in the growth channels. Inference based on bootstrap impulse responses is therefore warranted and adopted in subsequent sections.

**GRANGER CAUSALITY INTO CAGDP** Table B.10 summarizes Granger causality tests that assess whether return differentials help predict fluctuations in the U.S. current account balance. Across specifications, the null hypothesis that return differentials have no predictive content for the current account is strongly rejected. In the baseline Granger test, lagged return differentials ( $r\_diff\_pp$ ) significantly improve forecasts of the current account, with p-values below the 1% level.

The results are robust to two important extensions. First, the block exogeneity test shows that return differentials, the real effective exchange rate (REER), and the federal funds rate (FFR) jointly Granger-cause the current account, confirming the relevance of macro-financial conditions alongside relative returns. Second, the Toda–Yamamoto procedure, which guards against potential non-stationarity by augmenting the lag length, produces nearly identical conclusions. Taken together, these results underscore the central role of return differentials in shaping the U.S. external position, consistent with the argument that financial asymmetries allow the United States to sustain current account deficits without destabilizing reversals.

### 6.3 BASELINE VARX

Having validated the VARX specification, I now turn to the impulse-response analysis. I begin with shocks to the total return differential before moving to disaggregated DI and PI shocks. Figure C.1 reports generalized impulse responses of the U.S. current account to shocks in the return differential, the policy rate, and the real exchange rate. A positive return-differential shock (+1pp) initially improves the current account but the effect is short-lived and

reverses after a few quarters, suggesting that the adjustment operates through valuation and income channels that fade as liabilities reprice. By contrast, monetary and exchange-rate shocks display more cyclical profiles: a tighter FFR or a dollar appreciation both weigh on the current account, consistent with standard expenditure-switching and interest-rate parity channels. In all cases, bootstrap bands underscore the high volatility of external-balance dynamics at business-cycle horizons.

Figure C.2 examines the drivers of return differentials themselves. Foreign and domestic growth innovations exert positive but short-lived effects, while FFR and REER shocks transmit more persistently, lowering excess returns on U.S. assets relative to liabilities. These patterns align with the interpretation that return differentials capture the premium the U.S. earns when global growth is strong and financial conditions loose, but that advantage erodes when monetary tightening or dollar strength compresses yields. Together, the two panels confirm that the return differential is both a driver and a margin of adjustment: it directly affects the current account yet is itself shaped by macro-financial shocks.

## 6.4 SIGN-RESTRICTED SVAR

I move from the reduced-form VARX to structural interpretation using sign-restricted SVARs, since recursive orderings are implausible given contemporaneous co-movement among return differentials, monetary policy, and the real exchange rate; sign restrictions impose minimal directional structure while leaving magnitudes data-driven. The impact-only SR-SVAR, identified by sign restrictions on  $r_{\text{diff},\text{DI}}$  and  $r_{\text{diff},\text{PI}}$  (both constrained to be non-negative on impact, and  $\text{REER} \geq 0$  for the PI shock), yields economically coherent and statistically stable impulse responses. The acceptance rate of approximately 50% confirms that these minimal restrictions align well with the reduced-form dynamics (see Appendix D.1). By contrast, more demanding specifications—such as enforcing multi-quarter or lagged REER constraints—produced no admissible rotations, suggesting that financial-market reactions to changes in return differentials are highly contemporaneous, while the real-side adjustments (via the current account and income flows) unfold more gradually.

Below, we provide structural estimates of shocks in direct investment return differentials (DI shocks) and portfolio investment return differentials (PI shocks). The results are presented as structural IRFs for four variables, NPI (net primary income), REER, VIX, and CA/GDP. The impact of shocks on NPI, REER, and VIX is interpreted as an indicator of the transmission mechanism that intermediates the impact of return differential shocks on the current account. NPI is interpreted as the income channel, REER as the foreign exchange (FX) cum expenditure-switching channel, where relative competitiveness is measured, and VIX reflects the risk-premium channel, where return differential shocks lead to volatility in the global markets. Appendix D.2 provides a structural interpretation of DI and PI shocks under the SR-SVAR model based on categorical analysis of BEA ITA data.<sup>4</sup>

<sup>4</sup>Notice that the impact of the shocks are large because the shocks are large. A shock was measured as an innovation of 1 pp in  $r_{\text{diff},\text{DI}}$  and



**DI SHOCK** A positive DI shock—an exogenous increase in the U.S. return differential on direct investment—generates a two-step dynamic pattern across the external accounts and relative prices.

Net Primary Income (NPI) initially falls, then rises sharply after roughly four quarters, peaking near USD 10 billion before gradually reverting (Figure 6.1). This lagged improvement suggests that DI shocks operate primarily through the income channel, as higher returns on U.S. direct investment abroad are realized and repatriated over time. The current account balance (CAGDP) follows a similar pattern: it temporarily deteriorates by around 4–5 percentage points of GDP, then improves strongly over the medium term (Figure 6.2). The short-run deficit likely reflects outflows tied to reinvested earnings or valuation adjustments, while the subsequent rebound signals the income effects of stronger external asset performance. The REER depreciates persistently (by about 10–15 index points), implying a mild easing of external financial conditions (Figure 6.3), while the VIX shows a temporary spike followed by a return to baseline (Figure 6.4).

Overall, the DI shock transmits mainly through the income and valuation channels, with limited short-term feedback from financial markets. The adjustment path is gradual, consistent with structural rebalancing rather than speculative flows.

**PI SHOCK** A PI shock—an increase in the U.S. return differential on portfolio investment—produces a markedly different, high-frequency pattern dominated by financial-market channels.

The REER appreciates strongly and immediately (by 30–40 index points), confirming that the sign restriction captures a "dollar-pop" response to sudden portfolio inflows (Figure 6.5). At the same time, the VIX declines sharply (by up to 60 points) (Figure 6.6), signaling an improvement in global risk appetite and a compression of risk premia. NPI jumps on impact—rising by roughly USD 70 billion—but this gain is short-lived and reverses within a few quarters (Figure 6.7). Similarly, CAGDP rises sharply by nearly 10 percentage points of GDP before returning to baseline after about two years (Figure 6.8). These brief yet powerful effects indicate that PI shocks propagate through short-term valuation gains and transient liquidity flows, rather than through durable real-side adjustments.

In sum, PI shocks operate as financial disturbances that tighten global liquidity and temporarily boost the dollar, reflecting cyclical rather than structural asymmetries.

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$r_{\text{diff,PI}}$ , respectively. This means on average doubling  $r_{\text{diff,DI}}$  and multiplying  $r_{\text{diff,PI}}$  by a 4–10 times factor.

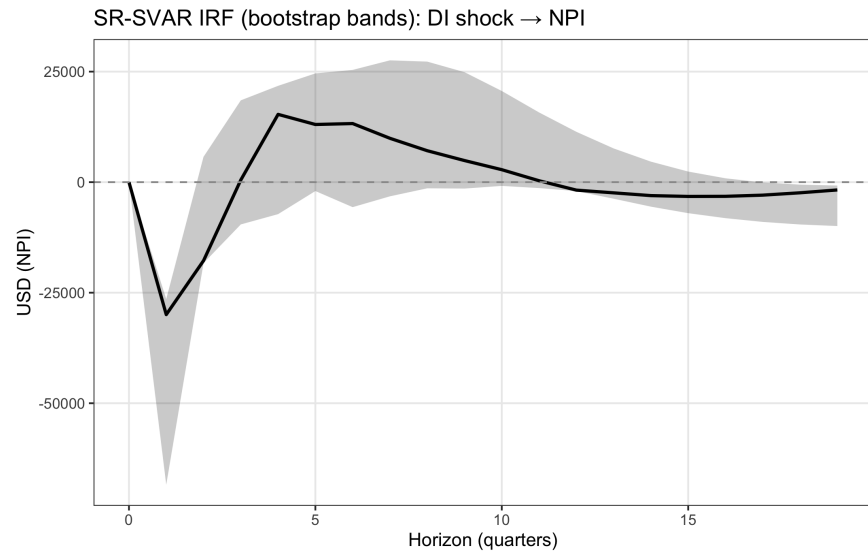


Figure 6.1: Response of NPI to a DI shock (68% bootstrap bands).

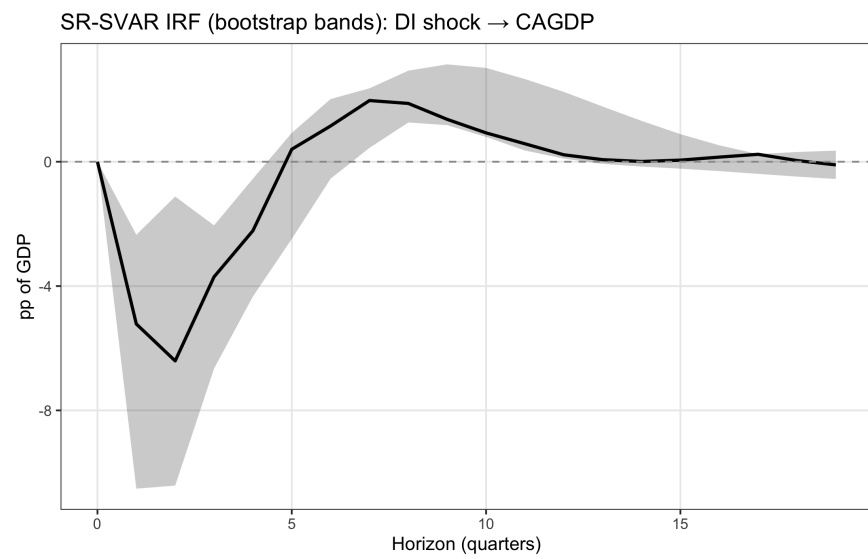


Figure 6.2: Response of the current account (as % of GDP) to a DI shock (68% bootstrap bands).

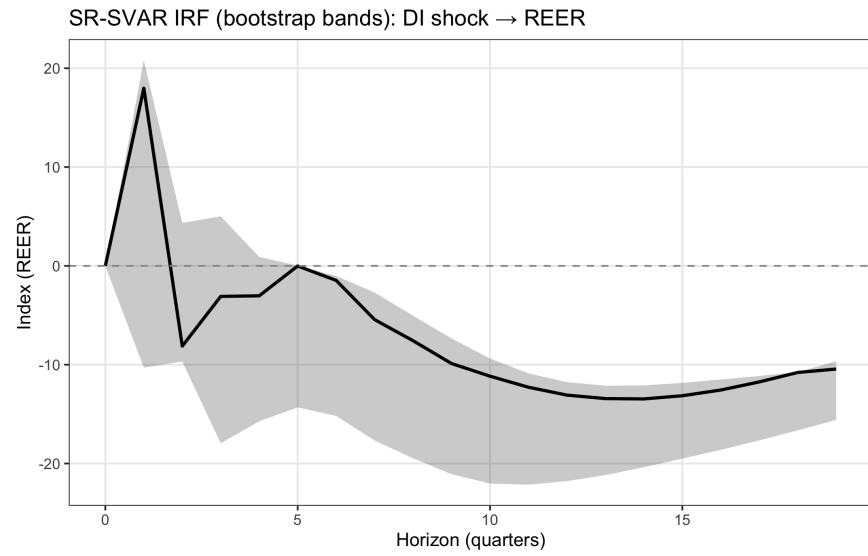


Figure 6.3: Response of REER to a DI shock (68% bootstrap bands).

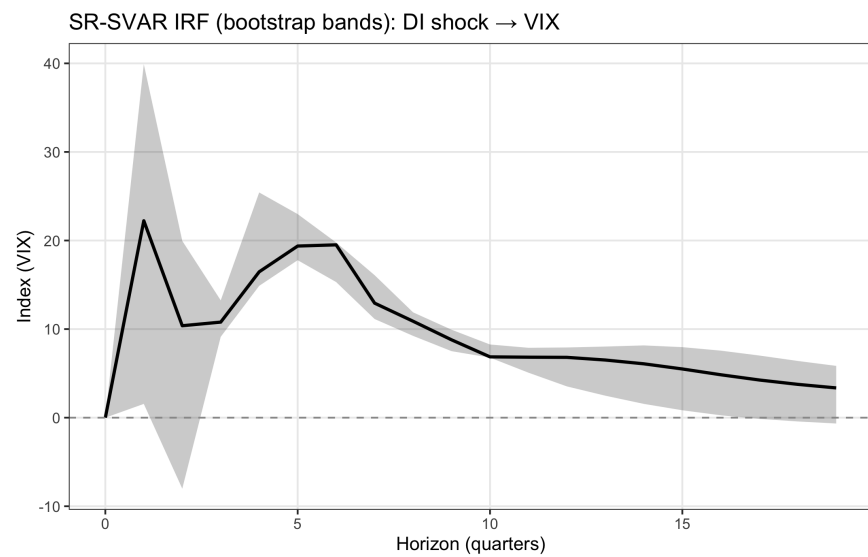


Figure 6.4: Response of VIX to a DI shock (68% bootstrap bands).

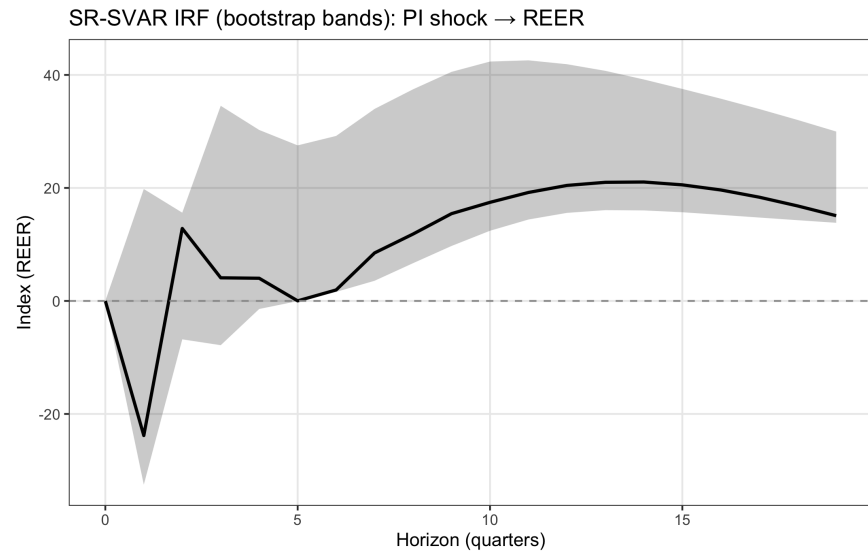


Figure 6.5: Response of REER to a PI shock (68% bootstrap bands).

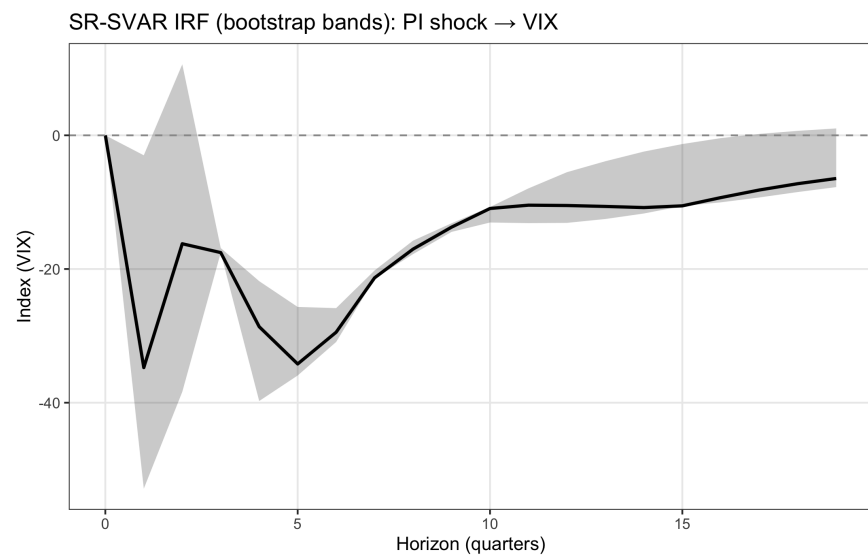


Figure 6.6: Response of VIX to a PI shock (68% bootstrap bands).

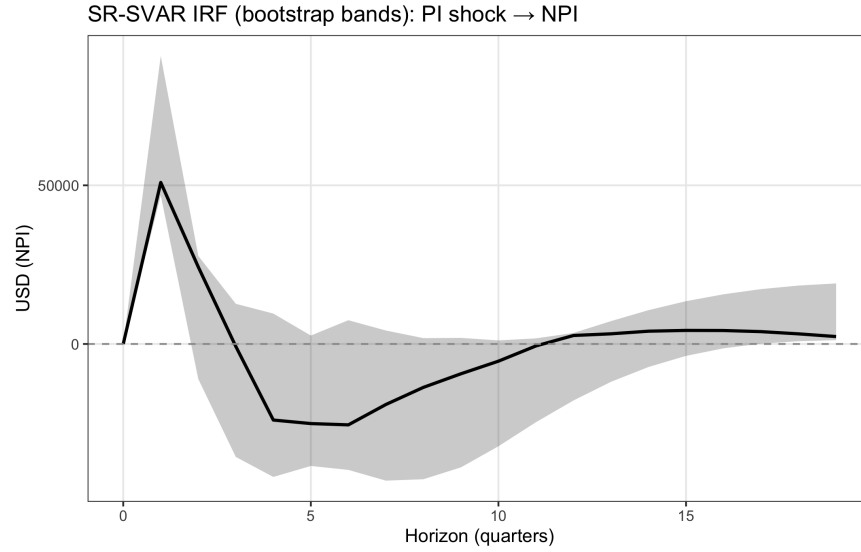


Figure 6.7: Response of NPI to a PI shock (68% bootstrap bands).

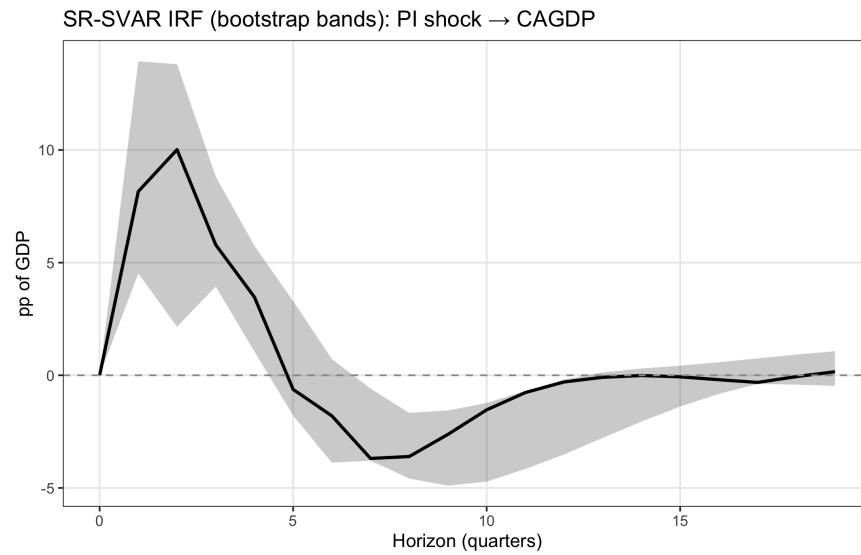


Figure 6.8: Response of the current account (as % of GDP) to a PI shock (68% bootstrap bands).

## 6.5 HISTORICAL DECOMPOSITION

Figure 6.9 presents the stacked historical decomposition of  $CA/GDP$  innovations under a representative admissible rotation of the main structural model (the Joint SR-SVAR). Each quarter's deviation is decomposed into the contributions of DI, PI, MP, and REER shocks. This visualization highlights how the combined impact of shocks explains most short-run fluctuations in the external balance. DI and PI shocks together account for large swings, while MP and REER shocks also feature prominently during specific episodes.

The stacked contributions reflect the interaction of impulse-response signs with the realized structural shocks.

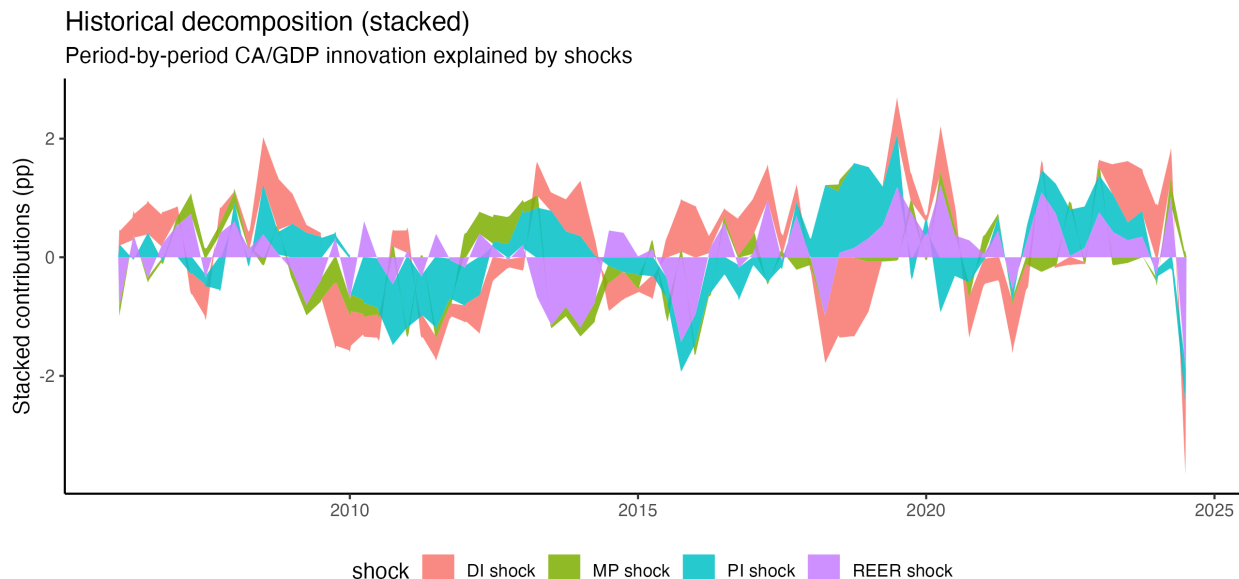


Figure 6.9: Historical decomposition of  $CA/GDP$  innovations (Joint SR–SVAR, representative admissible rotation). Notes: Period-by-period innovations are decomposed into the contributions of DI, PI, MP, and REER shocks. Positive areas reflect quarters in which the shock contributed to a higher  $CA/GDP$  balance; negative areas indicate the opposite. The stacked areas sum to the total  $CA/GDP$  innovation attributable to the identified shocks.

Because a positive DI shock worsens  $CA/GDP$ , a negative DI shock (risk-off) appears as a positive contribution in the decomposition. PI shocks, whose IRFs are less directionally robust, also contribute substantially, but with alternating signs across episodes, reflecting the weaker directional identification discussed earlier. MP and REER shocks appear as secondary but still material drivers of short-run volatility.

The decomposition aligns closely with major global events: sharp DI and PI contributions around the Global Financial Crisis and COVID, REER-driven fluctuations during phases of sustained dollar strength, and MP shocks visible around episodes of U.S. monetary easing and tightening. Taken together, the HD underscores that return-differential shocks (both DI and PI) are key proximate drivers of U.S. external-balance fluctuations, even if their average direction is harder to pin down in the baseline SR–SVAR.

## 6.6 INTERPRETING THE ROLE OF RETURN DIFFERENTIALS

The structural IRF and historical decomposition (HD) in the SR–SVAR model point in a complex, but coherent direction: first, both shocks in PI and DI showed significant impacts across the key variables. When it comes to CAGDP, the overall impact of DI and PI is opposite, with DI shocks having short-term negative response then temporarily oscillating to positive territory, before fading to zero. PI shocks, on the other hand, show the exact opposite pattern, with a short-term positive response, followed by a negative swing, before fading towards zero.

Second, comparing income, FX and risk-premium channels with  $CA/GDP$  responses provides a picture of the drivers

that transmit the shocks to the current account. The income channel shows the strongest short-term response and is the dominant means through which CAGDP is affected by the shocks. The oscillatory pattern of the NPI IRF evidences a thinning income effect even in the medium term. In the Medium term both Risk and FX channels respond in a more pronounced manner. But given the signal match between risk premium and CAGDP, we interpret this to mean a predominance of the risk-premium channel as the transmitter of return differentials shocks.

Following the interpretation proposed in Appendix D.2, based on the BEA ITA's categorical decomposition, DI shocks primarily represent innovations in equity profitability, whereas PI shocks mainly capture yield-driven disturbances. Although further analysis is needed to fully explain the responses to both DI and PI shocks, the patterns observed above suggest plausible mechanisms. On the PI side, a positive shock likely triggers an asset reallocation accompanied by net capital outflows. In the short term (one to three quarters after the shock), an increase in income is expected due to the higher return differential. Over the medium term (four to ten quarters), global capital tends to reallocate toward higher-yielding assets, gradually reducing the differential and dampening the initial income effect.

The negative response of NPI to a DI shock, followed by a delayed improvement, can be attributed to the relatively rigid nature of foreign direct investment. By definition, direct investment involves a greater degree of managerial participation and longer-term commitment. Capital movements in this category are therefore less fluid, and real investments tend to adjust slowly, often in sync with the business cycle. Higher profitability incentivizes multinational firms to retain earnings abroad rather than to repatriate profits or distribute higher dividends to U.S. residents immediately.

Interpreting medium-term responses to shocks in return differentials is more challenging and remains somewhat speculative. The results point to a predominance of the risk-premium channel over the income and FX channels during this horizon. A decline (increase) in the VIX indicates a reduction (rise) in market volatility. A priori, large DI and PI shocks should theoretically heighten financial instability in both the short and medium terms, yet this pattern is clearly confirmed only for DI shocks. The observed easing of the VIX in response to a PI shock appears counterintuitive. One possible explanation lies in the limits of the linear SR-SVAR framework, which may fail to capture the nonlinear, potentially disruptive effects that a one-percentage-point PI shock could produce in reality. Addressing this limitation would require extending the analysis to nonlinear or state-dependent designs.

## 7 CONCLUSION

This paper revisits the role of U.S. return differentials in shaping the external balance under the changing macro-financial environment of the past two decades. The analysis updates and extends the long-standing debate on the “exorbitant privilege” by quantifying the contribution of return differentials to the U.S. current account across the

zero-lower-bound (ZLB), Covid-19, and post-Covid periods. Since the mid-2000s, the U.S. external position has combined chronically negative trade balances with a persistently positive primary-income surplus. Understanding this resilience requires examining how return differentials—especially those linked to direct (DI) and portfolio investment (PI)—transmit through income, valuation, and financial channels. The evidence presented here shows that these wedges not only persist but remain central to the adjustment of the U.S. current account in an era of higher real rates and renewed dollar cycles.

The paper makes three main contributions. First, using a simple counterfactual exercise, it estimates the cumulative effect of return differentials on the U.S. current account at roughly \$9 trillion (2015 USD) between 1999 and 2024. More than two-thirds of this cumulative support stems from direct-investment returns, although the share of portfolio-investment differentials has grown since the global financial crisis. This quantitative accounting demonstrates that the U.S. advantage in external earnings remains large and persistent, despite successive episodes of global stress.

Second, the decomposition of yield differentials reveals that equity assets have been the main drivers of the U.S. return advantage, while debt instruments have acted as a drag. Within equity, the *return effect*—higher profitability within categories rather than a more favorable composition—dominates and explains most of the aggregate differential, especially on the DI side. In contrast, debt, particularly in the PI segment, depresses overall U.S. returns, with its negative contribution arising mainly from composition rather than pricing. In DI, the negative role of debt reflects within-class return effects, whereas in PI, it reflects the U.S. tendency to issue large volumes of safe, low-yield debt to global investors.

Third, the structural analysis quantifies how these return-differential shocks propagate through the U.S. external accounts. Using a VARX baseline and a sign-restricted SVAR, the results show that DI shocks—interpreted as equity-profitability disturbances—generate delayed but sustained effects on the current account through the income and valuation channels. PI shocks—interpreted as valuation-yield disturbances—act through the FX and risk-premium channels, producing rapid but short-lived movements dominated by financial-market conditions. In both cases, the estimated responses of the current account exhibit cyclical reversals consistent with the adjustment of global portfolios and the risk cycle. The historical decomposition confirms that DI and PI shocks together explain a sizable share of current-account fluctuations, especially around the GFC and Covid episodes.

Two limitations delimit the scope of this analysis and point to avenues for further research. First, data constraints—particularly the short quarterly span of consistent BEA position and income statistics—preclude the use of full cointegrated (VECM) specifications that would allow for richer long-run dynamics. Second, the linear SR-SVAR framework, while transparent, cannot capture the state-dependent and nonlinear feedbacks that likely characterize large shocks, especially in the portfolio channel. Extending the analysis to nonlinear or threshold VARs, or embedding it within a Bayesian framework with time-varying parameters, could better represent the asymmetries



observed in practice.

Overall, the results underscore that return differentials remain a defining feature of the U.S. external balance sheet and a key mechanism behind its resilience. Yet they also reveal the fragility of this privilege: as portfolio yields converge and global risk appetite shifts, the income cushion provided by return differentials may narrow, exposing the United States more directly to its structural current-account deficit. Understanding this evolving balance between privilege and duty remains central to interpreting the future of U.S. external adjustment in an era of higher global interest rates and contested monetary hegemony.

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## APPENDIX

### A SUPPLEMENTARY DESCRIPTIVE EVIDENCE

#### A.1 POSITIONS: LEVELS AND SHARES OF GDP

Figure [A.1](#) documents the expansion of U.S. external positions since 2006. Direct-investment (DI) liabilities rise from roughly \$3 trillion in 2006Q1 to about \$16 trillion by 2025Q1, while DI assets increase from about \$4 trillion to \$11 trillion. Portfolio-investment (PI) liabilities grow even more, from roughly \$8 trillion to \$35 trillion, with PI assets moving from about \$5 trillion to \$16 trillion. The implied net positions (assets minus liabilities) therefore deteriorate over the period: DI moves from a small positive (about \$1 trillion) to a sizable negative (around \$5 trillion), and PI deepens from roughly \$3 trillion to about \$19 trillion.

Panel shares in Figure [A.2](#) place these levels against the size of the U.S. economy. DI liabilities climb from roughly 20% of GDP in 2006 to about 75% by 2025, while DI assets rise from around 30% to about 50% of GDP; the DI net position swings from a modest surplus (about 7% of GDP) to a deficit near 25%. PI liabilities increase from roughly 50% of GDP to about 140%, with PI assets rising from around 30% to 70%. The PI net position widens from about -25% of GDP to roughly -70%.

# DI and PI positions: assets, liabilities, and net

Levels in — billions of USD. Source positions are reported in millions and converted to billions to match GDP units. Shaded GFC/Covid.

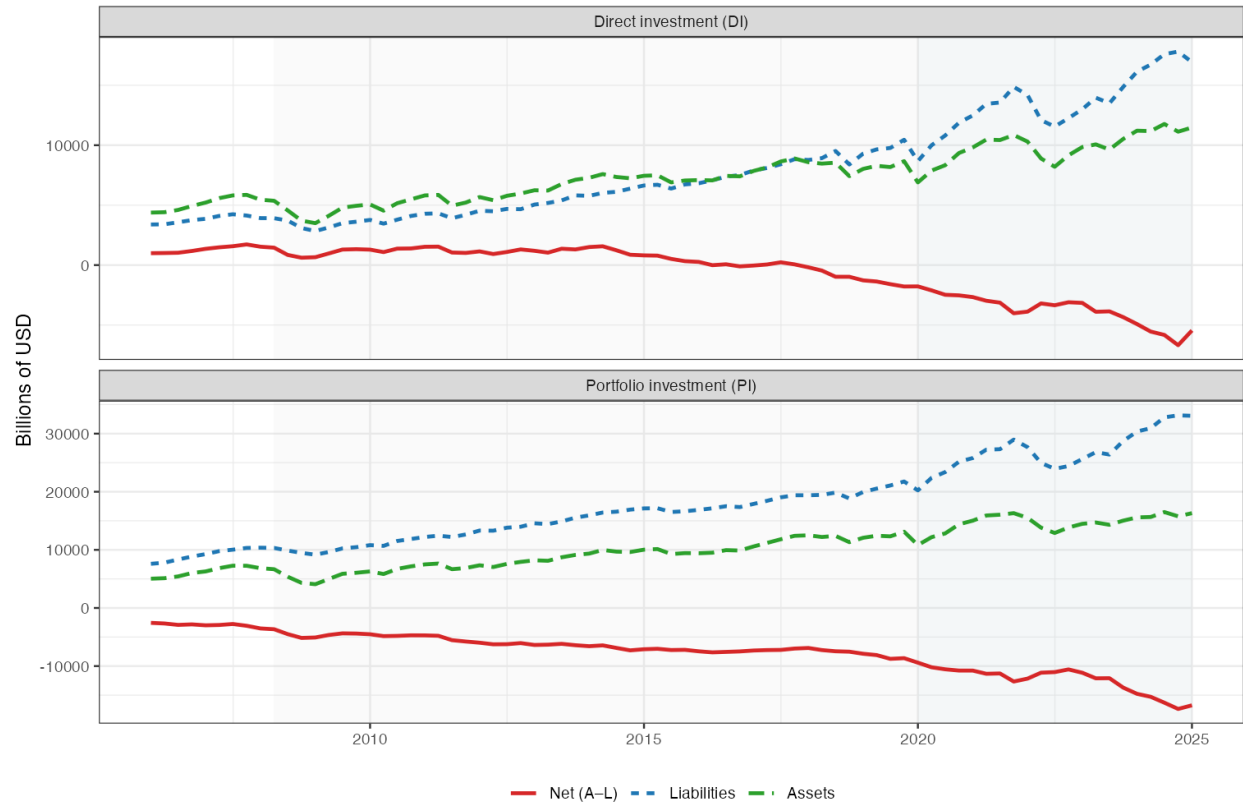


Figure A.1: Direct- and portfolio-investment positions (assets, liabilities, net) in billions of USD. Source positions are reported in millions and converted to billions; Net = Assets – Liabilities. Quarterly 2006Q1–2025Q1.

## DI and PI positions relative to GDP

Percent of GDP (pp). Positions are converted from millions to billions to match GDP units. Shaded GFC/Covid.

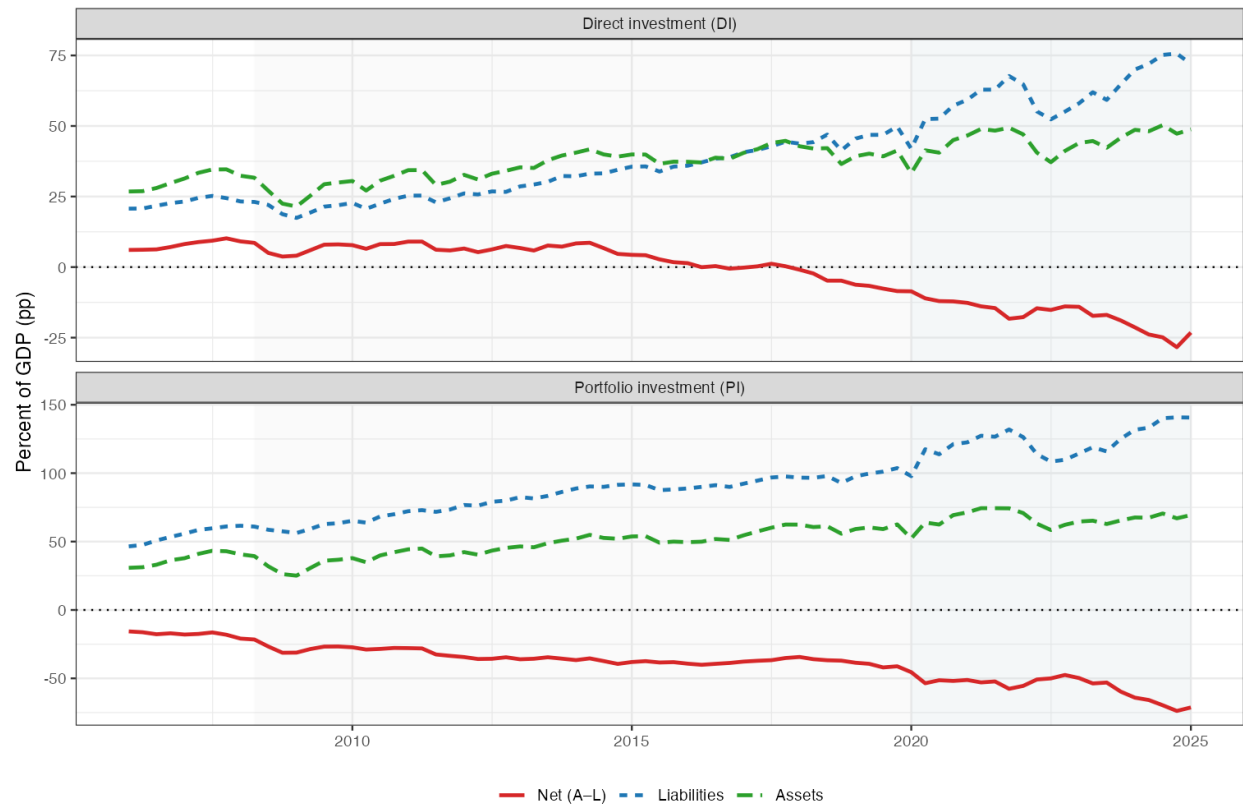


Figure A.2: Direct- and portfolio-investment positions as a share of GDP, in percentage points (pp) of GDP. Positions are converted from millions to billions, then scaled by GDP (billions). Quarterly 2006Q1–2025Q1.

## RISK COMPOSITION

### A.2 RISK VS. SAFE COMPOSITION AND OVERLAYS WITH DI/PI DIFFERENTIALS

**RISKY VS. SAFE CONFIGURATION (ASSETS AND LIABILITIES).** The United States is long risky assets (FDI and PI equity) and short safe liabilities (debt and bank/inter-office debt, plus reserves on the asset side). This “global insurer” configuration underlies the aggregate return effect.

U.S. external positions by risk class and side  
Annual, 1982–2024. Values in billions of USD (source data in millions).

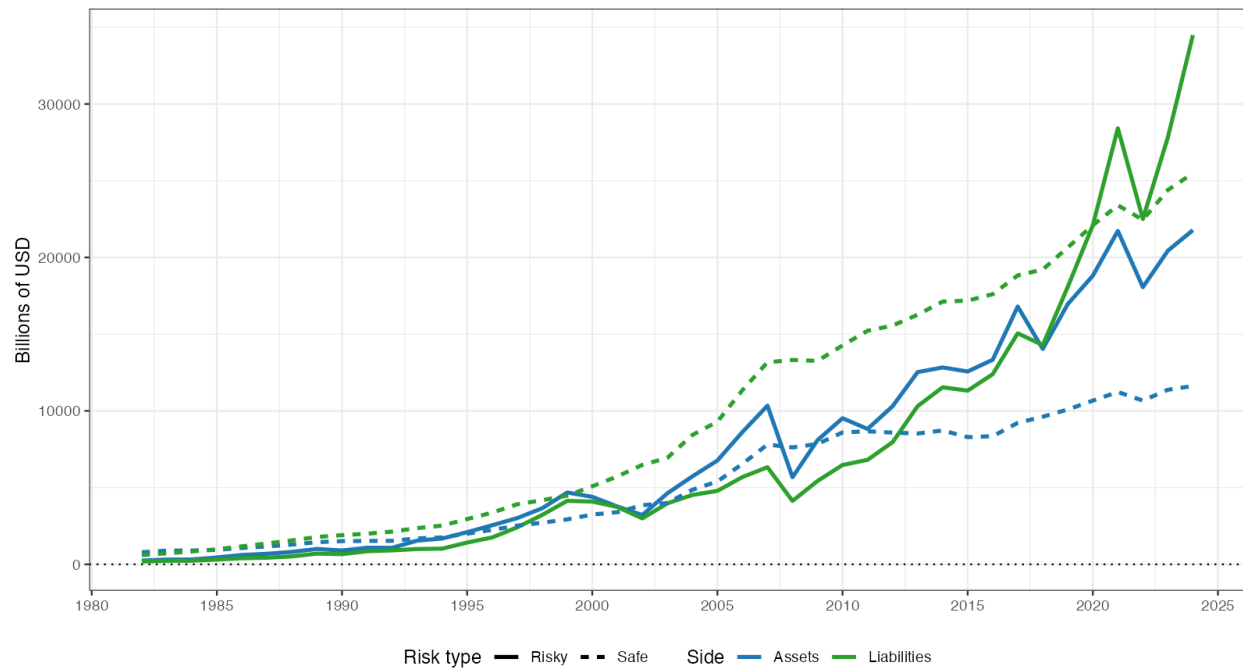


Figure A.3: U.S. external positions by risk class and side (assets vs. liabilities), annual 1982–2024. Values in billions of USD. Solid lines: risky; dashed: safe.

Direct investment (DI): positions by risk class and DI return differential  
Positions: billions of USD (left). DI return differential: percentage points (right). Annual 1982–2024.

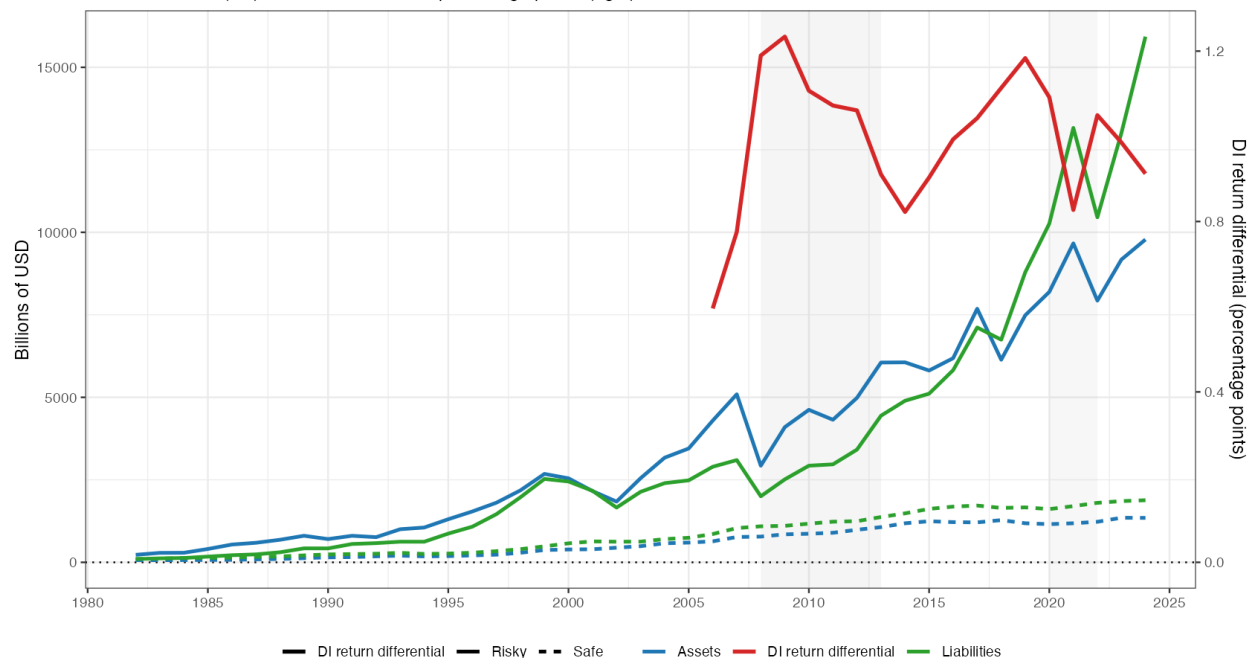


Figure A.4: Direct investment (DI): risky/safe assets and liabilities (left axis, billions of USD) and DI return differential (right axis, percentage points), annual 1982–2024. Shaded: 2008–2012 and 2020–2021.

### Portfolio investment (PI): positions by risk class and PI return differential

Positions: billions of USD (left). PI return differential: percentage points (right). Annual 1982–2024.

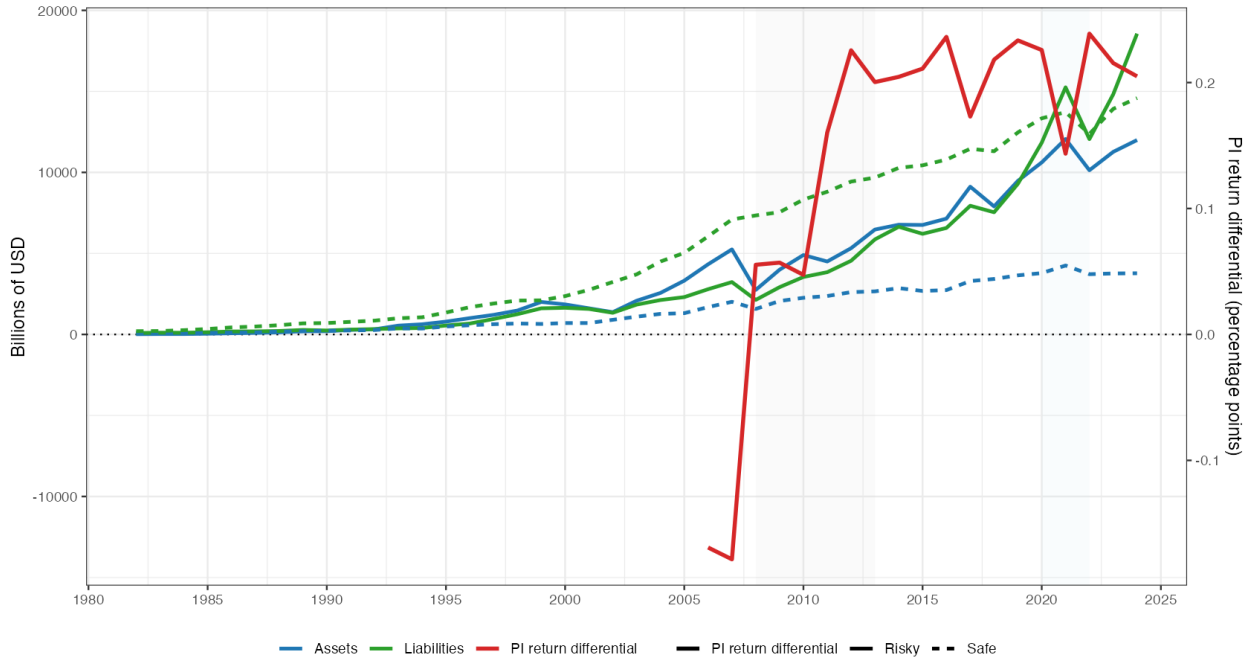


Figure A.5: Portfolio investment (PI): risky/safe assets and liabilities (left axis, billions of USD) and PI return differential (right axis, percentage points), annual 1982–2024. Shaded: 2008–2012 and 2020–2021.

## A.3 PORTFOLIO WEIGHTS AND RETURN DIFFERENTIAL DECOMPOSITION

Divergent stacked bars show that assets tilt toward risky categories (DI and PI equity) while liabilities tilt toward safe categories (PI debt and OI). This mix yields only a modest positive composition effect on average.

#### Weights of U.S. external positions by category: assets vs liabilities

Divergent stacked bars (assets above, liabilities below). Annual 1999...2024. Values in percentage points.

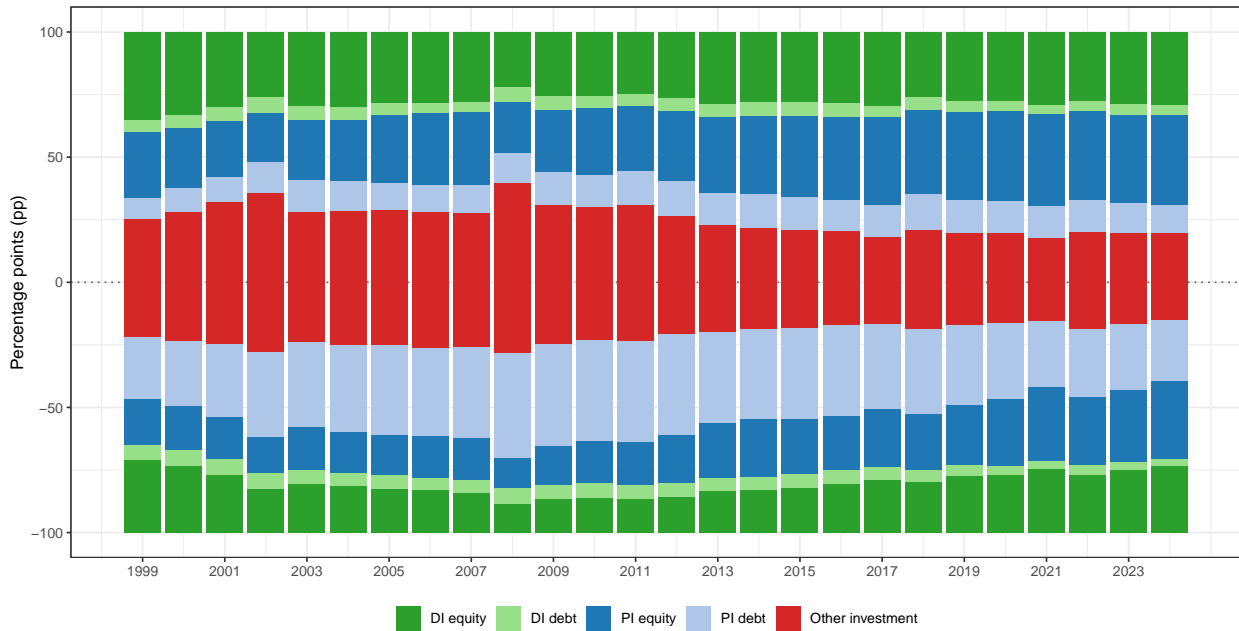


Figure A.6: Composition of U.S. external positions by category, with assets shown above zero and liabilities below. Divergent stacked bars, annual 1999–2024, expressed in percentage points. Notes: weights exclude financial derivatives other than reserves (IIP Table 1.1, assets line 5; liabilities line 13).

The decomposition clarifies that the U.S. external yield differential is driven mainly by return effects rather than by composition effects. Across all subperiods, the “Return” column in Table A.1 explains the bulk of the total differential, while the composition term is small and sometimes negative. Category-level rows show that direct investment (DI) equity is the workhorse: its return effect is large and positive in every subperiod, consistently contributing around one percentage point or more to the aggregate differential. In contrast, portfolio debt (PI debt) typically subtracts from the total—its “Total” entry is negative in most subperiods, reflecting either a liability-heavy composition, a low return gap, or both. DI debt and other investment are small in magnitude throughout.

The crisis chronology aligns with this pattern. During the GFC/Euro period, the aggregate differential remains positive because DI equity’s return advantage offsets weakness elsewhere, whereas composition effects do little on net. In the post-crisis and Covid & after periods, the total differential edges higher largely on the back of DI equity returns, with modest support from PI equity; composition continues to play a limited role.



Table A.1: Yield differential decomposition by category and subperiod (pp).

2*Category	Pre-GFC (1999-2007)			GFC/Euro (2008-2012)			Post-crisis (2013-2019)			Covid & after (2020-2024)		
	Comp.	Return	Total	Comp.	Return	Total	Comp.	Return	Total	Comp.	Return	Total
Total	-0.2	1.3	1.1	-0.0	1.4	1.5	0.1	1.9	1.9	0.0	1.9	1.6
DI equity	0.5	1.1	1.6	0.8	1.5	2.3	0.4	1.2	1.5	0.2	1.2	1.3
DI debt	-0.0	-0.1	-0.1	-0.0	-0.2	-0.2	0.0	-0.1	-0.0	0.0	-0.0	-0.0
PI equity	0.2	0.1	0.3	0.2	0.6	0.8	0.2	0.7	0.9	0.2	0.4	0.5
PI debt	-1.1	0.1	-1.0	-1.1	-0.5	-1.6	-0.6	0.0	-0.6	-0.4	0.2	-0.3
Other investment	0.2	0.1	0.3	0.0	-0.1	-0.1	0.1	0.0	0.1	0.1	0.1	0.1

Notes: Values are subperiod means of annual percentage-point contributions. "Comp." is the composition effect; "Return" is the within-category return-gap effect; "Total" equals the sum of the two (up to rounding). Subperiod order is Pre-GFC, GFC/Euro, Post-crisis, and Covid & after.

## B DIAGNOSTICS

Table B.1: Lag-length selection for the VARX( $p$ ) with exogenous controls (VIX, GFC, Covid)

Criterion	Selected lag $\hat{p}$
AIC	8
HQ	8
SC (BIC)	1
FPE	8

*Notes:* Search range  $p \in \{1, \dots, 8\}$ . Endogenous block: (CAGDP,  $g^*$ ,  $g$ , REER, FFR,  $r_{\text{diff}}$ ). Exogenous: (VIX, GFC, Covid). AIC/HQ/FPE favor a rich lag structure; SC/BIC favors parsimony. Baseline in the paper sets  $p = 2$  and validates adequacy by stability and LM tests.

Table B.2: Consolidated unit-root evidence (ADF, PP, KPSS), 2006Q1–2025Q1

Variable	ADF (ur.df)			PP ( $Z_\tau$ )			KPSS			Verdict			
	L(d)	L(t)	$\Delta(d)$	$\Delta(t)$	L(d)	L(t)	$\Delta(d)$	$\Delta(t)$	L( $\mu$ )		L( $\tau$ )	$\Delta(\mu)$	$\Delta(\tau)$
CAGDP	NR	NR	R	R	NR	NR	R	R	R	R	R	NR	I(1) (minor KPSS- $\Delta\mu$ inconsistency)
$g$	R	NR	R	R	NR	NR	R	R	NR	NR	NR	NR	I(0) / borderline
$g^*$	R	R	R	R	R	R	R	R	NR	NR	NR	NR	I(0)
REER	NR	NR	R	R	NR	NR	R	R	R	R	NR	NR	I(1)
FFR	NR	NR	R	NR	NR	NR	R	R	NR	R	NR	NR	I(1)
$r\_diff$	NR	NR	R	R	NR	NR	R	R	R	R	NR	NR	I(1)

*Notes.* Entries show decisions at the 5% level: **ADF** and **PP** test  $H_0$ : unit root ( $R$  = reject unit root;  $NR$  = fail to reject); **KPSS** tests  $H_0$ : (level/trend) stationarity ( $R$  = reject stationarity;  $NR$  = fail to reject). "d/t" denote drift (constant) / trend (constant+trend) deterministic components; "L" = levels, " $\Delta$ " = first differences. ADF decisions are based on the  $\tau$  statistic under each deterministic spec (drift or trend) using 5% critical values; a 10% rejection does not count as  $R$  here. Verdict synthesizes across tests with priority on agreement between ADF/PP in levels vs. differences and the KPSS direction of evidence. The small KPSS inconsistency for CAGDP in first differences does not overturn the I(1) classification given strong ADF/PP rejections in  $\Delta$ .

Table B.3: Consolidated unit-root evidence (ADF, PP, KPSS), 2006Q1–2025Q1

Variable	ADF (ur.df)			PP ( $Z_\tau$ )			KPSS			Verdict			
	L(d)	L(t)	$\Delta(d)$	$\Delta(t)$	L(d)	L(t)	$\Delta(d)$	$\Delta(t)$	L( $\mu$ )		L( $\tau$ )	$\Delta(\mu)$	$\Delta(\tau)$
CAGDP	NR	NR	R	R	NR	NR	R	R	R	R	R	NR	I(1) (minor KPSS- $\Delta\mu$ inconsistency)
$g$	R	NR	R	R	NR	NR	R	R	NR	NR	NR	NR	I(0) / borderline
$g^*$	R	R	R	R	R	R	R	R	NR	NR	NR	NR	I(0)
REER	NR	NR	R	R	NR	NR	R	R	R	R	NR	NR	I(1)
FFR	NR	NR	R	NR	NR	NR	R	R	NR	R	NR	NR	I(1)
$r\_diff$	NR	NR	R	R	NR	NR	R	R	R	R	NR	NR	I(1)

Notes. Entries show decisions at the 5% level: **ADF** and **PP** test  $H_0$ : unit root (R = reject unit root; NR = fail to reject); **KPSS** tests  $H_0$ : (level/trend) stationarity (R = reject stationarity; NR = fail to reject). "d/t" denote drift (constant) / trend (constant+trend) deterministic components; "L" = levels, " $\Delta$ " = first differences. ADF decisions are based on the  $\tau$  statistic under each deterministic spec (drift or trend) using 5% critical values; a 10% rejection does not count as R here. Verdict synthesizes across tests with priority on agreement between ADF/PP in levels vs. differences and the KPSS direction of evidence. The small KPSS inconsistency for CAGDP in first differences does not overturn the I(1) classification given strong ADF/PP rejections in  $\Delta$ .

Table B.7: System-wide ARCH-LM tests for heteroskedasticity (VARX p=2, total spec).

Test	Lag order
ARCH-LM (system-wide)	1, 2, 4, 8, 12

Table B.8: Per-equation ARCH-LM tests for heteroskedasticity (VARX p=2, total spec).

Equation	Lag	Statistic	p-value	Decision (5%)
r_diff_pp	1	2.46	0.117	Fail to reject
	2	5.29	0.071	Borderline (10%)
	4	6.02	0.198	Fail to reject
	8	8.24	0.410	Fail to reject
	12	14.17	0.290	Fail to reject
g_star	1	3.83	0.050	Borderline
	2	3.78	0.151	Fail to reject
	4	12.16	0.016	Reject
	8	14.71	0.065	Borderline (10%)
	12	14.03	0.299	Fail to reject
g	1	6.07	0.014	Reject
	2	8.02	0.018	Reject
	4	14.09	0.007	Reject
	8	18.47	0.018	Reject
	12	18.18	0.111	Fail to reject
FFR	1	2.66	0.103	Fail to reject
	2	3.05	0.217	Fail to reject
	4	3.72	0.445	Fail to reject
	8	4.59	0.800	Fail to reject
	12	10.52	0.573	Fail to reject
REER	1	0.13	0.717	Fail to reject
	2	1.15	0.562	Fail to reject
	4	4.78	0.311	Fail to reject
	8	7.51	0.483	Fail to reject
	12	8.72	0.726	Fail to reject
CAGDP	1	0.03	0.855	Fail to reject
	2	0.19	0.908	Fail to reject
	4	2.92	0.571	Fail to reject
	8	18.53	0.018	Reject
	12	37.27	0.000	Reject

Table B.4: VAR stability diagnostics: roots of the characteristic polynomial

Model (tag)	Endog. vars.	Lags $p$	# Roots	$\max \lambda $	Any $ \lambda  \geq 1$ ?	Verdict
total_varx_p1_base	6	1	6	0.9836		Stable
total_varx_p2_base	6	2	12	0.9513		Stable

*Notes:* Stability requires all eigenvalues of the VAR companion matrix to lie strictly inside the unit circle. Entries report the number of roots, the largest modulus  $\max|\lambda|$ , and whether any modulus is  $\geq 1$ . Values are computed from the saved models' root spectra; both specifications satisfy the stability condition.

Table B.5: Residual autocorrelation diagnostics for the baseline VARX( $p=2$ ), sample 2006Q1–2025Q1

<b>Panel A.</b> Breusch–Godfrey LM per equation: $p$ -values at lag $h$			
Equation	$h=4$	$h=8$	$h=12$
CAGDP	0.508	0.633	0.801
$g$	0.001***	0.001***	0.000***
$g^*$	0.000***	0.003***	0.008***
REER	0.421	0.492	0.535
FFR	0.908	0.885	0.739
$r_{diff}$ (pp)	0.505	0.787	0.561
<b>Panel B.</b> System-wide tests (statistic, df, $p$ -value)			
Test	$h$	Stat	$p$ -value
Breusch–Godfrey LM	4	237.629 (df=144)	0.000***
Breusch–Godfrey LM	8	393.023 (df=288)	0.000***
Breusch–Godfrey LM	12	450.000 (df=432)	0.265
Portmanteau (adjusted)	4	125.488 (df=72)	0.000***
Portmanteau (adjusted)	8	252.434 (df=216)	0.045**
Portmanteau (adjusted)	12	391.362 (df=360)	0.123
Portmanteau (asympt.)	4	120.517 (df=72)	0.000***
Portmanteau (asympt.)	8	237.021 (df=216)	0.156
Portmanteau (asympt.)	12	356.516 (df=360)	0.542

Notes: Stars mark significance at 10% (\*), 5% (\*\*), 1% (\*\*\*). Panel A reports equation-by-equation Breusch–Godfrey LM  $p$ -values for the null of no residual autocorrelation at lags  $h \in \{4, 8, 12\}$ . Panel B reports system-wide Breusch–Godfrey LM and Portmanteau tests. Portmanteau (asympt.) at  $h=12$  fails to reject serial independence ( $p=0.542$ ).<sup>a</sup>

Table B.6: Residual normality tests for VARX(2), total specification

Equation	JB statistic	$p$ -value	Normality decision (5%)
$r^{diff}$ (total return differential, pp)	2.56	0.28	Fail to reject normality
$g^*$ (foreign GDP growth)	455.03	0.000	Reject normality
$g$ (US GDP growth)	29.23	0.000	Reject normality
FFR (US Fed funds rate)	0.93	0.63	Fail to reject normality
REER (real effective exchange rate)	1.00	0.61	Fail to reject normality
CAGDP (current account / GDP)	25.92	0.000	Reject normality
<i>Multivariate tests (system-wide)</i>			
Joint Jarque–Bera	537.5	0.000	Reject normality
Skewness component	50.4	0.000	Reject normality
Kurtosis component	487.0	0.000	Reject normality

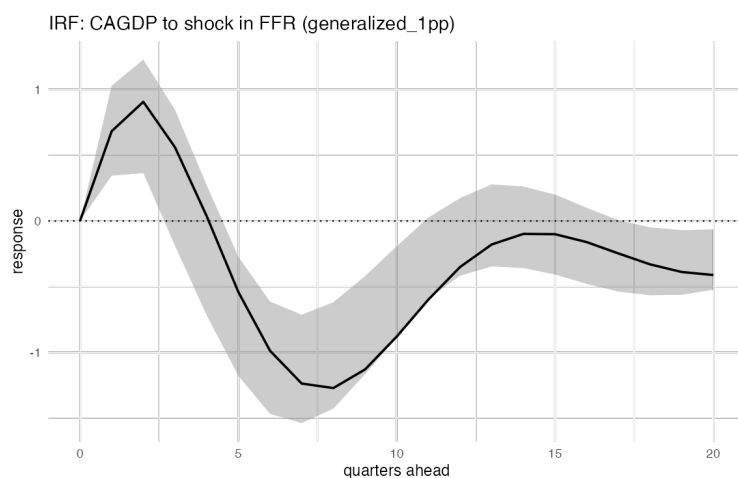
Notes: JB = Jarque–Bera test

for residual normality. The null hypothesis is that residuals are i.i.d. Gaussian. “Fail to reject” means residuals are not significantly different from Gaussian at the 5% level.

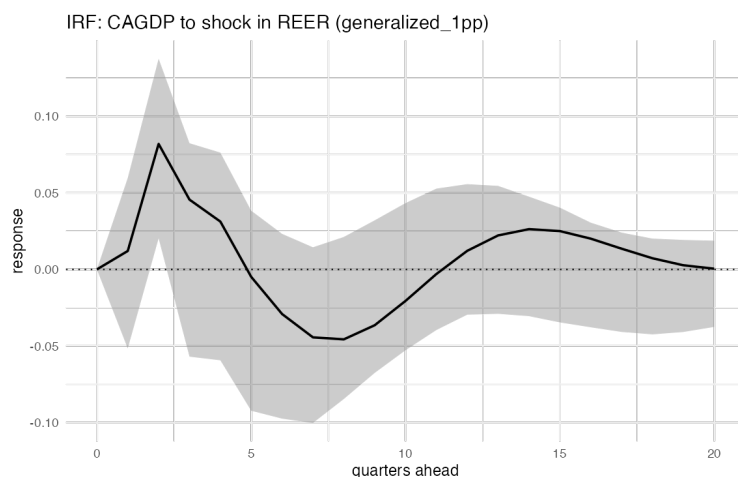
## C GENERALIZED (REDUCED-FORM) VARX IRFs



(a) CA/GDP to RD shock (+1 pp)



(b) CA/GDP to FFR shock (1 s.d.)



(c) CA/GDP to REER shock (1 s.d.)

Figure C.1: Generalized IRFs for the current account. Lines show median responses; shaded areas are bootstrap bands (68%). The return-differential shock is scaled to a +1 percentage-point move in  $r_{diff}$  on impact; other shocks are one-standard-deviation innovations. Horizons in quarters.



Table B.9: Structural stability diagnostics: coefficient tests and variance breaks (VARX,  $p = 2$ , total specification).

Equation	Coefficient stability tests			Variance breaks (Bai–Perron)	
	supF (p)	aveF (p)	expF (p)	# Breaks	Break dates
$r\_diff^{pp}$	32.6 (0.102)	24.9 (0.0267)	13.9 (0.0672)	0	—
$g^*$	801.0 (0.000)	140.0 (0.000)	397.0 (0.000)	2	2019Q3; 2022Q2
$g$	105.0 ( $1.29 \times 10^{-13}$ )	48.5 ( $1.12 \times 10^{-7}$ )	—	0	—
FFR	—	—	—	0	—
REER	—	—	—	0	—
CAGDP	—	—	—	1	2021Q4

Table B.10: Granger causality tests of return differentials on the U.S. current account balance (2006Q1–2025Q1).

Specification	Cause variables	Target	Test statistic	df	p-value
Simple Granger (Wald)	$r\_diff\_pp$	CAGDP	3.88	10	0.00005
Block exogeneity (manual Wald)	$r\_diff\_pp$ , REER, FFR	CAGDP	27.20	6	0.00013
Toda–Yamamoto robust VAR	$r\_diff\_pp$	CAGDP	19.03	2	0.00007

Notes: The table reports Wald test statistics for the null hypothesis that the lagged values of the “cause” variables do not Granger-cause the U.S. current account balance to GDP (CAGDP). The block exogeneity test jointly restricts lag coefficients of return differentials, the real effective exchange rate (REER), and the federal funds rate (FFR). The Toda–Yamamoto test augments the VAR with  $p + d_{\max}$  lags (here  $p = 2$ ,  $d_{\max} = 1$ ) to ensure validity under potential unit roots. All specifications include VIX, GFC, and Covid as exogenous controls.

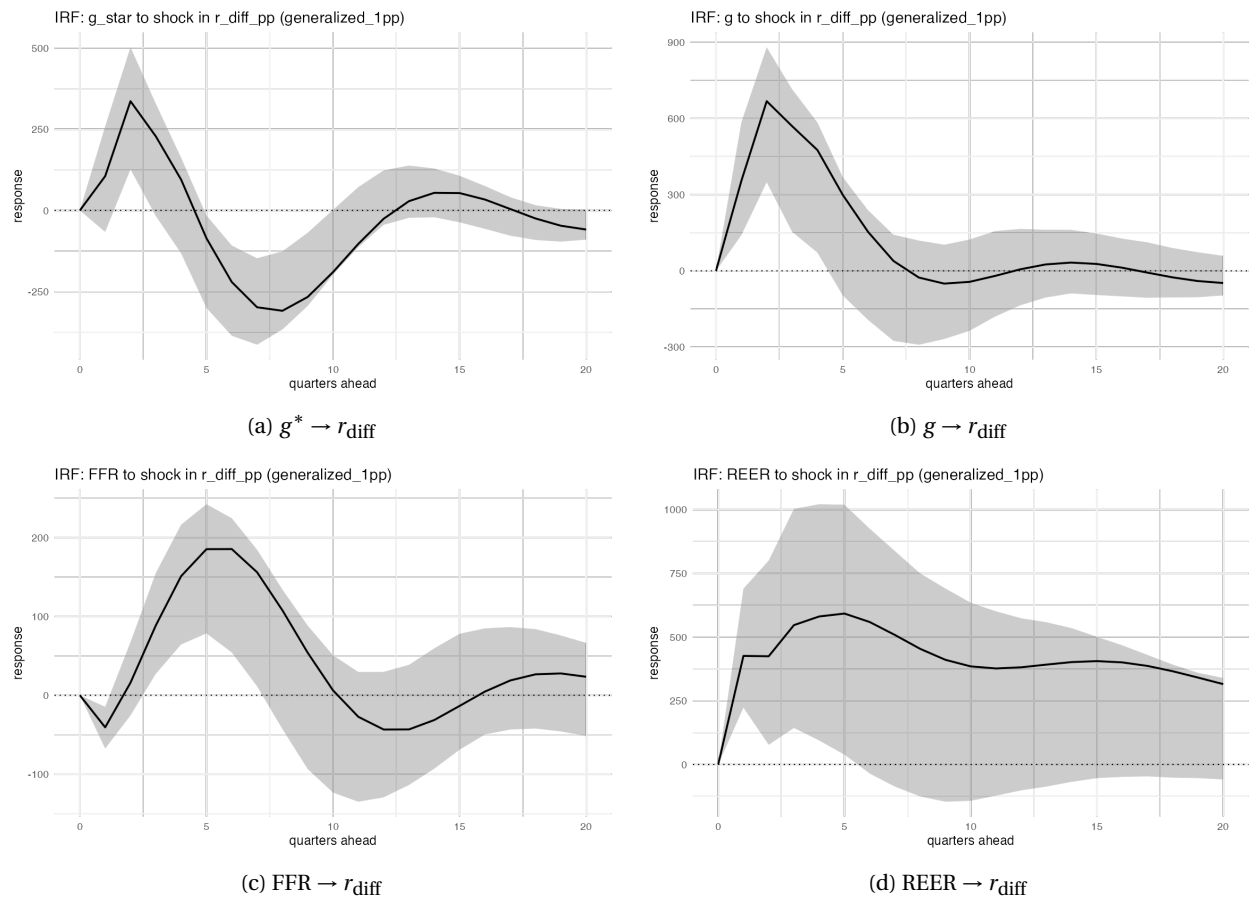


Figure C.2: Generalized IRFs for the return differential. Responses are in percentage points of  $r_{\text{diff}}$ . Shocks to  $g$ ,  $g^*$ , FFR, REER are one-standard-deviation innovations; bands are bootstrap 68%.

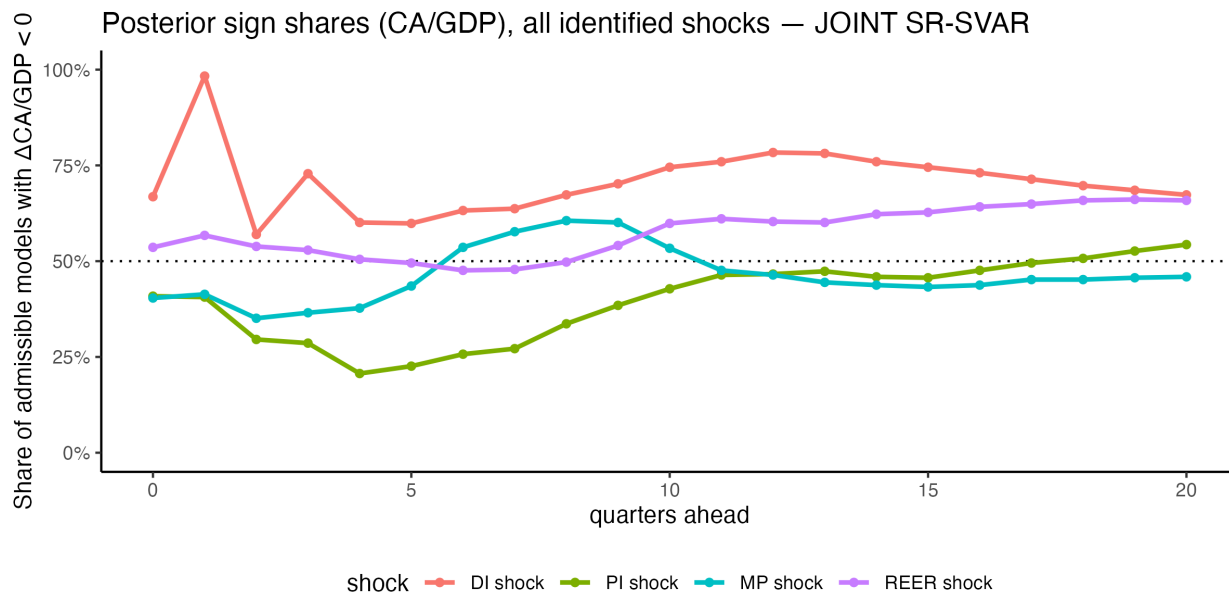


Figure D.1: Posterior sign shares for  $CA/GDP$  (share of admissible rotations with  $\Delta CA/GDP < 0$ ) for DI, PI, MP, and REER shocks.

## D JOINT SR-SVAR IMPULSE RESPONSES AND ROBUSTNESS

### D.1 POSTERIOR SIGN SHARE

Because sign-restricted identification averages over many admissible rotations, uncertainty bands often touch zero. Robustness is therefore summarized in Figure D.1, which reports posterior sign shares (the fraction of admissible models with  $\Delta CA/GDP < 0$ ). DI shocks exhibit robust directionality ( $\sim 60$ – $80\%$  probability of negative responses across horizons), while PI shocks are closer to indeterminate (below  $50\%$  near term, rising toward  $50$ – $55\%$  at longer horizons). MP shocks hover around  $40$ – $50\%$ , whereas REER shocks exceed  $50\%$  in the medium run.

Figure D.2 contrasts DI and PI shocks directly. Under the baseline identification (Stage 2), DI shocks reduce  $CA/GDP$  with high probability ( $P[\text{IRF} \leq 0] \approx 0.8$ – $0.9$ ), whereas PI shocks remain weakly identified, with posterior mass around zero. To probe robustness, I impose a weak inequality prior ( $\text{PI} \geq 0$  on impact), trimming implausible negative draws without altering the overall IRF profile. Conditional on this prior, the probability that PI shocks increase  $CA/GDP$  rises to  $\sim 0.7$ – $0.8$  at short horizons. This should be read not as a new baseline but as a sensitivity check highlighting the fragility of PI identification.

Figure D.3 compares the baseline PI response with two weak-prior variants (impact  $\geq 0$  and cumulative  $\geq 0$  over four quarters). All three profiles remain close to zero in the short run, drifting slightly negative or positive depending on the prior. The exercise reinforces that PI shocks do not deliver strong or robust effects on  $CA/GDP$ , unlike DI shocks.

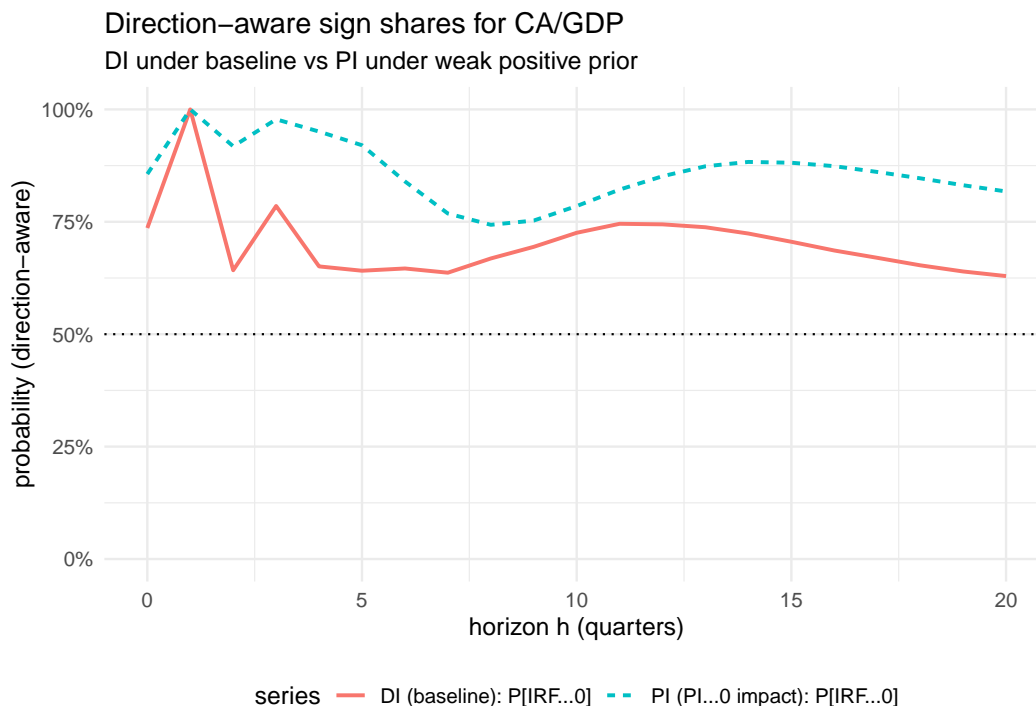


Figure D.2: Direction-aware sign shares for CA/GDP responses. The red line shows the unconditional baseline probability that DI shocks reduce CA/GDP ( $P[\text{IRF} \leq 0]$ ). The blue line shows the conditional probability that PI shocks increase CA/GDP under the weak inequality prior ( $P[\text{IRF} \geq 0]$ ). Both are well above 0.5, but only the DI case provides unconditional directionality; the PI case is conditional and should be interpreted as suggestive evidence.

## D.2 INTERPRETING STRUCTURAL DI AND PI SHOCKS

**DIRECT INVESTMENT SHOCKS AS EQUITY-PROFITABILITY DISTURBANCES** The analysis of the U.S. international investment income composition, based on BEA ITA Table 4.1, reveals that nearly all direct investment (DI) income is derived from equity positions rather than debt instruments. The *Interest* component of DI flows is quantitatively negligible, while the series for *Income on equity* almost perfectly overlaps with total DI income. Within equity income, *Dividends and withdrawals* and *Reinvested earnings* display a strong negative comovement, reflecting an accounting identity:

$$\text{Reinvested earnings} = \text{Total equity income} - \text{Dividends and withdrawals}.$$

Large opposing spikes in these components, most visibly in 2017–2018, correspond to the U.S. Tax Cuts and Jobs Act (TCJA), which triggered the repatriation of previously retained foreign profits. This mechanical shift from reinvested to distributed earnings produced large but temporary changes in recorded DI income, without necessarily indicating a change in underlying profitability or financing conditions.

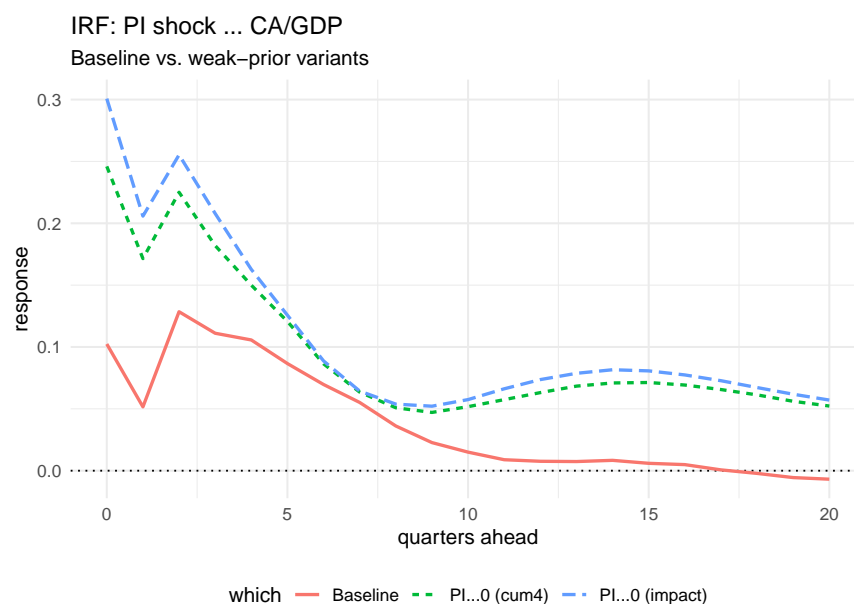


Figure D.3: Impulse responses of CA/GDP to a portfolio return-differential (PI) shock under the baseline sign set and two weak-prior variants ( $PI \geq 0$  on impact and  $PI \geq 0$  cumulatively over four quarters).

Consequently, the “DI shock” identified in the sign-restricted SVAR cannot be interpreted as a conventional interest-rate or debt-service disturbance. Instead, it represents a structural innovation in the *profitability and reinvestment behavior of multinational enterprises*. Quantitatively, this disturbance captures variations in the retained and distributed earnings of U.S. multinationals abroad relative to foreign-owned affiliates operating in the United States. It thus corresponds to shocks in the global profit cycle, tax-regime adjustments, and valuation changes in cross-border equity positions, rather than to intercompany credit conditions.

This reinterpretation carries several implications for the transmission channels. First, the DI shock primarily propagates through the *income channel*: higher foreign profits of U.S. multinationals directly raise income receipts and net primary income, even in the absence of new financial flows. Second, the shock has a natural link to the *risk-premium channel*: surges in retained earnings typically coincide with phases of strong global equity performance and lower volatility, while repatriation-driven swings may coincide with safe-haven episodes and dollar strength. Finally, the impact on the *exchange-rate channel* depends on the direction of profit repatriation: large dividend withdrawals, as in 2018, tend to appreciate the dollar through conversion of foreign-currency assets into domestic balances.

Overall, the evidence from the BEA income decomposition suggests that the DI shock should be understood as an *equity-profitability disturbance*—a shift in the global earnings advantage of U.S. multinationals vis-à-vis the rest of the world—rather than as a conventional yield or interest-rate shock. This refined interpretation aligns the empirical identification with the structural nature of modern U.S. external income, which is dominated by equity-based returns on foreign production and financial assets.

PORTFOLIO INVESTMENT SHOCKS AS VALUATION–YIELD DISTURBANCES The composition of portfolio investment (PI) income, as shown in the BEA ITA Table 4.1, differs sharply from that of direct investment. While direct investment income is overwhelmingly driven by equity earnings, portfolio income displays a more balanced structure between interest and dividends. On the asset side, U.S. investors receive income from two main sources: *interest on debt securities* (particularly long-term bonds) and *dividends on equity and investment fund shares*. Both components have grown substantially since the mid-2000s, but the former dominates in magnitude, reflecting the large stock of U.S. holdings of foreign sovereign and corporate bonds. On the liabilities side, income payments to the rest of the world are similarly divided, with *interest on U.S. debt securities* being the single largest category, underscoring the importance of Treasury and agency securities as vehicles for global portfolio investment into the United States. This structure implies that a “PI shock”—a positive innovation in the portfolio return differential—should be interpreted as a *valuation–yield disturbance* affecting tradable securities rather than as an equity-profitability or production shock. Such a disturbance may arise from movements in global interest-rate differentials, changes in asset prices and risk premia, or shifts in the demand for U.S. safe assets. In this sense, the PI shock corresponds to changes in the market valuation of the U.S. external balance sheet, driven by financial conditions and relative asset returns, rather than by real-side profitability of firms.

From a transmission perspective, the PI shock primarily propagates through the *valuation and exchange-rate channels*. A positive PI shock—interpreted as a rise in returns on U.S. portfolio assets or a fall in yields on U.S. liabilities—tends to generate a *dollar appreciation on impact*, consistent with sudden surges in demand for U.S. securities or safe-haven capital inflows. Over subsequent quarters, this appreciation may partially unwind as interest differentials normalize or risk appetite returns. The effect on the income account emerges more gradually, since dividend and coupon flows adjust with a lag relative to valuation movements.

In contrast to the DI shock, which reflects real-side corporate profitability and reinvestment decisions, the PI shock represents a *financial-market disturbance* tied to yield differentials, asset-price dynamics, and the liquidity premium of U.S. securities. Together, these two shocks capture complementary structural forces: the DI shock describes shifts in the income-producing capacity of U.S. multinationals, while the PI shock captures changes in the market valuation of the financial claims through which that capacity is priced and traded.