Dominant Drivers of Current Account Dynamics*

Lukas Boer[†], Jaewoo Lee[‡] and Mingzuo Sun[§]

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Abstract

What are the dominant shocks that drive movements of current account balances? We estimate shocks that explain most of the variation in the current account both at business cycle frequencies and over the long run. Using a standard open-economy macro model, we explore which macroeconomic shocks are behind the empirical dominant drivers of the current account at business-cycle frequency. Rather than financial shocks or aggregate shocks to supply or demand, shocks to relative demand between home and foreign goods are found to play the most important role in driving the current account.

JEL classification: C32, E32, F31, F32.

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[†]International Monetary Fund, Research Department, Email: lboer@imf.org

[‡]International Monetary Fund, Research Department, Email: jlee3@imf.org

[§]Johns Hopkins University, Department of Economics, Email: msun27@jhu.edu

1 Introduction

As a key metric of international macroeconomics, current account imbalances often reflect cross-country differences in (desirable) saving and investment, corresponding to the international flows of goods and finance that are consistent with economic fundamentals. But they can sometimes emanate from economic and financial distortions, and can mirror rising vulnerabilities to crises (Obstfeld, 2012). The relative importance of these two types of current account imbalances would eventually depend on the nature of underlying shocks that drive them. Accordingly, numerous papers have examined the effects of various shocks on current account movements.[1]

Adopting a slightly different angle from the existing literature, this paper explores those shocks that explain most of the fluctuations in current account imbalances. Starting with an agnostic examination of US and G7 data, we estimate Bayesian structural vector autoregression (SVAR)-based shocks that account for the largest share of the volatility of current account dynamics over the short-run and long-run horizons. The joint responses of the current account, exchange rate, and several additional macroeconomic variables are documented as potential guideposts in discerning the underlying economic shocks. We next turn to a more structural investigation. Taking up a standard open-economy macro model that also allows for international financial shocks and demand shifts, we explore which estimated model-based macroeconomic shocks come close to the dominant short-run driver of the current account uncovered by the SVAR analysis.

To uncover the primary drivers of current account movements (at business cycle frequencies and in the long term), we use the max-share identification following Angeletos et al. (2020) who examine the main determinants of business cycles. Similarly, Chahrour et al. (2021) and Miyamoto et al. (2023) use the approach to study the main determinants of exchange rates. We study current account fluctuations in G7 countries with relatively long data: the US, Canada, France, Germany, Italy, Japan, and the UK, while putting

[1] See the next section for a discussion of the literature.

special emphasis on the US.

We show that dominant current account shocks are distinct from dominant exchange rate shocks that display a gradual current account response driven by expenditure switching, i.e., a strong initial appreciation leads to a gradual fall in the current account balance. Despite some heterogeneity across countries, dominant shocks to the current account at business cycle frequencies induce a strong and persistent improvement in the current account that tends to be accompanied by an appreciation in the exchange rate. The shocks reduce domestic consumption and investment in the short to medium term while foreign consumption tends to increase on impact.. For the current account's major long-run determinant, we instead observe a depreciating exchange rate when the current account improves, as evidence for expenditure switching as a primary channel for rebalancing current account imbalances in the long run.

As our identification strategy relies on minimal assumptions, the resulting shocks do not necessarily need to correspond one-to-one to the shocks identified by particular structural open-macro models. Still, they can provide informative guideposts for identifying such structural economic shocks that play an important role in explaining the majority of the variation in the current account. From this viewpoint, we next try to decode the VAR-estimated dominant business-cycle CA shock using a dynamic open-macro model.

Our model augments a representative two-country new Keynesian open-economy macro model (Itskhoki and Mukhin, 2021) by additional shocks. In particular, we introduce a relative demand shock that alters the degree of home bias, as used in Stockman and Tesar (1995) and Pavlova and Rigobon (2007). The two economies are symmetric, apart from dominant currency pricing and the relative demand shock that is specific to the foreign region. We estimate the model with Bayesian techniques using US data for the same variables as in our empirical SVAR analysis.

Analyzing the impulse-response functions, the forecast error variance decomposition, and the shock series, we find that the most prominent candidate for explaining the dominant current account shock is a shock that shifts the international relative demand toward home goods. Increased relative demand for home goods appreciates the exchange rate while bolstering the current account surplus. The same shock also lowers domestic expenditure in the short run while later increasing domestic investment. A regression analysis using the dominant CA shock and the estimated model shocks shows that financial shocks–that have been shown to play a major role in explaining exchange rate dynamics–play only a secondary role in explaining current account dynamics. Moreover, applying the same max-share VAR approach to different sets of model-simulated data yields further evidence that the relative demand shock resembles the main CA shock closest.

1.1 Related Literature

In exploring the dominant drivers of current account movements, our paper offers one way to compare numerous papers on current account dynamics. With this in mind, we try to provide a brief review of the literature.

Before the inter-temporal approach to the current account emerged, the absorption approach (Alexander, 1952; Hahn, 1959) and elasticities approach (Magee, 1973; Goldstein and Khan, 1985) highlighted the roles of overall spending and relative prices in accounting for trade in goods and services, which in turn accounted for the bulk of current account balances. The inter-temporal approach (Sachs et al., 1981; Obstfeld and Rogoff, 1995) synthesized these two competing approaches by introducing the macroeconomic factors that drive relative prices and spending over time, highlighting the role of temporary shocks in determining the current account balance as the gap between the economy-wide saving and investment. Subsequent dynamic open-economy macroeconomic models [ADD REFERENCES?] have built on the intertemporal approach by embedding the current account in a rich dynamic and often stochastic general equilibrium analysis, incorporating all key insights of earlier approaches and risk sharing across countries.

Early time-series analyses of current account dynamics have yielded rather limited success. Empirical implementations of the inter-temporal approach based on present value tests had difficulties in explaining current account dynamics (e.g. Sheffrin and Woo, 1990; Bergin and Sheffrin, 2000). Econometric analyses based on New Open-Economy Macroeconomics models have found that current account dynamics were not primarily driven by policy shocks but rather by financial shocks or technology shocks (Bergin, 2006; Kim and Lee, 2015).

The large deficit of the U.S. has motivated several insightful papers. Engel and Rogers (2006) examined the role of the expected share of the US in the world economy, which is driven by stronger growth in the US than in other advanced economies. Blanchard et al. (2005) examined the implications of the increased demand for US assets. Providing a concrete context to one source of the demand for US assets, Caballero et al. (2008) brought out the global excess demand for safe assets, of which the US is an undisputed major supplier. Mendoza et al. (2009) highlighted the role of different degrees of financial market developments in generating the large global imbalances. Although these papers have focused on the US deficit (rather than the surplus and deficit of an average country), they have highlighted the role of financial shocks and external (global) developments in understanding the current account even of the US, the largest economy.

Papers that combined dynamic macro models and trade models put forward the role of trade costs in current account movements. Obstfeld and Rogoff (2001) developed the possible effects of trade costs on the effective interest rates and, ultimately, on the current account. Alessandria and Choi (2021) find trade policy and resulting changes in trade barriers were an important driver of the US trade balance since the 1980s. Mullen and Woo (2024) develop a model framework that captures both financial and trade shocks and successfully generates the comovement between the US real exchange rates and net exports across different time horizons.

Regarding more traditional or low-frequency drivers of current accounts, a cross-country panel empirical literature, initiated by Chinn and Prasad (2003), has identified several main determinants (or correlates) of current account balances, which include structural fundamentals like demographics, institutional quality, and natural resources, as well as macroeconomic fundamentals like expected real growth, economic policies, and cross-country differences in business cycles (see e.g., Lee et al. (2008), Allen et al. (2023), Chinn and Ito (2022) and Coutinho et al. (2022)). This literature has put more emphasis on medium-term movements in current accounts, using data at an annual frequency or averaged over several years. Resonating with this empirical literature, the role of demographic transitions has been developed in the context of dynamic models by Ferrero (2010), Backus et al. (2014), and Barany et al. (2023).

However, no consensus emerged on the core drivers of current account movements. Studies that highlight demographics, for example, do not necessarily find the demographic factors to play the most important role. For example, Ferrero (2010) finds productivity to have played a greater role than demographic factors. Similar limitations apply to other studies, in that no set of variables have been widely recognized as the primary driver of current account dynamics in quantitative terms.

We take a step back from these different factors identified in the literature and place as few ex-ante restrictions on our empirical structural model as possible. Our approach yields an agnostic description of the empirical comovements of macroeconomic aggregates associated with unexpected fluctuations in the current account. Our findings point towards international relative demand shocks as the major drivers behind the current account, which might be better analyzed by a more sectoral approach.

The remainder of the paper is structured as follows. Section 2 briefly describes the data and lays out the econometric methodology. It presents the empirical results of the dominant current account shocks for the US and the G7, after contrasting the shocks to the dominant exchange rate shock. Section 3 discusses the model and its estimation. In section 4 we present the model results and reconcile them with the empirical evidence. Finally, section 5 concludes.

2 Empirical Analysis

This section describes the empirical framework and presents its findings.

2.1 Data and Empirical Framework

Our empirical exercise aims to discover the statistical properties of the main empirical driver of current account fluctuations. To keep the structural identification restrictions to a minimum, we rely on the max-share approach as in Angeletos et al. (2020), developed by Faust (1998) and Uhlig (2003). The approach identifies one dominant shock that is the largest contributor to the volatility of a single variable at a particular frequency. It has the advantage that we do not need to form an a priori view on potentially problematic timing or sign restrictions or come up with an instrument that might be difficult to find. Moreover, the approach can easily be applied to different countries and allows for flexibility in choosing the set of model variables.

We estimate a reduced-form VAR

$$\mathbf{y}_t = \mathbf{a} + \mathbf{A}_1 \mathbf{y}_{t-1} + ... + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t \ , \tag{1}$$

with a lag length of $p = 4$ quarters, where $\mathbf{a}$ denotes a constant, $\mathbf{A}_i$ the reduced-form VAR coefficients and $\mathbf{u}_t$ the reduced-form forecast errors. These errors have no economic interpretation.

The endogenous variables in $\mathbf{y}_t$ include quarterly macroeconomic data on our country of interest, i.e., the US, or the remaining G7 countries vis-à-vis a trade-weighted aggregate of G6 economies as in Engel (2016) and Chahrour et al. (2021): (i) the current account to GDP ratio, (ii) the nominal exchange rate expressed in domestic currency per foreign currency (i.e., an increase is a depreciation of the domestic currency), (iii) domestic real consumption and investment, (iv) foreign, i.e., G6, real consumption and investment, (v) the CPI price level differential, (vi) the interest rate differential, (vii) a measure of domestic total factor productivity.[2] The sample runs from 1975:Q1-2022:Q3, and the

[2]We note the potential discrepancy that the current account relates to a country's transactions with all foreign countries while we focus on the G6 as the rest of the world for the remaining variables. As a robustness exercise, we replace the nominal exchange rate vs. G6 with the nominal effective exchange rate vs. 51 countries from Darvas (2021).

variables enter the VAR in log levels except for the current account to GDP ratio which is not transformed. Baseline results for the G6 countries are estimated without measures of TFP. The appendix holds additional information on data sources and construction. To estimate the VAR, we use a Minnesota-type prior implemented via a Gibbs sampler as in Angeletos et al. (2020) and Miyamoto et al. (2023).[3]

The reduced-form VAR in (1) can be expressed in a structural form given by

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t. \tag{2}$$

In equation (2), $\boldsymbol{\varepsilon}_t$ are independent structural shocks with an economic interpretation. These are related to the reduced-form errors via the linear transformation $\mathbf{u}_t = \mathbf{B}_0^{-1}\boldsymbol{\varepsilon}_t$. Thus, $\mathbf{B}_0^{-1}$ contains the impact effects of the structural shocks on the endogenous variables in $\mathbf{y}_t$. By assuming a unit variance for the uncorrelated structural shocks, i.e., $\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathbf{I}_n$ (an identity matrix), the reduced-form covariance matrix $\boldsymbol{\Sigma}_u$ is related to the structural impact multiplier matrix as $\boldsymbol{\Sigma}_u = \mathbb{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{B}_0^{-1}\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t')\mathbf{B}_0^{-1\prime} = \mathbf{B}_0^{-1}\mathbf{B}_0^{-1\prime}$.

There exists a large set of observationally equivalent $\mathbf{B}_0^{-1}$ matrices and we can write $\mathbf{B}_0^{-1} = \boldsymbol{\Sigma}_{u,tr}\mathbf{Q}$ where $\boldsymbol{\Sigma}_{u,tr}$ denotes the unique lower triangular Cholesky matrix of $\boldsymbol{\Sigma}_u$ with non-negative diagonal coefficients, and $\mathbf{Q}$ is an orthogonal matrix, i.e., $\mathbf{QQ'} = I$ and $\mathbf{Q}^{-1} = \mathbf{Q}'$ (see Uhlig, 2005). Concentrating on the relation of reduced-form residuals to structural shocks, we obtain $\mathbf{u}_t = \boldsymbol{\Sigma}_{u,tr}\mathbf{Q}\boldsymbol{\varepsilon}_t$.

We denote the reduced-form VAR in equation (1) in its moving average representation $\mathbf{y_t} = \mathbf{B}(\mathbf{L})\mathbf{u}_t$ where $\mathbf{B}(\mathbf{L})$ is an infinite matrix polynomial. Inserting for $\boldsymbol{u}_t$ we obtain

$$\boldsymbol{y_t} = \boldsymbol{B}(\boldsymbol{L})\boldsymbol{\Sigma}_{u,tr}\mathbf{Q}\boldsymbol{\varepsilon}_t = \boldsymbol{\Gamma}(\boldsymbol{L})\boldsymbol{\varepsilon}_t \tag{3}$$

where $\boldsymbol{\Gamma}(\boldsymbol{L}) = \sum_{T=0}^{\infty}\Gamma_T L^T$ and $\{\Gamma_T\}_{T=0}^{\infty}$ represents the IRFs of the variables to the

[3]For estimation we drop the extreme observation 2020:Q2. Our results are robust to weighing down the observations of 2020:Q2 and the following quarters as proposed in Lenza and Primiceri (2022).

structural shocks.

To identify a single shock by the requirement that it exhibits the maximal share of the contribution to the volatility of a particular variable in a particular frequency band, we leverage the $\mathbf{Q}$ matrix. We pick that column $\mathbf{q}$ from $\mathbf{Q}$ which relates to the structural shock that is the dominant driver of the current account balance at the business cycle frequency between 6 and 32 quarters and separately in the long run, which refers to a range between 80 quarters and ∞ following Angeletos et al. (2020) and Miyamoto et al. (2023).

For that, we use the spectral density, a frequency domain characterization of time series directly related to the autocovariance time domain representation. The spectral density of the variable y at frequency w is given by

$$f_X(y) = \frac{1}{2\pi}\boldsymbol{C}(\boldsymbol{e}^{-\boldsymbol{iw}})\boldsymbol{Q}\boldsymbol{Q}'\boldsymbol{C}(\boldsymbol{e}^{-\boldsymbol{iw}})', \tag{4}$$

where $\boldsymbol{C}(\boldsymbol{L}) = \boldsymbol{B}(\boldsymbol{L})\boldsymbol{\Sigma}_{u,tr}$. The volatility of the variable y can be computed via the integral of the spectral density function (4), in terms of contributions of all the Cholesky-transformed residuals, over a frequency band, for instance, $[\underline{w}, \overline{w}] = [2\pi/32, 2\pi/6]$ for the business cycle frequency.

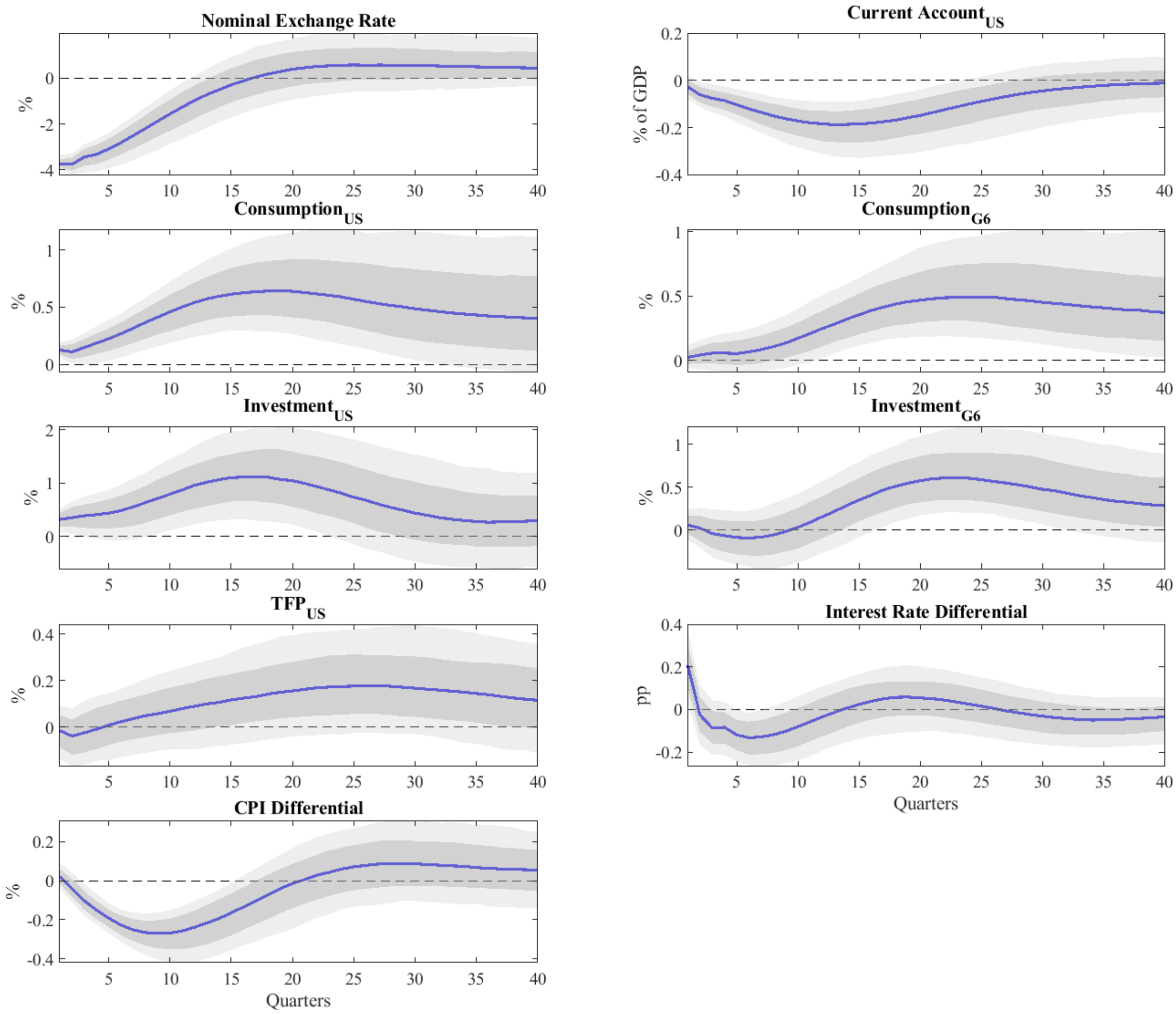
Each column vector q can be used to represent the contribution of a corresponding shock to the spectral density of the variable y as $q'\boldsymbol{\Theta}q$ where $\boldsymbol{\Theta}$ is the integral of the matrix obtained as the product of the complex conjugate transpose of $\boldsymbol{C}(\boldsymbol{e}^{-\boldsymbol{iw}})$'s row that applies to variable y and the row itself (see Angeletos et al., 2020 for more details). The column vector q that corresponds to the dominant shock is then the eigenvector associated with the largest eigenvalue of the matrix $\boldsymbol{\Theta}$ and can thus be identified without making assumptions on the matrix $\boldsymbol{Q}$.

2.2 Dominant Exchange Rate Shock

Using our VAR system for seven (or six) variables, we first estimate the *dominant (or main) exchange rate shock* at business cycle frequency for the US. This serves as a test run of our choice of the VAR system in studying open macroeconomic questions. The dominant exchange rate shock for the US is characterized by an appreciation of the US dollar vis-à-vis G6 currencies, with a peak response of 4% on impact and reverting to its steady state after around four years (Figure 1). The appreciated nominal exchange rate leads to a gradual decline in the current account. After 14 quarters the CA/GDP ratio has decreased by 0.2 percentage points and then slowly reverts back to its steady state. The shock gradually increases domestic consumption, investment and TFP. Chahrour et al. (2021) link this immediate appreciation to positive news about future fundamentals. Miyamoto et al. (2023) emphasize the shock's disconnect from macroeconomic aggregates when they compare it to a major business cycle shock which explains most of the variation in macroeconomic aggregates. The impact on consumption and investment (similarly to the current account) builds up only gradually, and when displayed as US vs. G6 consumption or investment differences, is small compared to the 4% appreciation.

Alternatively or complementary to the interpretation as a news shock, the shock could represent foreign financial inflows (e.g., foreign purchases of US dollars as FX reserves and treasury bonds as safe assets) which induce an exchange rate appreciation and lead to higher investment, consumption and imports in the US, as consumer prices decrease due to a substitution of domestic production with imports. On impact the shock explains less than 5% of the variation in the current account and its share increases to a maximum of close to 30% five years out (see Figure B.1).

Figure 1: Impulse Responses to the Dominant Exchange Rate Shock



Notes: Point-wise median impulse responses to the dominant business cycle frequency exchange rate shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differentials are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, the UK and Japan.

2.3 Dominant Current Account Shocks

This section presents the structural impulse responses to the dominant drivers of the current account (CA), denoted as *dominant or main CA shocks*, for the US and the remaining G7 countries at business cycle frequency and over the long run. The dominant business-cycle frequency CA shock for the US displays a distinct pattern compared to the dominant exchange rate shock analyzed in the last section and seems to be driven by a different set of economic forces. This is in line with the main exchange rate shock's explanatory share below 30% for the current account, especially over the first quarters.

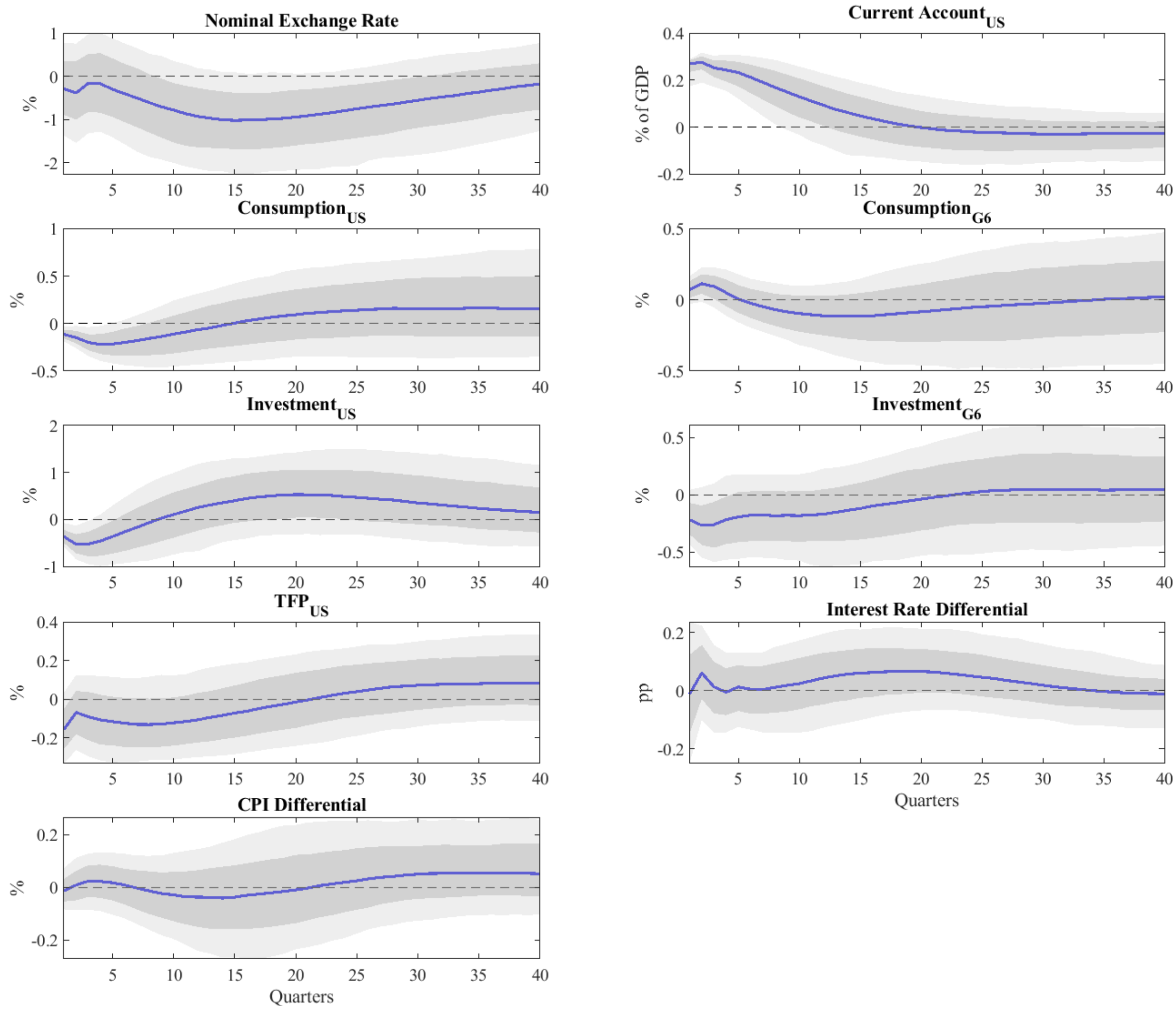
Figure 2 displays the dominant CA shock at business cycle frequency estimated for US data. The shock induces a peak increase in the CA-to-GDP ratio by 0.25-0.3 percentage points over the first year. The CA slowly reverts to its steady state over a protracted period of four to five years. The nominal US dollar exchange rate vs. G6 economies remains muted on impact but displays a persistent appreciation after one year and peaks at -1% after 15 quarters.[4] The shock is characterized by a short-lived decline in domestic consumption and investment for around 2 years accompanied by a worsening of TFP. After 3-4 years the investment response turns positive with a peak increase of 0.5% after 20 quarters. The G6 agglomerate consumption slightly increases on impact, while G6 investment decrease for several quarters. The CPI differential displays no discernible effect which might result from the rather similar domestic and foreign investment responses. The interest rate differential tends to rise over the medium term.[5] Overall, this short-lived recessionary shock, followed by a boom in investment that coincides with an exchange rate appreciation, speaks against the role of exchange-rate induced expenditure switching in driving CA variations at business cycle frequencies.

The shock explains around 80% of the volatility in the CA-to-GDP ratio for the first 4 quarters. Then the share drops to around 30% after 20 quarters where it remains(see the forecast error variance decomposition in Figure B.2). The explained share of the nominal exchange rate volatility is close to 0 on impact and rises above 10% several quarters out while the shock explains less than 10% at all horizons of the remaining macroeconomic variables.

[4] The real exchange rate behaves nearly identically (see Figure B.4).

[5] Replacing the interest rate differential with the US interest rate level we observe a slight decrease for 2 to 3 years. The US federal funds rate, instead, displays no change over the first three years.

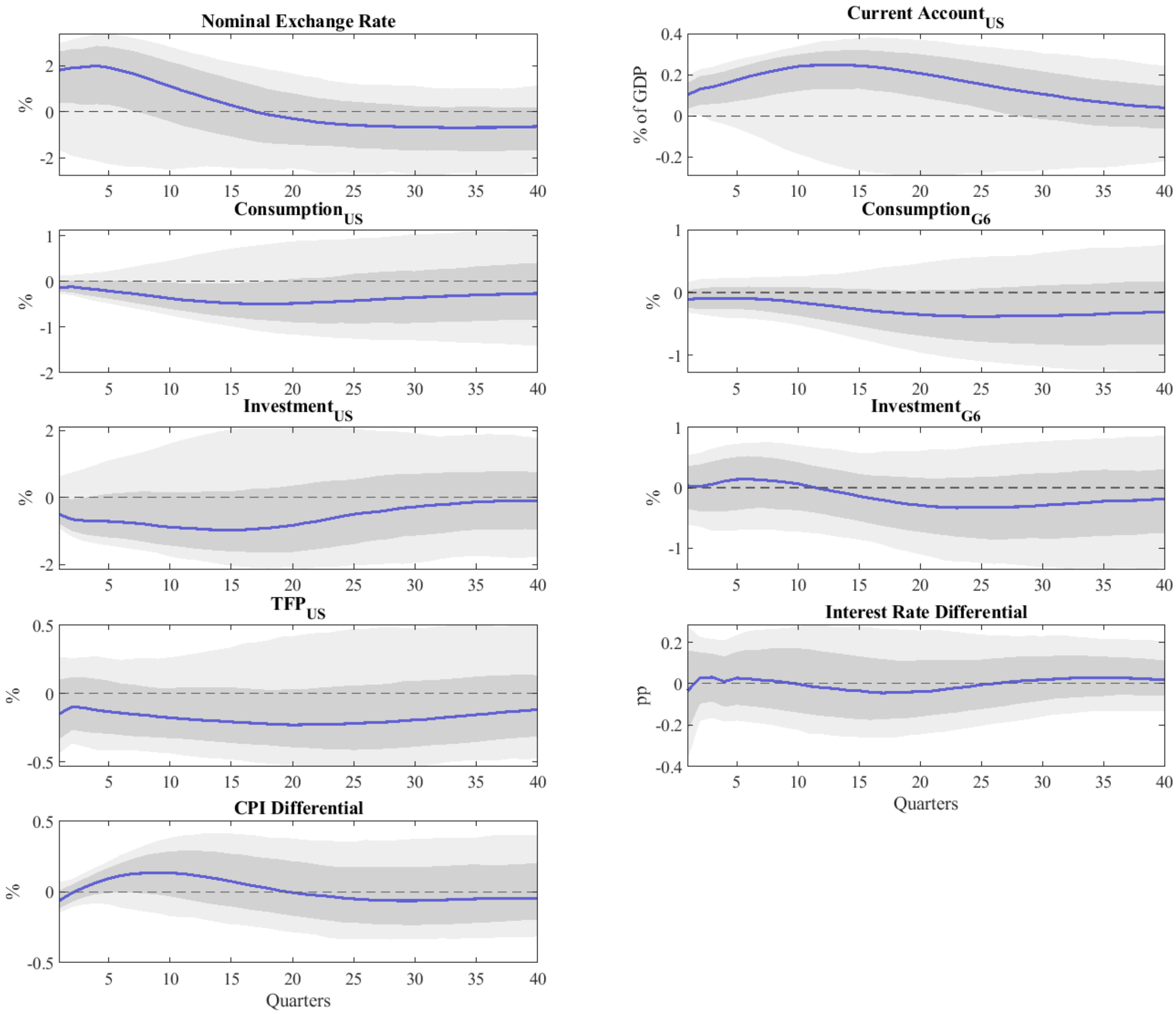
Figure 2: Impulse Responses to the Dominant Current Account Shock



Notes: Point-wise median impulse responses to the dominant business cycle frequency CA (current account) shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differentials are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Turning to the dominant long-run CA shock's impulse responses in Figure 3, we observe a protracted increase in the CA with a peak response after 10-15 quarters before slowly tapering off. Consumption, investment, and TFP drop on impact and remain persistently depressed for several years, though with very low statistical significance. Relative US prices

Figure 3: Impulse Responses to the Dominant Long Run CA Shock



Notes: Point-wise median impulse responses responses to the dominant long run CA (current account) shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differentials are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

increase somewhat while the interest rate differential shows no discernible response. In a strong contrast to the CA-exchange rate relationship for the short-run dominant CA shock, the nominal exchange rate depreciates strongly by around 2% remaining depreciated for 3-4 years, implying a clear role of expenditure-switching for the long-run fluctuations in the CA. The shock explains around two thirds of the forecast error variance of the CA-to-GDP ratio several years out (see figure B.3). In contrast to the main driver at business-cycle frequency, the main long-run CA shock explains a larger share of the nominal exchange rate volatility: around 20-35% for the 10-year horizon.

2.3.1 Other Country Results

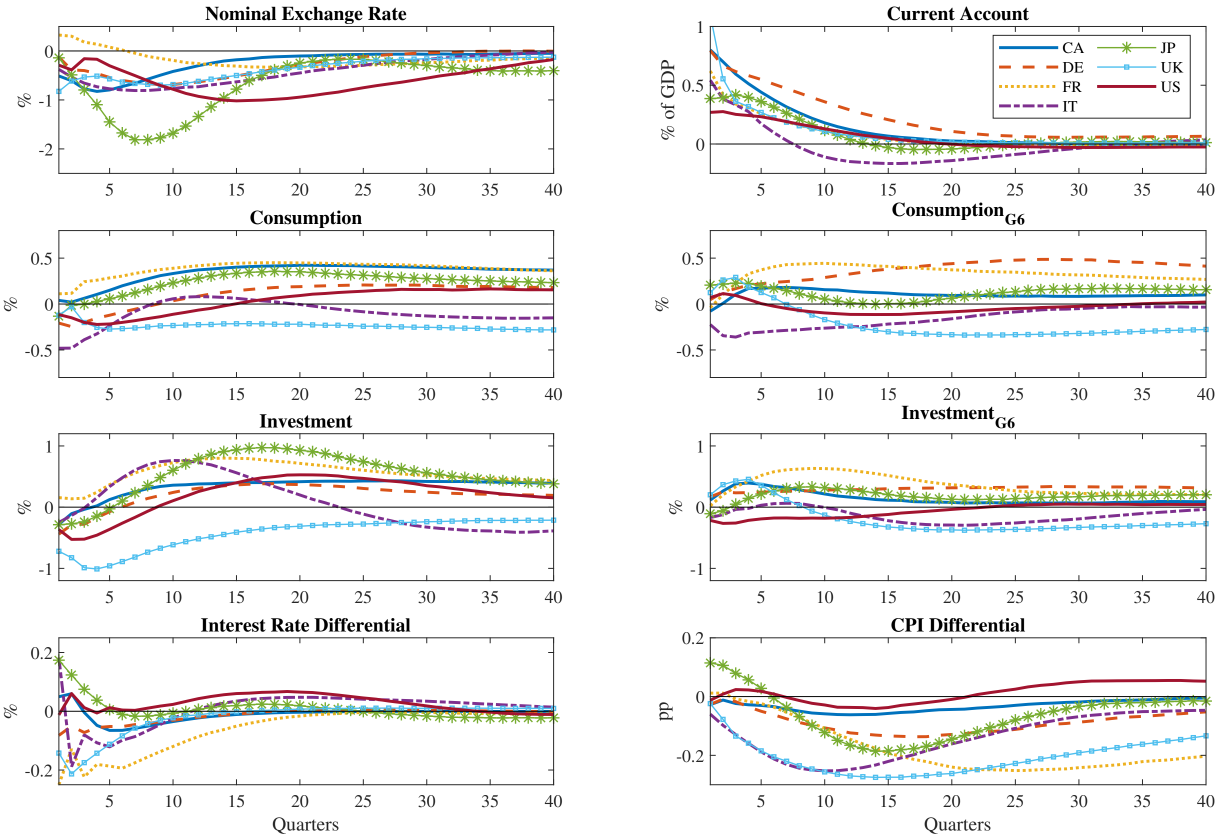
We run separate VARs for the remaining G7 countries relying on the same identification strategy. For these countries, we do not have data on TFP for the sample 1975:Q1-2022Q3 and estimate the baseline VAR without TFP. In an extension we include the utilization-adjusted TFP measures from Schmidt et al. (2021) for France, Germany, Italy and the UK at the cost of a significantly shorter horizon 1991Q1 - 2019Q4 and from Cao (2021) for Canada for the horizon 1976:Q1 - 2018:Q3.

Figure 4 displays the median impulse responses after the dominant CA shocks at business cycle frequency for each G7 economy. The shocks drive up the CA-to-GDP ratio by an average of around 0.5% on impact reverting back to zero over a horizon of 2 years for Italy and more than 5 years for Germany. The shocks induce nominal exchange rate appreciations for each country already on impact and for several years except for France where the exchange rate response remains close to zero and appreciates only slightly after several quarters.

All countries but the UK experience a delayed increase in investment. The CPI differential displays an immediate or delayed decrease for all. Consumption mostly increases after several quarters while the interest rate differential and foreign consumption and investment show less common responses.[6]

[6]Figure B.31 in the appendix displays impulse responses for the dominant long-run CA shocks of all G7 countries which are more inconclusive and display a positive correlation between the CA and the exchange

Figure 4: Impulse Responses to the Dominant CA Shocks for G7 Countries



Notes: Point-wise median impulse responses responses to the dominant business cycle frequency CA (current account) shock for all G7 countries. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differentials are expressed as individual country vs. G7 excluding the individual country. G7 countries include Canada, France, Germany, Italy, Japan, the UK and the US.

Note that we would not necessarily expect the dominant current account shock to display the exact same types of characteristics across different countries. The seven economies we have analyzed here have quite different historical patterns in their current account balances which can be due to different economic policies (e.g., social systems, trade policies, or tax systems), structural characteristics (e.g., demographics or being part of a currency union) and the exposure to different economic and financial shocks over time.

rate, i.e., evidence of expenditure switching, only for the US, Canada, Germany and Japan.

2.4 Robustness

Our findings for the dominant business cycle CA shock in the US are robust to exchanging the nominal exchange rate vs. G6 currencies with the real exchange rate vs. G6 countries and with the nominal effective exchange rate (see figures B.5 and figure B.4).Results are robust to ending the sample in 2019:Q4 (figure B.12, weighing down the Covid observations following Lenza and Primiceri (2022) (figure B.14) or increasing the lag length to 8 quarters (figure B.15). We also report results ending the sample before the Great Recession in 2007:Q4 for which the error bands become very wide but the negative correlation over the first few quarters between the nominal exchange rate and the current account remains intact (figure B.12). Moreover, we show additional responses for exports and imports (figure B.18), the exports-to-imports ratio (Figure B.9, replacing CPI and interest rate differentials with the US variables (figure B.10) and adding the federal funds rate (figure B.11). We also show that the dominant CA business cycle shock is a mixture of the two dominant shocks to its components: a dominant net exports shock (figure B.16) and a dominant income balance shock (figure B.17) which are both rather similar to the dominant CA shock. In contrast, a dominant shock to the exports-to-imports ratio induces a positive correlation between the exchange rate and the exports-to-imports ratio (figure B.18). A more conventional dominant business cycle shock that explains most of the variation in domestic consumption shares the recessionary similarities on impact with the dominant CA shock (figure B.19) but displays more protracted downswings in consumption and investment. The exchange rate response is muted and the shock explains merely a maximum of 10% of the current account after two years.

Results for the long run dominant CA shock are qualitatively robust to using the real exchange rate and the nominal effective exchange rate (see figures B.6 and B.7).

3 Model and Estimation

This section tries to interpret the empirical dominant CA shock at business-cycle frequency through the lens of a structural open-economy macro model. We resort to a Dynamic Stochastic General Equilibrium (DSGE) model with standard New Keynesian features and investigate which structural shocks resemble the dominant CA shock. The model encompasses eight shocks related to domestic fundamentals, international fundamentals, and the international financial landscape. Estimating the model on US data, international shocks to relative demand for domestic goods and assets stand out as the primary drivers of the current account, explaining over 80 and 10 percent of its variation, respectively.

3.1 Key Model Elements

We adapt the open economy model with international financial market frictions of Itskhoki and Mukhin (2021).While the model has addressed a series of exchange rate puzzles through a capital flow shock, the correlation between the exchange rate and current account balance is close to one, far exceeding the data.[7] Thus, we enhance the model by incorporating three additional shocks considered in the open-macro literature.

In addition to shocks related to TFP, monetary policy, and capital flows, we include domestic and foreign aggregate demand shocks and a shock to relative demand between home and foreign goods originating in the foreign country.[8] The aggregate demand shocks are textbook-style subjective discount factor shocks (Galí, 2015), and the relative demand shock alters the weight of home goods in foreign households' consumption basket, similar to the preference shocks advocated in Stockman and Tesar (1995) and Pavlova and Rigobon (2007).[9] These shocks allow to decrease the current account-exchange rate correlation in

[7] Using quarterly data on the nominal exchange rate vs. G6 countries and the current account to GDP ratio as used in section 2, the contemporaneous correlation is around 60% for the US, 3% for Germany and -68% for the UK.

[8] This relative demand shock could equivalently be introduced to home preferences.

[9] In a closed-economy context, Fornaro and Romei (2023) studies a similarly specified demand reallocation shock.

the model and are found to be significantly related to the main CA shock estimated in the previous section.

3.1.1 Households

The economy is populated by a unit continuum of identical households. The representative household seeks to maximize the objective function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) e^{\Omega_t} \quad \text{for } \sigma > 0 \tag{5}$$

where C_t is final goods consumption, N_t denotes hours worked, and Ω_t is an exogenous preference shifter. C_t is a CES aggregator of home and foreign goods,

$$C_t = \left(\int_0^1 \left[(1-\gamma)^{1/\theta} C_{Ht}(i)^{(\theta-1)/\theta} + \gamma^{1/\theta} C_{Ft}(i)^{(\theta-1)/\theta} \right] \mathrm{d}i \right)^{\theta/(\theta-1)},$$

where C_{Ht} denotes the quantity consumed of home goods, and C_{Ft} the quantity consumed of foreign goods with the elasticity of substitution among goods θ. The parameter γ reflects the weight of foreign goods in the home basket, which is less than 0.5. Hence, households' preferences display a home bias for domestically produced goods.

The preference shifter Ω_t in equation (5) evolves as an AR(1) process,

$$\Omega_t = \rho_\Omega \Omega_{t-1} + \epsilon_{\Omega,t},, \quad \epsilon_{\Omega,t} \sim iid(0, \sigma_\Omega^2), \tag{6}$$

where $\epsilon_{\Omega,t}$ denotes a domestic aggregate demand shock.

Foreign households possess a utility structure analogous to domestic households with the same discount factor β and relative risk-aversion σ. They are subject to an aggregate demand shifter Ω_t^*, which also follows an AR(1) process similar to Ω, though their auto-correlation and shock variance can differ. We assume the innovation terms to aggregate demand shifters are positively correlated between the two countries. Like home households, foreign households' final consumption is defined as

$$C_t^* = \left(\int_0^1 \left[\gamma_t^{*1/\theta} C_{Ht}^*(i)^{(\theta-1)/\theta} + (1-\gamma_t^*)^{1/\theta} C_{Ft}^*(i)^{(\theta-1)/\theta} \right] \mathrm{d}i \right)^{\theta/(\theta-1)}$$

They exhibit a consumption bias, $\gamma_t^* < 0.5$, towards their domestically produced goods, C_{Ft}^*, that in contrast to the domestic home bias evolves stochastically as

$$\gamma_t^* - \gamma = \rho_\gamma(\gamma_{t-1}^* - \gamma) + \epsilon_{\gamma,t}$$

where $\epsilon_{\gamma,t}$ is the relative demand shock.

3.1.2 International Funds Intermediation

International capital markets are segmented. Home and foreign households can only trade bonds denominated in their own currencies with international financiers and noise traders (Itskhoki and Mukhin, 2021 and Gabaix and Maggiori, 2015). The modified uncovered interest rate parity (UIP) condition, derived from the expected profit maximization of international financiers, is given by

$$i_t - i_t^* - E_t \Delta e_{t+1} = \psi_t - \chi b_t \tag{7}$$

where i_t and i_t^* represent the domestic and foreign nominal interest rates between t and $t+1$, respectively. $E_t \Delta e_{t+1} = E_t[\log(\mathcal{E}_{t+1}) - \log(\mathcal{E}_t)]$ denotes the expected depreciation of the nominal exchange rate, where $\mathcal{E}_t$ is the nominal exchange rate, representing the amount of local currency required to purchase one unit of foreign currency (an increased $\mathcal{E}_t$ indicates a home currency depreciation). Additionally, ψ_t represents noise traders' demand for foreign currency bonds financed by issuing home currency bonds, and $\epsilon_{\psi,t}$ is the capital flow shock affecting this demand represented by the AR(1) process:

$$\psi_t = \rho_\psi \psi_{t-1} + \epsilon_{\psi,t}, \quad \epsilon_{\psi,t} \sim iid(0, \sigma_\psi^2)$$

3.1.3 Production

Firms' production of domestic output is based on a Cobb-Douglas technology that involves labor L_t, capital K_t, and intermediate inputs X_t:

$$Y_t = \left(e^{a_t} K_t^{\vartheta} L_t^{1-\vartheta}\right)^{1-\phi} X_t^{\phi} \tag{8}$$

where ϑ is the elasticity of substitution between capital and labor, and ϕ is the elasticity of substitution between 'value added" and intermediates.

Productivity (e^{a_t}) follows an AR(1) process in logs,

$$a_t = \rho_a a_{t-1} + \epsilon_{a,t}, \quad \epsilon_{a,t} \sim iid(0, \sigma_a^2), \tag{9}$$

where $\epsilon_{a,t}$ is the TFP shock.

Foreign firms have a production function of the same form with equal shares of capital, labor, and intermediate goods. Their TFP process follows an AR(1) process similar to equation (9). We allow positively correlated TFP shocks between the home and foreign countries.

3.1.4 Price Setting

Both domestic and foreign markets are characterized by monopolistic competitition. Under nominal price rigidity each domestic firm maximizes its expected discounted sum of profits,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \Theta_t \Pi_t(i), \quad \text{with} \quad \Pi_t(i) = \left(P_{Ht}(i) - MC_t\right) Y_{Ht}(i) + \left(P_{Ht}^*(i)\mathcal{E}_t - MC_t\right) Y_{Ht}^*(i),$$

where P_t is the final consumption good price in home currency, P_{Ht} and P_{Ht}^* are the home-made good prices in home and foreign currencies, respectively, $\Theta_t \equiv \beta^t \frac{C_t^{-\sigma}}{P_t}$ represents the nominal stochastic discount factor, and MC_t is the nominal marginal cost of production, common to all domestic firms. Calvo pricing implies that in every period, a firm has probability $(1-\lambda_p)$ of being able to adjust its prices. Under these conditions, we derive the log-linearized New Keynesian Phillips Curve (NKPC) for domestically sold goods:

$$\pi_{H_t} = \kappa_p \left(mc_t - p_{Ht}\right) + \beta E_t \pi_{H_{t+1}}, \tag{10}$$

where mc_t is the real marginal cost of one unit of home goods, and p_{Ht} is the relative price of home goods to home final goods, both expressed in log deviations from their steady-state values. The slope parameter $\kappa_p \equiv \frac{(1-\beta\lambda_p)(1-\lambda_p)}{\lambda_p}$ reflects how responsive the aggregate price changes are to the marginal cost changes.

The NKPC for home exports depends on the price-setting regime. For countries like the United States whose currency is the invoicing currency for its exports, we assume a producer-currency-pricing regime (PCP). In this scenario, the NKPC is given by

$$\pi^*_{Ht} + \Delta e_t = \kappa_p \left(mc_t - q_t - p^*_{Ht}\right) + \beta E_t(\pi^*_{Ht+1} + \Delta e_{t+1}) \tag{11}$$

where q_t is the home country's real exchange rate in log-deviations, with a higher q_t denoting a depreciation of the home real exchange rate, and p^*_{Ht} is the relative price of home goods in the foreign consumption bundle.

Under local currency pricing (LCP), i.e., when the foreign currency is the invoicing currency for exports, the NKPC is given by

$$\pi^*_{Ht} = \kappa_p \left(mc_t - q_t - p^*_{Ht}\right) + \beta E_t(\pi^*_{Ht+1}). \tag{12}$$

3.1.5 Monetary Policy

We assume that central banks in both home and foreign countries adopt an inflation-targeting monetary policy regime. The home monetary authority adjusts the nominal interest rate i_t according to the following Taylor rule:

$$i_t = \rho_m i_{t-1} + (1-\rho_m)(\phi_\pi \pi_t + \phi_y y_t) + v_t. \tag{13}$$

Here, ρ_m is the interest rate smoothing parameter, ϕ_π is the Taylor coefficient for the CPI inflation rate π_t, and ϕ_y is the Taylor coefficient for detrended output y_t. An exogenous monetary policy shock v_t evolves according to the AR(1) process:

$$v_t = \rho_v v_{t-1} + \epsilon_{v,t}, \quad \epsilon_{v,t} \sim iid(0, \sigma_v^2). \tag{14}$$

A positive realization of $\epsilon_{v,t}$ represents a contractionary monetary policy shock, leading to a rise in the nominal interest rate, given a certain level of inflation.

The foreign country has a similar monetary policy regime, although parameters regarding the Taylor rule and monetary policy shocks are not necessarily the same. Again, we allow for a positive correlation between home and foreign monetary policy shocks.

3.1.6 Potential Candidates for the Dominant CA Shock

Consider net exports at period t, which are defined by

$$NX_t \equiv \mathcal{E}_t P_{Ht}^* Y_{Ht}^* - P_{Ft} Y_{Ft}.$$

If we linearize the model around a steady state with a zero net foreign asset position for the home country, the current account balance equals the net export value.[10]

Denote $nx_t = \frac{NX_t}{GDP_t}$ as normalized net exports[11], y_{Ht}^* and y_{Ft} as the domestic demand for home and foreign goods, respectively, and $s_t = p_{Ft} - q_t - p_{Ht}^*$ as the terms of trade.[12] With these notations, net exports can be expressed as

$$nx_t = \frac{\gamma}{1-\phi}(y_{Ht}^* - y_{Ft} - s_t). \tag{15}$$

[10] For many countries, net exports are the main driver of the current account with the income balance being small. For example, the empirical correlation between the current account balance and net exports, based on quarterly data since 1975, is 97%, 96% and 81% for the US, Germany and the UK, respectively.

[11] The economy's output Y_t is not equal to its GDP in our model due to expenditures on intermediate goods.

[12] Excluding net exports and net foreign assets, lowercase variables indicate log deviations from their steady-state values.

Denote aggregate expenditure in Home by $AE_t \equiv C_t + X_t + Z_t$, aggregate expenditure in Foreign by $AE_t^* \equiv C_t^* + X_t^* + Z_t^*$, where Z and Z^* denote domestic and foreign investment, and the home bias difference as $\hat{\gamma}_t^* = \frac{\gamma_t^* - \gamma}{\gamma}$, then equation (15) can be expressed as

$$nx_t = \frac{\gamma}{1-\phi}\Big(\underbrace{(\epsilon - 1)s_t + \epsilon\, q_t}_{\text{expenditure switching}} + \underbrace{\log(\frac{AE_t^*}{AE_t}) + \hat{\gamma}_t^*}_{\text{expenditure changing}} \Big) \tag{16}$$

Equation (16) decomposes the current account dynamics into two primary channels: expenditure switching and expenditure changing. The first two terms on the right-hand side of (16) encapsulate the expenditure switching effect. Specifically, under $\epsilon > 1$, a deterioration in the terms of trade (a higher s_t) or a depreciated real exchange rate (a higher q_t) would, all else equal, increase the current account balance (larger surplus or smaller deficit). The last two terms embody the expenditure-changing effect, suggesting that an increase in foreign aggregate expenditure relative to domestic aggregate expenditure or a larger share of home-produced goods demanded (in the basket of foreign final goods) results in a higher current account for the home economy.

Equation (16) alone does not enable us to identify the key shock that drives current account movements because all variables are endogenous and affected by various shocks. In terms of the expenditure switching channel, q_t is sensitive to the capital flow shock, the terms of trade s_t can be affected by the TFP shock (via marginal costs), the monetary policy shock (via the nominal exchange rate and marginal costs), the capital flow shock (via the nominal exchange rate), domestic and foreign demand shocks (via marginal costs), and the relative demand shock (via marginal costs). Regarding the expenditure-changing effect, TFP, aggregate demand, monetary policy, and relative demand shocks all affect the demand for home versus foreign goods on the international goods market.

Given the complex and intertwined sources of current account dynamics, estimating the model on data is one informative way to identify the contribution of each shock to variations in the current account. Therefore, we conduct a Bayesian analysis to explore the major determinants, i.e., the driving structural shock(s), of current account dynamics.

3.2 Estimation

This section conducts a Bayesian analysis of the model. We first discuss several parameters that are calibrated and then the rest that are estimated by Bayesian methods.

3.2.1 Calibrated Parameters

Table 1 shows the parameters that are kept constant during the estimation process. We set the subjective discount factor at 0.99 and the demand elasticity between Home and Foreign goods at 1.5. The macro Frisch elasticity, denoted as $\frac{1}{\varphi}$, is established at 1. The proportion of intermediate goods, ϕ, is 0.5, while the capital's share in the effective labor-capital combination, ϑ, is 0.3. Additionally, the probability that firms cannot adjust their prices, denoted by λ_p, is 0.75. These parameters reflect widely accepted values in the international macroeconomics literature. Furthermore, we set the depreciation rate, δ, at 0.05, slightly above its conventional value. While a lower value of $\delta = 0.02$ would align with the empirical investment-to-GDP ratio, it would also overstate the long-term consumption share in GDP and result in overly volatile investments.

Table 1: Calibrated Parameters for Estimation

Parameter	Symbol	Value	Source
Subjective discount factor	β	0.99	Conventional value
Demand elasticity between Home and Foreign goods	θ	1.5	Feenstra et al. (2018)
Macro Frisch elasticity	φ^{-1}	1	Conventional value
Share of intermediate goods	ϕ	0.5	Conventional value
Capital share in the effective labor-capital combination	ϑ	0.3	Conventional value
Depreciation rate	δ	0.05	Conventional value
Calvo probability for prices	λ_p	0.75	Conventional value

3.2.2 Prior Distributions of the Estimated Parameters

The remaining parameters, mostly concerning the exogenous shock processes, are estimated using Bayesian techniques. We utilize the beta distribution for parameters that are bounded between 0 and 1, including all autoregressive coefficients, the interest rate smoothness ρ_m and ρ_m^*, correlations between identical types of shocks across the two countries, and the strength of home bias in consumption, $1-\gamma$. The prior mean is set at 0.6 for all autoregressive coefficients and at 0.3 for the cross-country shock correlations. For shock standard deviations, we apply the inverse gamma distribution with all prior means set at 0.01. Finally, the normal distribution is employed for unbounded parameters, with prior means adhering to conventional values found in the literature. Table 2 shows priors and posterior estimates. Notably, our estimation uses identical priors for all G7 countries.

3.2.3 Estimation Results

To estimate our model with eight exogenous shocks, we select eight observables for matching, in line with our VAR specification: the current account Δnx_t, the nominal exchange rate Δe_t, domestic CPI inflation π_t, foreign CPI inflation π_t^*, domestic consumption c_t (log-deviation), foreign consumption c_t^* (log-deviation), domestic nominal interest rate i_t, and foreign nominal interest rate i_t^*.[13] We report the main estimation results for the US in t able 2 and other G6 countries in the appendix table B.7.

Among the parameters not directly related to shocks, the posterior mean for trade openness-related parameter, γ, is approximately 0.009, significantly below its prior mean of 0.07[14]. The 90% highest posterior density (HPD) interval for γ is narrow, ranging from 0.0067 to 0.0109. This suggests that the low estimate of γ is data-driven, considering the discrepancy with the prior mean. Regarding the Taylor rule coefficients, the posterior mean of ϕ_π and ϕ_y for Home are about 1.35 and 0.45, respectively, lower than their prior mean of 1.5 and 0.5. Their foreign counterparts ϕ_π^* and ϕ_y^* are of similar values of 1.54 and 0.48, close to their prior mean. The capital adjustment cost coefficient, κ, is estimated at

[13] It is widely acknowledged in Bayesian estimation that a model cannot be estimated with fewer shocks than observables, as this leads to stochastic singularity (Pfeifer, 2014). As a result, many influential studies in the literature employ an equal number of shocks and observables (Rabanal and Rubio-Ramírez, 2005; Smets and Wouters, 2007). However, it is not unusual to have more shocks than observables (Ireland, 2004; Schmitt-Grohé and Uribe, 2012), and this does not pose any issues as long as the parameters being estimated are still identified.

[14] The prior mean of 0.07 is the calibrated value of γ in Itskhoki and Mukhin (2021), which is an attempt to match U.S. trade openness.

Table 2: Parameters Estimation

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0086	0.0088	[0.0067,0.0109]	Beta	0.02
κ	8.7	7.5907	7.517	[6.6445,8.4225]	Normal	0.5
ϕ_π	1.5	1.3485	1.3653	[1.2063,1.5281]	Normal	0.1
ϕ_π^*	1.5	1.5402	1.5422	[1.3788,1.6966]	Normal	0.1
ϕ_y	0.5	0.4545	0.4526	[0.3649,0.5364]	Normal	0.05
ϕ_y^*	0.5	0.4798	0.4774	[0.3990,0.5556]	Normal	0.05
χ_2	0.001	0.0014	0.0016	[0.0002,0.0028]	Normal	0.001
ρ_a	0.6	0.6757	0.6662	[0.5517,0.7830]	Beta	0.1
ρ_a^*	0.6	0.6817	0.6804	[0.6047,0.7502]	Beta	0.1
ρ_ψ	0.6	0.7146	0.708	[0.6504,0.7743]	Beta	0.1
ρ_m	0.6	0.7606	0.75	[0.7007,0.7994]	Beta	0.1
ρ_m^*	0.6	0.7912	0.7837	[0.7407,0.8275]	Beta	0.1
ρ_v	0.6	0.1576	0.1733	[0.1055,0.2450]	Beta	0.1
ρ_v^*	0.6	0.2171	0.232	[0.1513,0.3135]	Beta	0.1
ρ_Ω	0.6	0.7042	0.7032	[0.6311,0.7665]	Beta	0.1
ρ_Ω^*	0.6	0.7084	0.7008	[0.6495,0.7569]	Beta	0.1
ρ_γ	0.6	0.8012	0.8045	[0.7431,0.8720]	Beta	0.1
σ_a	0.01	0.0191	0.0194	[0.0154,0.0228]	Inverse Gamma	Inf
σ_a^*	0.01	0.0129	0.013	[0.0112,0.0147]	Inverse Gamma	Inf
σ_ψ	0.01	0.0127	0.013	[0.0101,0.0157]	Inverse Gamma	Inf
σ_v	0.01	0.0054	0.0056	[0.0047,0.0065]	Inverse Gamma	Inf
σ_v^*	0.01	0.0033	0.0034	[0.0029,0.0038]	Inverse Gamma	Inf
σ_Ω	0.01	0.02	0.0201	[0.0183,0.0220]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.0166	0.0167	[0.0151,0.0181]	Inverse Gamma	Inf
σ_γ	0.01	0.0016	0.0016	[0.0015,0.0017]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.3641	0.3619	[0.2700,0.4641]	Beta	0.1
ρ_{v,v^*}	0.3	0.2267	0.2333	[0.1341,0.3253]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.3387	0.338	[0.2475,0.4350]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

approximately 7.6, with its prior mean of 8.7 outside its 90% HPD interval. The interest rate smoothing parameters, ρ_m and ρ_m^*, are both around 0.8. Lastly, the estimate of ξ_2 aligns well with its prior means, falling within the 90% HPD intervals.

Our estimation shows that shocks are generally less persistent than previously suggested in the literature. Specifically, monetary policy shocks display minimal persistence domestically and abroad, characterized by AR(1) coefficients near 0.2. This observation is consistent with some specifications incorporating an i.i.d. innovation term within the Taylor rule (13) (e.g., Galí and Rabanal 2004). In contrast, other types of shocks exhibit notably higher persistence. The persistence of TFP shocks is identified at approximately 0.68 for each country. This value is close to the persistence found in non-tradable goods (0.63) and markedly surpasses that of tradable goods (0.15) in Stockman and Tesar (1995). Both capital flow and aggregated demand shocks demonstrate a persistence level of around 0.70. The relative demand shock stands out with the highest persistence of around 0.8. It is important to note that, aside from TFP shocks—which can be estimated using micro-level data—all other shock types are unobservable and necessitate estimation within a DSGE model.

The posterior standard deviations of shock terms are not far from their priors, with narrow 90% HPD intervals, which supports the rationale for employing a first-order linearized model. If we measure a shock's volatility in terms of its log deviation from the steady state, then the relative demand shock displays the largest volatility around 0.19. The estimated inter-country correlations for identical shock types range from 0.3 to 0.4, aligning with the calibrations for TFP and monetary policy shocks used in Itskhoki and Mukhin (2021) and other papers.

3.3 Model Fit

Table B.1 evaluates the model fit of the G7 countries by comparing the theoretical moments to their empirical counterparts. In general, the unconditional moments of the model are close to the actual data. However, there is some degree of heterogeneity in the model fit across different variables for the same country and across different countries for the same variable.

Our model accurately captures the volatility of the current account for all countries examined, closely matching aggregate data. However, it diverges slightly from actual domestic consumption data, with the degree of deviation varying across countries. Notably, the model demonstrates high accuracy for the US, UK, and Germany and relatively low accuracy for France, Canada, and Japan. Regarding foreign consumption, the US stands out as its model-implied foreign consumption volatility is very close to the empirical moment, while other countries see substantial discrepancies between the two. Additionally, our analysis reveals that the model overestimates investment volatility across the G7 nations. This tendency towards higher volatility primarily arises because investment dynamics are not the central focus of our Bayesian estimation process. The observed high volatility is not unique to our model; similar observations have been reported in other studies, including Stockman and Tesar (1995), which suggests incorporating a non-tradable goods sector to address this issue.

The model closely approximates actual exchange rate volatility but presents noticeable deviations for the UK, France, and Italy. It consistently forecasts higher volatility for both domestic and foreign interest rates, with the most pronounced overprediction for Italy. In contrast, the model matches CPI inflation rates more precisely, with negligible differences for domestic inflation rates and slightly larger, yet reasonable, discrepancies for foreign inflation rates.

Regarding the correlation coefficient between current account balances and exchange rate changes, our model significantly reduces the traditionally strong linkage between the two variables by incorporating relative demand shocks, which we will explain later. Although some differences between the model-implied and actual data correlations exist for individual countries, they are within a tolerable range. This represents a considerable improvement over the high correlation of over 0.95 reported in Itskhoki and Mukhin (2021) where all shocks induce an expenditure-switching effect. Notably, our model tends to underpredict this correlation for the UK, Italy, and Canada while overestimating it for other countries.

4 Which Shock Matters

This section brings together the SVAR analysis and the estimated model part to show which structural shocks drive current account dynamics across the business cycle and are potentially behind the empirical dominant CA shock. We begin by conducting a forecast error variance decomposition (FEVD) to assess each estimated shock's contribution to current account variability at different horizons. Subsequently, we provide an analysis of the impulse responses. Using regression analysis, we then link the empirically identified shocks from the max-share SVAR analysis to the structural shocks. Finally, we provide additional evidence by applying the max-share identification to the model-simulated data. All these practices indicate that, despite some heterogeneity across countries, the relative demand shock is pivotal in influencing current account dynamics over the business cycle.

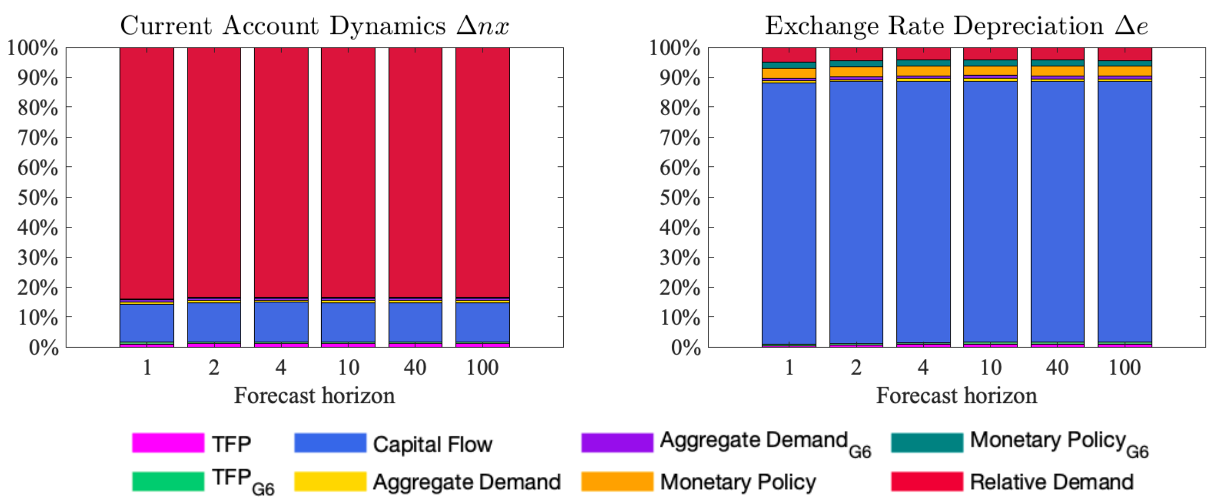
4.1 Variance Decomposition

The left panel of figure 5 illustrates the FEVD of current account dynamics Δnx_t for the US. Across all horizons, the relative demand shock indicated by the red bars emerges as the predominant factor influencing the US current account, accounting for more than 80% of its variation. The capital flow shock (the blue bars) contributes another non-negligible share of over 10 percent. This finding markedly differs from the results presented in Itskhoki and Mukhin (2021) and Miyamoto et al. (2023), where the primary influence on exchange rate fluctuations also drives current account fluctuations.

The right panel of figure 5 displays the FEVD of US nominal exchange rate fluctuations Δe_t. Capital flow shocks are identified as the dominant driver across all horizons, corroborating the popular argument that short-term exchange rate movements often reflect fluctuations in international asset markets more than economic fundamentals. Together, relative demand shocks, domestic monetary policy shocks, and foreign monetary policy shocks account for approximately 10% of the variance in nominal exchange rate fluctuations, both in the short and long term.

Figures B.39 and B.40 present the FEVD of Δnx_t and Δe_t for the other six countries. Across all horizons, the relative demand shock accounts for the largest share of current account fluctuations, and the capital flow shock explains the largest share of exchange rate fluctuations. These findings suggest a considerable degree of generality of the relevance of the relative demand shock for current account volatility.

Figure 5: Forecast Error Variance Decomposition: US



4.2 Why Relative Demand Shocks: An Impulse-Response View

The preceding FEVD analysis indicates that relative demand shocks are the major driving forces of current account (CA) fluctuations in the estimated model. An inspection of the impulse responses to the different shocks explains why this is the case (see the appendix figures in section B.5). Among the structural shocks analyzed, only relative demand and monetary policy shocks display a negative correlation between the exchange rate and the current account that characterizes the dominant CA shock at business-cycle frequency. In other words, only these shocks can suppress expenditure switching in the short term. Thus, it is essential for current account dynamics to reflect shocks that inhibit expenditure switching.

Our model estimation, aimed at aligning with empirical data on the joint dynamics of the current account and the exchange rate, indicates a preeminent role for relative demand shocks in influencing current account fluctuations. The relative demand shock is characterized by foreigners placing more weight on home goods, i.e., foreign households demand relatively more home goods relative to the demand of foreign goods by home households. It improves the domestic current account balance and yields a real exchange rate appreciation (see figure B.48). Home consumption and investment decrease as home-made goods, the major component of the home final goods, are temporarily shifted to the foreign country's use. The higher bias towards home goods, i.e., increased γ, is a negative demand shock to foreign goods, which generates PPI deflation in the foreign country (i.e., $\pi^*_{Ft} < 0$). Although imports inflation $\pi^*_{Ht} > 0$, the overall CPI inflation π^*_t is still negative due to the larger share of foreign goods in the foreign consumption basket. Negative CPI inflation and negative detrended output ($y^*_t < 0$) in the foreign country urges the central bank to lower the interest rate. As a result, foreign investment and consumption increase. The relative demand shock is expansionary to the home country as the overall demand for home goods increases. This pushes up domestic inflation as well as the nominal interest rate. Therefore, we observe positive inflation and interest rate differentials in the short to medium term after the shock.

Monetary policy shocks, in contrast, cannot be the main driver behind the dominant CA shock because they exhibit low persistence in both home and foreign contextsyielding a temporary positive current account balance effect lasting up to four quarters as depicted in figure B.46–the SVAR findings (shown in figure 2) demonstrate that current account improvements may persist for approximately 20 quarters. In addition, monetary policy shocks cannot generate positive foreign consumption and negative domestic consumption. This extended duration suggests a need for shocks with greater persistence, with the relative demand shock's high AR(1) coefficient positioning it as the primary candidate.

4.3 A Regression Examination

The previous FEVD and impulse-response analysis underscores the importance of the relative demand shock in accounting for current account fluctuations. This subsection relates the empirical dominant CA shock series more systematically to the model-based individual shock series. As shocks contributing to CA fluctuations with a small share might be crucial in influencing some particular macro variables we conduct a regression approach to identify those structural shocks that most closely relate to the dominant CA shock.

We estimate the following regression equation with OLS separately for each country

$$\text{dominant CA shock}_t = \sum_i \beta_i * \text{structural DSGE shock}_{i,t} + u_t$$

The dominant CA shock_t is the empirical dominant CA shock series uncovered by the max-share SVAR, and structural DSGE $\text{shock}_{i,t}$ are the Kalman-filtered smoothed shock series extracted from the estimated DSGE model, where t is the quarter indicator, and u_t is the error term in quarter t. β_i is the parameter for shock series i, e.g., the relative demand shock. The regression results are reported in table 3.

The regression results identify two structural shocks as critical components of the dominant CA shock: the capital flow shock and the relative demand shock, showing statistically significant coefficients across all G7 countries. A larger coefficient in magnitude signifies a larger share of the shock in the main CA driver. Consistent with the FEVD findings, the relative demand shock exhibits the most sizable coefficient.[15] This result is still valid if we normalize all structural shocks by their standard deviations. Therefore, the relative demand shock contributes to the CA variation across these countries the most among all shocks.

In addition to capital flow and relative demand shocks, each G7 country has its unique

[15]The correlation between the dominant CA shock and the relative demand shock is 0.75 for the US. figure B.38 in the appendix plots the SVAR and estimated model shock series.

shock-type composition within its main CA driver. For instance, the TFP shock is integral to the main CA driver in the UK, France, Italy, and Canada, whereas the foreign TFP shock plays a similar role in the US, UK, Italy, and Canada. Such notable cross-country heterogeneity is also evident in aggregate demand and monetary policy shocks. The estimated model can account for a significant portion of the empirical main CA driver's variation, including country-specific shocks, capital flow, and relative demand shocks, as shown by high R^2 values exceeding 0.7 for all G7 countries.

Table 3: Regression Results: Short-run Main CA Drivers

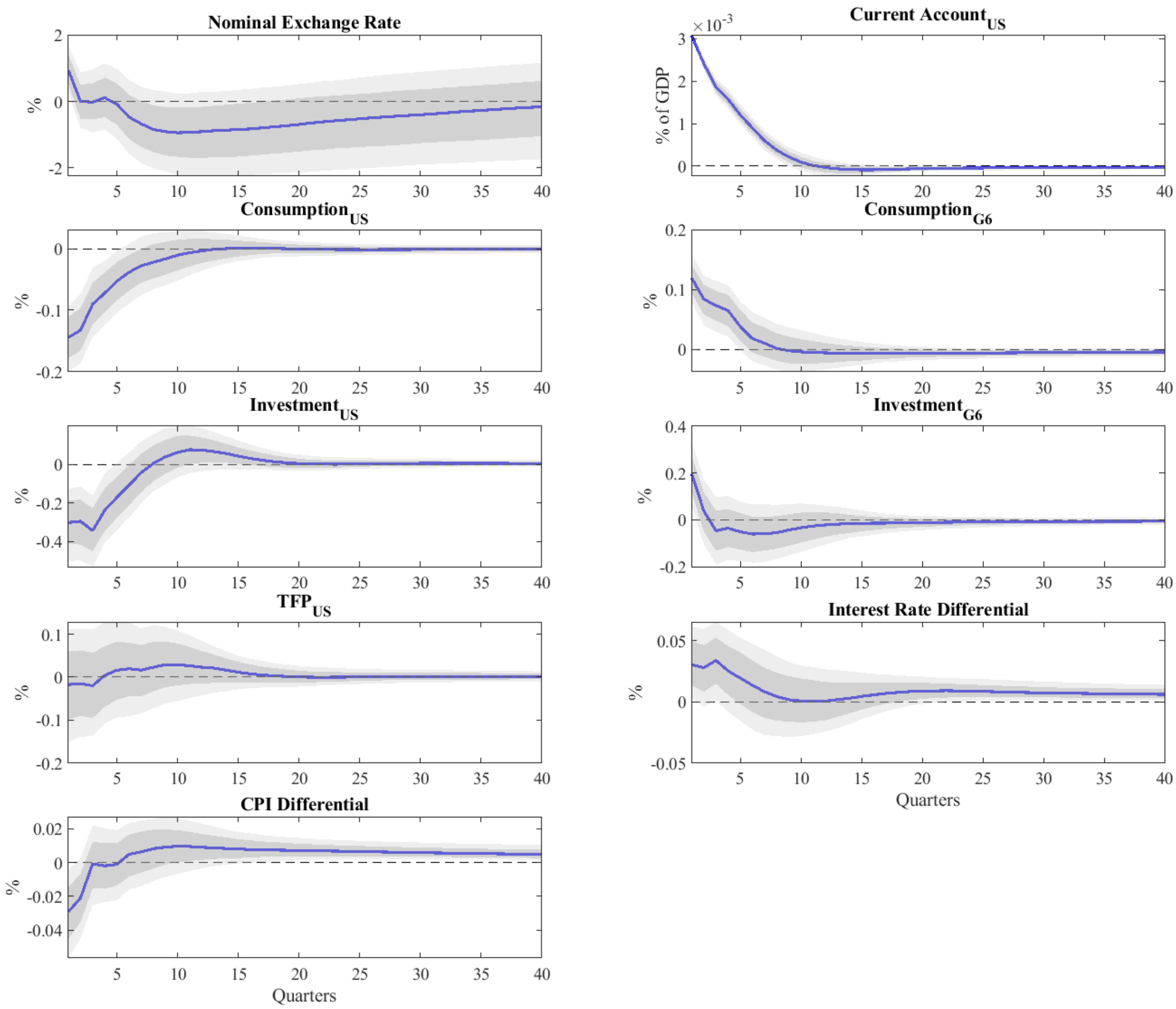
	US	UK	DE	FR	IT	CA	JP
TFP	0.014	0.041**	0.022	0.058**	-0.107**	-0.075**	0.025
	(0.048)	(0.018)	(0.031)	(0.030)	(0.052)	(0.032)	(0.021)
TFP_{G6}	0.113*	-0.038*	-0.050	0.008	-0.048	0.122***	-0.035
	(0.063)	(0.022)	(0.031)	(0.031)	(0.037)	(0.035)	(0.025)
Capital Flow	0.278***	0.213***	0.191***	0.136*	0.296***	0.246***	0.238***
	(0.063)	(0.053)	(0.071)	(0.077)	(0.095)	(0.066)	(0.063)
Aggregate Demand	-0.038	-0.012	-0.034	-0.017	-0.064**	0.004	-0.062**
	(0.042)	(0.017)	(0.033)	(0.032)	(0.032)	(0.037)	(0.031)
$\text{Aggregate Demand}_{\text{G6}}$	0.050	0.032**	0.035*	0.009	0.030	-0.042	0.030**
	(0.049)	(0.014)	(0.018)	(0.019)	(0.023)	(0.028)	(0.015)
Monetary Policy	-0.170	-0.242*	0.208	-0.081	0.163***	0.488**	0.904***
	(0.187)	(0.137)	(0.418)	(0.060)	(0.057)	(0.244)	(0.218)
$\text{Monetary Policy}_{\text{G6}}$	-0.178	0.128	-0.155	-0.312	-0.182	-0.223	-0.744**
	(0.227)	(0.229)	(0.235)	(0.346)	(0.350)	(0.231)	(0.290)
Relative Demand	4.818***	1.394***	2.021***	2.507***	1.877***	3.277***	2.183***
	(0.479)	(0.101)	(0.182)	(0.199)	(0.230)	(0.289)	(0.156)
R^2	0.726	0.874	0.783	0.803	0.712	0.791	0.843

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample is 1976Q1-2022Q3.

4.4 Max-share SVAR on Model-Simulated Data

This subsection tests the consistency of the empirical main CA driver with our open economy NewKeynesian model, aimed to investigate the pivotal role of the relative demand shock in influencing the main CA drivers. More specifically, we use the max-share SVAR approach to identify the main CA based on model-simulated data. We compare such model-based main CA driver with its empirical counterpart and other model-based main CA drivers under alternative shock specifications.

Figure 6: Impulse Responses to the Dominant CA Shock from Simulated Data



Notes: Point-wise median impulse responses to the dominant business cycle frequency exchange rate shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation.

First, we simulate the model over 1000 periods and utilize the max-share SVAR approach to identify the dominant CA shock. Figure 6 illustrates the impulse responses of this hypothetical dominant CA driver. It reveals that the current account increases upon impact while domestic consumption and investment decrease, consistent with empirical observations. Additionally, foreign consumption also exhibits a short-term increase. The trajectory of TFP, initially declining before rising, also aligns with empirical trends. However, the nominal exchange rate initially depreciates over three quarters[16], diverging from empirical findings, but subsequently shows a persistent appreciation for more than 35 quarters, in line with observed data. Despite these similarities to the empirics, the model-based dominant CA driver does not accurately reflect empirical patterns in CPI and interest rate differentials and fails to capture the initial decline of foreign investment, which suggests room for future improvement of the model.

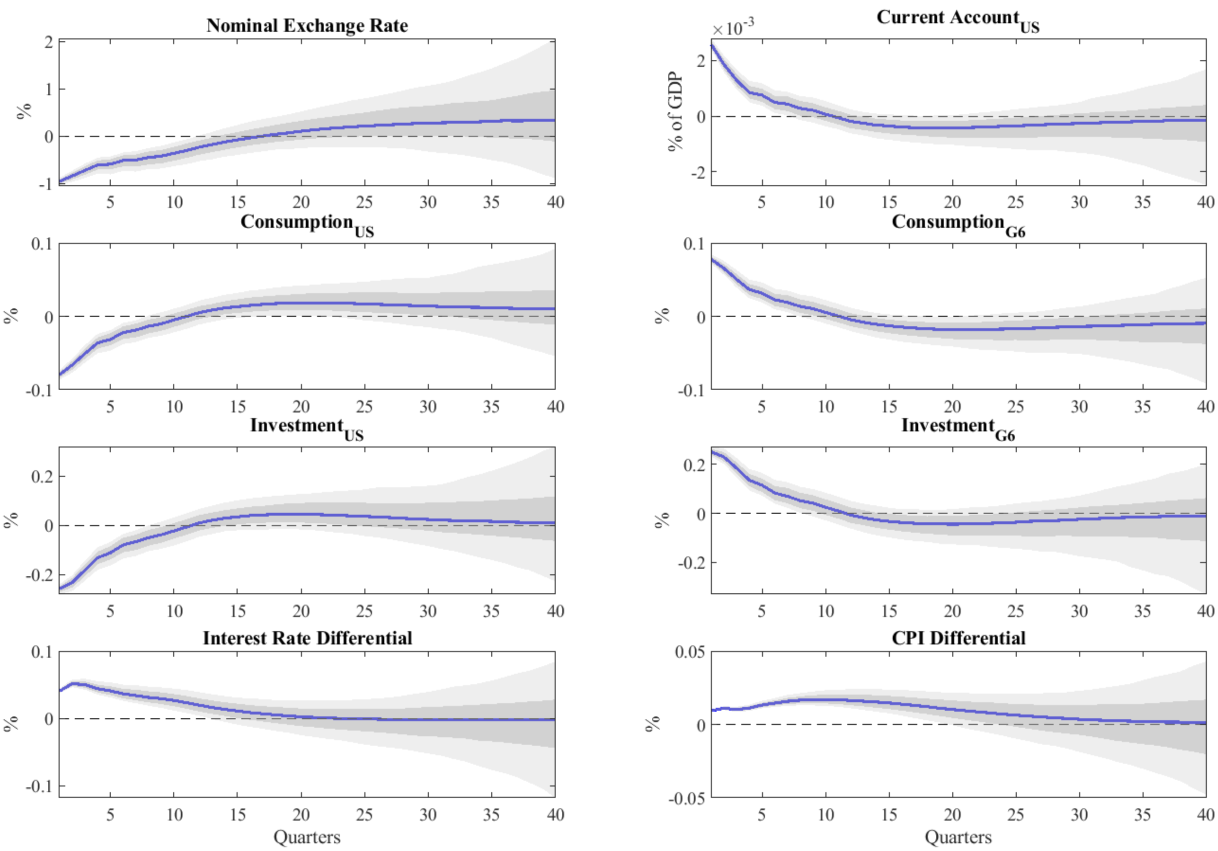
Next, we exclude all shocks other than the relative demand shock and simulate the calibrated model for 1000 periods. We then apply the max-share SVAR to the model-simulated data. We plot the IRFs of the obtained main CA shock in figure 7. While the dynamics of aggregate quantity variables are qualitatively similar to those of the dominant CA shock based on the complete set of shocks, the nominal exchange appreciates immediately after the shock.

As a comparison, we also simulate the model excluding only the relative demand shock and present the IRFs of the obtained dominant CA shock in figure B.49 in the appendix. We can see a significant expenditure switching in the short run after the main CA shock, which contradicts the data and the full-shock model. In addition, consumption and investment display some irregular dynamics not observed in the empirical, full-shock, and single relative demand shock scenarios.

Overall, our max-share SVAR identification of model-simulated data demonstrates the unique role of the relative demand shock in shaping the joint dynamics of the current account and other macro variables.

[16]The transitory exchange depreciation is mainly a result of a negative capital flow shock, which has been shown highly correlated with the dominant empirical CA driver in Table 3.

Figure 7: Impulse Responses to the Dominant CA Shock from Simulated Data with only the Relative Demand Shock



Notes: Point-wise median impulse responses to the dominant business cycle frequency exchange rate shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation.

4.5 Discussion

We find that for the US and also for the other G7 countries, relative demand shocks play an important role in accounting for current account fluctuations at business cycle frequency. The dominant CA shock is characterized by an increase in the current account balance and an exchange rate appreciation, which implies a shift in preferences for domestic over foreign goods, thereby more than offsetting a potential expenditure switching effect from other underlying structural shocks. Conventional aggregate shocks, be they demand or supply, will work through the expenditure switching channel and thus do not induce the observed comovement that is generated by the dominant CA shock. The relative demand shock's importance is reminiscent of the thesis of Stockman and Tesar (1995) that taste shocks are needed to bring about data-consistent comovements between consumption and prices in open-economy real business cycle models.

Ironically, the role of relative demand shocks seems to diminish in the long term, though with some heterogeneity. In the case of the US, the long-run dominant CA shock brings about an increase in the current account balance and exchange rate depreciation. The resurgence of the expenditure switching effect in the long run could be due to the low persistence of the relative demand shock, the lagged supply response to the persistent relative demand shock, which allows the expenditure switching channel to resurface, or the combination of both. The lagged supply response appears consistent with the recovery of investment over the medium term, even in response to the dominant CA shock at business cycle frequency.

5 Conclusion

Although current account imbalances frequently capture economic and political attention, their primary drivers remain elusive. This paper narrows this knowledge gap by empirically documenting the dominant CA shocks and comparing them with the shocks uncovered from an open-economy DSGE model, focusing on seven advanced economies.

We estimated the dominant CA shocks at business cycle frequency and over the long run using the max-share identification that places minimal restriction on the data. Our findings contradict the belief in the expenditure-switching effects dominate in the short term: associated with higher (smaller) current account surpluses (deficits), we often observe the real exchange rate appreciating or remaining relatively stable rather than depreciating. In addition, these dominant CA shocks are frequently associated with reductions in consumption and investment expenditure in the near to medium term, albeit with some cross-country heterogeneity.

By employing a DSGE model for our analysis, we shed light on the structural factors that help to interpret the dominant CA shock. A key result is the pivotal role of relative demand shocks driving the dominant CA shock. The relative demand shock is closely correlated with the dominant CA shock, when the estimated shock series are regressed on one another. When we apply the max-share identification to the simulated data generated only on the basis of the relative demand shock, the dominant CA shock uncovered from the simulated data exhibits impulse responses that come close to those of the dominant CA shock uncovered from the actual data.

These results, of course, do not imply that traditional aggregate shocks play no significant roles in current account movements, as they will be key factors behind current account movements orthogonal to the main CA shock. Current account movements are bound to reflect all major shocks, when consumption, saving, and investment are determined by the interaction of all shocks. Rather, the results highlight the importance of relative demand, which has hitherto received little attention in the literature on current account determinants.

Several extensions can be considered for future research. First, the model's data-matching ability and explanatory power can be strengthened by adding additional structures (e.g. consumption habits and non-tradables) or by deconstructing relative demand shocks into more primitive shocks. Second, models better suited for long-run analyses can be developed to interpret the dominant long-run CA shock. Third, in emerging markets that include commodity exporters and countries actively engaged in foreign exchange interventions, different factors might emerge behind the dominant CA shock.

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Appendices

A Data

Table A.1: Data Description, Sources and Coverage

Variable	Description	Source	Sample
Baseline Variables			
Consumption	Real private consumption	IMF Global Data Source	1975q1 - 2022q3
Investment	Real gross fixed capital formation	IMF Global Data Source	1975q1 - 2022q3
Nominal Exchange Rates	Bilateral USD exchange rates: Foreign Exchange Rates H.10	Board of Governors of the Federal Reserve System	1975q1 - 2022q3
Current Account	Sum of net primary income, net secondary income and net exports, all in % of GDP, seasonally adjusted	IMF International Financial Statistics	1975q1 - 2022q3
Interest Rates	1 month deposit rates: ECCAD1M, ECFFR1M, ECITL1M, ECWGM1M, ECJAP1M, ECUKP1M, ECUSD1M	Refinitiv Eikon Datastream	1975q1 - 2022q3
CPI	Consumer Price Index	IMF Global Data Source	1975q1 - 2022q3
Utilization-adjusted US TFP	Fernald (2014)	Fernald's webpage	1975q1 - 2022q3
Additional Variables			
BOGZ1FL072052006Q	Effective Federal Funds Rate	FRED	1975q1 - 2022q3
Exports	Real exports (s.a.)	IMF Global Data Source	1975q1 - 2022q3
Imports	Real imports (s.a.)	IMF Global Data Source	1975q1 - 2022q3
Utilization-adjusted TFP (DE, FR, IT, UK)	Schmidt et al. (2021)	Elstner's webpage	1991q1 - 2019q4
TFP Canada	Cao (2021)	Cao's webpage	1976q1 - 2018q3
Current Account Japan	Sum of net primary income, net secondary income and net exports, all in % of GDP, seasonally adjusted	CEIC Data Global Database	1975q1 - 2022q3

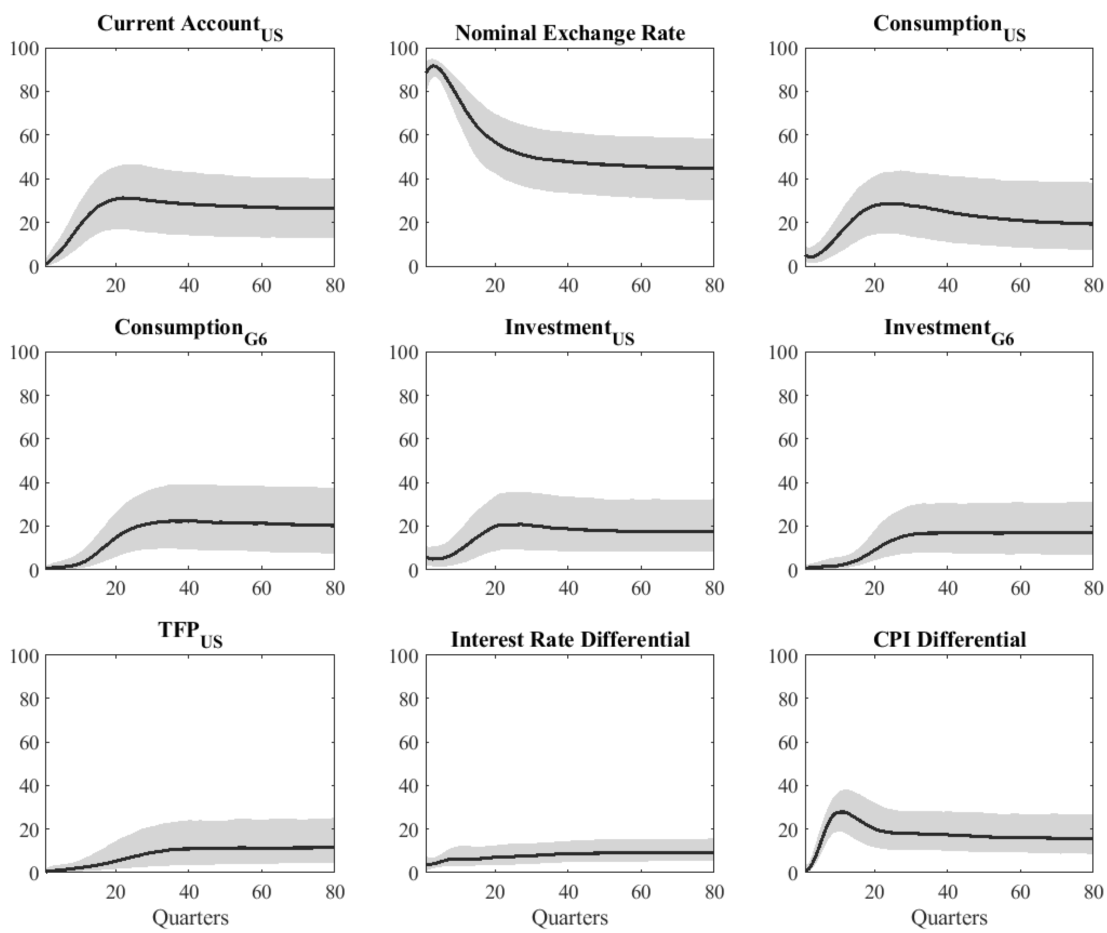
The interest rate data from Refinitiv Eikon Datastream are midpoint of the offer and bid rates. The quarterly nominal exchange rates are calculated as the end-of-period daily rates from the Fed Board. The weights for each country to calculate the G6 averages are yearly world trade weights taken from the IMF Direction of Trade Statistics. To calculate the averages for the nominal exchange rate, consumption, investment, the interest rate and CPI, we calculate a geometric average, e.g. as $cpi_{G6} = \Pi_{j=1}^{6}(1 + cpi_j)^{weight_j}$ for the average G6 CPI and $i_{G6} = \Pi_{j=1}^{6}(1 + i_j/100)^{weight_j} - 1$ for the average G6 interest rate. The interest rate differential for country j is calculated as $log((1 + i_j/100)/log(1 + i_{G6}))$ and the CPI differential as $log(CPI_j/CPI_{G6})$.

B Empirical Part - Additional Results

B.1 Additional US Results

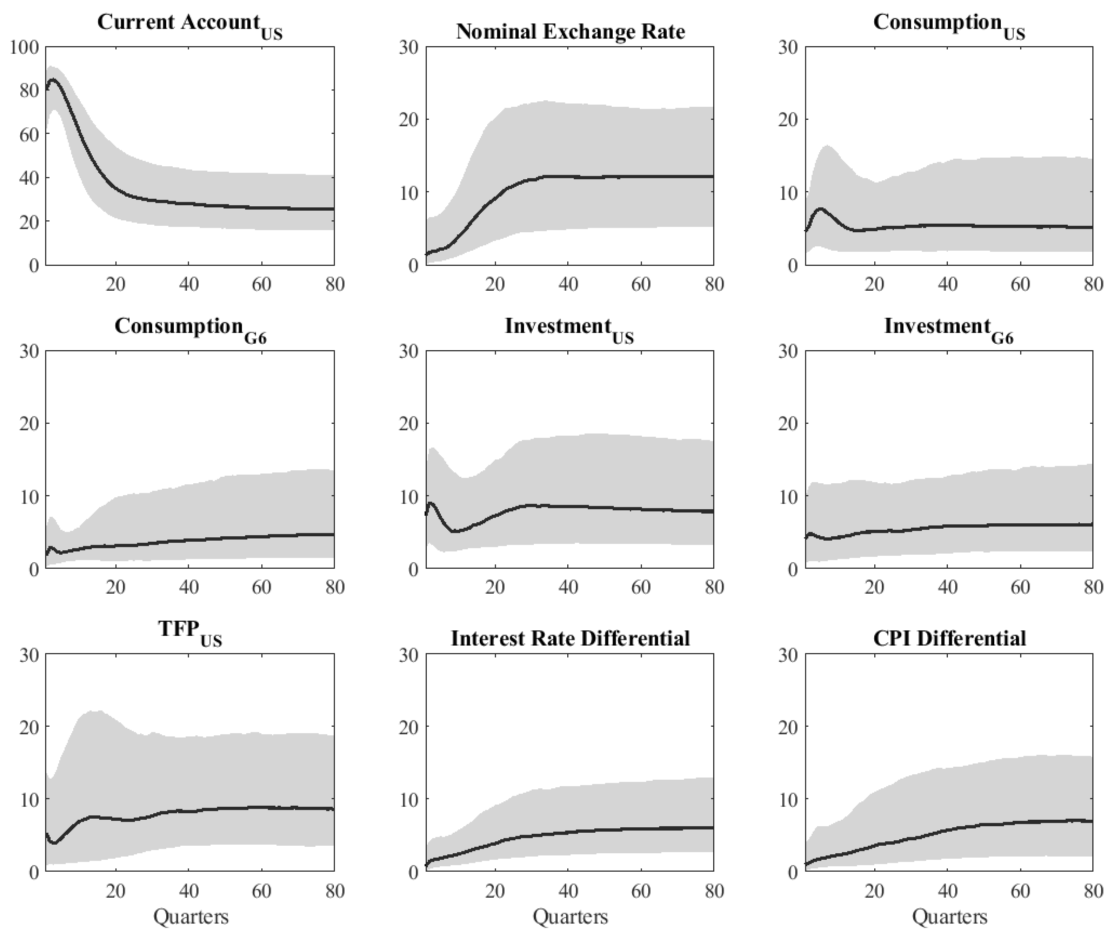
B.1.1 Forecast Error Variance Decomposition

Figure B.1: Forecast Error Variance Decomposition for the Dominant Business Cycle Exchange Rate Shock



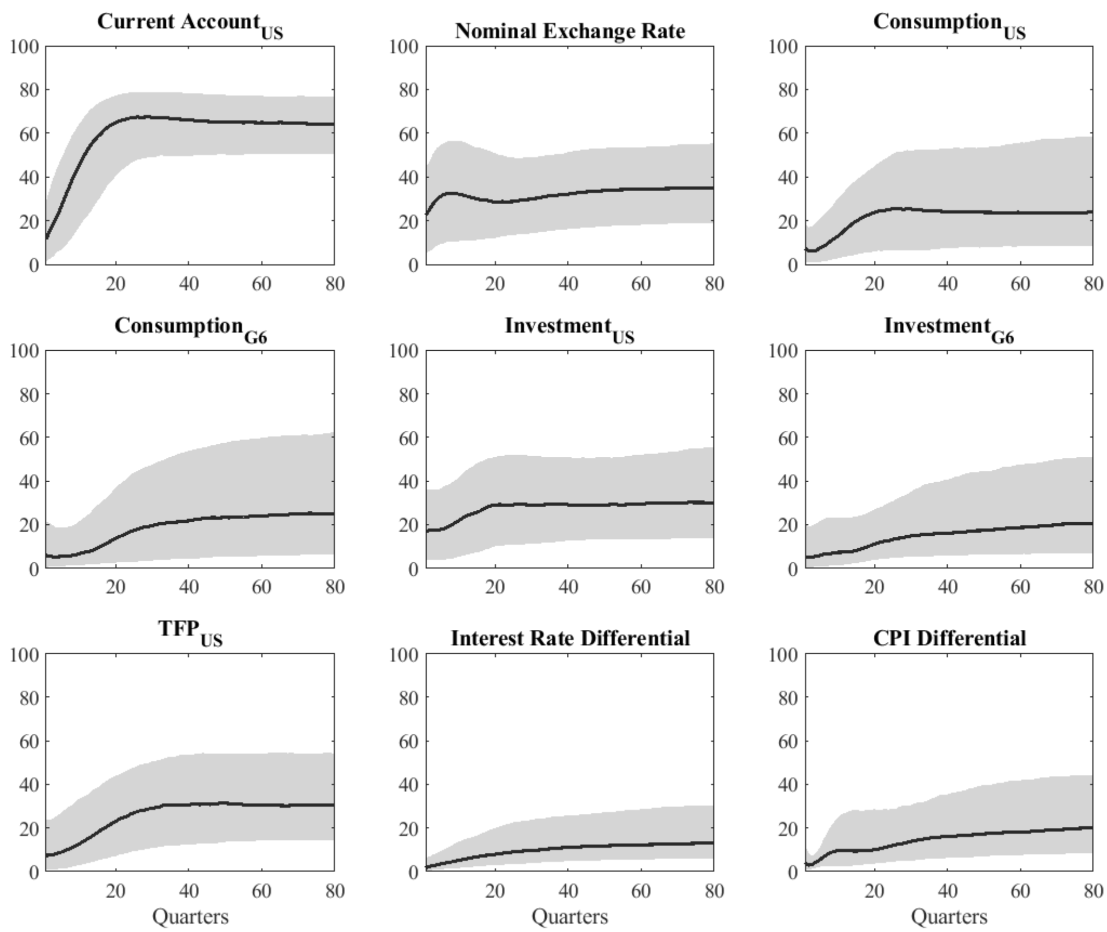
Notes: Forecast error variance decomposition with 68% highest posterior density credible sets based on 1000 draws.

Figure B.2: Forecast Error Variance Decomposition for the Dominant Business Cycle CA Shock



Notes: Forecast error variance decomposition with 68% highest posterior density credible sets based on 1000 draws. Note the different y-axis scales.

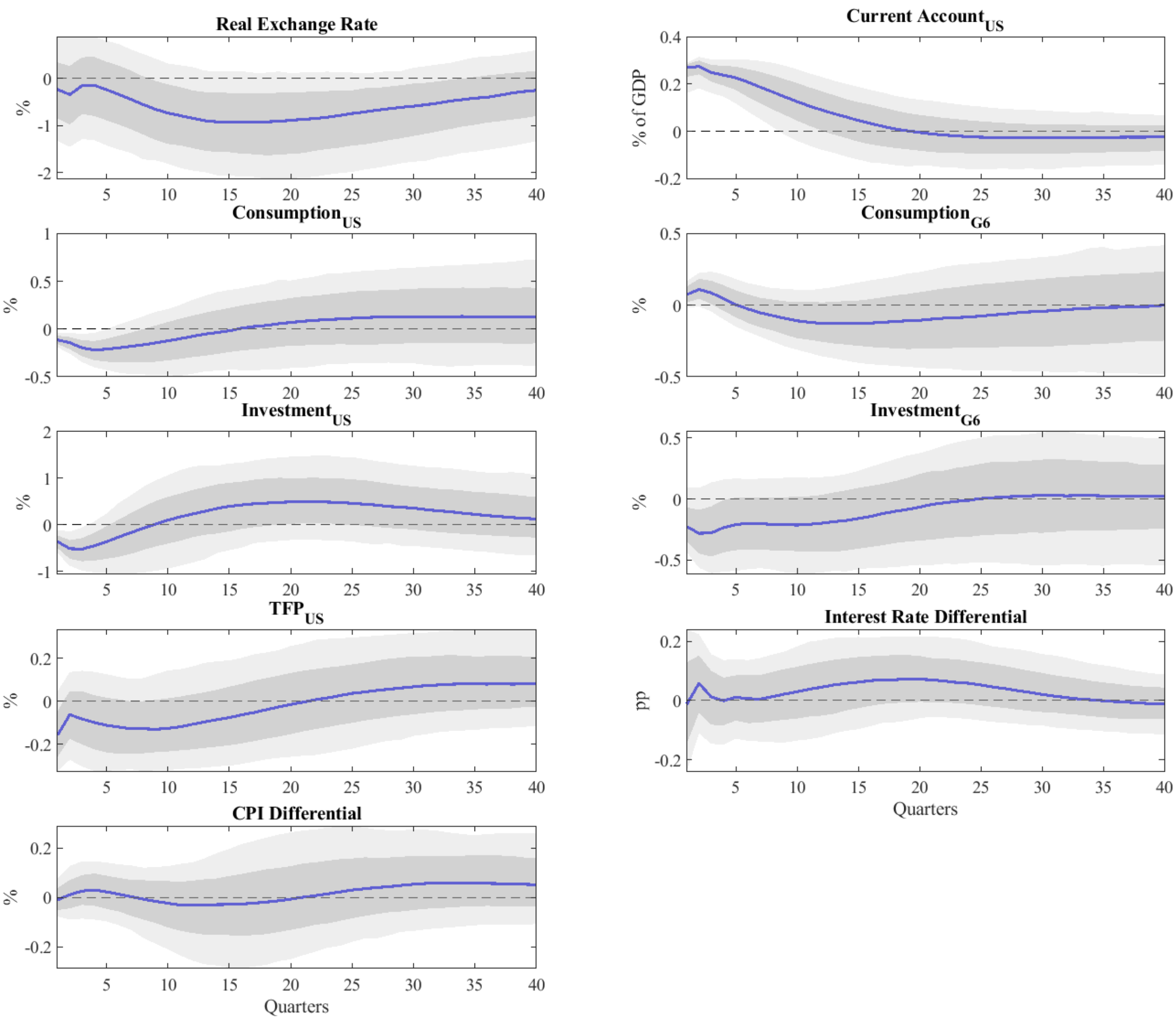
Figure B.3: Forecast Error Variance Decomposition for the Dominant Long Run CA Shock



Notes: Forecast error variance decomposition with 68% highest posterior density credible sets based on 1000 draws.

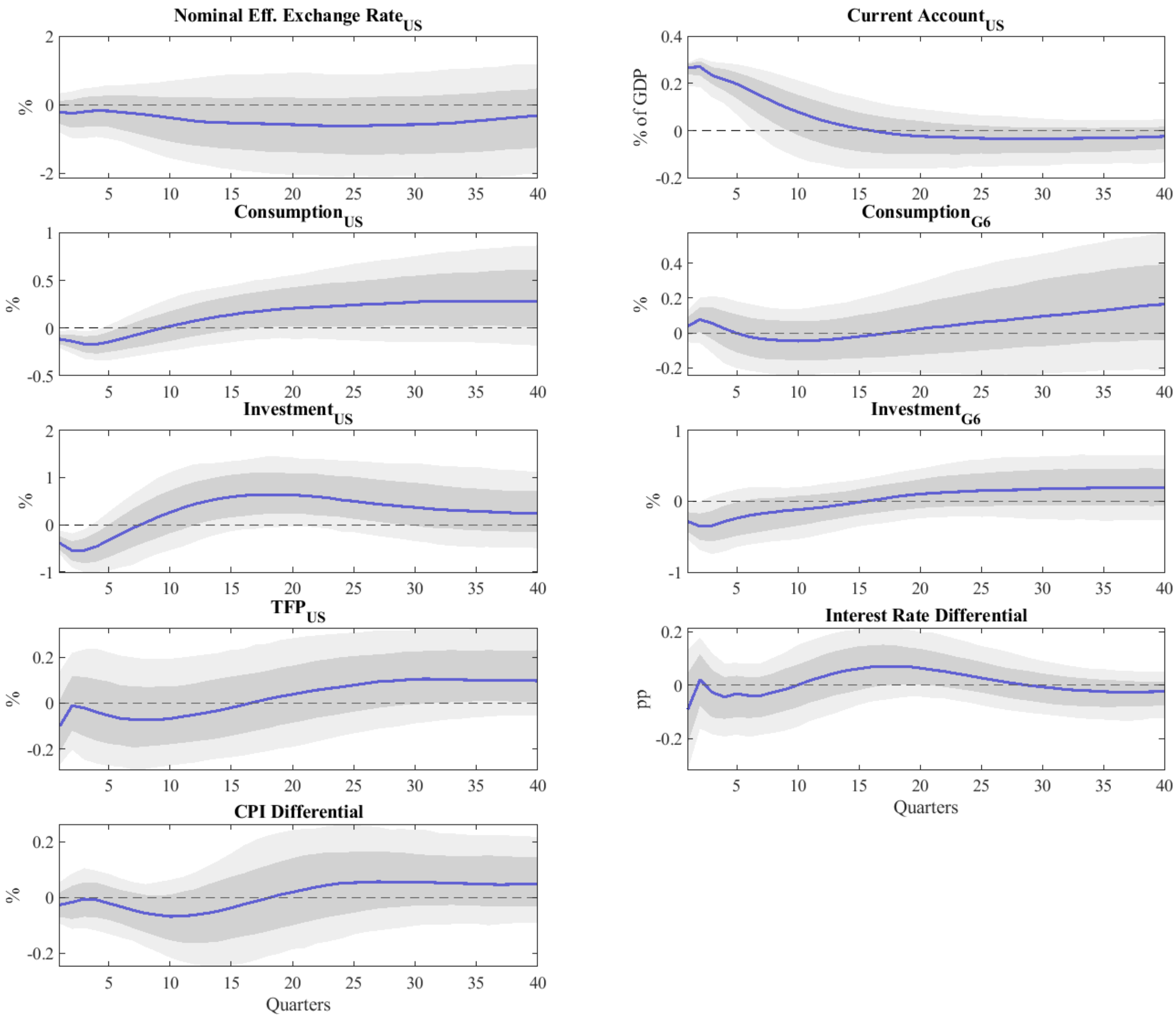
B.1.2 Different Exchange Rate Variables: Dominant Business Cycle Frequency CA Shock

Figure B.4: Impulse Responses to the Dominant Business Cycle Frequency CA Shock: Real Exchange Rate



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the real exchange rate is a depreciation vs. G6 countries' currencies. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

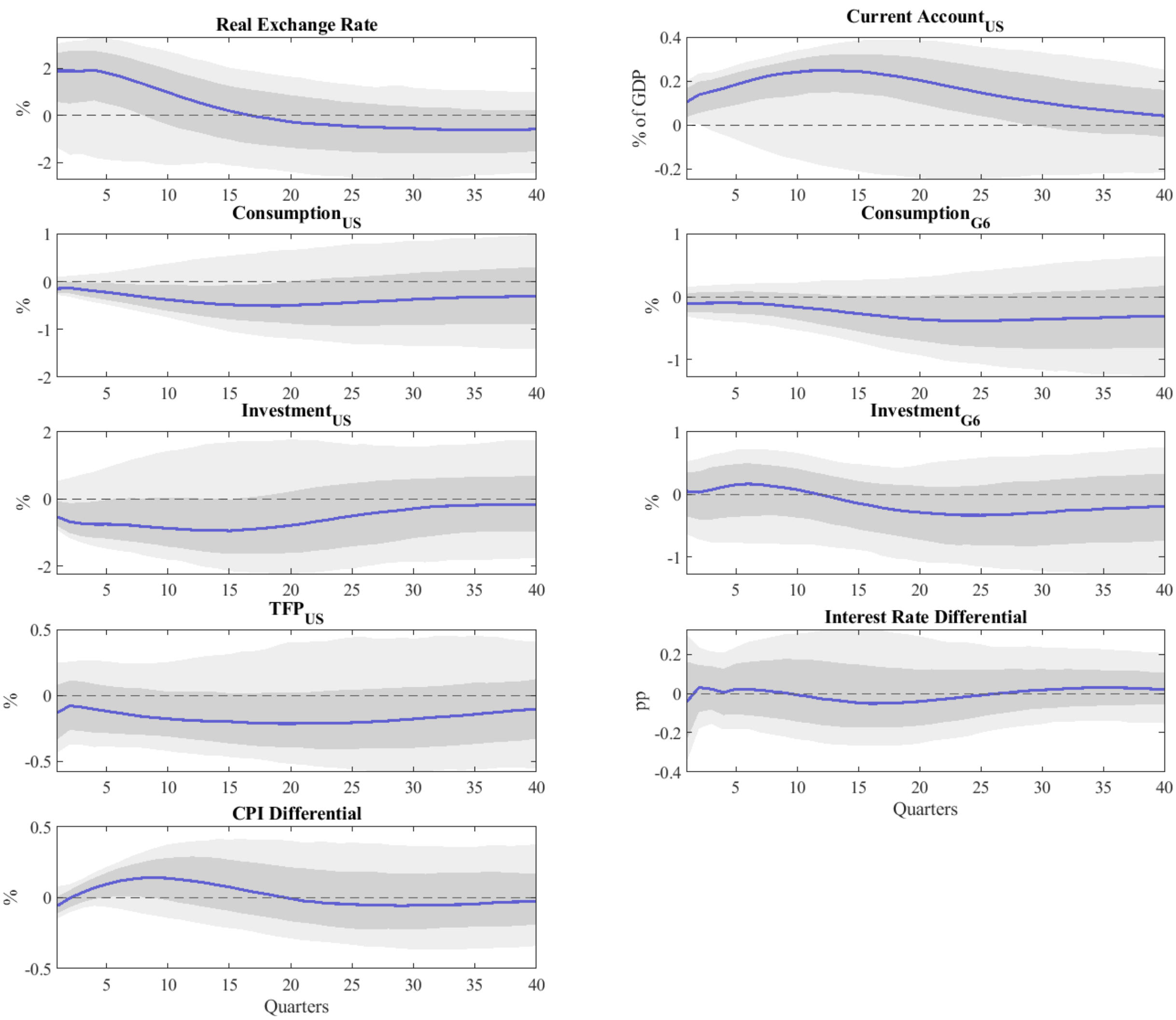
Figure B.5: Impulse Responses to the Dominant Business Cycle CA Shock: Nominal Eff. Exchange Rate



Notes: Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal effective exchange rate vs. 51 countries is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

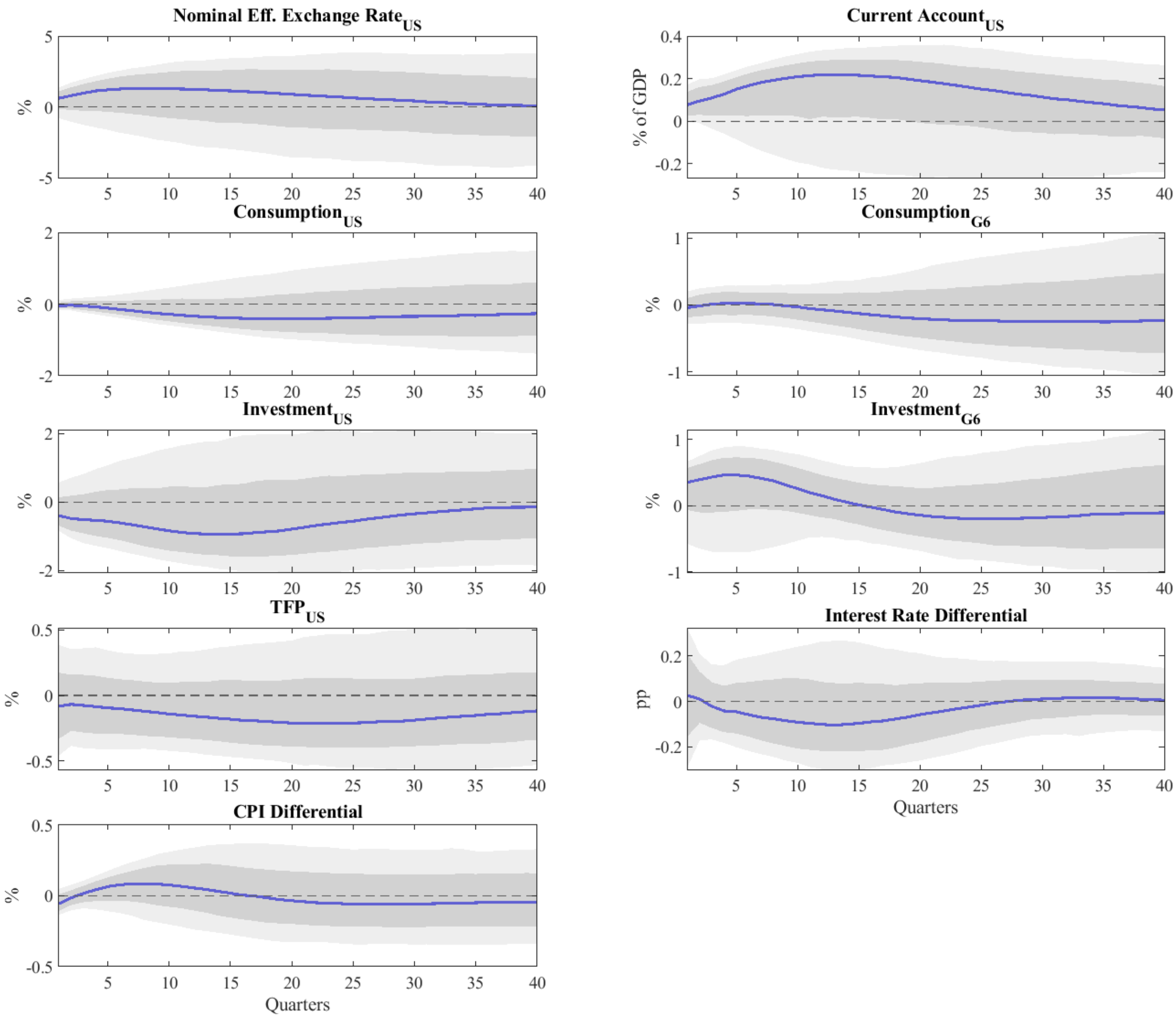
B.1.3 Different Exchange Rate Variables: Dominant Long Run CA Shock

Figure B.6: Impulse Responses to the Dominant Long Run CA Shock: Real Exchange Rate



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the real exchange rate is a depreciation vs. G6 countries' currencies. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

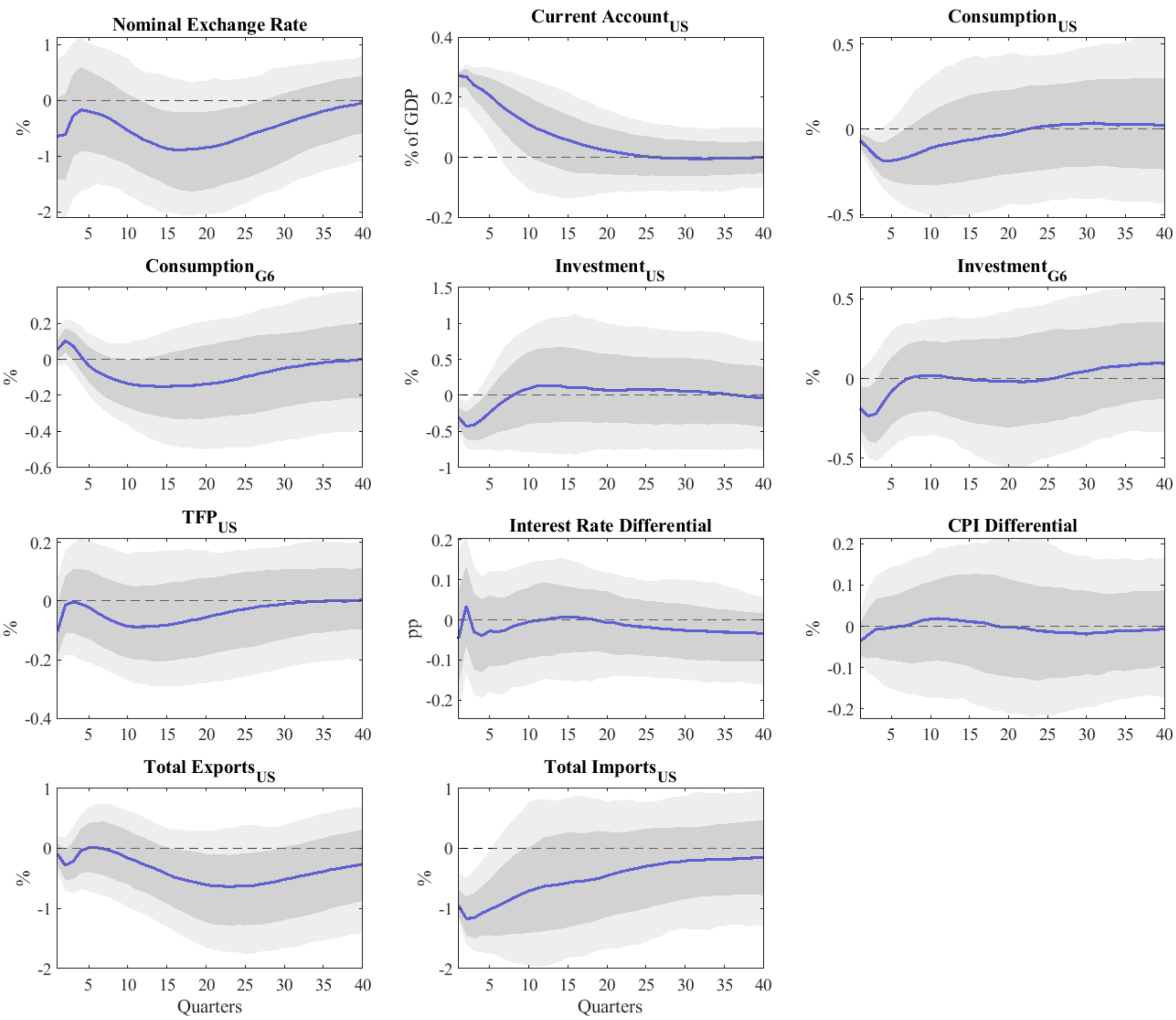
Figure B.7: Impulse Responses to the Dominant Long Run CA Shock: Nominal Eff. Exchange Rate



Notes: Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal effective exchange rate vs. 51 countries is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

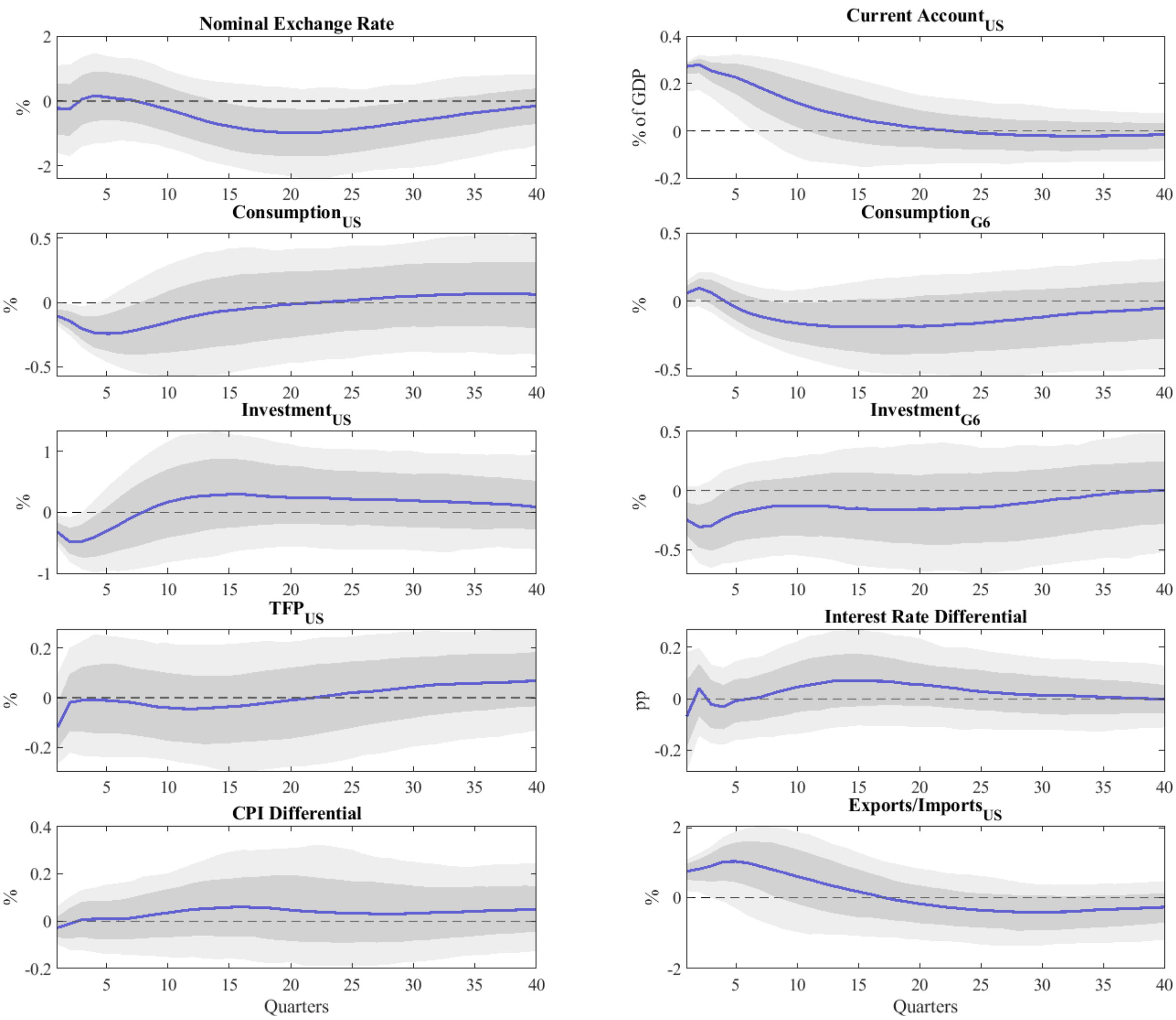
B.1.4 Further US Specifications: Dominant Business Cycle Frequency CA Shock

Figure B.8: Impulse Responses to the Dominant Business Cycle CA Shock: Total Exports and Imports Added



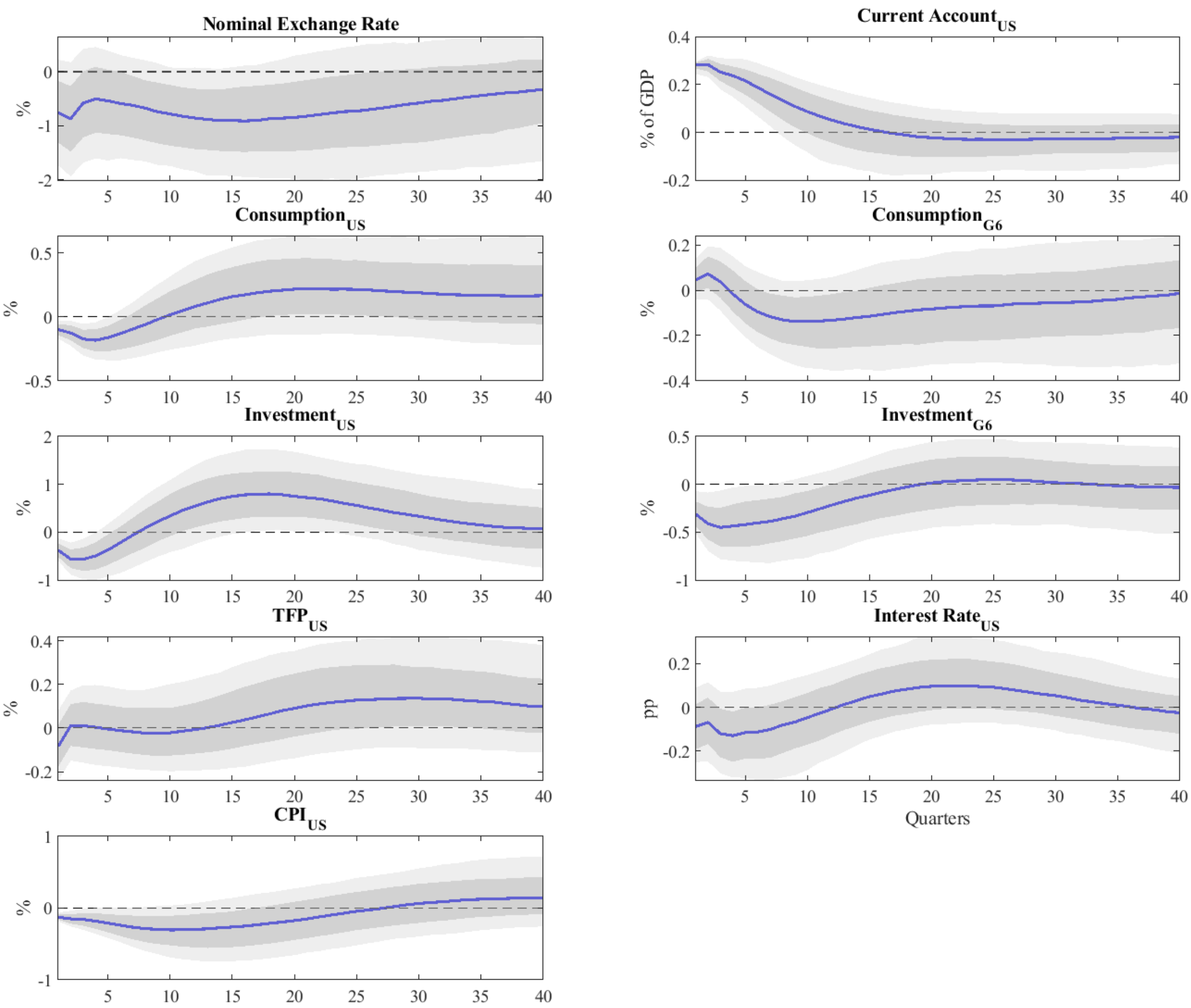
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.9: Impulse Responses to the Dominant Business Cycle CA Shock: Exports/Imports Ratio Added



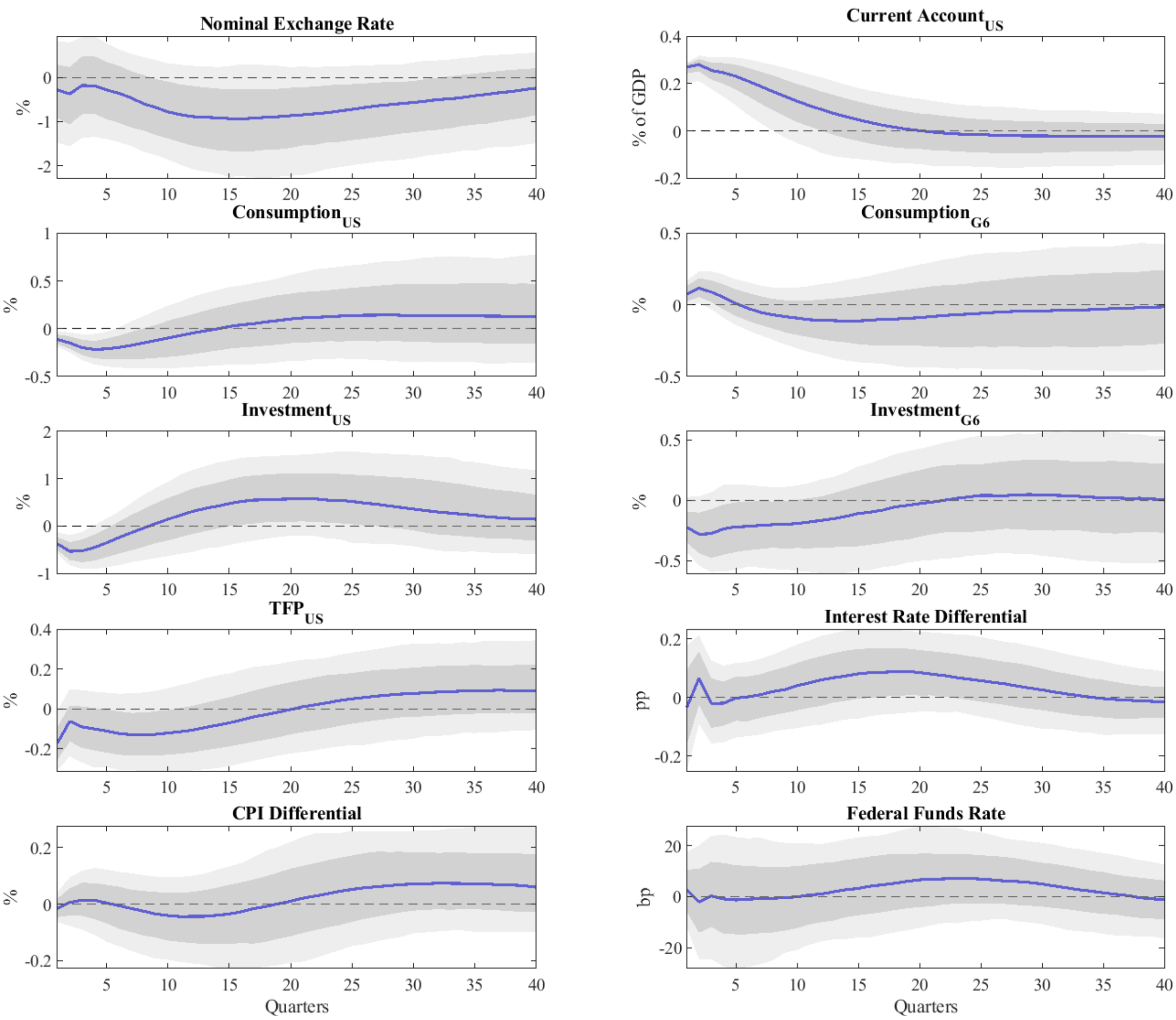
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.10: Impulse Responses to the Dominant Business Cycle CA Shock: CPI and Interest Rate Level



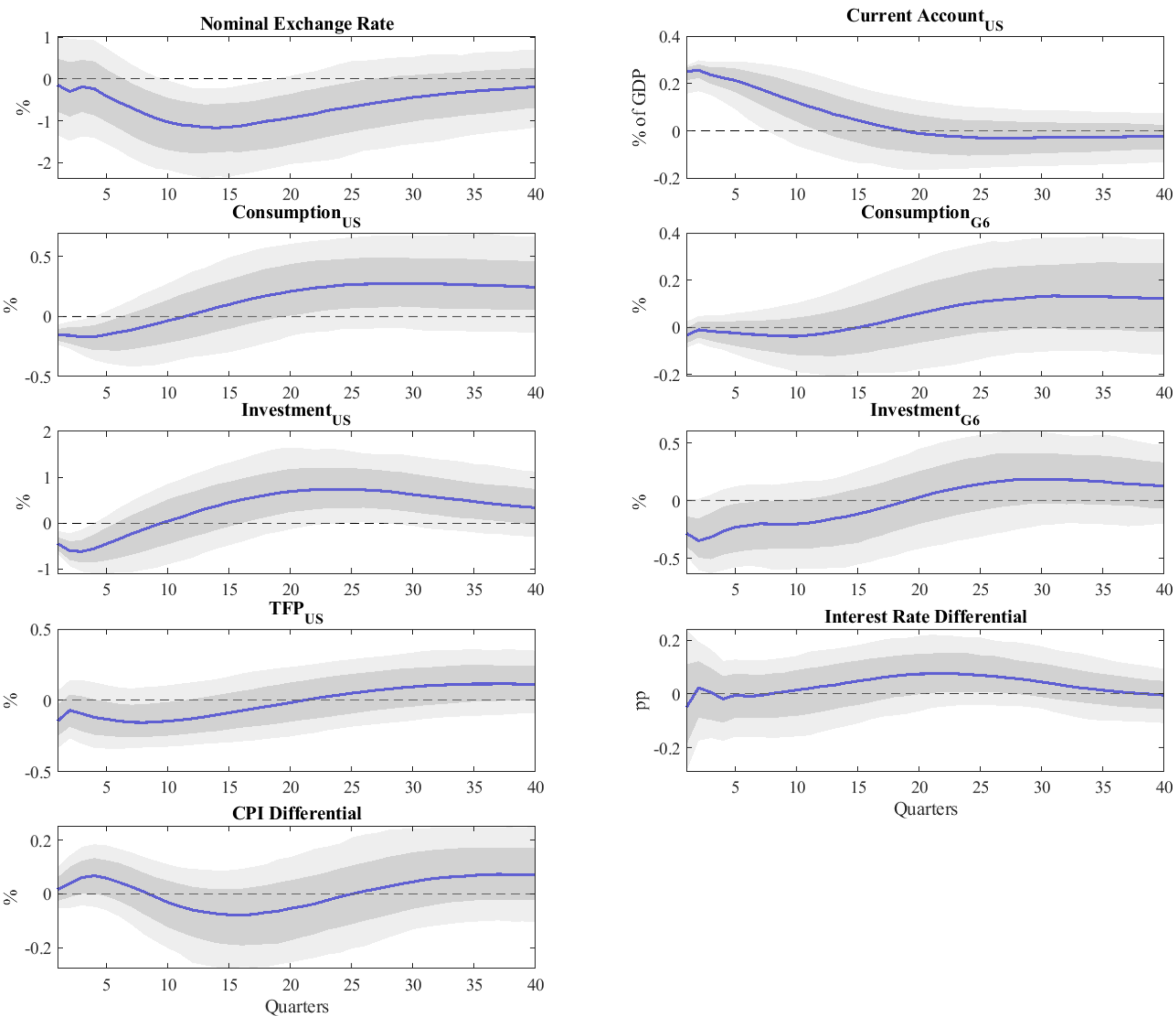
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.11: Impulse Responses to the Dominant Business Cycle CA Shock: Federal Funds Rate Added



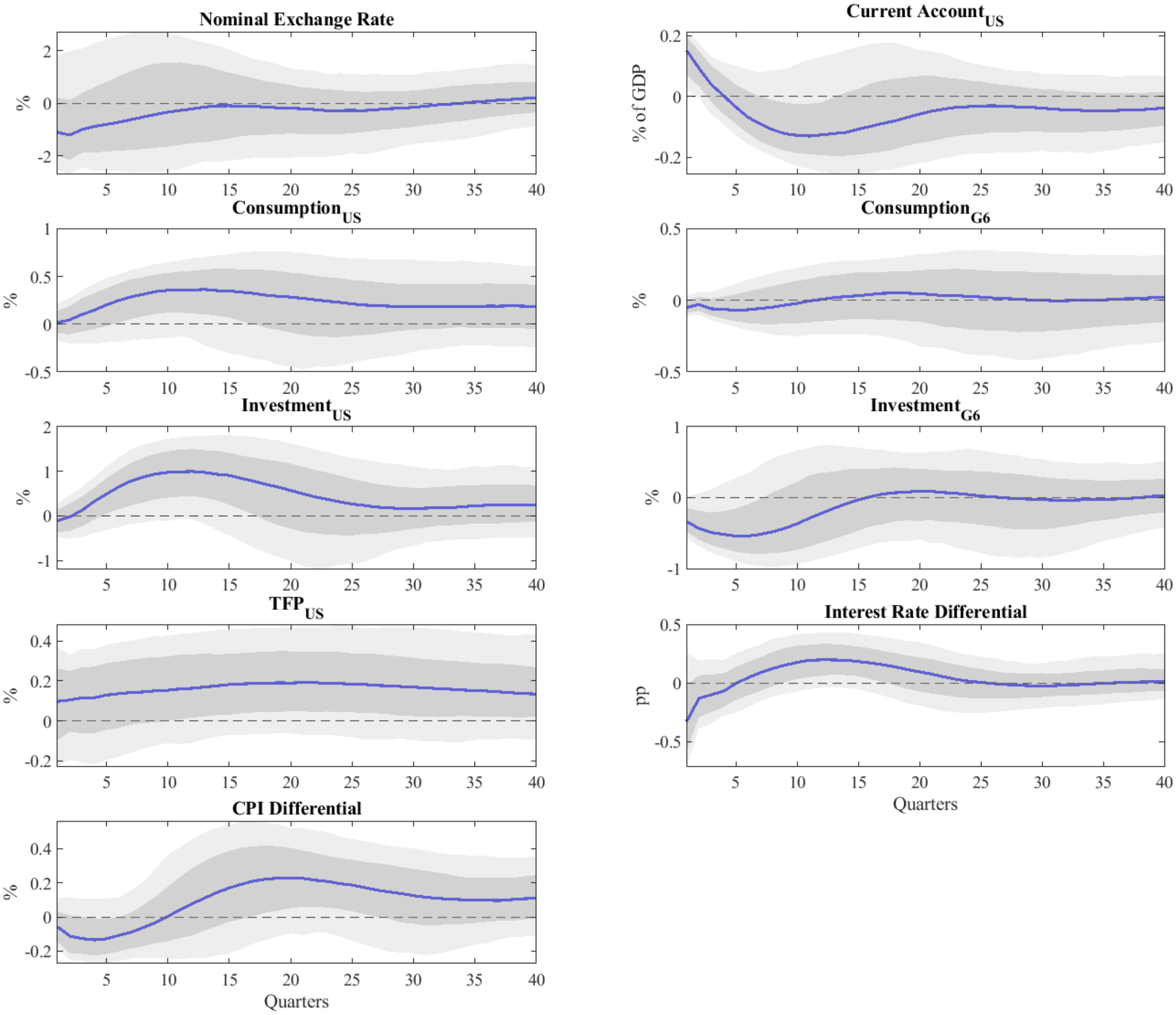
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.12: Impulse Responses to the Dominant Business Cycle CA Shock: Sample ends in 2019q4



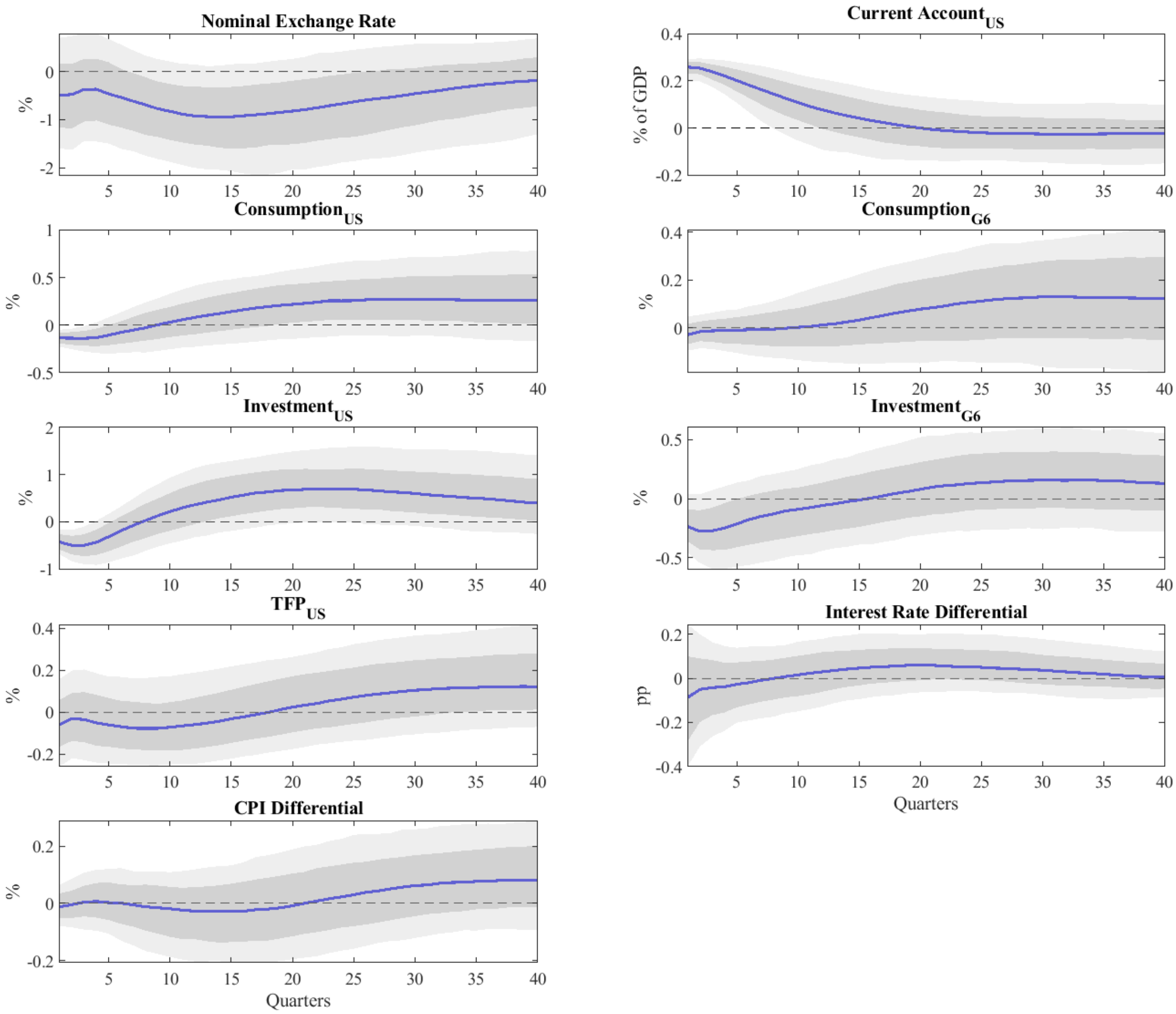
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.13: Impulse Responses to the Dominant Business Cycle CA Shock: Sample ends in 2007q4



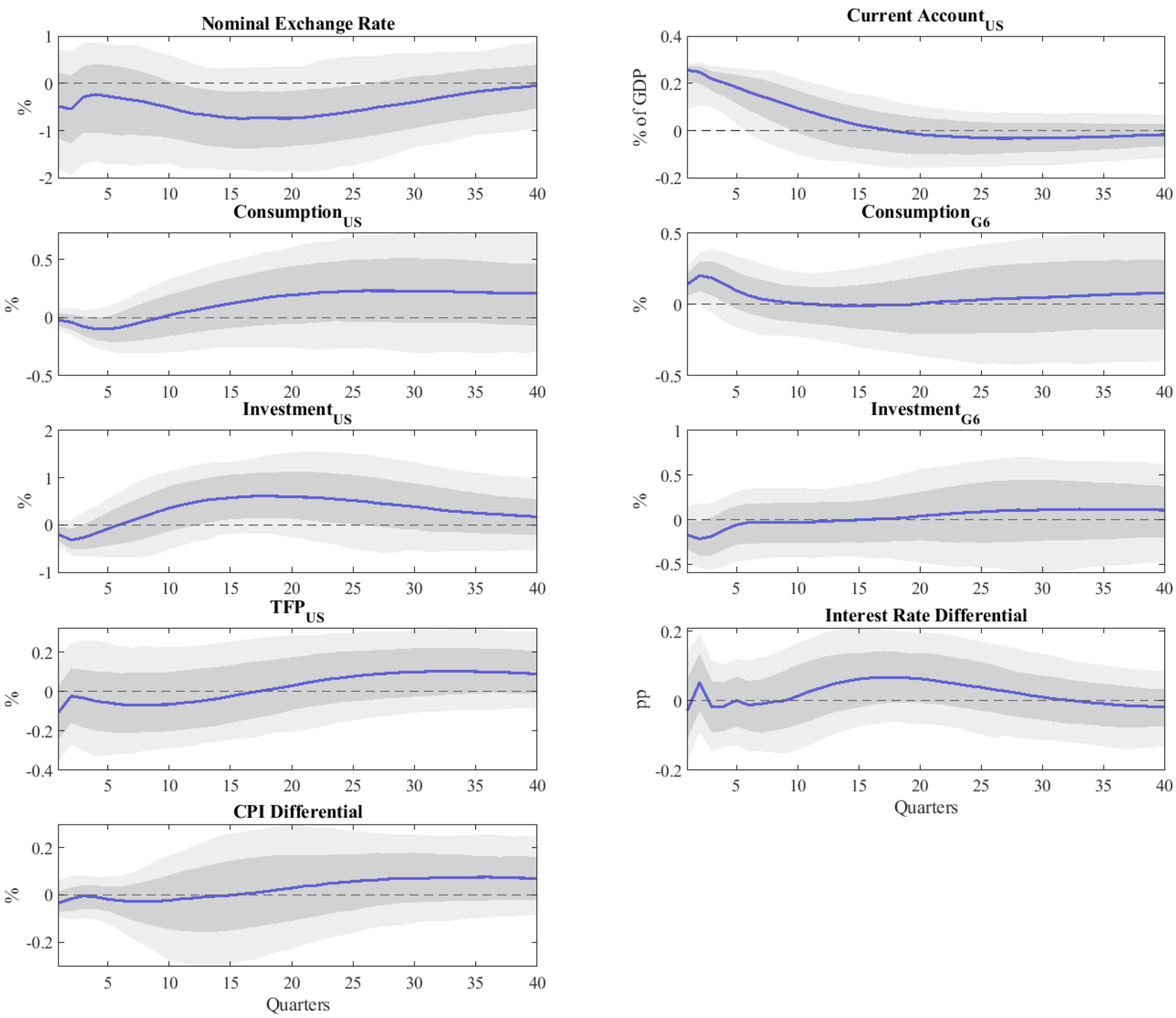
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.14: Impulse Responses to the Dominant Business Cycle CA Shock: Estimation via Lenza-Primiceri (2021) algorithm



Notes: The reduced-form VAR is estimated as in Lenza and Primiceri (2022); Giannone et al. (2015) by downweighing the importance of observations during the Covid period and selecting the Minnesota prior parameters via prior hyper-parameters to maximize the marginal data density. Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

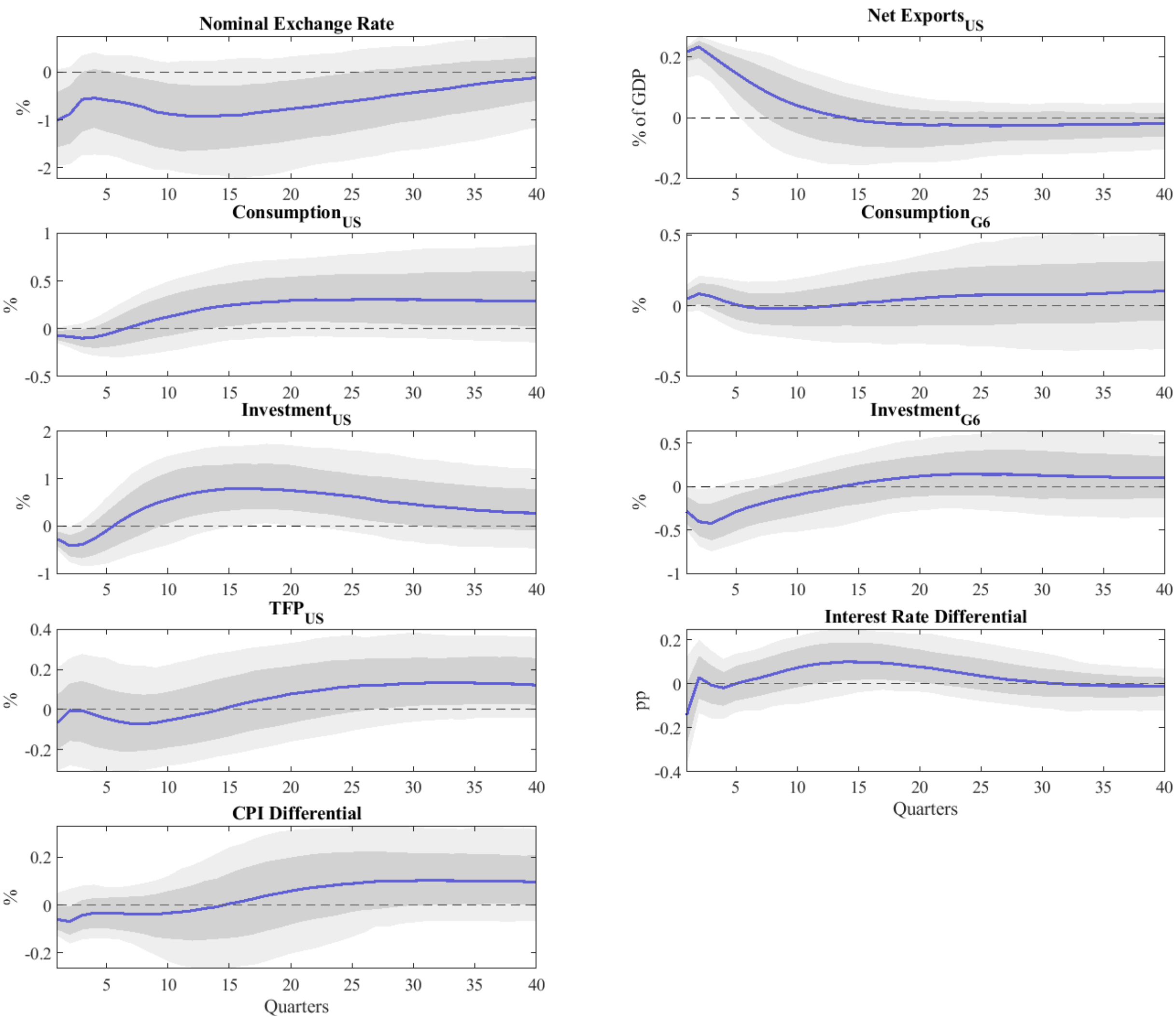
Figure B.15: Impulse Responses to the Dominant Business Cycle CA Shock: Lag Length of 8 Quarters



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

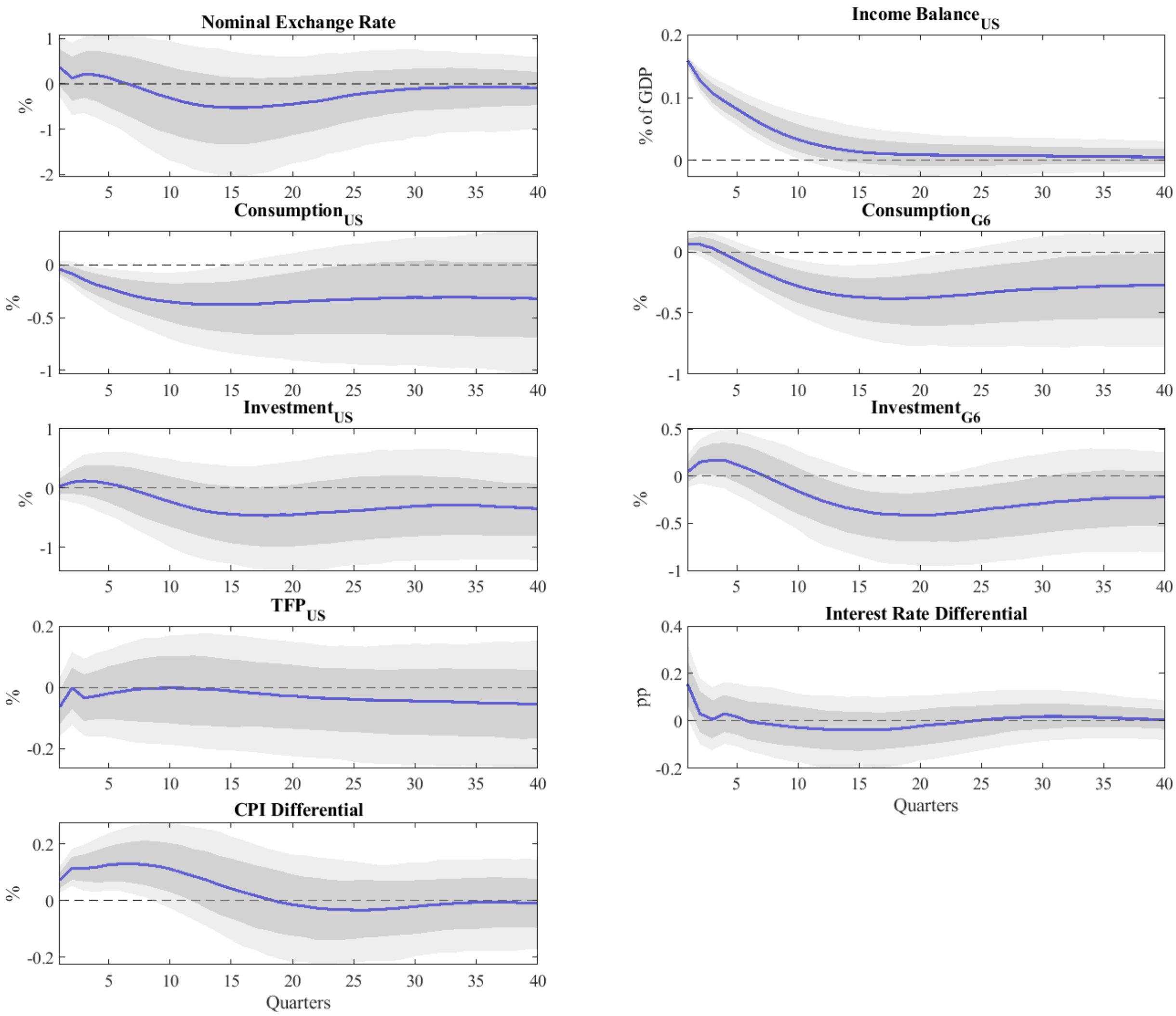
B.1.5 Further US Specifications: Related Dominant Business Cycle Frequency Shocks

Figure B.16: Impulse Responses to the Dominant Business Cycle Net Exports Shock



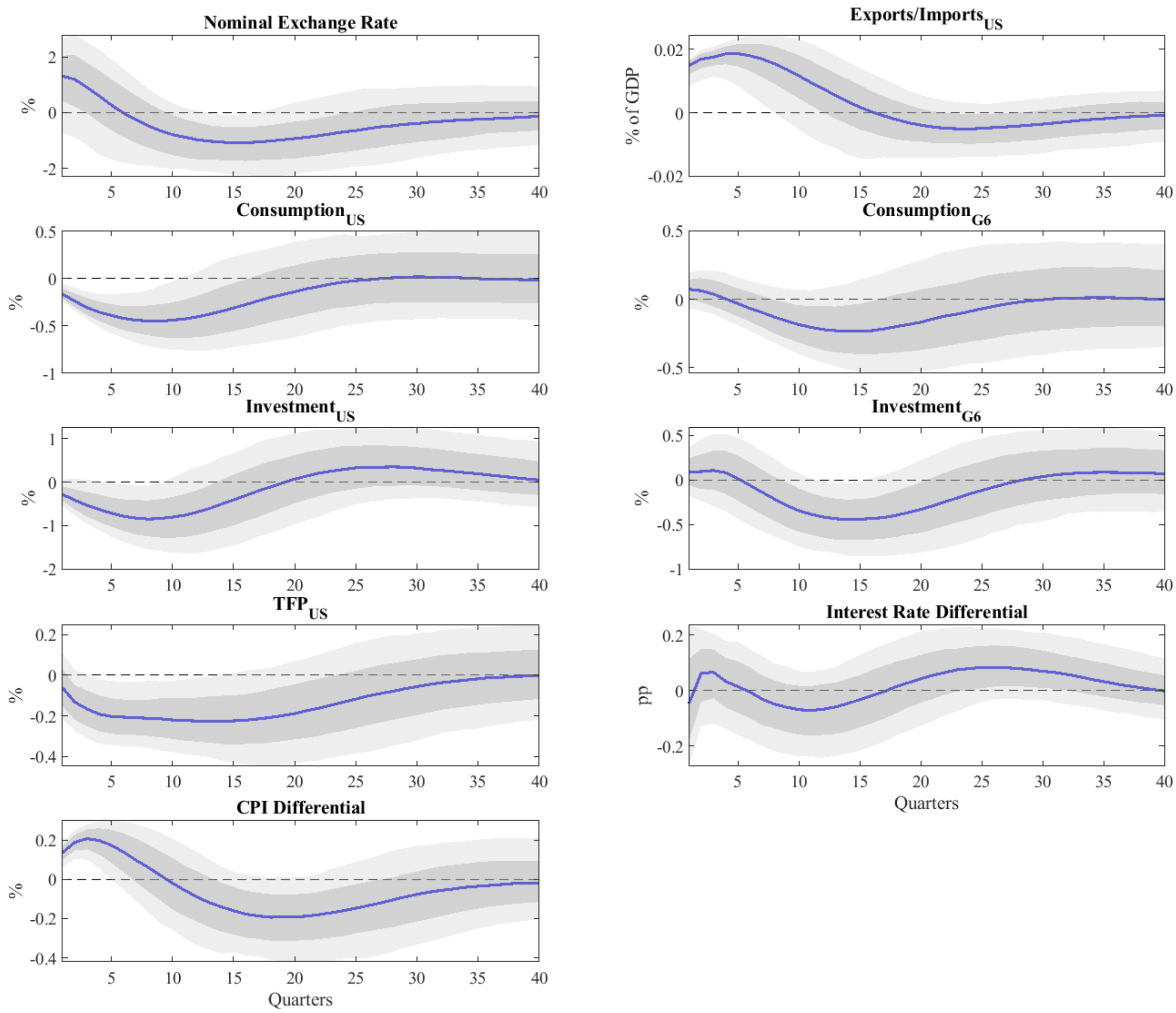
Notes: The shock is identified as maximizing the explained variation of US net exports/GDP at business cycle frequency. Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.17: Impulse Responses to the Dominant Business Cycle Income Balance Shock



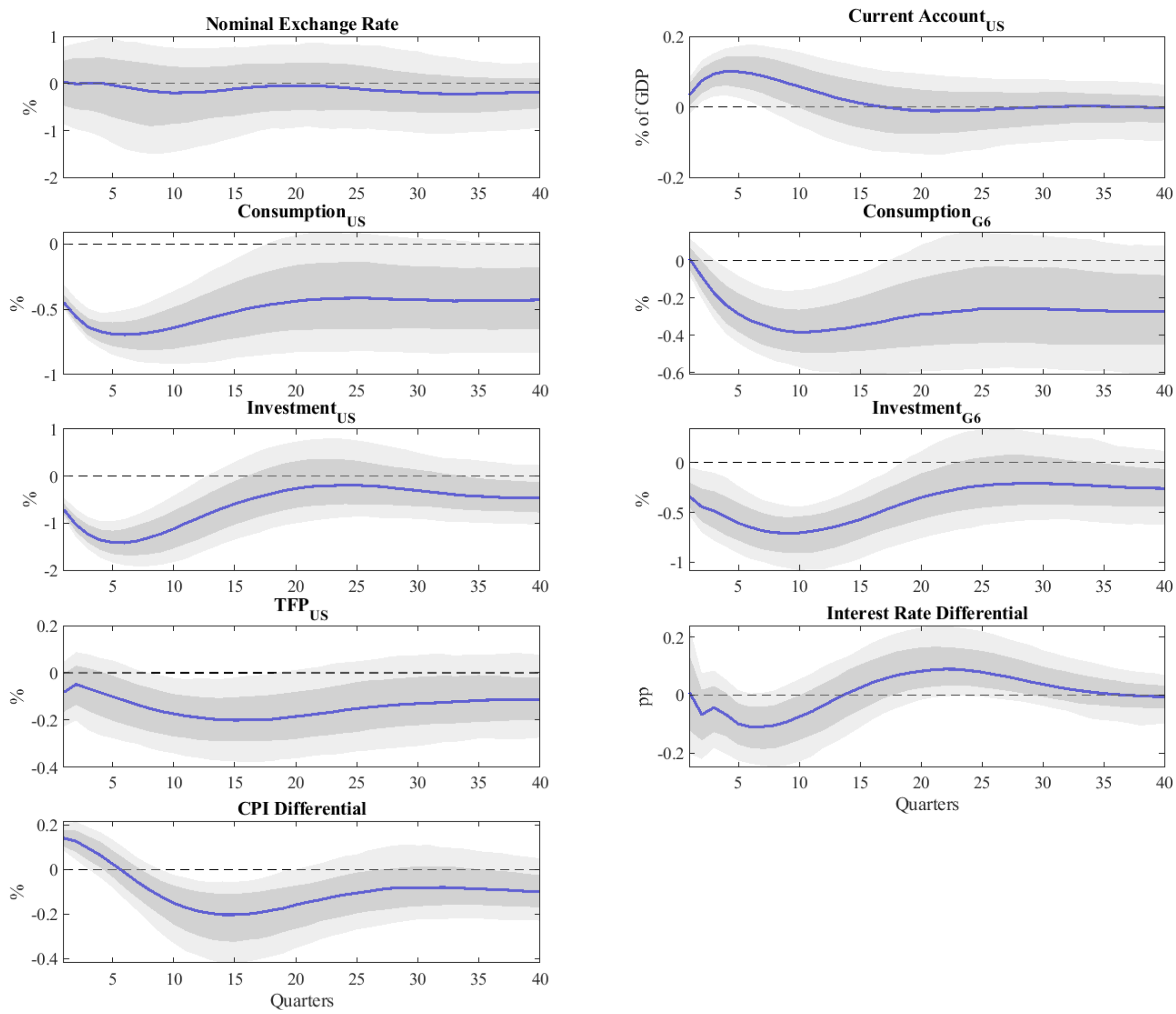
Notes: The shock is identified as maximizing the explained variation of the US income balance/GDP at business cycle frequency. Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

Figure B.18: Impulse Responses to the Dominant Business Cycle Export/Import Ratio Shock



Notes: The shock is identified as maximizing the explained variation of US total exports over total imports at business cycle frequency. Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

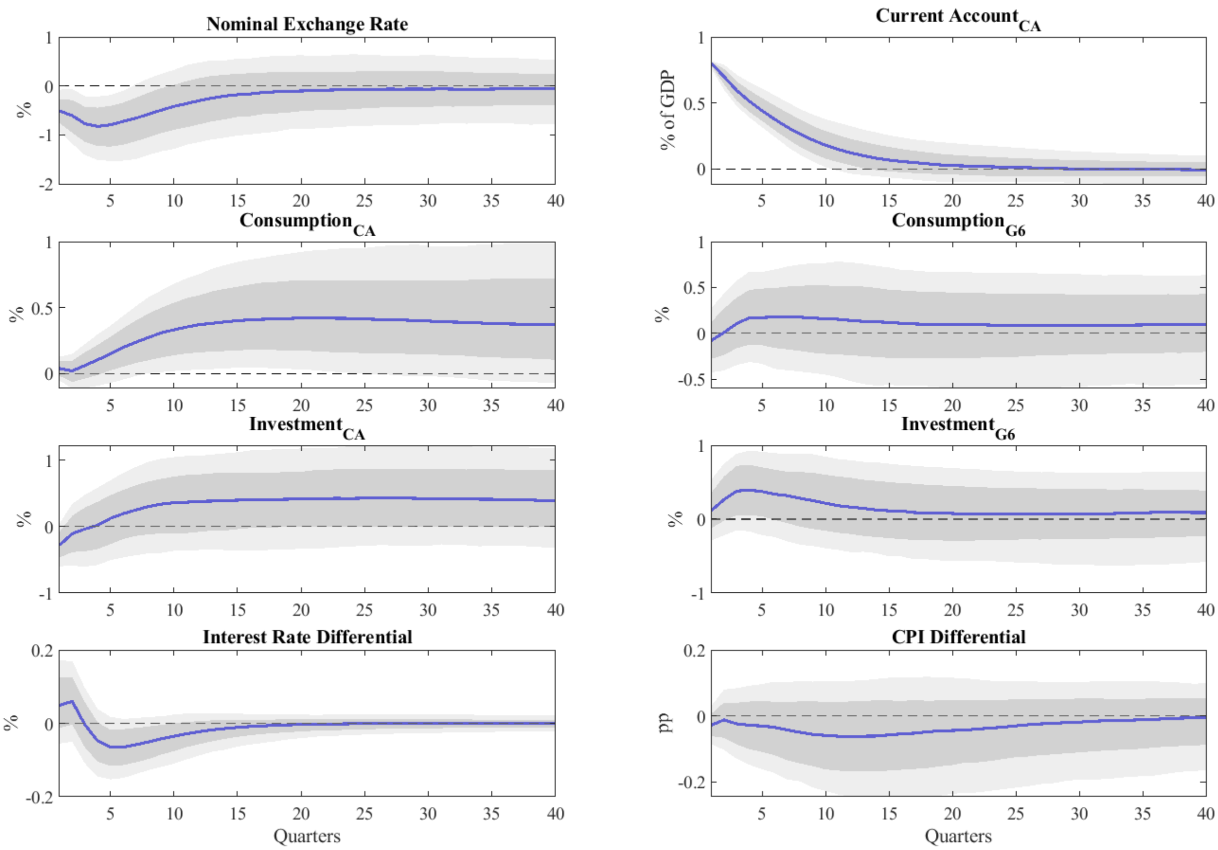
Figure B.19: Impulse Responses to the Dominant Business Cycle (Consumption) Shock



Notes: The shock is identified as maximizing the explained variation of US consumption at business cycle frequency. Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the UK.

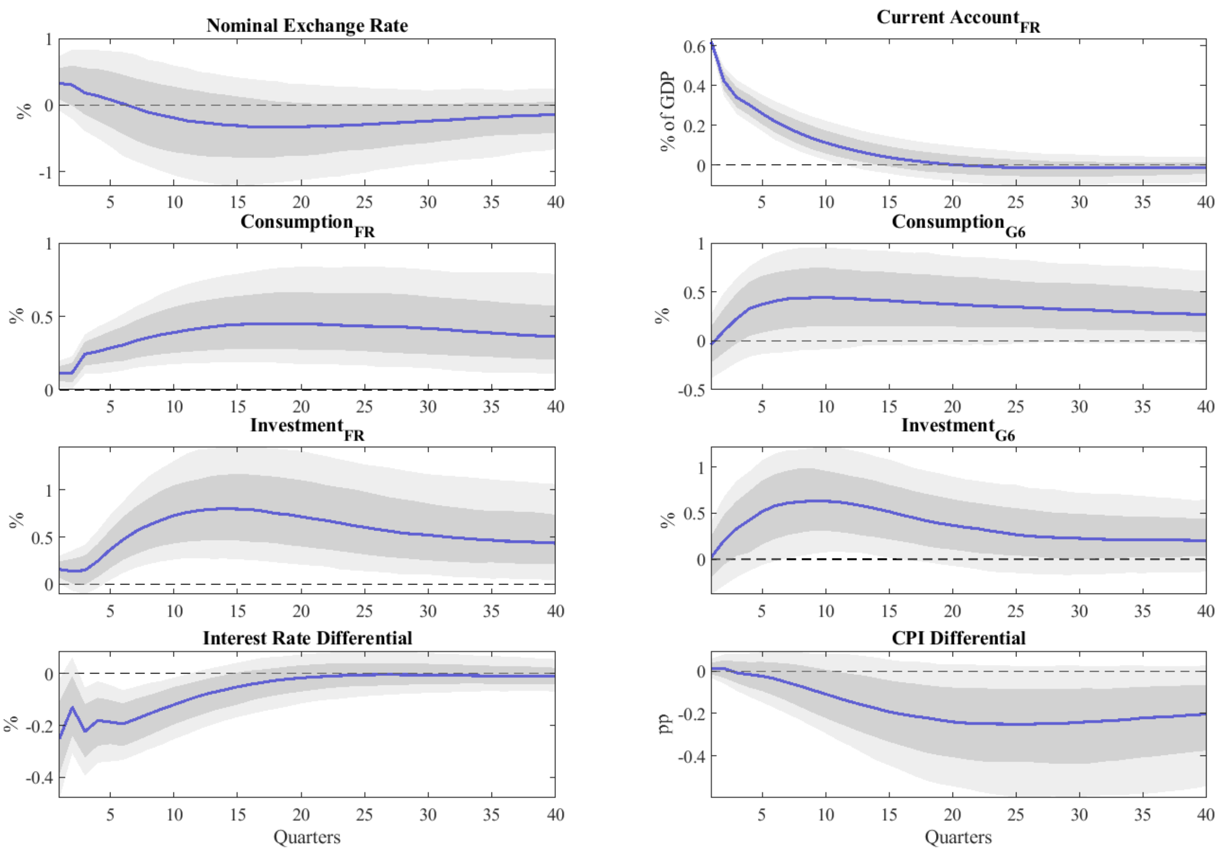
B.1.6 Additional Country Results: Dominant Business Cycle Frequency CA Shocks for other G7 Countries

Figure B.20: Impulse Responses to the Dominant Business Cycle CA Shock: Canada



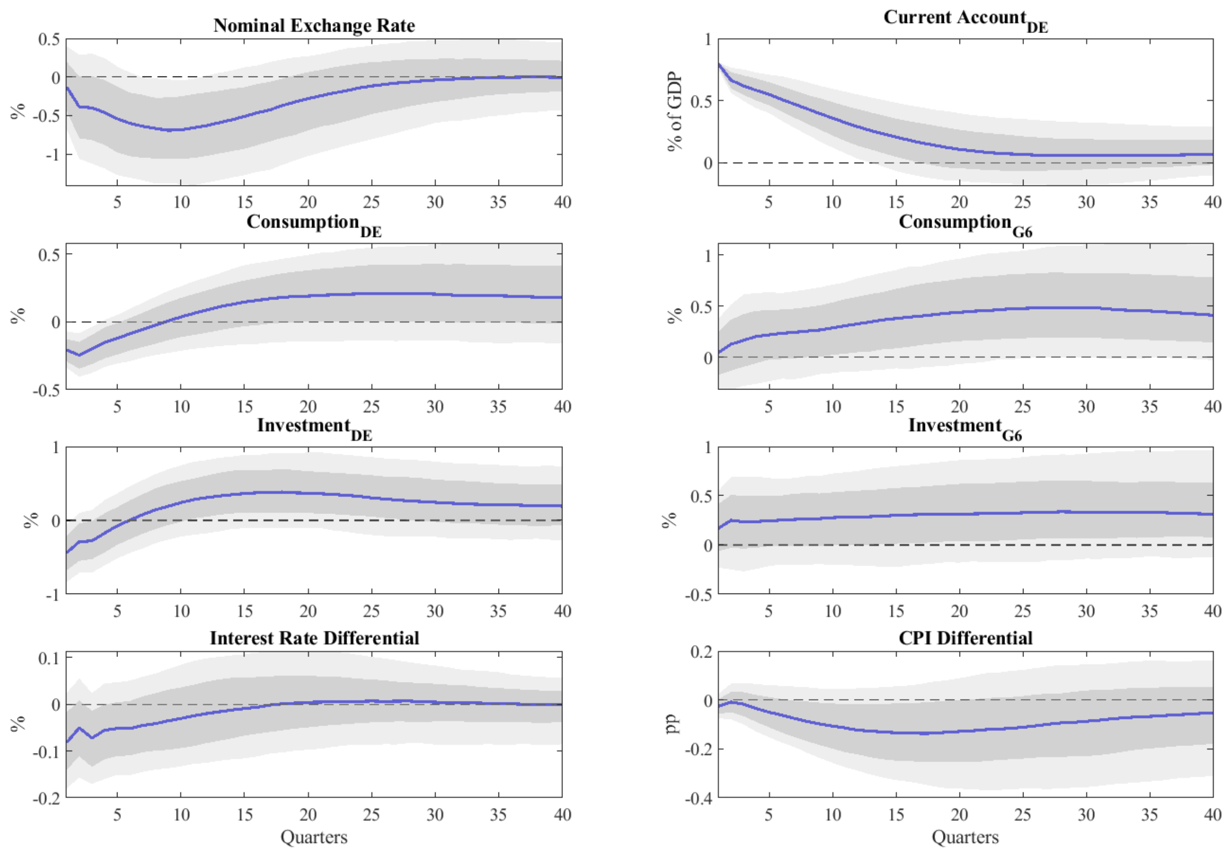
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.21: Impulse Responses to the Dominant Business Cycle CA Shock: France



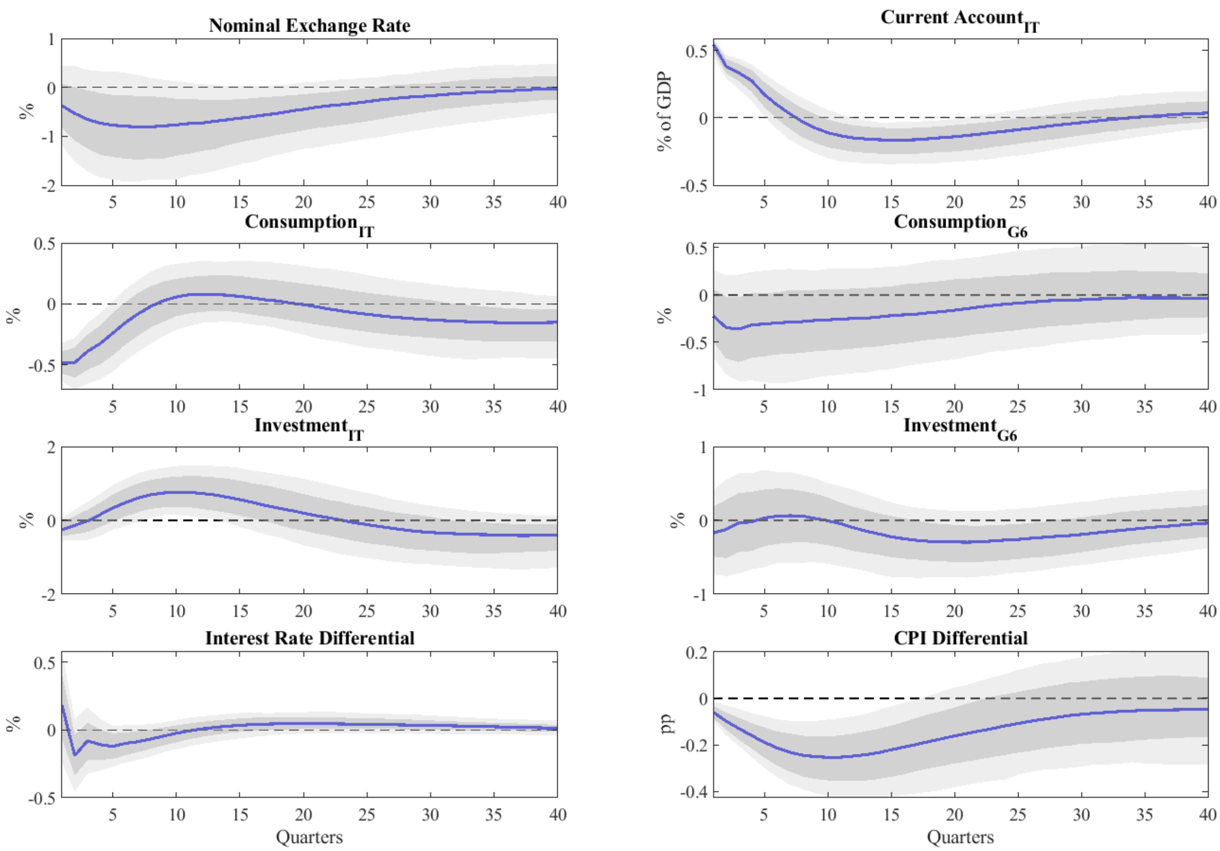
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, Germany, Italy, Japan, the UK and the US.

Figure B.22: Impulse Responses to the Dominant Business Cycle CA Shock: Germany



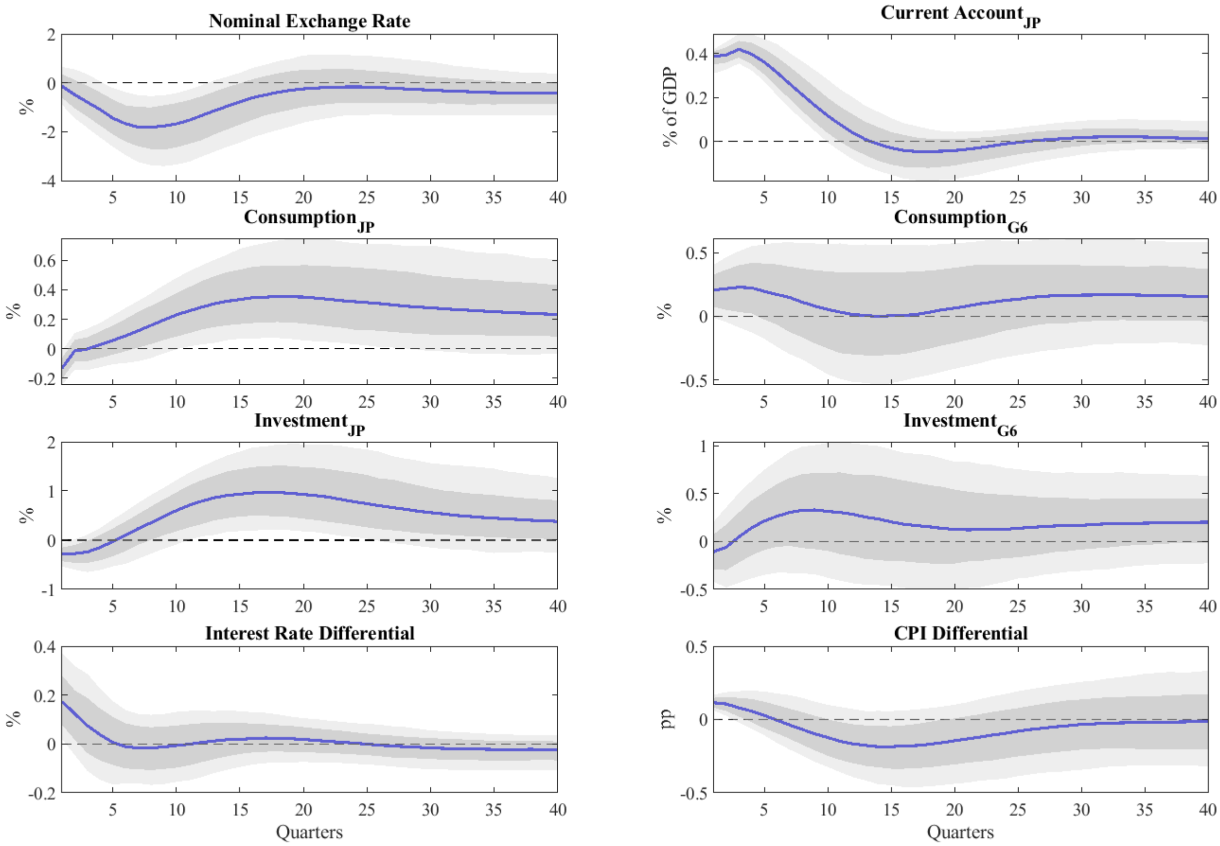
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Italy, Japan, the UK and the US.

Figure B.23: Impulse Responses to the Dominant Business Cycle CA Shock: Italy



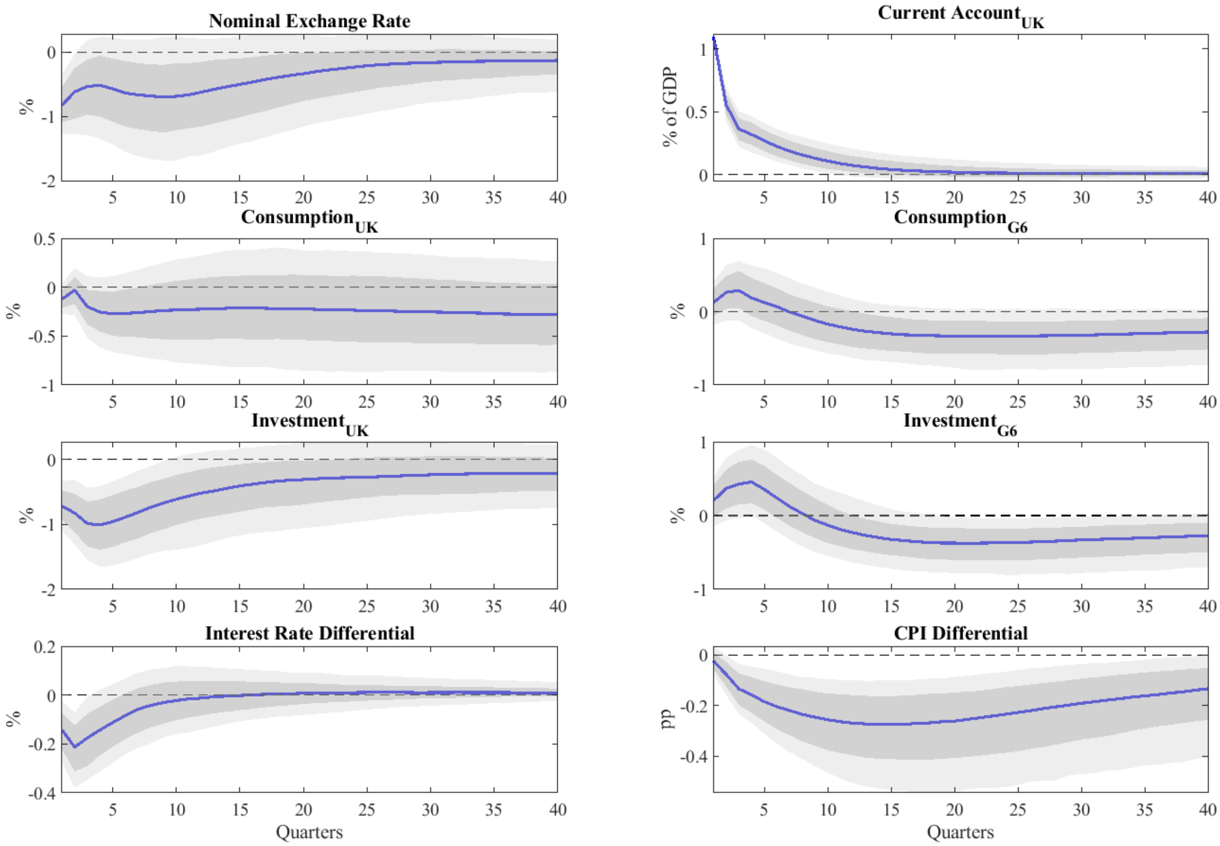
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Japan, the UK and the US.

Figure B.24: Impulse Responses to the Dominant Business Cycle CA Shock: Japan



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, the UK and the US.

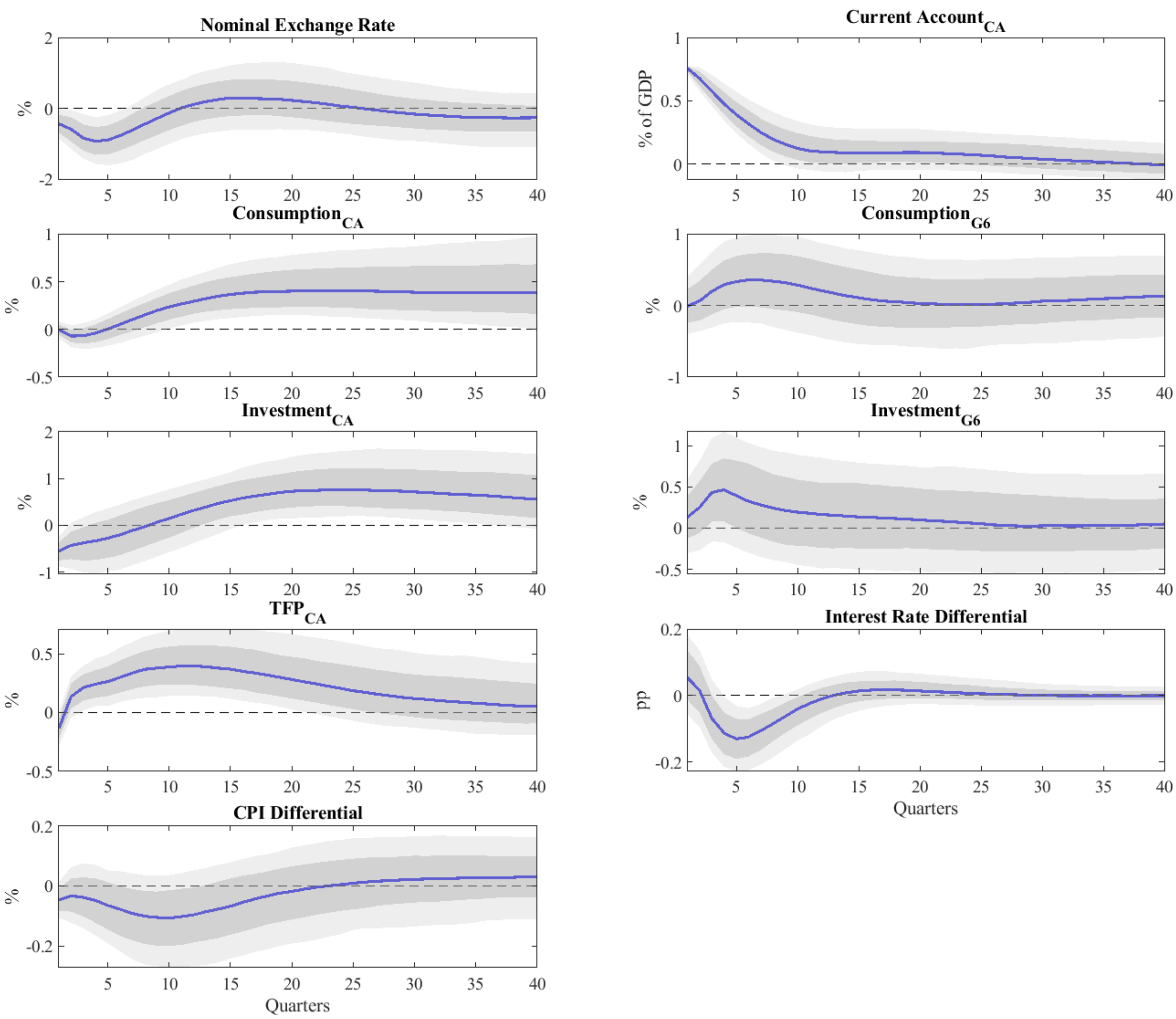
Figure B.25: Impulse Responses to the Dominant Business Cycle CA Shock: UK



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan, and the US.

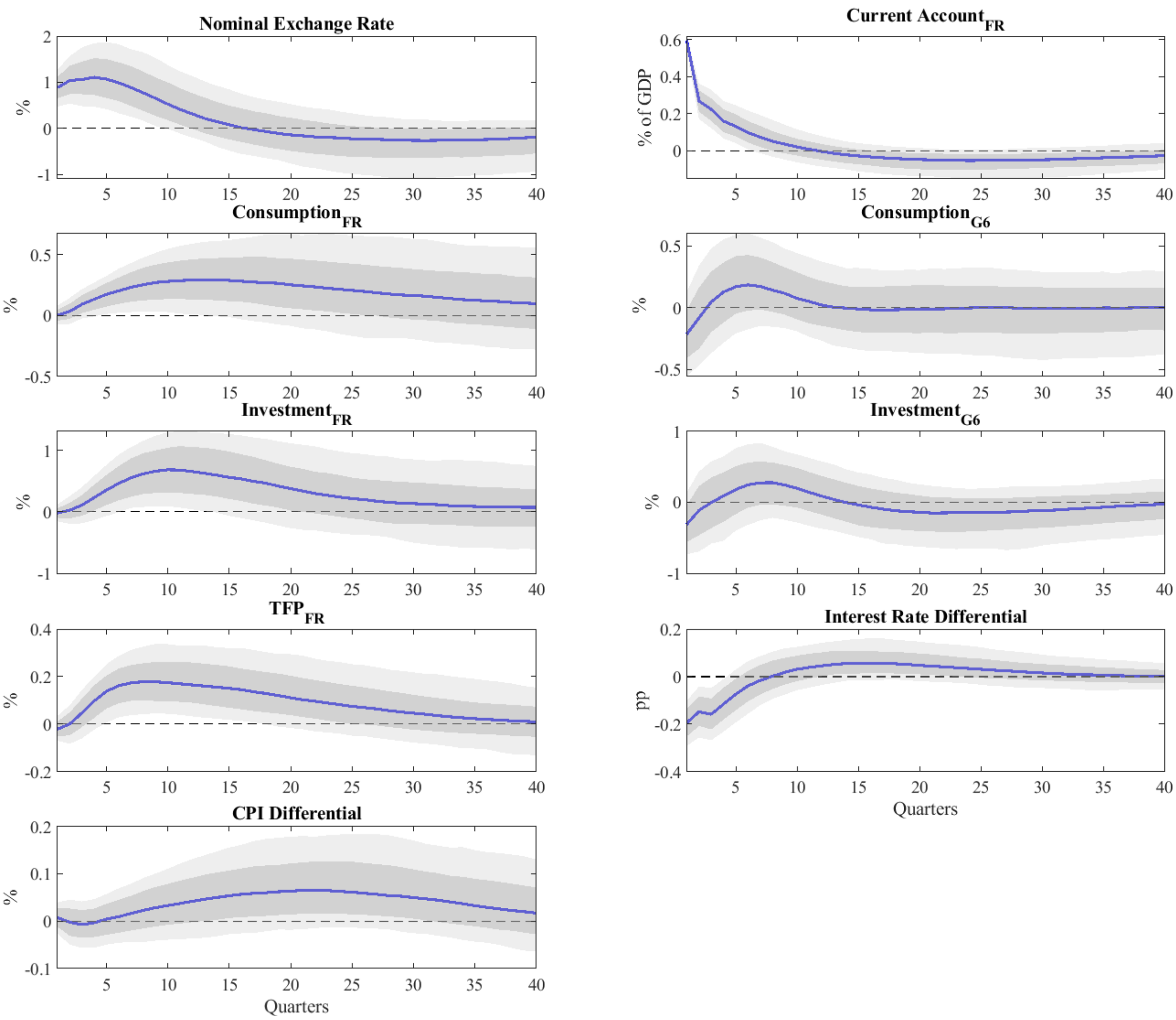
B.1.7 Additional Country Results: Dominant Business Cycle Frequency CA Shocks for other G7 Countries Including TFP

Figure B.26: Impulse Responses to the Dominant Business Cycle CA Shock including TFP: Canada



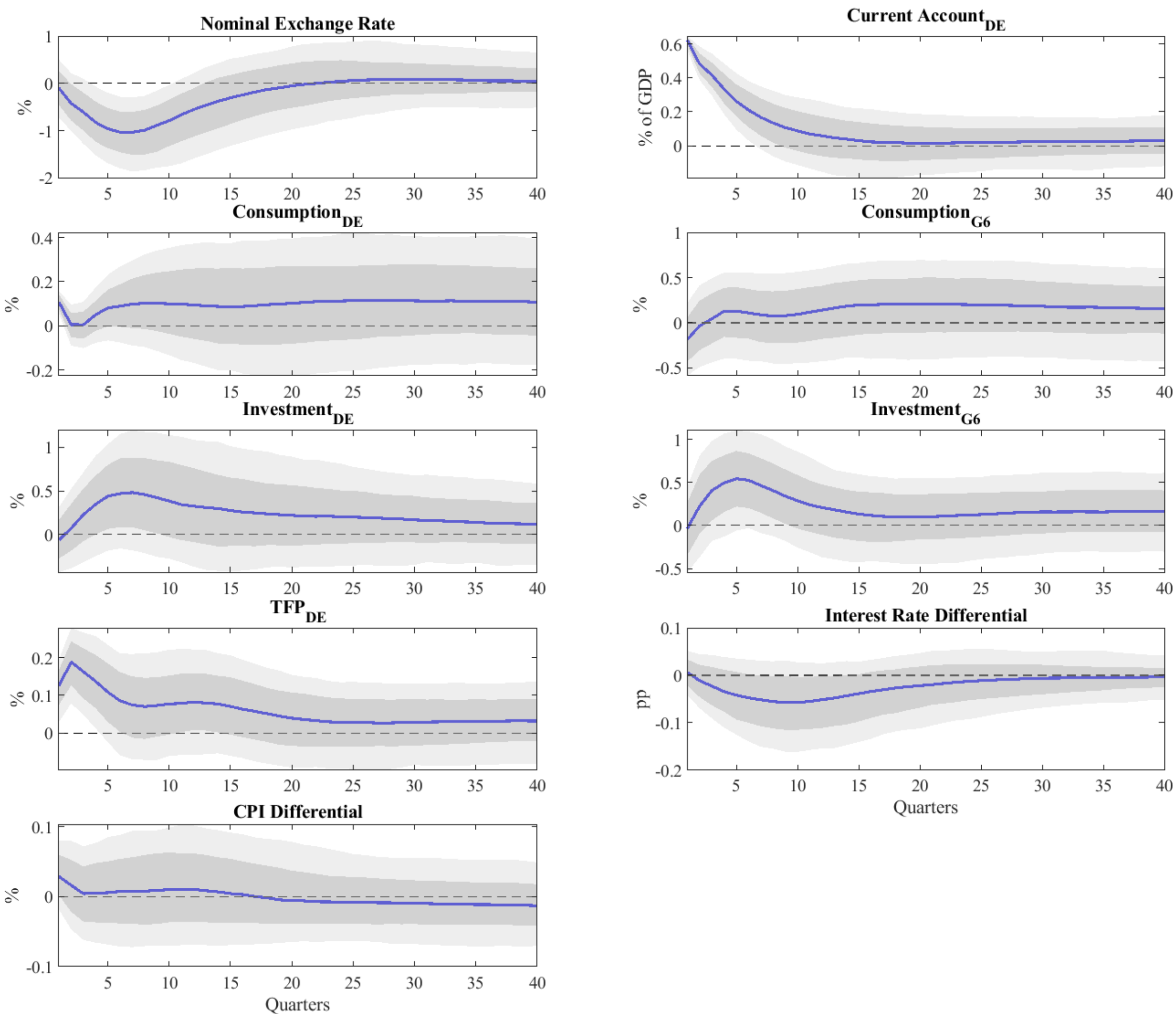
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US. Sample 1976q1 - 2018q3.

Figure B.27: Impulse Responses to the Dominant Business Cycle CA Shock including TFP: France



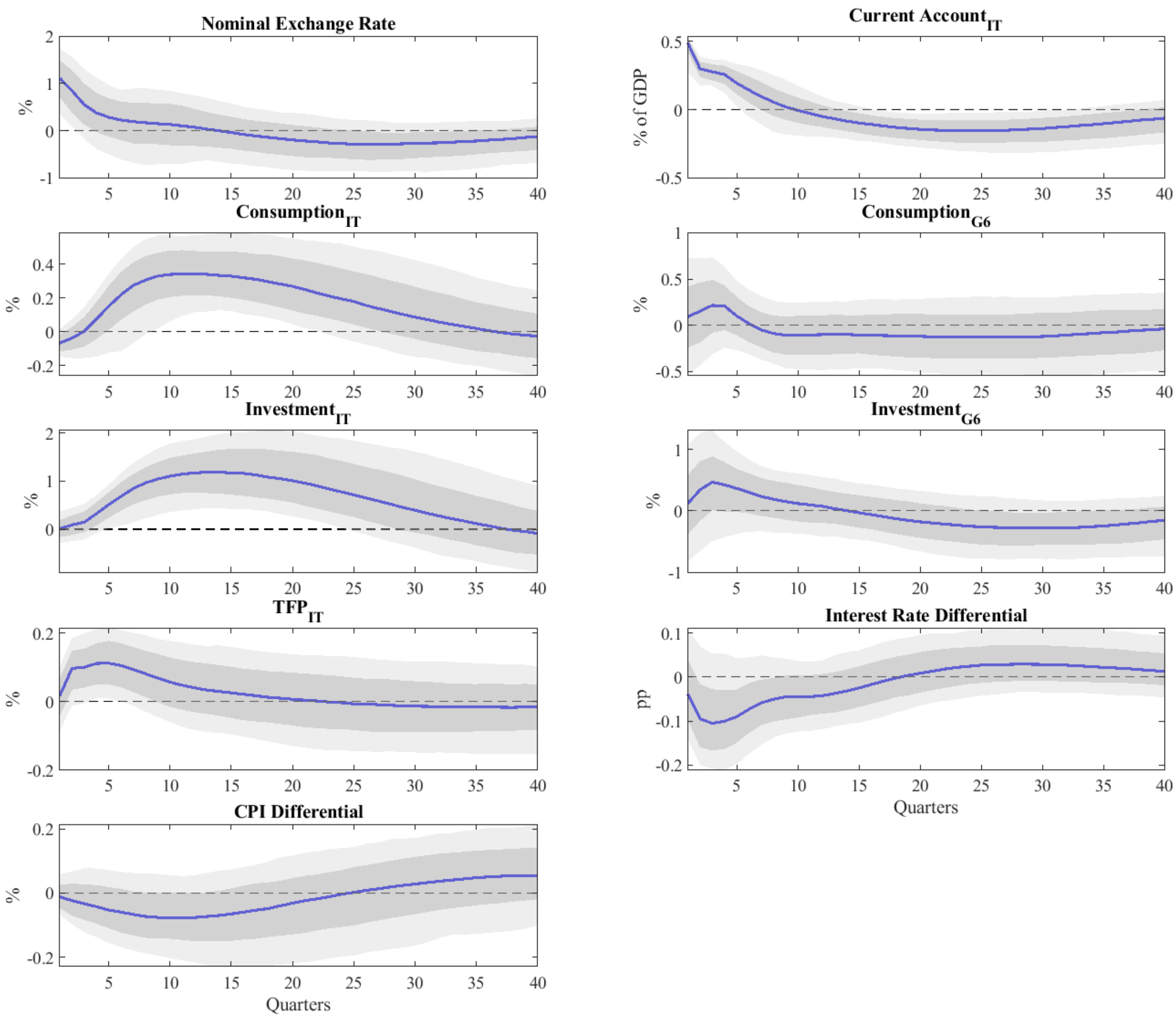
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, Germany, Italy, Japan, the UK and the US. Sample 1991q1 - 2019q4.

Figure B.28: Impulse Responses to the Dominant Business Cycle CA Shock including TFP: Germany



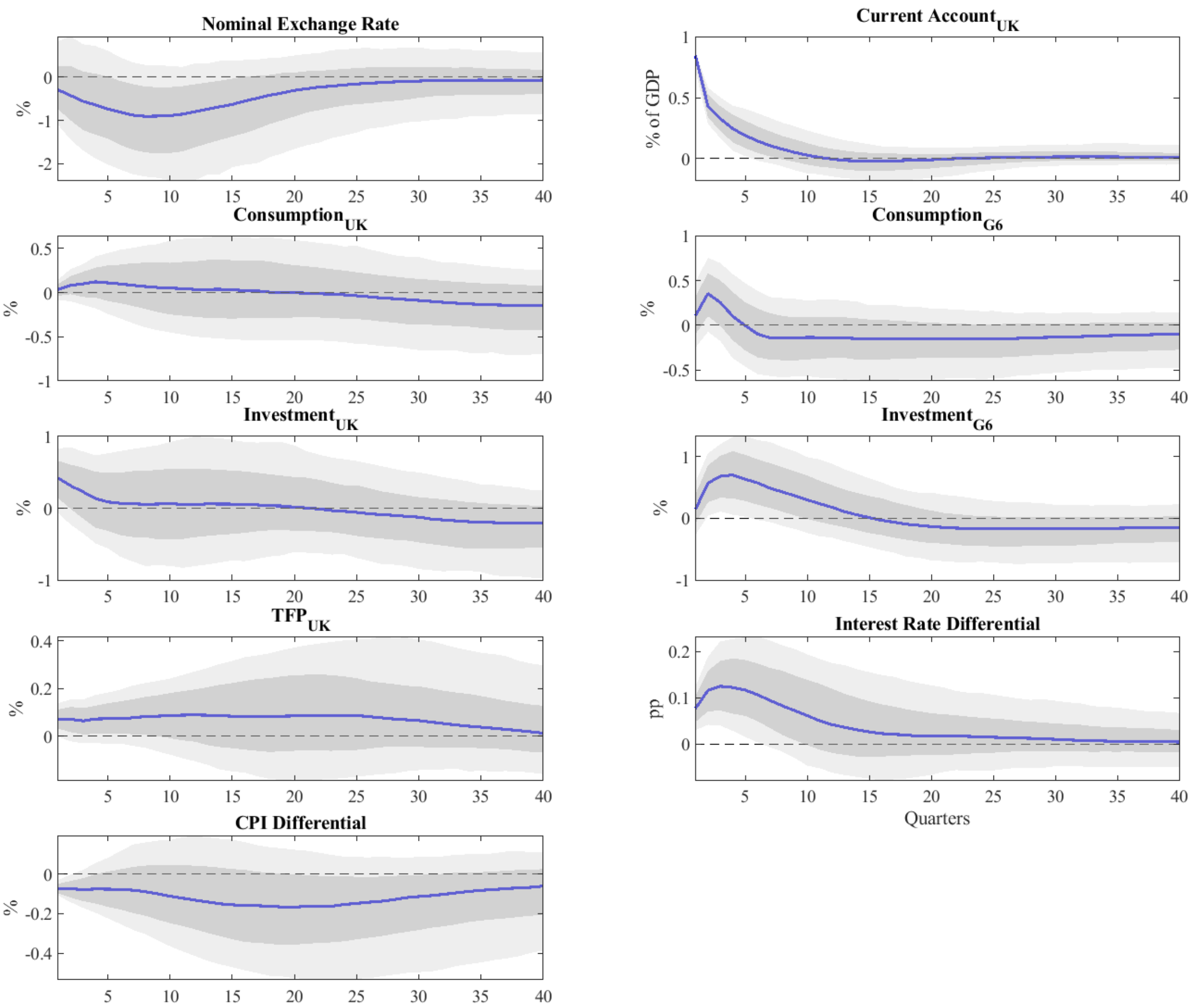
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Italy, Japan, the UK and the US. Sample 1991q1 - 2019q4.

Figure B.29: Impulse Responses to the Dominant Business Cycle CA Shock including TFP: Italy



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Japan, the UK and the US. Sample 1991q1 - 2019q4.

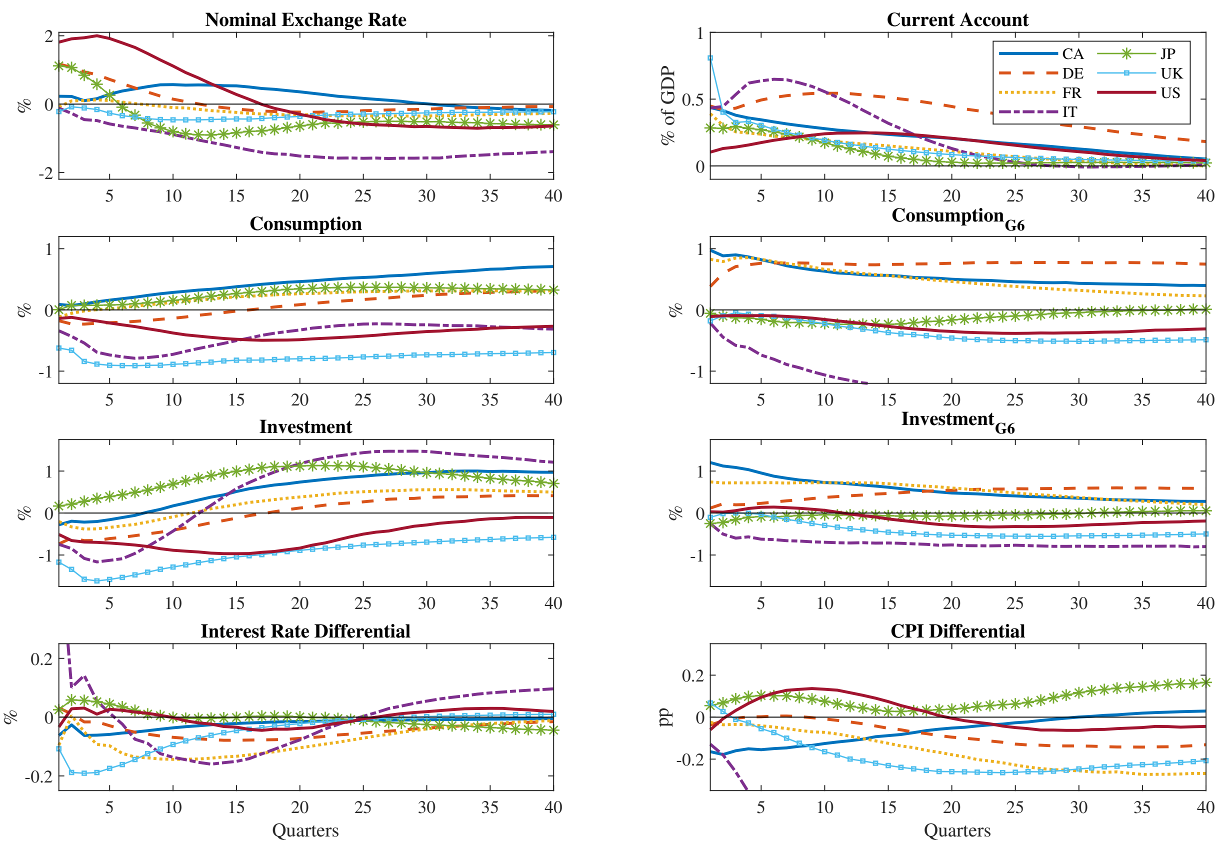
Figure B.30: Impulse Responses to the Dominant Business Cycle CA Shock including TFP: UK



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the US. Sample 1991q1 - 2019q4.

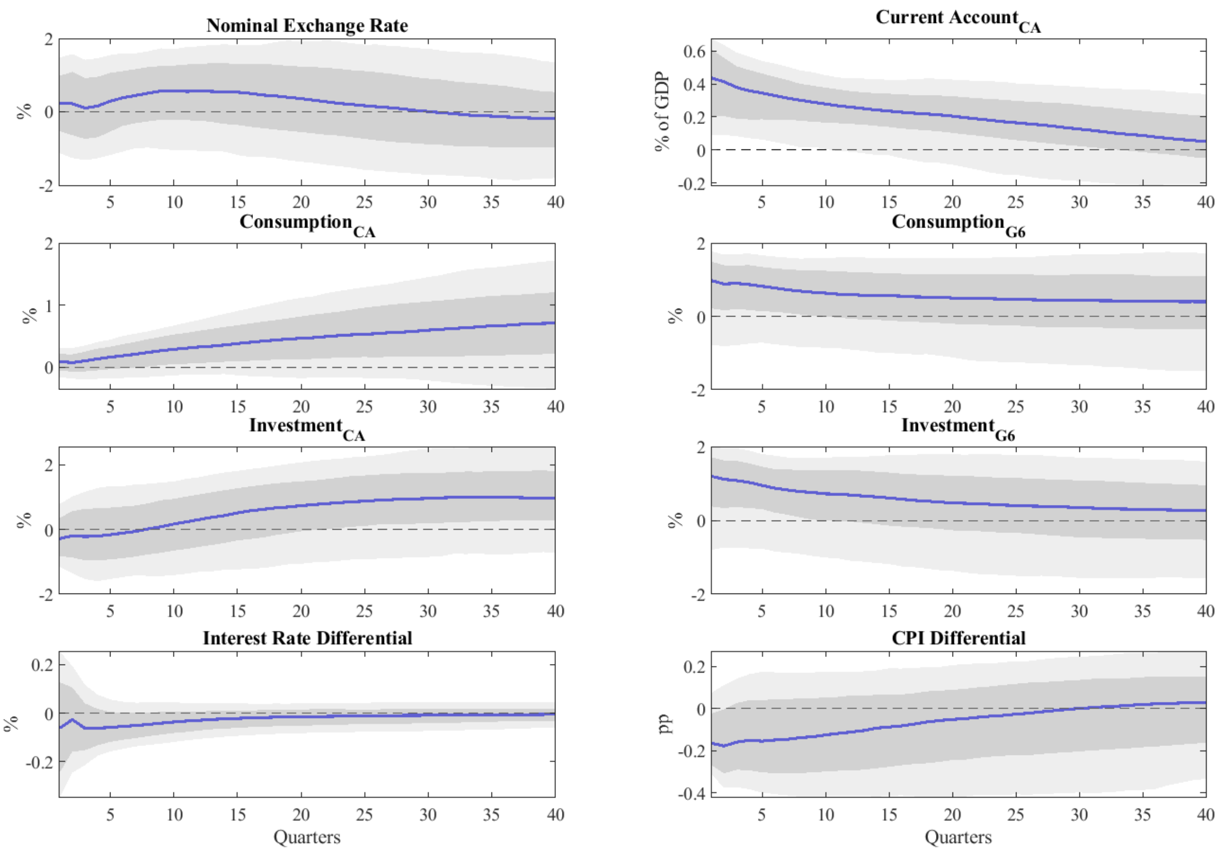
B.1.8 Additional Country Results: Dominant Long Run CA Shocks for other G7 Countries

Figure B.31: Impulse Responses to the Dominant Long Run CA Shocks for G7 Countries



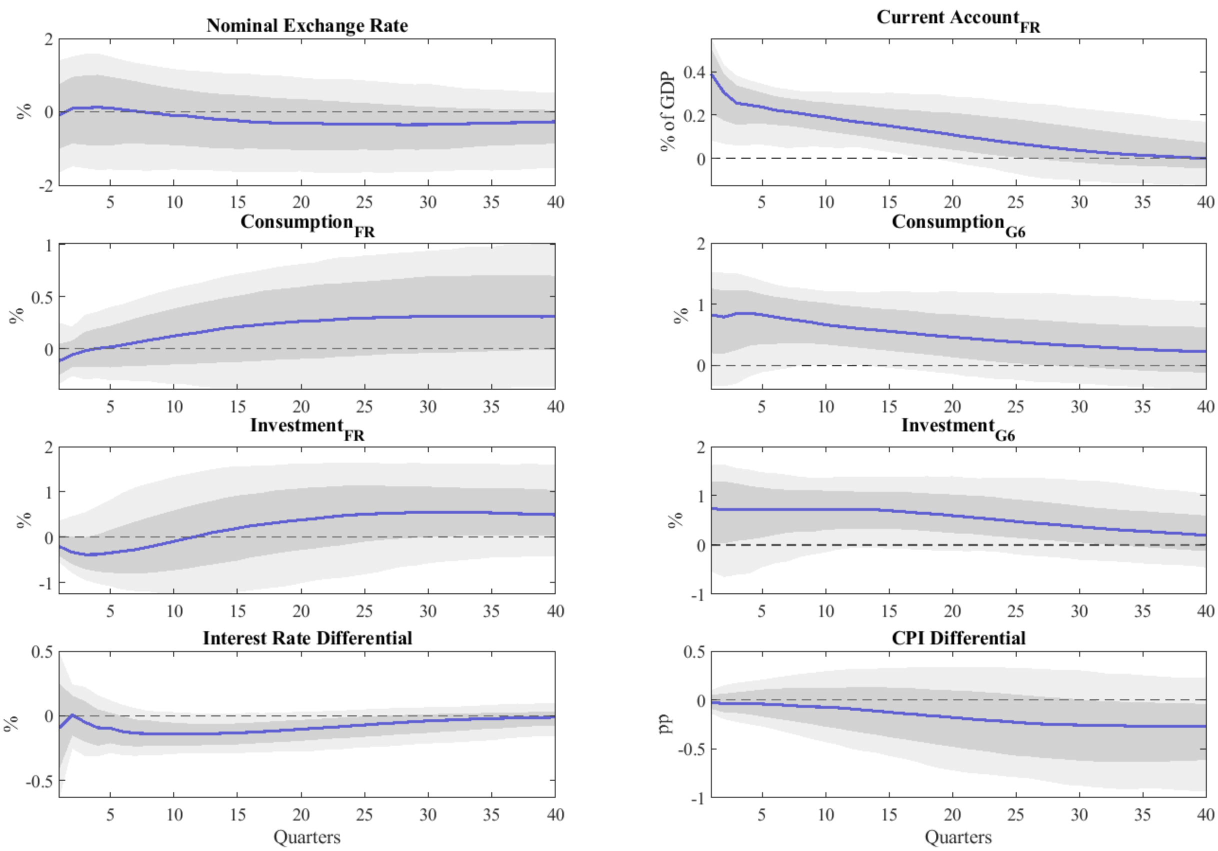
Notes: Point-wise median impulse responses responses to the dominant business cycle frequency CA (current account) shock for all G7 countries. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as individual country vs. G7 excluding the individual country. G7 countries include Canada, France, Germany, Italy, Japan, the UK and the US.

Figure B.32: Impulse Responses to the Dominant Long Run CA Shock: Canada



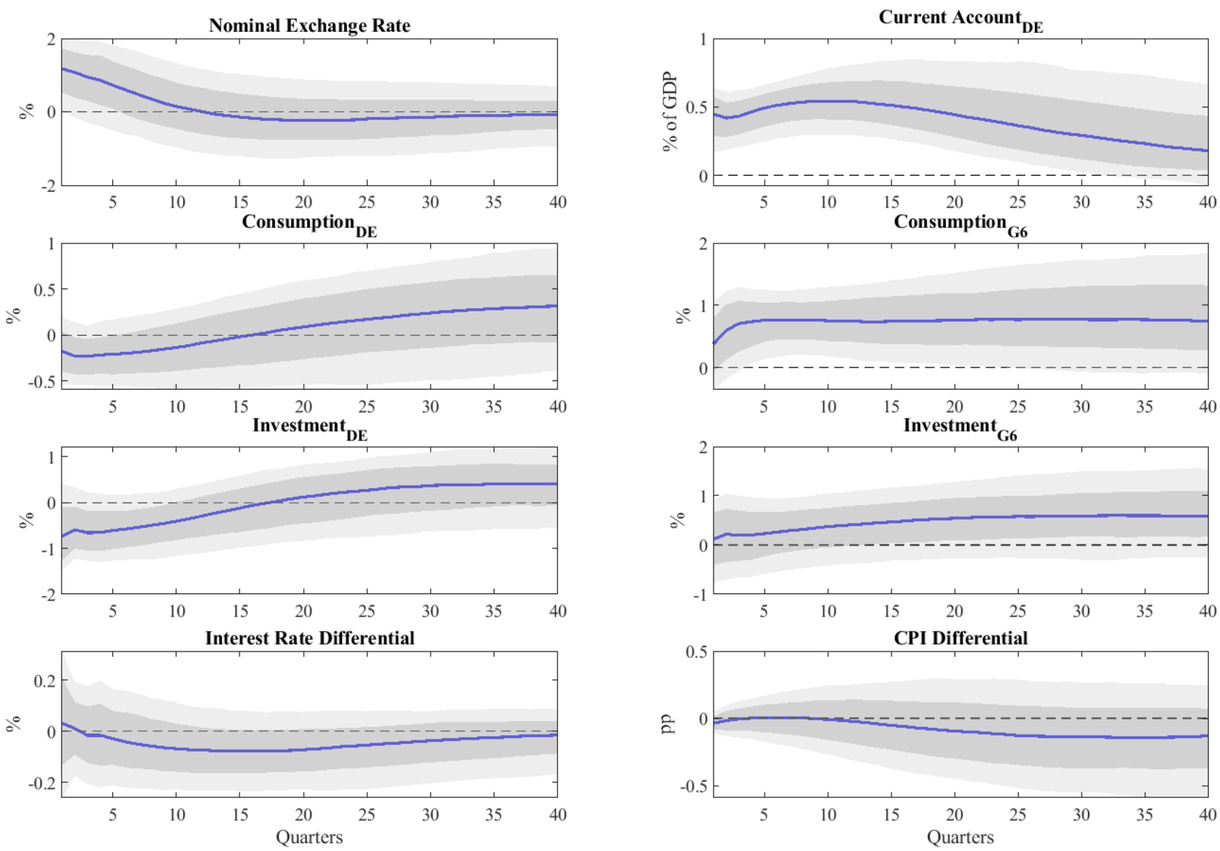
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.33: Impulse Responses to the Dominant Long Run CA Shock: France



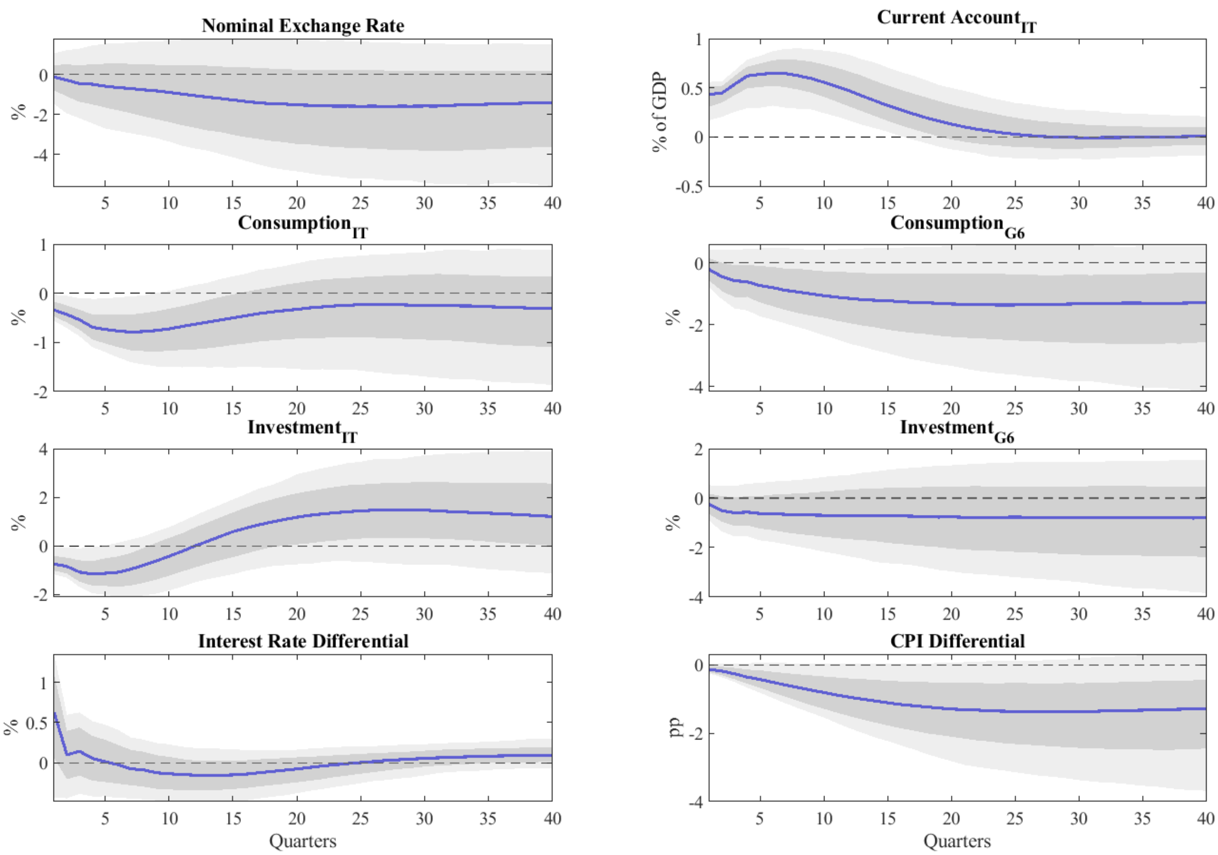
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, Germany, Italy, Japan, the UK and the US.

Figure B.34: Impulse Responses to the Dominant Long Run CA Shock: Germany



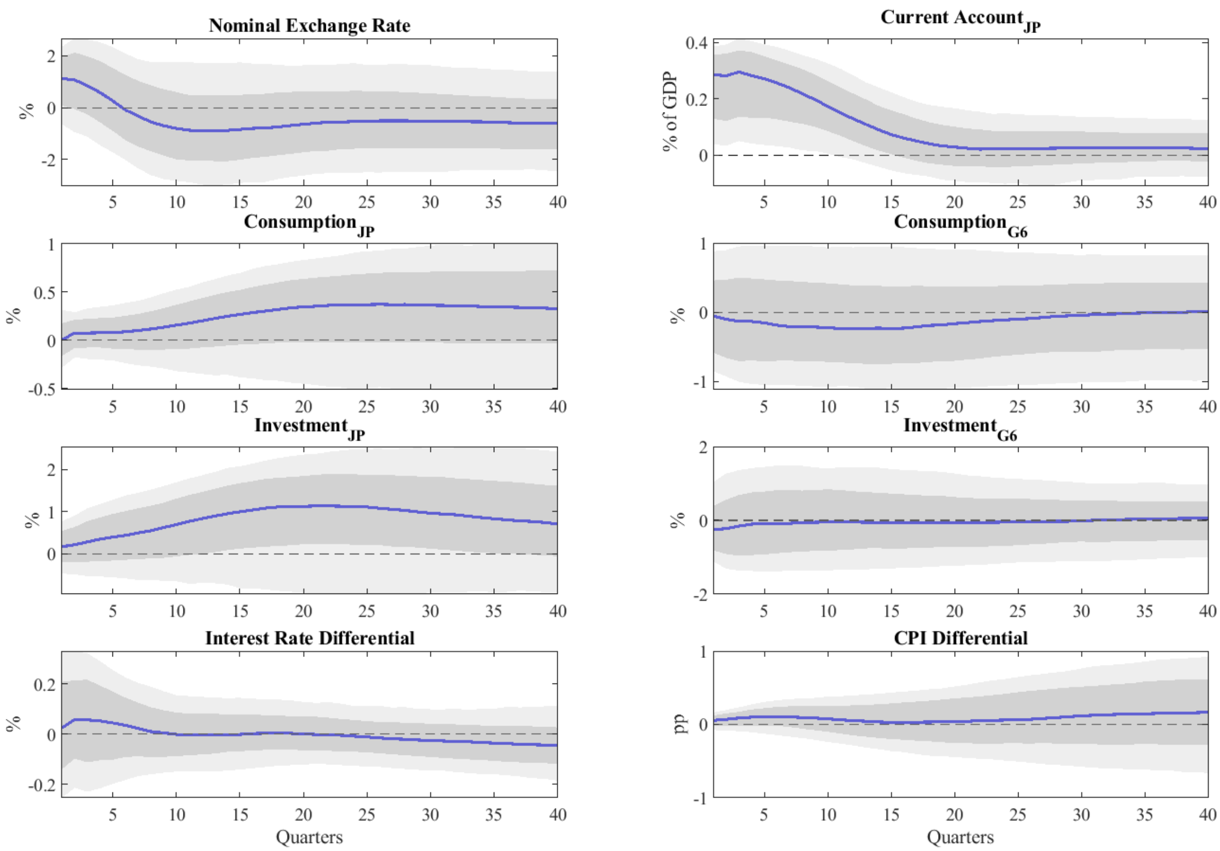
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Italy, Japan, the UK and the US.

Figure B.35: Impulse Responses to the Dominant Long Run CA Shock: Italy



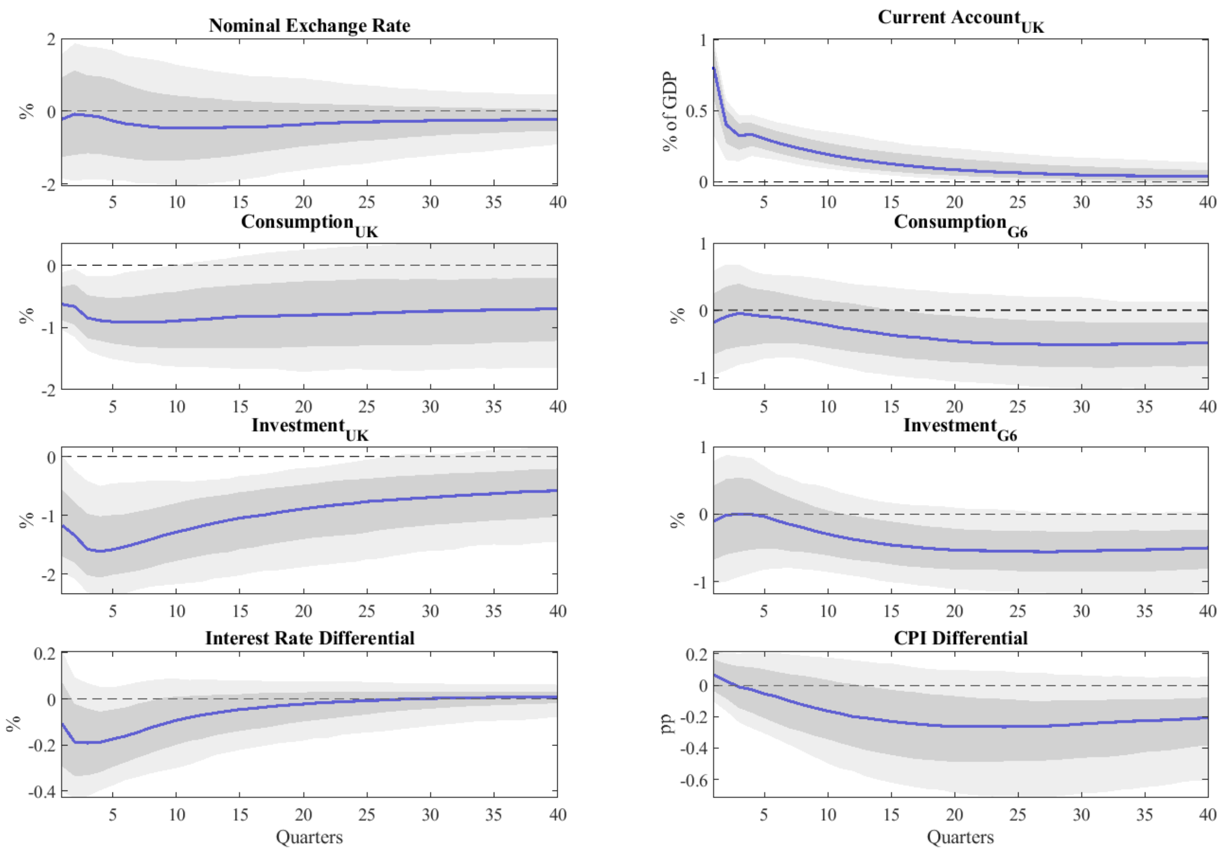
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Japan, the UK and the US.

Figure B.36: Impulse Responses to the Dominant Long Run CA Shock: Japan



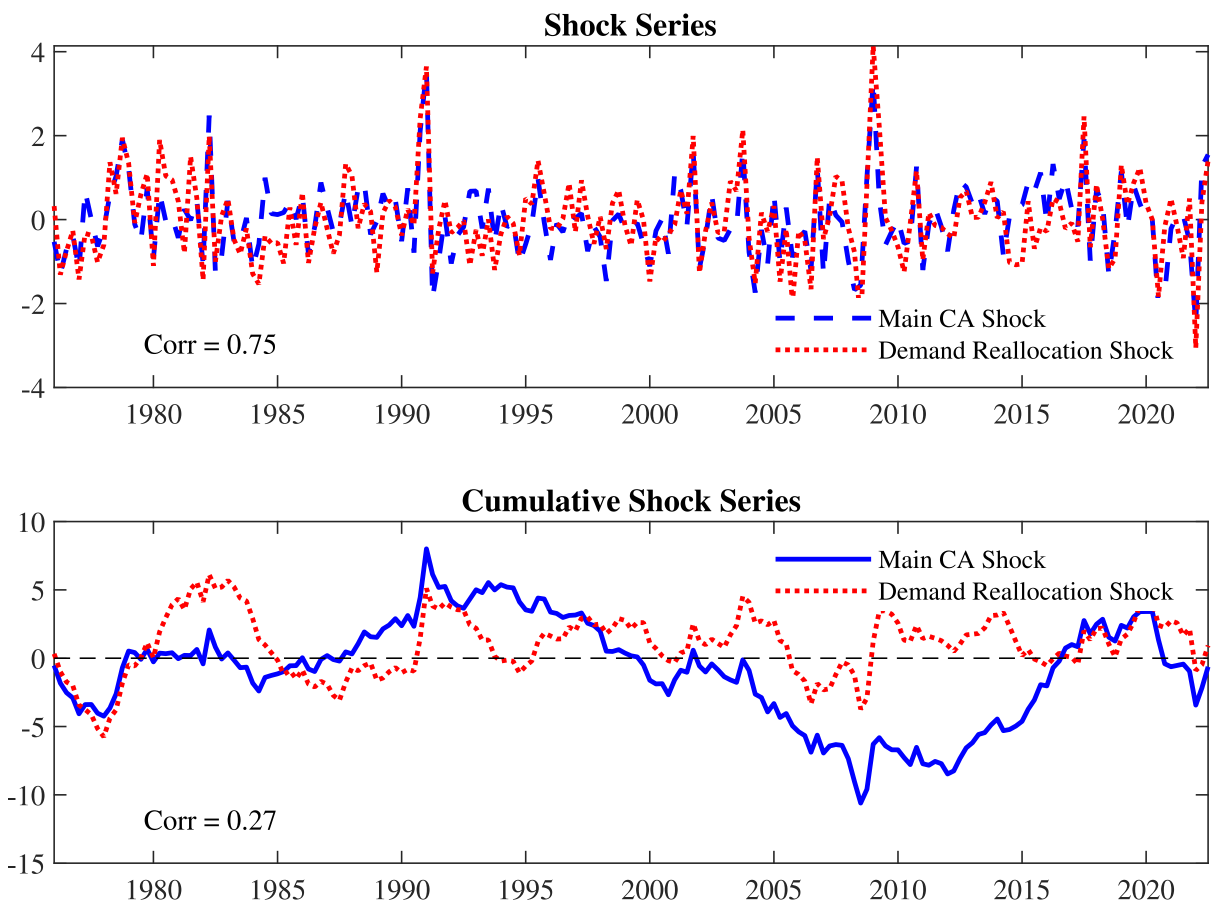
Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, the UK and the US.

Figure B.37: Impulse Responses to the Dominant Long Run CA Shock: the UK



Notes: Point-wise median impulse responses with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation. The interest rate and CPI differential are expressed as US vs. G6. G6 countries include Canada, France, Germany, Italy, Japan and the US.

Figure B.38: Empirical to Model Shock Series Comparison: US



Notes: Series of US main CA shock from section 2.3 and the US foreign relative demand shock from section 4.

B.2 The Full Quantitative Model

B.2.1 Case of the United States

We adapt the full-fledged model in Itskhoki and Mukhin (2021) by replacing the Kimball consumption function with a CES function and removing the wage rigidity. We direct readers to the online appendix of the IM paper for a more comprehensive understanding of the model details.

The conditions in our model are presented in a conventional manner: a set of equations corresponding to an equivalent number of endogenous variables. Specifically, the equilibrium is defined over 46 **stationary** endogenous variables:

c_t : Final good consumption for Home

c_t^* : Final good consumption for Foreign

l_t : Domestic Labor input

l_t^* : Foreign Labor input

w_t : Domestic real wages

w_t^* : Foreign real wages

mc_t : Real marginal cost of home goods production

mc_t^* : Real marginal cost of foreign goods production

k_t : Pre-determined Home capital stock at period t

k_t^* : Pre-determined Foreign capital stock at period t

z_t : Domestic gross investment

z_t^* : Foreign gross investment

y_t : Domestic Output

y_t^* : Foreign Output

y_{Ht} : Domestic demand for home goods

y^*_{Ht} : Foreign demand for home goods

y_{Ft} : Domestic demand for Foreign goods

y^*_{Ft} : Foreign demand for Foreign goods

p_{Ht} : Relative price of home produced goods to home final goods

p^*_{Ht} : Relative price of home produced goods to foreign final goods

p_{Ft} : Relative price of foreign produced good to home final goods

p^*_{Ft} : Relative price of foreign produced good to foreign final goods

x_t : Domestic intermediate goods

x^*_t : Foreign intermediate goods

i_t : Home nominal interest rate

i^*_t : Foreign nominal interest rate

rk_t : Domestic real capital rental price

rk^*_t : Foreign real capital rental price

b_t : Real net foreign asset position of Home, $b_t = \frac{B_t}{\bar{P}\bar{Y}}$

nx_t : Real net exports for Home, $nx_t = \frac{NX_t}{\bar{P}\bar{Y}}$

π_t : Home CPI inflation

π_{Ht} : Home PPI inflation

π^*_{Ht} : PPI of Home exports

π_{Ft} : Home imports inflation

π^*_{Ft} : Foreign PPI inflation

Δe_t : $e_t - e_{t-1}$ Exchange rate depreciation of Home currency

q_t : Real exchange rate

s_t : Terms of trade

a_t : Domestic TFP

a_t^* : Foreign TFP

ψ_t : Noise traders' demand over foreign assets

Ω_t : Home Aggregate Demand shifter

Ω_t^* : Foreign Aggregate Demand shifter

v_t : Domestic nominal interest rate shifter

v_t^* : Foreign nominal interest rate shifter

γ_t : Expenditure share of home goods in Foreign's consumption basket

satisfying the following 33 equilibrium conditions

Domestic Households' Problem:

$$\sigma c_t + \nu l_t = w_t \quad \text{(C.1)}$$

$$c_t = E_t c_{t+1} - \frac{1}{\sigma}(i_t - E_t \pi_{t+1}) + \frac{1}{\sigma}(1-\rho_\Omega)\Omega_t \quad \text{(C.2)}$$

$$-\sigma c_t + \kappa\delta z_t - \kappa\delta k_t = -\sigma E_t c_{t+1} + \beta\kappa\delta E_t z_{t+1} - \beta\kappa\delta k_{t+1} + E_t \beta(\frac{1}{\beta} - 1 + \delta) r k_{t+1} \quad \text{(C.3)}$$

$$k_{t+1} = \delta z_t + (1-\delta) k_t \quad \text{(C.4)}$$

Foreign Households' Problem:

$$\sigma c_t^* + \nu l_t^* = w_t^* \quad \text{(C.5)}$$

$$c_t^* = E_t c_{t+1}^* - \frac{1}{\sigma}(i_t^* - E_t \pi_{t+1}^*) + \frac{1}{\sigma}(1-\rho_\Omega^*)\Omega_t^* \quad \text{(C.6)}$$

$$-\sigma c_t^* + \kappa\delta z_t^* - \kappa\delta k_t^* = -\sigma E_t c_{t+1}^* + \beta\kappa\delta E_t z_{t+1}^* - \beta\kappa\delta k_{t+1}^* + E_t \beta(\frac{1}{\beta} - 1 + \delta) r k_{t+1}^* \quad \text{(C.7)}$$

$$k_{t+1}^* = \delta z_t^* + (1-\delta) k_t^* \quad \text{(C.8)}$$

Domestic Firms' Problem:

$$w_t + l_t = mc_t + y_t \quad \text{(C.9)}$$

$$rk_t + k_t = mc_t + y_t \quad \text{(C.10)}$$

$$x_t = mc_t + y_t \quad \text{(C.11)}$$

$$y_t = (1-\phi)a_t + (1-\phi)\vartheta k_t + (1-\phi)(1-\vartheta)l_t + \phi x_t \quad \text{(C.12)}$$

Foreign Firms' Problem:

$$w_t^* + l_t^* = mc_t^* + y_t^* \quad \text{(C.13)}$$

$$rk_t^* + k_t^* = mc_t^* + y_t^* \quad \text{(C.14)}$$

$$x_t^* = mc_t^* + y_t^* \quad \text{(C.15)}$$

$$y_t^* = (1-\phi)a_t^* + (1-\phi)\vartheta k_t^* + (1-\phi)(1-\vartheta)l_t^* + \phi x_t^* \quad \text{(C.16)}$$

Market Clearing of Home Goods:

$$y_t = (1-\gamma)y_{Ht} + \gamma y_{Ht}^* \quad \text{(C.17)}$$

$$y_{Ht} = \phi mc_t + \phi y_t - \theta p_{Ht} + (1-\phi)dc_t + (1-\phi)(1-d)z_t \quad \text{(C.18)}$$

$$y_{Ht}^* = \phi mc_t^* + \phi y_t^* - \theta p_{Ht}^* + (1-\phi)dc_t^* + (1-\phi)(1-d)z_t^* + (\gamma_t - \gamma)/\gamma \quad \text{(C.19)}$$

$$(1-\gamma)p_{Ht} + \gamma p_{Ft} = 0 \quad \text{(C.20)}$$

Market Clearing of Foreign Goods:

$$y_t^* = (1-\gamma)y_{Ft}^* + \gamma y_{Ft} \quad \text{(C.21)}$$

$$y_{Ft}^* = \phi mc_t^* + \phi y_t^* - \theta p_{Ft}^* + (1-\phi)dc_t^* + (1-\phi)(1-d)z_t^* - (\gamma_t - \gamma)/\gamma \quad \text{(C.22)}$$

$$y_{Ft} = \phi mc_t + \phi y_t - \theta p_{Ft} + (1-\phi)dc_t + (1-\phi)(1-d)z_t \quad \text{(C.23)}$$

$$(1-\gamma)p_{Ht}^* + \gamma p_{Ft}^* = 0 \quad \text{(C.24)}$$

Home Resource Constraint:

$$\beta b_t - b_{t-1} = nx_t \quad \text{(C.25)}$$

$$nx_t = \frac{\gamma}{1-\phi}(y^*_{Ht} - y_{Ft} - s_t) \quad \text{(C.26)}$$

Domestic Interest Rate Rule:

$$i_t = \rho_m i_{t-1} + (1-\rho_m)\phi_\pi \pi_t + v_t \quad \text{(C.27)}$$

Foreign Interest Rate Rule:

$$i^*_t = \rho^*_m i^*_{t-1} + (1-\rho^*_m)\phi^*_\pi \pi_t + v^*_t \quad \text{(C.28)}$$

Definition of Terms of Trade:

$$s_t = p_{Ft} - q_t - p^*_{Ht} \quad \text{(C.29)}$$

Definition of Nominal Exchange Depreciation:

$$\Delta e_t = q_t - q_{t-1} + \pi_t - \pi^*_t \quad \text{(C.30)}$$

NKPC for Home Goods in Home:

$$\pi_{Ht} = p_{Ht} - p_{Ht-1} + \pi_t \quad \text{(C.31)}$$

$$\pi_{Ht} = \kappa_p(mc_t - p_{Ht}) + \beta E_t \pi_{Ht+1} \quad \text{(C.32)}$$

NKPC for Home's Exports:

$$\pi^*_{Ht} = p^*_{Ht} - p^*_{Ht-1} + \pi^*_t \quad \text{(C.33)}$$

$$\text{PCP:} \qquad \pi^*_{Ht} + \Delta e_t = \kappa_p(mc_t - q_t - p^*_{Ht}) + \beta E_t(\pi^*_{Ht+1} + \Delta e_{t+1})$$

$$\text{LCP:} \qquad \pi^*_{Ht} = \kappa_p(mc_t - q_t - p^*_{Ht}) + \beta E_t \pi^*_{Ht+1} \quad \text{(C.34)}$$

NKPC for Foreign Goods in Foreign:

$$\pi^*_{Ft} = p^*_{Ft} - p^*_{Ft-1} + \pi^*_t \quad \text{(C.35)}$$

$$\pi^*_{Ft} = \kappa_p(mc^*_t - p^*_{Ft}) + \beta E_t \pi^*_{Ft+1} \quad \text{(C.36)}$$

NKPC for Foreign's Exports:

$$\pi_{Ft} = p_{Ft} - p_{Ft-1} + \pi_t \quad \text{(C.37)}$$

$$\text{PCP: :} \qquad \pi_{Ft} - \Delta e_t = \kappa_p(mc^*_t - p_{Ft} + q_t) + \beta E_t(\pi_{Ft+1} - \Delta e_{t+1})$$

$$\text{LCP:} \qquad \pi_{Ft} = \kappa_p(mc^*_t - p_{F_t} + q_t) + \beta E_t \pi_{Ft+1} \quad \text{(C.38)}$$

Shock Processes:

$$\psi_t = \rho_\psi \psi_{t-1} + \epsilon_{\psi t} \quad \text{(C.39)}$$

$$a_t = \rho_a a_{t-1} + \epsilon_{at} \quad \text{(C.40)}$$

$$a^*_t = \rho^*_a a^*_{t-1} + \epsilon^*_{at} \quad \text{(C.41)}$$

$$\Omega_t = \rho_\Omega \Omega_{t-1} + \epsilon_{\Omega t} \quad \text{(C.42)}$$

$$\Omega^*_t = \rho^*_\Omega \Omega^*_{t-1} + \epsilon^*_{\Omega t} \quad \text{(C.43)}$$

$$v_t = \rho_v v_{t-1} + \epsilon_{vt} \quad \text{(C.44)}$$

$$v^*_t = \rho_v v^*_{t-1} + \epsilon^*_{vt} \quad \text{(C.45)}$$

$$\gamma_t = (1 - \rho_\gamma)\gamma + \rho_\gamma \gamma_{t-1} + \epsilon_{\gamma,t} \quad \text{(C.46)}$$

Note: We linearize our model around the symmetric steady state where $P_H = P_F = P_H^* = P_F^* = \mathcal{Q} = 1$ and $B = B^* = \bar{NX} = 0$. The parameter $d \equiv 1 - \frac{\vartheta\delta}{(\frac{1}{\beta} - 1 + \delta)}$ is the steady-state share of consumption in GDP.

B.3 Model Fit

	US		UK		DE		FR		IT		CAD		JP	
	model	data	model	data	model	data	model	data	model	data	model	data	model	data
std(Δnx_t)	0.0034	0.0031	0.0125	0.0128	0.0083	0.0082	0.0074	0.0072	0.0077	0.0073	0.0091	0.0084	0.0051	0.0047
std(Δe_t)	0.0483	0.0411	0.0471	0.0353	0.0401	0.034	0.039	0.0285	0.0415	0.0293	0.0428	0.0377	0.0537	0.0516
std(c_t)	0.0125	0.011	0.0206	0.0199	0.0134	0.0124	0.0123	0.0101	0.0145	0.016	0.0166	0.0125	0.0127	0.0104
std(c_t^*)	0.0097	0.0098	0.0239	0.0306	0.0225	0.0286	0.0228	0.0293	0.0231	0.0297	0.0268	0.0351	0.0149	0.0183
std(i_t)	0.0072	0.0037	0.0059	0.0041	0.0036	0.0027	0.0085	0.006	0.0094	0.0065	0.0056	0.0038	0.005	0.0029
std(i_t^*)	0.005	0.0029	0.005	0.0027	0.0054	0.0029	0.0044	0.0027	0.0049	0.0026	0.005	0.0027	0.005	0.0029
std(π_t)	0.0051	0.0048	0.0076	0.0068	0.0048	0.0038	0.0045	0.004	0.0051	0.0042	0.0073	0.0069	0.005	0.0042
std(π_t^*)	0.0036	0.003	0.0058	0.0036	0.0058	0.0042	0.0058	0.0037	0.0056	0.0035	0.0063	0.0037	0.0044	0.0034
std(z_t)	0.0399	0.0353	0.1297	0.0403	0.0763	0.0304	0.0913	0.0243	0.0956	0.0306	0.1175	0.0383	0.081	0.0273
std(z_t^*)	0.0302	0.0224	0.1119	0.0368	0.1061	0.035	0.1079	0.0358	0.1059	0.0368	0.121	0.04	0.0806	0.0284
$\rho(\Delta nx_t, \Delta e_t)$	0.1716	0.155	-0.0684	0.1253	0.0561	0.0715	-0.019	-0.0713	-0.0159	0.0361	0.0543	0.1989	0.042	-0.0351

Table B.1: Comparison of Model and Empirical Moments

B.4 FEVD: G6

Figure B.40: FEVD of the Nominal Exchange Rate Fluctuation Δe_t: G6

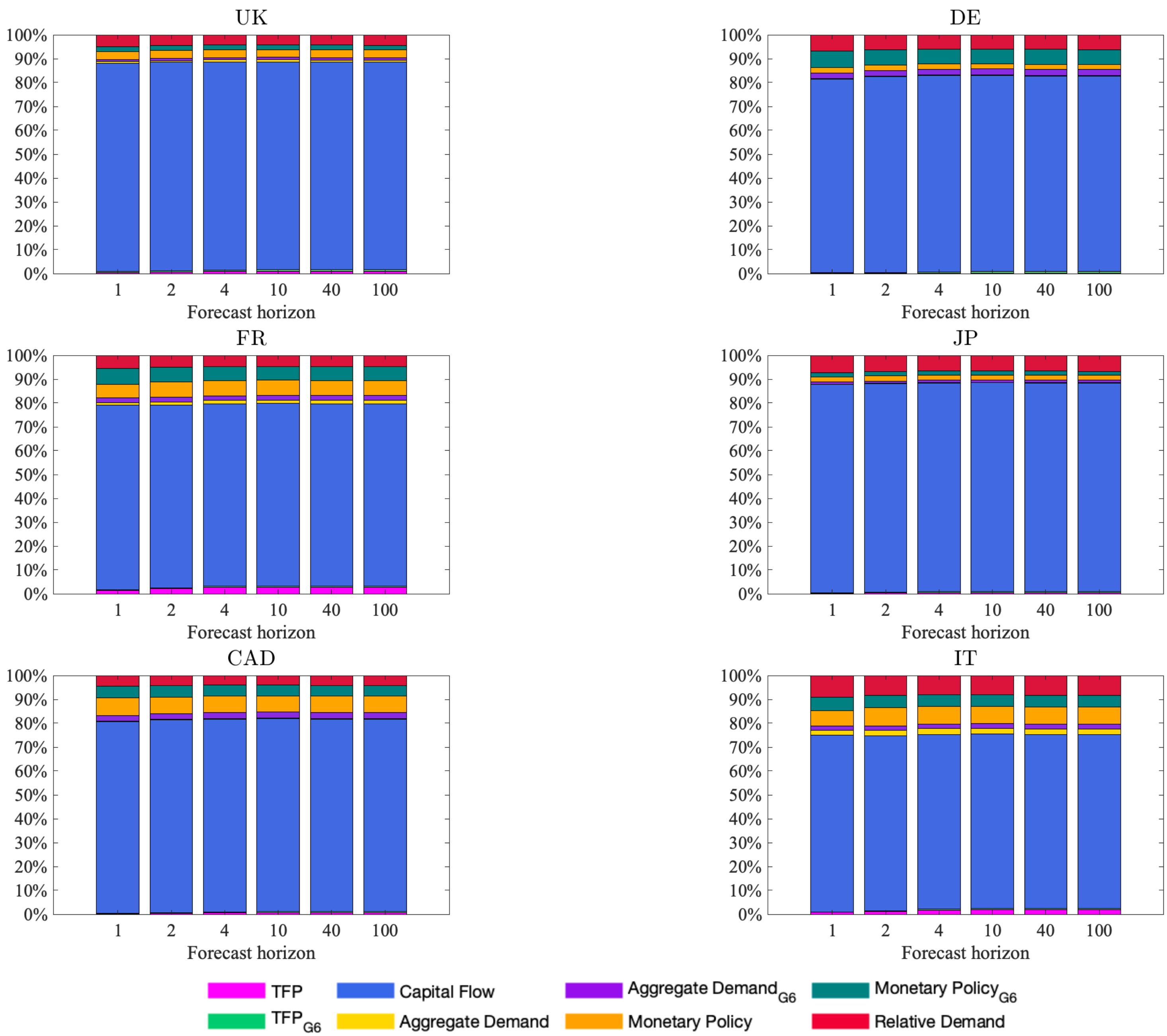
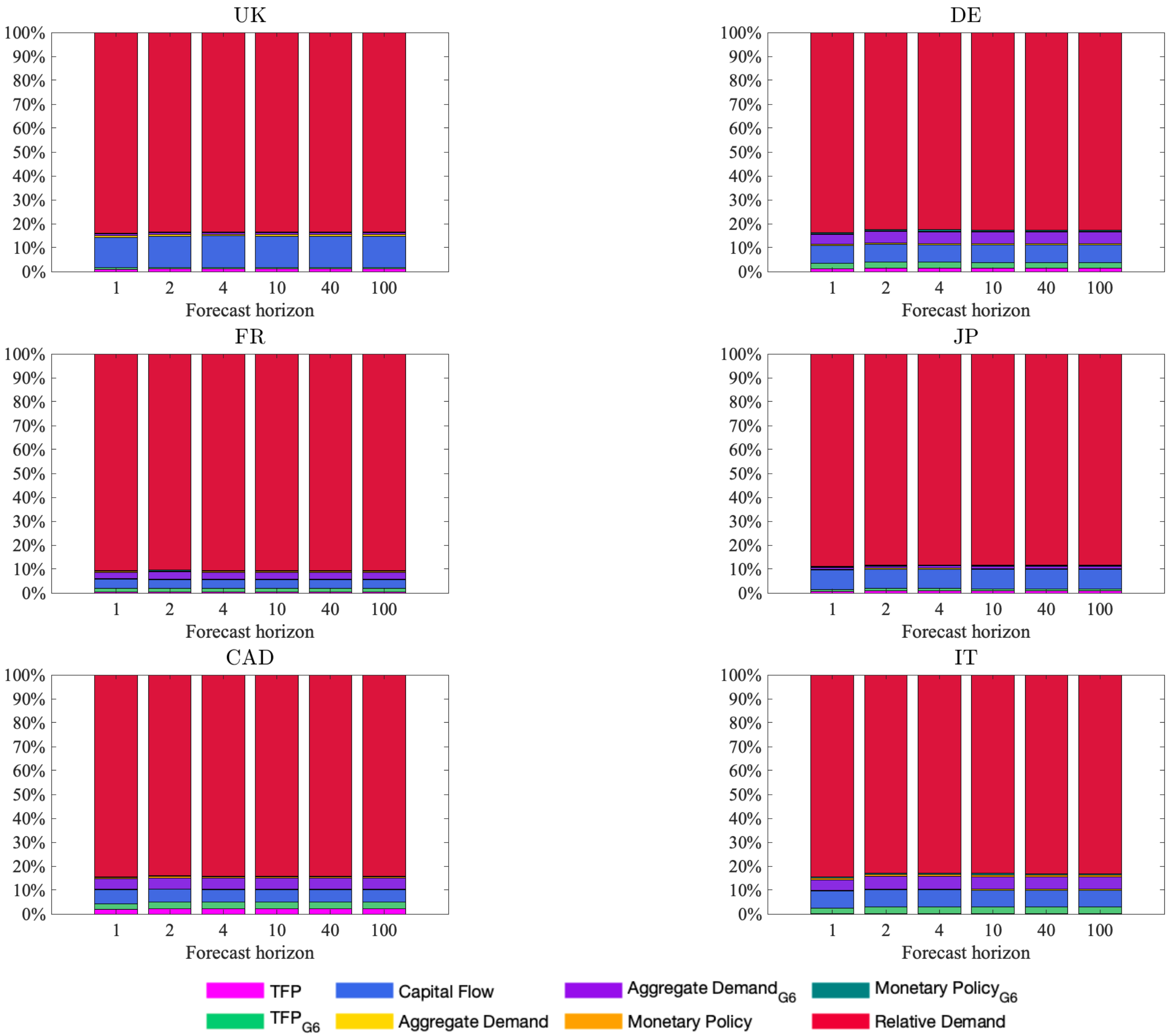
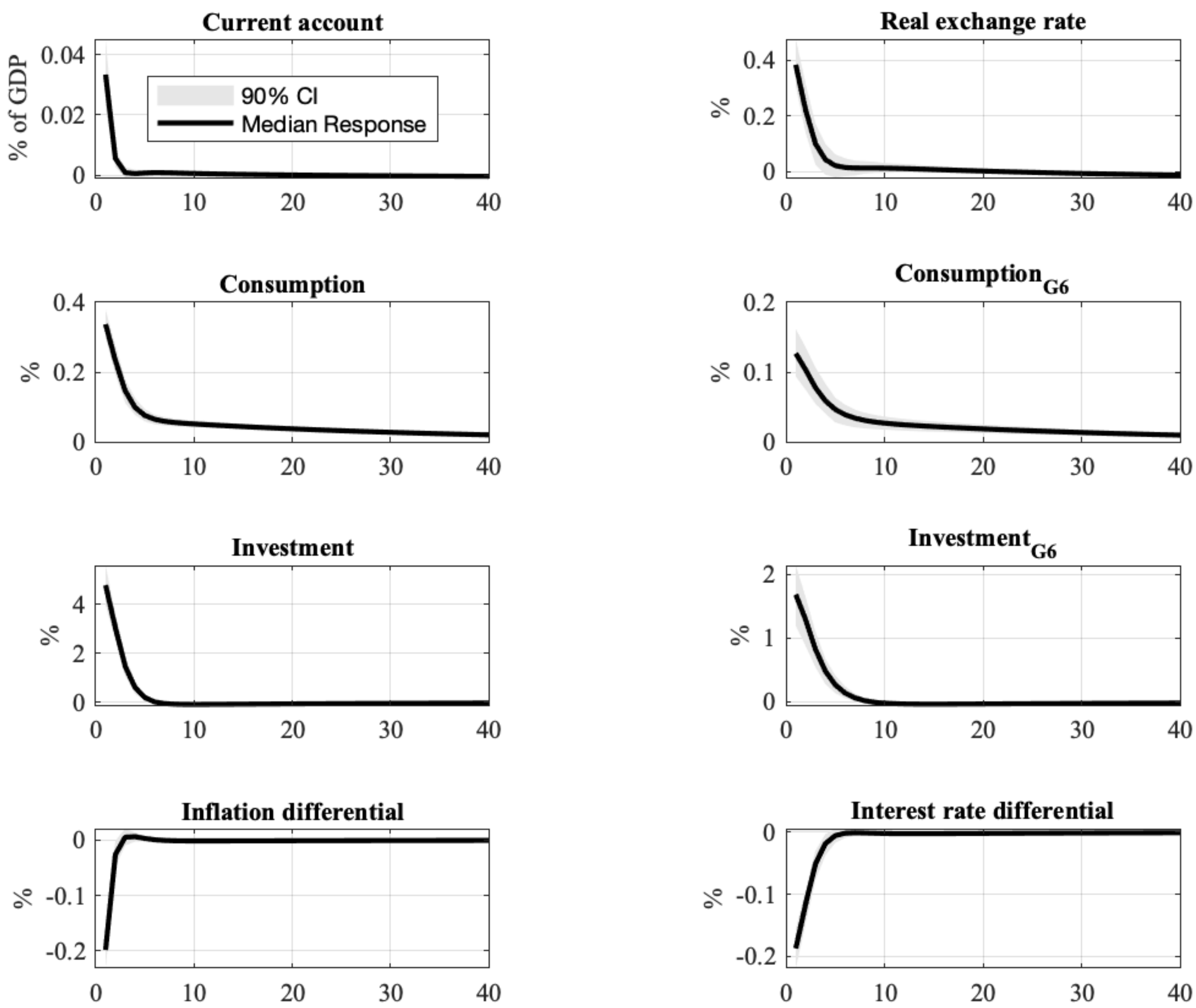


Figure B.39: FEVD of the Current Account Dynamics Δnx_t: G6



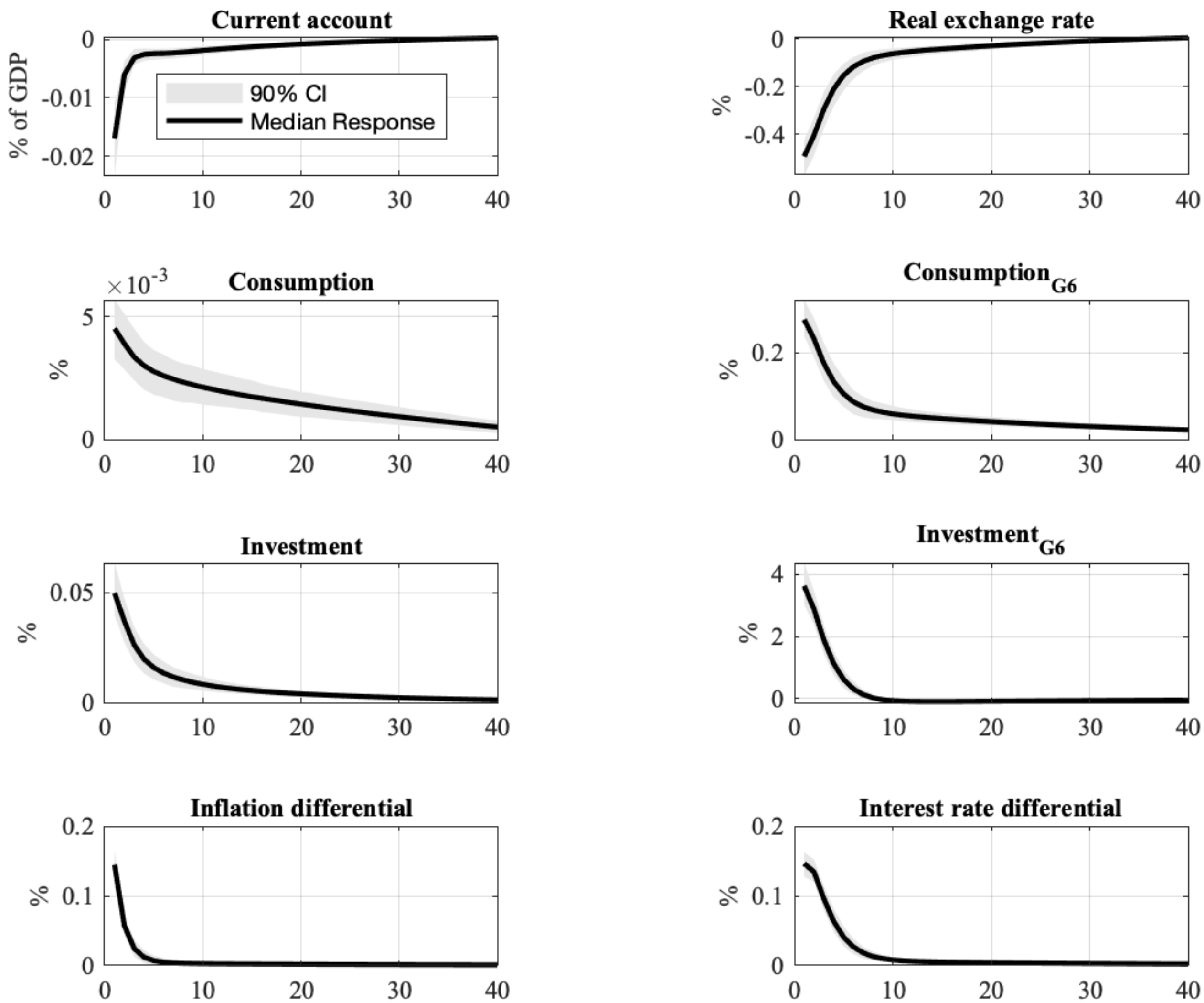
B.5 IRFs of Individual Structural Shocks for the US

Figure B.41: Impulse-Responses of the TFP Shock



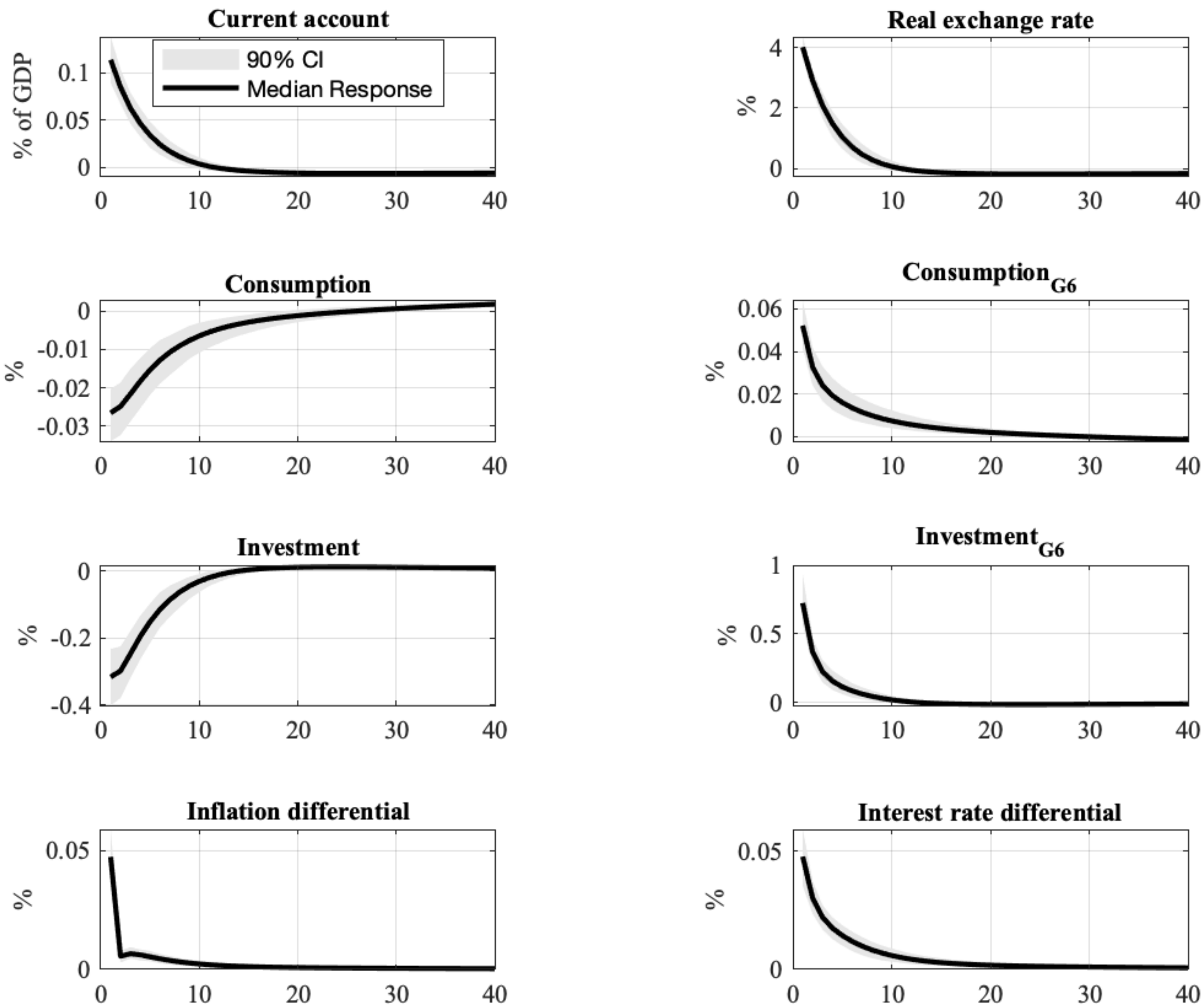
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.42: Impulse-Responses of the Foreign TFP Shock



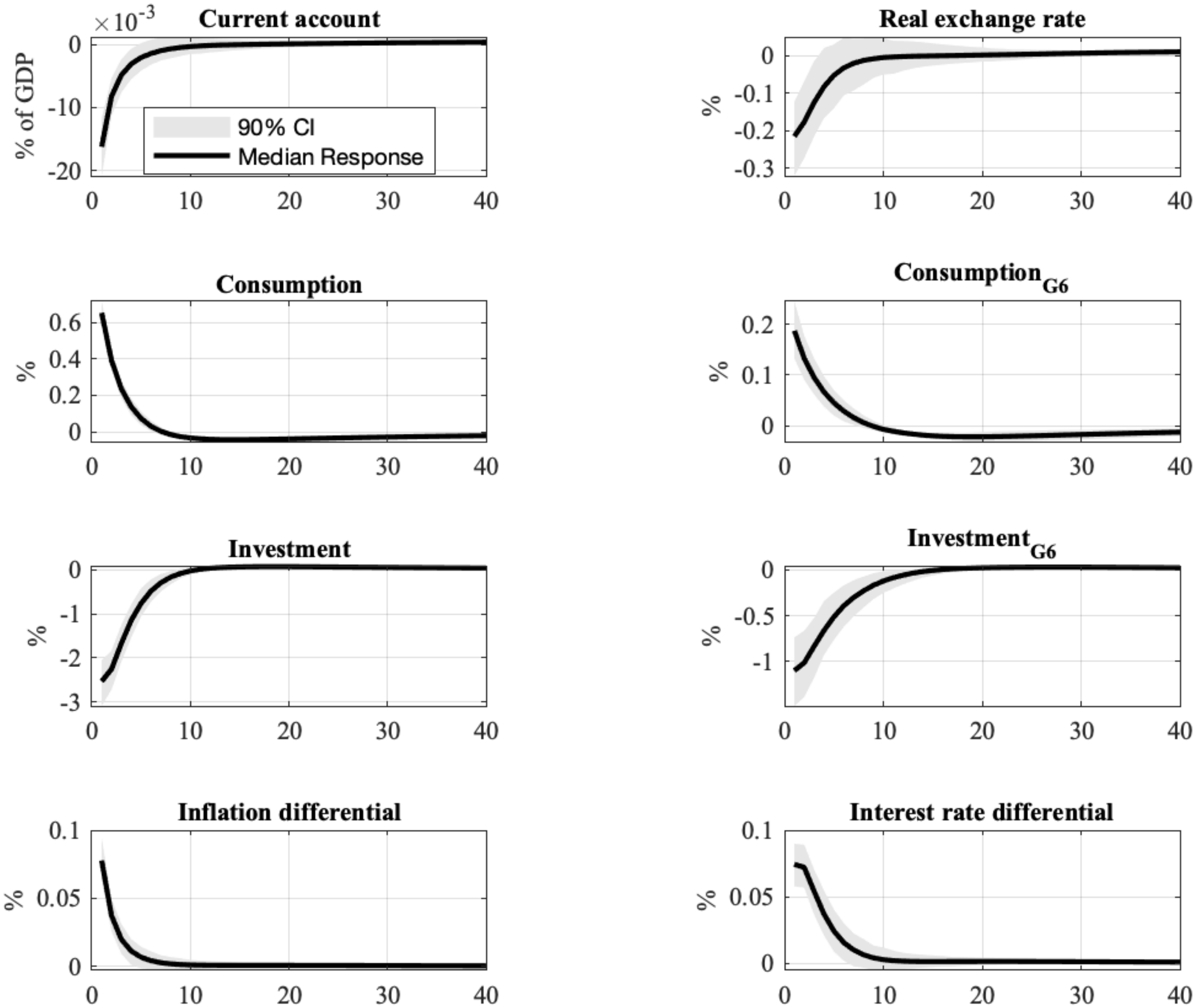
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.43: Impulse-Responses of the Capital Flow Shock



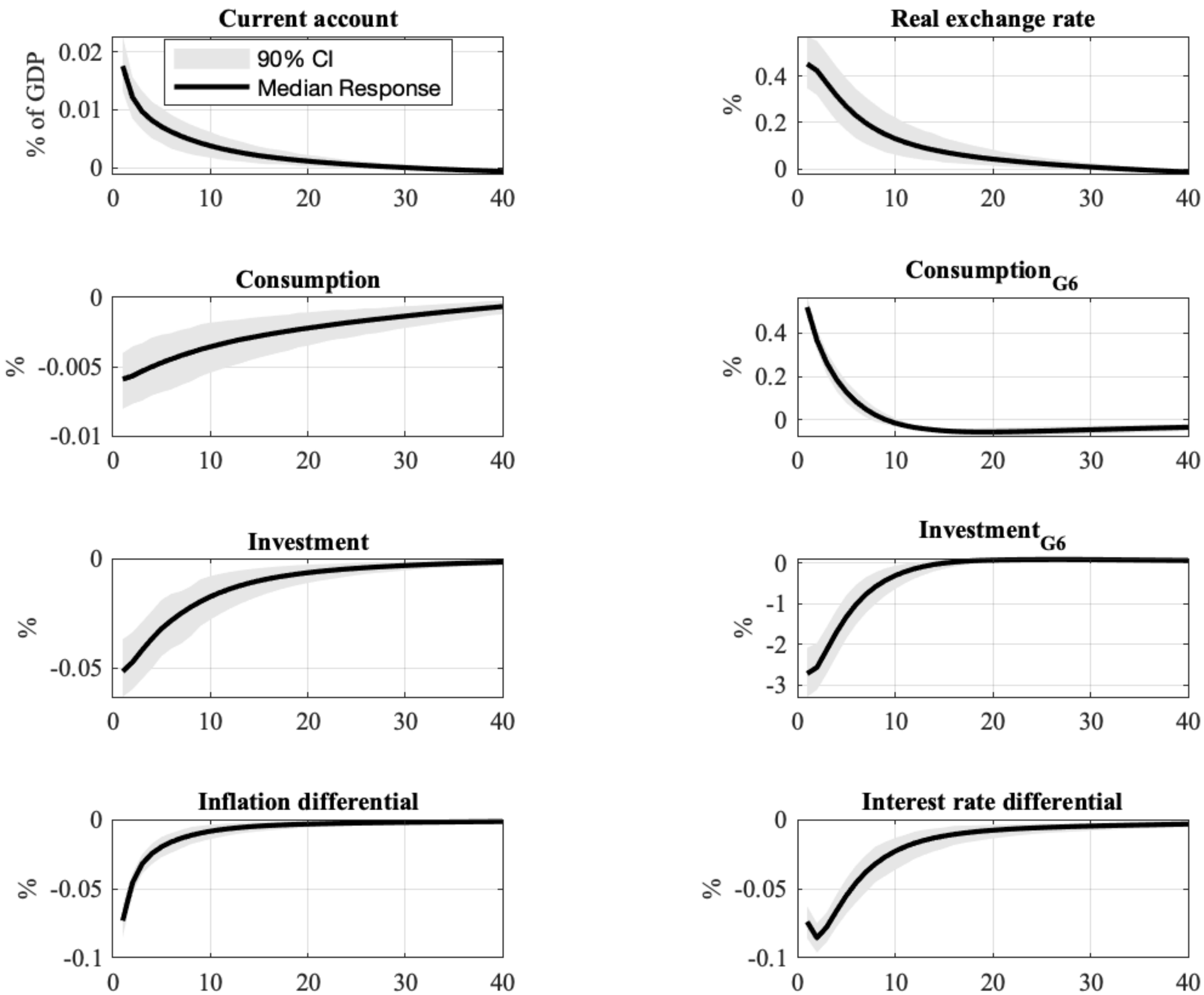
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.44: Impulse-Responses of the Aggregate Demand Shock



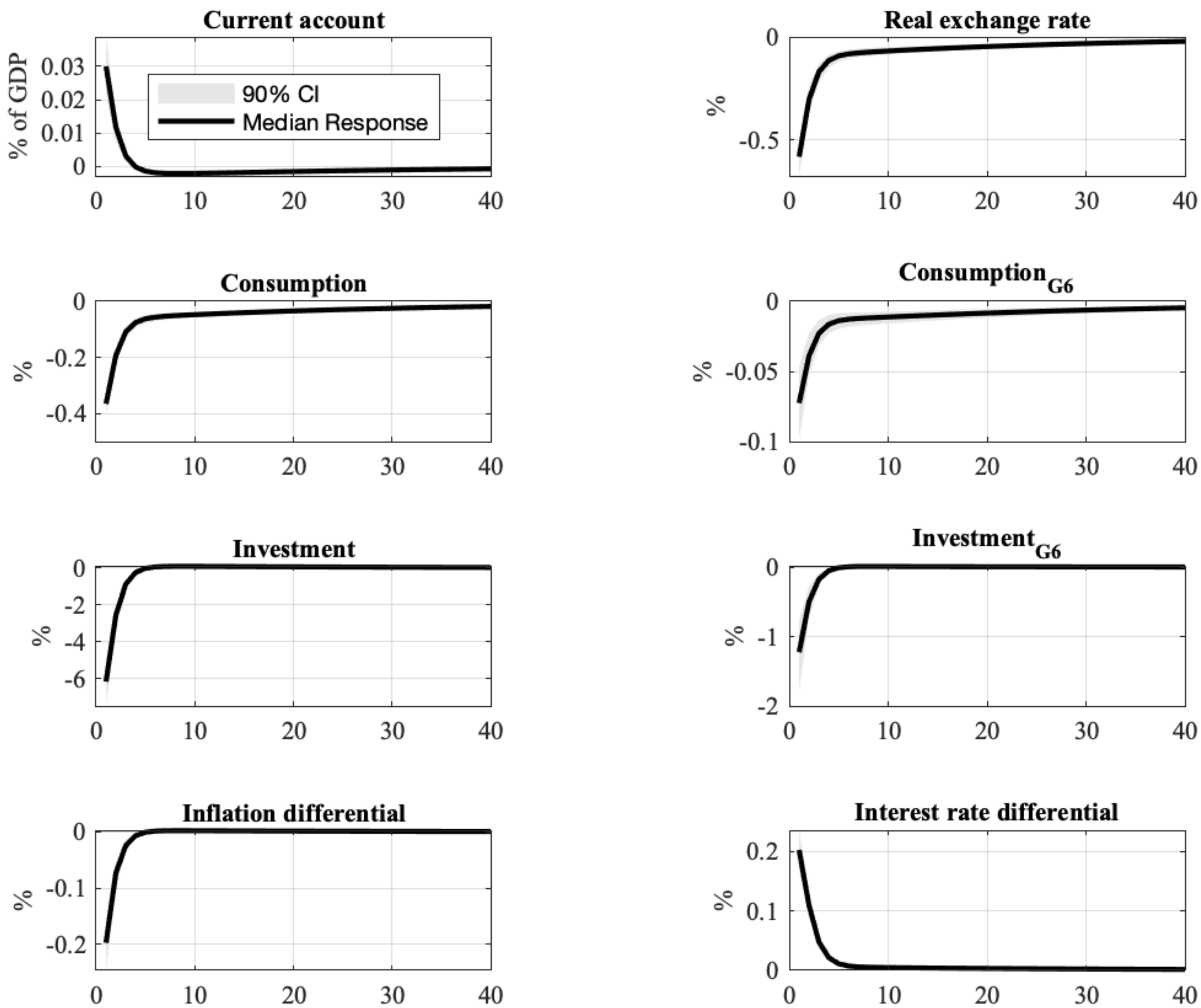
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.45: Impulse-Responses of the Foreign Aggregate Demand Shock



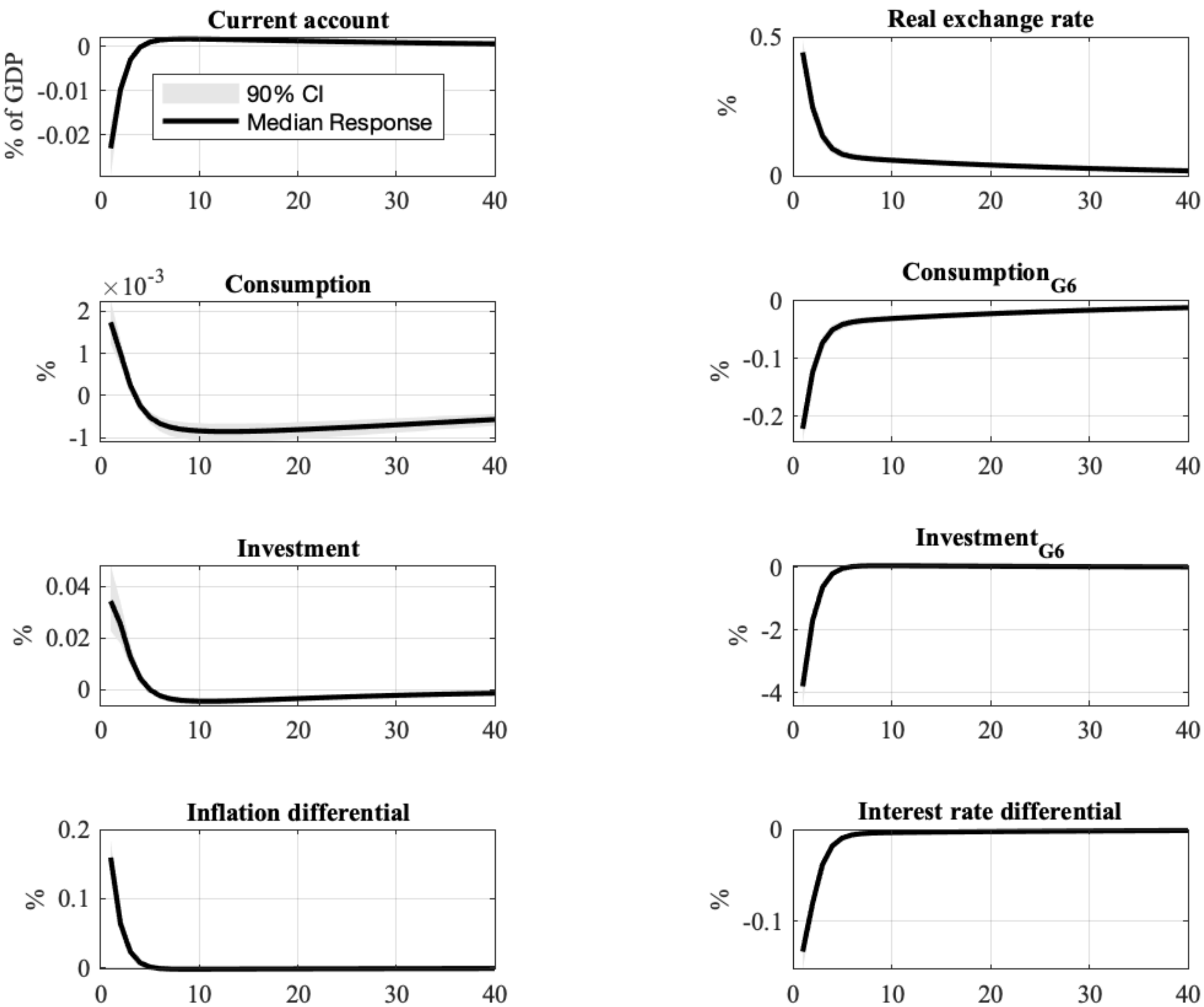
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.46: Impulse-Responses of the Monetary Policy Shock



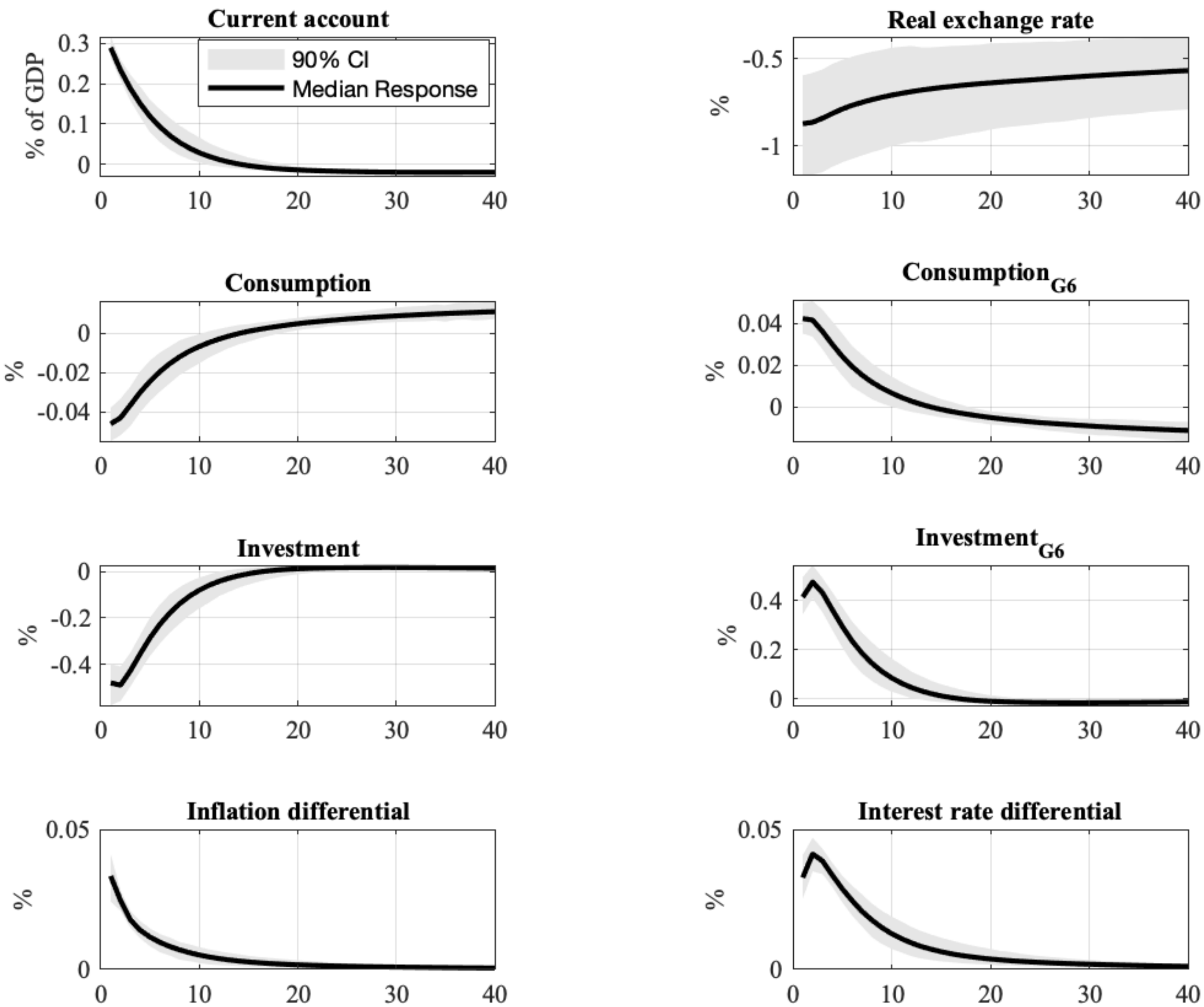
Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

Figure B.47: Impulse-Responses of the Foreign Monetary Policy Shock



Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

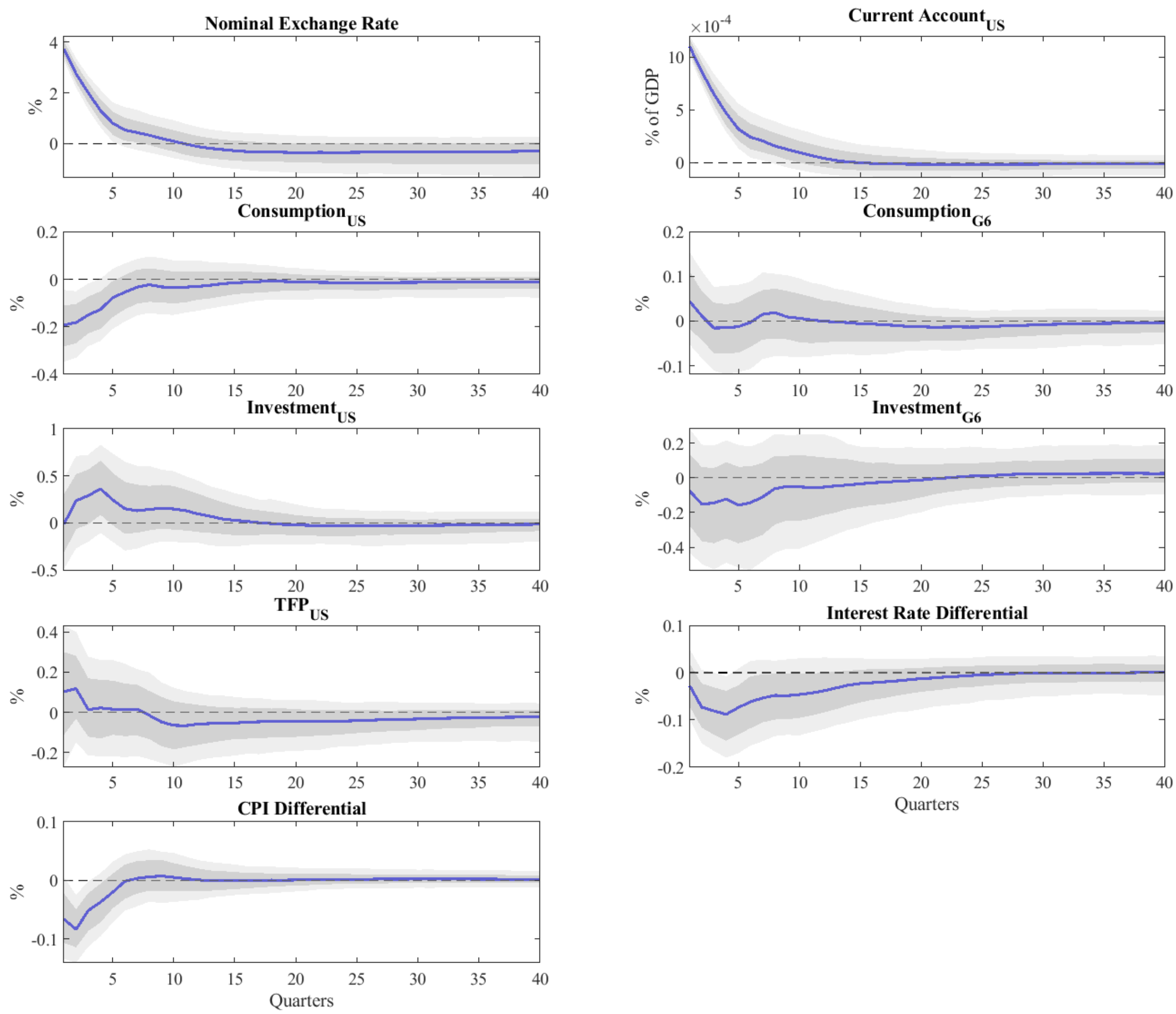
Figure B.48: Impulse-Responses of the Relative Demand Shock



Point-wise median impulse responses with 90% highest posterior density credible sets based on 100000 draws. An increase in the real exchange rate is a depreciation. The interest rat and CPI differentials are expressed as US vs. G6. G6 countries include France, Germany, Italy, Japan, the UK and the US.

B.6 SVAR on Simulated Data

Figure B.49: Impulse Responses to the Dominant CA Shock from Simulated Data Shutting off the Relative Demand Shock



Notes: Point-wise median impulse responses to the dominant business cycle frequency exchange rate shock with 68% (dark gray) and 90% (light gray) highest posterior density credible sets based on 1000 draws. An increase in the nominal exchange rate is a depreciation.

B.7 Estimation for G6 Countries

Table B.2: Parameters Estimation: UK

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0133	0.014	[0.0097,0.0182]	Beta	0.02
κ	8.7	7.6542	7.7059	[6.8347,8.5268]	Normal	0.5
ϕ_π	1.5	1.5164	1.51	[1.3433,1.6643]	Normal	0.1
ϕ_π^*	1.5	1.6072	1.6113	[1.4647,1.7713]	Normal	0.1
ϕ_y	0.5	0.4634	0.4585	[0.3727,0.5433]	Normal	0.05
ϕ_y^*	0.5	0.4457	0.4434	[0.3607,0.5335]	Normal	0.05
χ_2	0.001	0.0012	0.0014	[0.0002,0.0026]	Normal	0.001
ρ_a	0.6	0.6116	0.6114	[0.5321,0.6907]	Beta	0.1
ρ_a^*	0.6	0.5388	0.5352	[0.4691,0.5999]	Beta	0.1
ρ_ψ	0.6	0.7308	0.7206	[0.6566,0.7867]	Beta	0.1
ρ_m	0.6	0.8995	0.8967	[0.8760,0.9176]	Beta	0.1
ρ_m^*	0.6	0.9138	0.9115	[0.8942,0.9303]	Beta	0.1
ρ_v	0.6	0.3076	0.3125	[0.2440,0.3858]	Beta	0.1
ρ_v^*	0.6	0.1399	0.1459	[0.0941,0.1956]	Beta	0.1
ρ_Ω	0.6	0.6336	0.6313	[0.5771,0.6913]	Beta	0.1
ρ_Ω^*	0.6	0.5901	0.5886	[0.5316,0.6462]	Beta	0.1
ρ_γ	0.6	0.4508	0.4554	[0.3623,0.5508]	Beta	0.1
σ_a	0.01	0.0308	0.0309	[0.0265,0.0355]	Inverse Gamma	Inf
σ_a^*	0.01	0.032	0.0324	[0.0279,0.0364]	Inverse Gamma	Inf
σ_ψ	0.01	0.0108	0.0114	[0.0086,0.0140]	Inverse Gamma	Inf
σ_v	0.01	0.0047	0.0047	[0.0040,0.0053]	Inverse Gamma	Inf
σ_v^*	0.01	0.0025	0.0026	[0.0023,0.0029]	Inverse Gamma	Inf
σ_Ω	0.01	0.0348	0.0352	[0.0322,0.0384]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.0474	0.0479	[0.0436,0.0519]	Inverse Gamma	Inf
σ_γ	0.01	0.0055	0.0056	[0.0051,0.0060]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.2135	0.2121	[0.1292,0.2973]	Beta	0.1
ρ_{v,v^*}	0.3	0.2209	0.2237	[0.1372,0.3109]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1782	0.1875	[0.1019,0.2699]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

Table B.3: Parameters Estimation: DE

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0207	0.0209	[0.0167,0.0255]	Beta	0.02
κ	8.7	8.027	7.9711	[7.1658,8.8764]	Normal	0.5
ϕ_π	1.5	1.5434	1.5447	[1.3829,1.7028]	Normal	0.1
ϕ_π^*	1.5	1.5857	1.585	[1.4314,1.7534]	Normal	0.1
ϕ_y	0.5	0.4778	0.4771	[0.3975,0.5644]	Normal	0.05
ϕ_y^*	0.5	0.4422	0.4401	[0.3585,0.5244]	Normal	0.05
χ_2	0.001	0.0012	0.0013	[0.0002,0.0024]	Normal	0.001
ρ_a	0.6	0.5842	0.5805	[0.5011,0.6562]	Beta	0.1
ρ_a^*	0.6	0.6269	0.6236	[0.5561,0.6877]	Beta	0.1
ρ_ψ	0.6	0.7122	0.7054	[0.6395,0.7755]	Beta	0.1
ρ_m	0.6	0.9172	0.9153	[0.9003,0.9302]	Beta	0.1
ρ_m^*	0.6	0.8974	0.8933	[0.8721,0.9149]	Beta	0.1
ρ_v	0.6	0.3001	0.3054	[0.2217,0.3819]	Beta	0.1
ρ_v^*	0.6	0.1364	0.1474	[0.0945,0.1982]	Beta	0.1
ρ_Ω	0.6	0.5852	0.5807	[0.5166,0.6478]	Beta	0.1
ρ_Ω^*	0.6	0.5853	0.5826	[0.5264,0.6399]	Beta	0.1
ρ_γ	0.6	0.7106	0.7105	[0.6352,0.7927]	Beta	0.1
σ_a	0.01	0.0251	0.0254	[0.0219,0.0287]	Inverse Gamma	Inf
σ_a^*	0.01	0.0262	0.0266	[0.0228,0.0305]	Inverse Gamma	Inf
σ_ψ	0.01	0.0103	0.0106	[0.0080,0.0129]	Inverse Gamma	Inf
σ_v	0.01	0.0018	0.0019	[0.0017,0.0021]	Inverse Gamma	Inf
σ_v^*	0.01	0.0032	0.0033	[0.0029,0.0037]	Inverse Gamma	Inf
σ_Ω	0.01	0.0225	0.0227	[0.0209,0.0247]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.0444	0.0446	[0.0410,0.0481]	Inverse Gamma	Inf
σ_γ	0.01	0.0039	0.0039	[0.0036,0.0042]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.2044	0.2065	[0.1238,0.2867]	Beta	0.1
ρ_{v,v^*}	0.3	0.1931	0.2038	[0.1175,0.2910]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1873	0.1881	[0.1071,0.2692]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

Table B.4: Parameters Estimation: FR

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0133	0.0135	[0.0095,0.0170]	Beta	0.02
κ	8.7	7.5329	7.4602	[6.6109,8.3916]	Normal	0.5
ϕ_π	1.5	1.4876	1.4895	[1.3385,1.6620]	Normal	0.1
ϕ_π^*	1.5	1.6083	1.6118	[1.4363,1.7682]	Normal	0.1
ϕ_y	0.5	0.4774	0.4804	[0.3947,0.5573]	Normal	0.05
ϕ_y^*	0.5	0.433	0.4374	[0.3527,0.5247]	Normal	0.05
χ_2	0.001	0.0013	0.0015	[0.0001,0.0027]	Normal	0.001
ρ_a	0.6	0.5053	0.5117	[0.4172,0.6176]	Beta	0.1
ρ_a^*	0.6	0.5881	0.5826	[0.5144,0.6498]	Beta	0.1
ρ_ψ	0.6	0.7048	0.6972	[0.6312,0.7613]	Beta	0.1
ρ_m	0.6	0.5381	0.5137	[0.4148,0.6019]	Beta	0.1
ρ_m^*	0.6	0.9218	0.9204	[0.9049,0.9355]	Beta	0.1
ρ_v	0.6	0.155	0.1712	[0.1054,0.2353]	Beta	0.1
ρ_v^*	0.6	0.2396	0.2483	[0.1800,0.3249]	Beta	0.1
ρ_Ω	0.6	0.4969	0.4948	[0.4139,0.5727]	Beta	0.1
ρ_Ω^*	0.6	0.5776	0.5748	[0.5178,0.6317]	Beta	0.1
ρ_γ	0.6	0.5728	0.5723	[0.4850,0.6566]	Beta	0.1
σ_a	0.01	0.0251	0.025	[0.0221,0.0284]	Inverse Gamma	Inf
σ_a^*	0.01	0.0285	0.0289	[0.0248,0.0330]	Inverse Gamma	Inf
σ_ψ	0.01	0.0098	0.0101	[0.0079,0.0125]	Inverse Gamma	Inf
σ_v	0.01	0.0132	0.0139	[0.0115,0.0163]	Inverse Gamma	Inf
σ_v^*	0.01	0.0022	0.0023	[0.0020,0.0025]	Inverse Gamma	Inf
σ_Ω	0.01	0.0218	0.0219	[0.0200,0.0239]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.0448	0.0453	[0.0418,0.0491]	Inverse Gamma	Inf
σ_γ	0.01	0.0033	0.0034	[0.0031,0.0036]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.2188	0.2221	[0.1366,0.3020]	Beta	0.1
ρ_{v,v^*}	0.3	0.2945	0.2913	[0.2020,0.3875]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1698	0.1791	[0.0988,0.2555]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

Table B.5: Parameters Estimation: IT

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0183	0.0188	[0.0143,0.0231]	Beta	0.02
κ	8.7	7.7623	7.7415	[6.8977,8.5769]	Normal	0.5
ϕ_π	1.5	1.585	1.5857	[1.4216,1.7380]	Normal	0.1
ϕ_π^*	1.5	1.5954	1.5837	[1.4228,1.7378]	Normal	0.1
ϕ_y	0.5	0.4969	0.4981	[0.4206,0.5758]	Normal	0.05
ϕ_y^*	0.5	0.4353	0.4286	[0.3420,0.5261]	Normal	0.05
χ_2	0.001	0.0009	0.0012	[0.0001,0.0023]	Normal	0.001
ρ_a	0.6	0.6614	0.6553	[0.5816,0.7302]	Beta	0.1
ρ_a^*	0.6	0.5644	0.5628	[0.5002,0.6343]	Beta	0.1
ρ_ψ	0.6	0.7227	0.7146	[0.6530,0.7839]	Beta	0.1
ρ_m	0.6	0.4485	0.4376	[0.3411,0.5351]	Beta	0.1
ρ_m^*	0.6	0.9083	0.9035	[0.8845,0.9243]	Beta	0.1
ρ_v	0.6	0.1477	0.1546	[0.0944,0.2090]	Beta	0.1
ρ_v^*	0.6	0.186	0.1948	[0.1283,0.2596]	Beta	0.1
ρ_Ω	0.6	0.5918	0.5882	[0.5237,0.6532]	Beta	0.1
ρ_Ω^*	0.6	0.5713	0.5658	[0.5080,0.6254]	Beta	0.1
ρ_γ	0.6	0.7634	0.758	[0.6945,0.8255]	Beta	0.1
σ_a	0.01	0.018	0.0183	[0.0158,0.0211]	Inverse Gamma	Inf
σ_a^*	0.01	0.0288	0.0292	[0.0253,0.0329]	Inverse Gamma	Inf
σ_ψ	0.01	0.0098	0.0102	[0.0077,0.0125]	Inverse Gamma	Inf
σ_v	0.01	0.0155	0.016	[0.0134,0.0184]	Inverse Gamma	Inf
σ_v^*	0.01	0.0025	0.0026	[0.0023,0.0029]	Inverse Gamma	Inf
σ_Ω	0.01	0.0272	0.0274	[0.0248,0.0297]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.0459	0.0463	[0.0423,0.0504]	Inverse Gamma	Inf
σ_γ	0.01	0.0036	0.0037	[0.0033,0.0040]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.246	0.2478	[0.1574,0.3301]	Beta	0.1
ρ_{v,v^*}	0.3	0.1725	0.1796	[0.1027,0.2553]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1979	0.2039	[0.1239,0.2985]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

Table B.6: Parameters Estimation: CAD

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.0176	0.0181	[0.0139,0.0220]	Beta	0.02
κ	8.7	7.6343	7.6256	[6.7728,8.5228]	Normal	0.5
ϕ_π	1.5	1.4178	1.4059	[1.2355,1.5714]	Normal	0.1
ϕ_π^*	1.5	1.6175	1.6155	[1.4558,1.7735]	Normal	0.1
ϕ_y	0.5	0.4617	0.4611	[0.3683,0.5513]	Normal	0.05
ϕ_y^*	0.5	0.4439	0.4351	[0.3578,0.5271]	Normal	0.05
χ_2	0.001	0.0013	0.0015	[0.0002,0.0025]	Normal	0.001
ρ_a	0.6	0.5501	0.5524	[0.4311,0.6813]	Beta	0.1
ρ_a^*	0.6	0.5437	0.5407	[0.4691,0.6098]	Beta	0.1
ρ_ψ	0.6	0.7655	0.7576	[0.6970,0.8209]	Beta	0.1
ρ_m	0.6	0.9073	0.9038	[0.8848,0.9234]	Beta	0.1
ρ_m^*	0.6	0.9247	0.9212	[0.9040,0.9366]	Beta	0.1
ρ_v	0.6	0.2332	0.2424	[0.1748,0.3105]	Beta	0.1
ρ_v^*	0.6	0.1353	0.146	[0.0927,0.1978]	Beta	0.1
ρ_Ω	0.6	0.7452	0.7392	[0.6818,0.7959]	Beta	0.1
ρ_Ω^*	0.6	0.5954	0.5964	[0.5432,0.6515]	Beta	0.1
ρ_γ	0.6	0.6096	0.6061	[0.5288,0.6873]	Beta	0.1
σ_a	0.01	0.038	0.0379	[0.0316,0.0443]	Inverse Gamma	Inf
σ_a^*	0.01	0.034	0.0346	[0.0294,0.0390]	Inverse Gamma	Inf
σ_ψ	0.01	0.009	0.0094	[0.0069,0.0118]	Inverse Gamma	Inf
σ_v	0.01	0.004	0.0041	[0.0035,0.0047]	Inverse Gamma	Inf
σ_v^*	0.01	0.0024	0.0025	[0.0022,0.0028]	Inverse Gamma	Inf
σ_Ω	0.01	0.0228	0.0229	[0.0210,0.0250]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.053	0.0535	[0.0492,0.0582]	Inverse Gamma	Inf
σ_γ	0.01	0.004	0.0041	[0.0038,0.0045]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.2102	0.2146	[0.1222,0.3011]	Beta	0.1
ρ_{v,v^*}	0.3	0.3791	0.3755	[0.2762,0.4666]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1967	0.2033	[0.1193,0.2876]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.

Table B.7: Parameters Estimation: JP

Parameters	Prior Mean	Post. Mean	Mode	90% HPD Interval	Prior	Prior stdev
γ	0.07	0.009	0.0093	[0.0068,0.0116]	Beta	0.02
κ	8.7	7.9093	7.8827	[7.0552,8.7699]	Normal	0.5
ϕ_π	1.5	1.5345	1.539	[1.3891,1.6906]	Normal	0.1
ϕ_π^*	1.5	1.5661	1.5722	[1.4271,1.7394]	Normal	0.1
ϕ_y	0.5	0.4796	0.4824	[0.3991,0.5623]	Normal	0.05
ϕ_y^*	0.5	0.4792	0.4756	[0.3944,0.5520]	Normal	0.05
χ_2	0.001	0.0014	0.0017	[0.0003,0.0029]	Normal	0.001
ρ_a	0.6	0.5721	0.5697	[0.4885,0.6626]	Beta	0.1
ρ_a^*	0.6	0.5793	0.5754	[0.4929,0.6528]	Beta	0.1
ρ_ψ	0.6	0.7984	0.7878	[0.7252,0.8454]	Beta	0.1
ρ_m	0.6	0.8604	0.8553	[0.8245,0.8831]	Beta	0.1
ρ_m^*	0.6	0.853	0.8479	[0.8180,0.8777]	Beta	0.1
ρ_v	0.6	0.2232	0.2369	[0.1606,0.3159]	Beta	0.1
ρ_v^*	0.6	0.1949	0.21	[0.1247,0.2832]	Beta	0.1
ρ_Ω	0.6	0.5132	0.5058	[0.4223,0.5905]	Beta	0.1
ρ_Ω^*	0.6	0.6224	0.6194	[0.5660,0.6770]	Beta	0.1
ρ_γ	0.6	0.8148	0.8138	[0.7492,0.8823]	Beta	0.1
σ_a	0.01	0.0264	0.0265	[0.0227,0.0300]	Inverse Gamma	Inf
σ_a^*	0.01	0.0223	0.0225	[0.0194,0.0256]	Inverse Gamma	Inf
σ_ψ	0.01	0.0102	0.0108	[0.0078,0.0140]	Inverse Gamma	Inf
σ_v	0.01	0.0037	0.0038	[0.0033,0.0044]	Inverse Gamma	Inf
σ_v^*	0.01	0.003	0.0031	[0.0027,0.0035]	Inverse Gamma	Inf
σ_Ω	0.01	0.0202	0.0204	[0.0187,0.0223]	Inverse Gamma	Inf
σ_Ω^*	0.01	0.028	0.0284	[0.0258,0.0311]	Inverse Gamma	Inf
σ_γ	0.01	0.0024	0.0025	[0.0022,0.0027]	Inverse Gamma	Inf
ρ_{a,a^*}	0.3	0.2159	0.2193	[0.1309,0.3089]	Beta	0.1
ρ_{v,v^*}	0.3	0.2191	0.2186	[0.1221,0.3074]	Beta	0.1
ρ_{Ω,Ω^*}	0.3	0.1845	0.1902	[0.0945,0.2700]	Beta	0.1

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm.