Exchange Rate Disconnect Revisited[*]

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Abstract

We find that variation in expected U.S. productivity explains over half of G6 exchange rate fluctuations vis-a-vis the USD. Both correctly-anticipated changes in productivity and expectational "noise," which influences expectations of productivity but not the actual realization, have significant effects on exchange rates. Together, these two types of disturbances generate many stylized exchange rate facts, including predictable excess returns, low Backus-Smith correlations, and excess volatility. Thus, our findings suggest these well-known puzzles have a common empirical origin, which is linked to (expected) productivity. We argue this has been obscured from previous analysis due to not accounting for noise in expectations.

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1 Introduction

The real exchange rate — the relative price of consumption across countries — plays a crucial role in clearing markets for both real goods and financial assets in most international macroeconomic models. As a result, models typically imply that exchange rates are tightly linked to cross-country differentials in macroeconomic quantities, real interest rates, and other asset prices in the economy. However, in the data, exchange rates turn out to be largely "disconnected" from such macro fundamentals: real exchanges rates exhibit virtually no correlation with current and past macro quantities (e.g. Meese and Rogoff (1983), Engel and West (2005))) or interest rates (e.g. Fama (1984)), and at the same time are surprisingly volatile (e.g. Rogoff (1996)). A tremendous amount of research seeks to understand what could potentially generate these stylized facts in equilibrium models, however there is relatively little direct empirical evidence of what actually drives this disconnect in the data.

In this paper, we step back from indirect structural inference, and attempt to uncover the main empirical drivers of exchange rate fluctuations in a model-agnostic way. Our key finding is that noisy news about future TFP account for more than half of the overall variation in *both* real exchange rates and macroeconomic variables, but the impact on exchange rates leads that on the macroeconomy, contributing to an apparent "disconnect" when looking at the data unconditionally. We decompose these noisy news into orthogonal disturbances to (i) partially anticipated actual changes to future productivity and (ii) expectational "noise" disturbances that move expectations, *but never materialize in realized productivity.* We find that the conditional responses to these two disturbances generate a number of famous "exchange rate puzzles", suggesting that well-known anomalies have a common, fundamental origin in noisy news about future TFP. Furthermore, the sizable expectational noise component we estimate helps us understand how this link between exchange rates and future TFP has been obscured from previous empirical analysis that does not control for the noise.

Our analysis proceeds in two steps. First, we seek an agnostic description of the basic comovement patterns associated with surprise changes in exchange rates in the data. To do this, we follow the VAR procedure of Uhlig (2003) to recover a set of orthogonal reduced form shocks ordered by their importance in explaining exchange rate variation. We find that the first shock – the one most important to exchange rate fluctuations – explains two-thirds of exchange rate variation *and* around 40% of the variation in macro aggregates. However, while the shock impacts the exchange rate immediately, its effect on macroeconomic quantities such as consumption, output and TFP are delayed. Thus, this shock only generates a correlation between exchange rates and *future* macro aggregates, leaving exchange rates effectively "disconnected" from contemporaneous macro aggregates. And in particular, the shock has no initial impact on Fernald's utilization-adjusted TFP, but leads to a significant increase in TFP between three and five years in the future.

Intuitively, these results suggest that we are uncovering the reaction of a forward-looking asset price, the exchange rate, to the arrival of salient news about the future. This motivates the second, and most important, step of our analysis, in which we specifically identify and isolate disturbances to expectations about future US TFP, and then estimate their impacts on the real exchange rates and other cross-country macro variables. To identify these disturbances, we follow the approach of Chahrour and Jurado (2021), which allows us to separately identify TFP changes that are imperfectly anticipated, and expectational "noise" shocks that influence the expectations of future productivity, but are themselves not related to actual changes in productivity at any lead or lag. Intuitively, this identification approach is designed to separately identify the signal from the noise component in noisy news.

Implementing this approach in our baseline VAR, we find that both correctly-anticipated future TFP changes and "noise" in TFP expectations play an important role in driving exchange rates – these two disturbances together account for more than 60% of the variation in the real exchange rate. Moreover, we find that these noisy news of future TFP also drive a significant fraction of the variation in macroeconomic quantities, such as consumption, investment and etc.. However, as can be expected the impact on macro aggregates is delayed relative to the response on exchange rates. We also study the impulse responses of a number of other variables of interest, such as the trade balance and stock prices, and similarly find the intuitive results that the US current account deteriorates and US stock prices rise in anticipation of an improvement of future productivity. Thus, noisy news about future TFP prove to be the rare structural shocks that drives both real exchange rates, international business cycles and also other asset prices.[1]

Moreover, the Impulse Response Functions (IRFs) to both disturbances we have identified generate a number of famous "exchange rate puzzles". First, we find that our disturbances cause significant fluctuations in expected excess currency returns, which generate violations of interest parity that are consistent with both the classic UIP puzzle of high interest rates forecasting high domestic currency returns (Fama, 1984) and the recently documented "reversal" in this forecastability pattern at longer horizons (Engel, 2016; Valchev, 2020). Second,

[1] On the other hand, we find that the pure surprise component of TFP innovations has very little impact on exchange rates.

the conditional responses of exchange rates and consumption differentials across countries exhibit a weak negative correlation, in line with the Backus et al. (1993) puzzle documented unconditionally. Third, the conditional responses we estimate also imply the real exchange rate dynamics are close to random walk, and exhibit large volatility, two well-known features of unconditional exchange rate dynamics that the literature often dubs the "PPP Puzzle" or the excess volatility of the exchange rate (e.g. Rogoff (1996)).

Taken together with the apparent disconnect that our identified shocks generate, the results showcase that a constellation of famous anomalies in exchange rate behavior share a common, fundamental origin, tied specifically to noisy news about future TFP. Furthermore, we find that the two disturbances we uncover transmit to the exchange rate primarily by driving time-variation in expected currency returns and the resulting UIP wedge. Thus, our result present sharp guidance for the construction of general equilibrium models. The results share the intuition of a recent theoretical literature that puts a volatile UIP wedge at the center of exchange rate puzzles (e.g. Gabaix and Maggiori (2015); Itskhoki and Mukhin (2021), however, our results are more discriminating, as they imply that the wedge should be endogenous and specifically driven by noisy news of future TFP, and not a separate set of orthogonal shocks. This is in contrast to the emerging consensus that the key lessons of these previous studies is to include exogenous UIP shocks to our models. Instead, our preliminary conclusion is that the results speak in favor of models in the vein of the long-run risk literature (e.g. Colacito and Croce (2013)).

Lastly, we want to stress that our estimates suggest that the news that matter for the exchange rate are about *medium-to-long horizon* TFP changes, and not short-run changes in future TFP. For example, our VAR estimates show that the TFP innovations we estimate are (partially) anticipated up to 5 years in advance. This can help us understand why previous previous studies that, similar to us, have emphasized the forward-looking nature of exchange rates, have still failed to find a robust relationship between exchange rates and future TFP (and macro variables more broadly). In short, the bulk of such studies have focused their attention at much shorter horizons, looking for lead-lag relationships at horizons of one to two years (e.g. Engel and West (2005), Sarno and Schmeling (2014), among others). Moreover, in addition to capturing longer run news, our VAR results are also strengthened by the fact that we separately identify both the TFP innovation itself and the noise in the TFP expectations, as both affect the exchange rate substantially.

Related literature This paper is related to several different strands of the international finance and macro literatures. First, we speak to the exchange rate determination puzzle, that is the lack of correlation between exchange rates and macroeconomic fundamentals, both contemporaneously and in terms of forecasting future exchange rates with current macroeconomic fundamentals (Meese and Rogoff, 1983; Cheung et al., 2005; Engel and West, 2005; Miyamoto et al., 2022).[2] A related observation is that the exchange rate is "excessively" volatile and persistent, as compared to macroeconomic fundamentals; see for example Obstfeld and Rogoff (2000), Chari et al. (2002), Sarno (2005), Steinsson (2008).

Contrary to this literature, we find that there is indeed a strong connection between exchange rates and macroeconomic fundamentals, but one that relates current exchange rates and future fundamentals. This timing inverts the common empirical hypothesis that current and past macro variables might predict future exchange rates, for which past studies find only weak evidence (Meese and Rogoff, 1983; Rogoff and Stavrakeva, 2008). Instead, our evidence is in line with Engel and West's (2005) observation that exchange rates are forward looking and hence should predict, rather than lag behind, macroeconomic variables. Our results contribute to this discussion in two ways. First, we show that the link between current exchange rates and future fundamentals runs specifically through *imperfect* and *noisy* anticipation of future productivity. Second, in failing to account for the expectational noise component, the previous literature has suffered from weak statistical power which contributes to the fact that previous studies only find weak and inconclusive evidence of exchange rates Grange-causing macro aggregates. (Engel and West, 2005; Sarno and Schmeling, 2014).[3]

Relative to the papers discussed above, our results also show that the noisy news shocks we identify transmit to the exchange rate primarily by causing large fluctuations in expected excess returns and deviations from uncovered interest parity (UIP). Moreover, since these excess returns-driven fluctuations are related to the arrival of news about the future, we also find that the resulting exchange rate fluctuations are not strongly correlated with current consumption differentials across countries. Thus, in addition to finding that noisy news about future TFP can generate the famous puzzles of exchange rate disconnect and excess

[2]Lilley et al. (2020) find a contemporaneous correlation between US purchases of foreign bonds and the USD, but only in the post-2009 period. Such correlations have proven elusive over a longer time span.

[3]Another literature uses survey of expectations to measure the surprises in macroeconomic announcements and studies their effect on exchange rates (Andersen et al., 2003; Faust et al., 2007; Engel et al., 2008). In a recent paper, Stavrakeva and Tang (2020) find that the new information about *past* macroeconomic fundamentals that the market obtains upon a new statistical release is an important driver of exchange rate fluctuations. Our definition of "news" is different, however, as we specifically identify disturbances to the forecast of *future U.S. TFP* changes, as opposed to revision of beliefs about *past* variables such as output.

volatility, we also find that these two structural shocks are also behind two other seminal puzzles in the literature – the UIP puzzle (Fama, 1984; Engel, 2014) and the Backus-Smith puzzle (Backus and Smith, 1993). Both puzzles have received extensive theoretical attention, however the great majority of such models are driven by surprise shocks in TFP, not by news about future TFP, which is what we find is actually the empirically relevant case.[4]

Put another way, our empirical results imply that many famous exchange rate puzzles have a common, fundamental origin in noisy news, as propagated to the exchange rate via volatile currency excess returns. This empirical result has both parallels and contrasts with a recent theoretical literature which emphasizes models driven by currency-markets-specific "noise trader" shocks (Eichenbaum et al., 2020; Itskhoki and Mukhin, 2021).[5] Our empirical evidence agrees with one key insight of this literature, which is that fluctuations in excess currency returns are at the center of several exchange rate puzzles. However, our results go further, and indicate that in the data the excess returns fluctuations are specifically caused by the arrival of noisy news about future TFP. Moreover, let us stress the subtle difference in the notions of"noise" used in our case relative to this literature. In the UIP-shock literature, the "noise" is typically an exogenous shift in the demand for one currency relative to another, while we use the term "noise" to denote a shock to the expectations of future TFP. Hence, while our notion of noise is also in truth orthogonal to actual TFP, agents do not know this in real time and react to it as if it truly carries information about future productivity.[6]

Lastly, there is a small but growing literature specifically documenting the effects of "news shocks" in the international data and developing international RBC models driven in part by news shocks. That literature, however, has typically focused on the question of comovement between macro aggregates across countries, and not on exchange rate dynamics and related puzzles. In that vein, Siena (2015) argues that news shocks only lead to a small amount

[4]For example, time-varying risk (Alvarez et al., 2009; Verdelhan, 2010; Bansal and Shaliastovich, 2012; Farhi and Gabaix, 2015; Gabaix and Maggiori, 2015), non-rational expectations (Gourinchas and Tornell, 2004; Burnside et al., 2011; Ilut, 2012; Candian and De Leo, 2021) and liquidity premia (Engel, 2016; Valchev, 2020) have been proposed as explanations of the UIP Puzzle. On the other hand, Corsetti et al. (2008), Colacito and Croce (2013), and Karabarbounis (2014) develop models that explain the Backus-Smith puzzle.

[5]Such shocks have a long tradition in the literature; see also (Devereux and Engel, 2002; Jeanne and Rose, 2002; Kollmann, 2005; Bacchetta and van Wincoop, 2006; Farhi and Werning, 2012). Relatedly, Huo et al. (2020) find that international comovement between macro aggregates is also likely explained by non-fundamental shocks, though they do not speak to correlation with exchange rates

[6]Models in which investors have dispersed information about future fundamentals and learn from equilibrium exchange rate movements, as in Bacchetta and van Wincoop (2006) appear as an interesting middle ground. In these models, the exchange rate acts as a public signal for future fundamentals and "noise-trader shocks" act as the noise in this (public) signal. This framework thus equates the two notions of noise. Our evidence quantifies the relative contribution of signal and noise in equilibrium exchange rate movements.

of comovement between macro aggregates across countries, contrary to previous evidence by Beaudry and Portier (2014).[7] Perhaps most closely related to us is the work of Nam and Wang (2015), who use Barsky and Sims' (2011) approach to identifying news-to-TFP shocks. In contrast to us, however, they do not separately identify the effects of correctly anticipated TFP improvements and expectational noise shocks, and also do not consider how news are propagated to the exchange rate. A key differentiating result of our analysis is that UIP deviations as caused by *noisy* news about future TFP are at the heart of many famous exchange rate puzzles, and exchange rate volatility overall.

2 Data and Basic Empirical Framework

Our empirical analysis centers on a VAR

$$Y_t = C(L)Y_{t-1} + u_t, \tag{1}$$

where the vector Y_t contains data on the U.S. and a trade-weighted aggregate for the other G6 economies. For our benchmark analyses, the vector Y_t contains eight variables: (i) the nominal exchange rate S_t expressed in units of USD per foreign currency, (ii) Fernald's (2012) series on utilization-adjusted U.S. TFP, (iii) and (iv) are the U.S. real consumption and investment, (v) and (vi) are G6 real consumption and investment, (vii) the nominal interest rate differential, (viii) and the CPI price level differential between the U.S. and the G6 aggregate. Hereinafter, we will refer to the U.S. and the G6 economies as the "home" and "foreign" economies, respectively, and use the $\star$ notation to denote foreign variables so that the variables in our VAR can be denoted as:

$$Y_t' \equiv \left[\ln\left(S_t\right), \ln\left(TFP_t\right), \ln\left(C_t\right), \ln\left(C_t^\star\right), \ln\left(I_t\right), \ln\left(I_t^\star\right), \ln\left(\frac{1+i_t}{1+i_t^\star}\right), \ln\left(\frac{CPI_t}{CPI_t^\star}\right)\right].$$

Using a G6 aggregate as the "foreign" country is standard in the literature (e.g. Engel (2016)), but we have also conducted our analysis on six bilateral VARs between the US and each G6 country separately and the results are reported in Appendix B.3. The results and the emerging conclusions of the bilateral VARs are very similar, hence we have found that a VAR with a G6 trade weighted aggregate is a good way to summarize the results and serve

[7] Gornemann et al. (2020), instead, develop an international model of endogenous TFP growth, and show that at their calibration it can account well for the low frequency movements in real exchange rates.

as a useful benchmark we report in the main text. Results when we use a simple average across the G6 countries (as opposed to a trade-weighted average), are also virtually the same.

For our benchmark results, we use quarterly data for the time period 1978:Q3-2008:Q1. The sample stops in 2008:Q1 out of abundance of caution, to guard against a possible structural break in the aftermath of the financial crisis, which is a potential pitfall as argued by Baillie and Cho (2014) and Du et al. (2018). However, in Appendix B.1 we conduct our analysis on an extended sample through the end of 2018 (most recent data download) and the results remain very similar. Thus, we think the potential structural break is not a concern for our analysis, but to respond to potential concerns we make the sample that stops in 2008:Q1 the benchmark we report in the main text.

We describe the data and their sources in detail in Appendix A. As a brief overview, the exchange rate is the average of the daily exchange rates within a quarter, obtained from Datastream. The interest rate differential is the average of daily Eurodollar rates within a quarter, obtained from Datastream.[8] The CPI indices and the consumption and investment series are from the OECD database. Lastly, the US TFP is from John Fernald's website.

We do not have a comparable, utilization-adjusted quarterly TFP series for the G6 countries. Recently, a few papers have constructed novel utilization-adjusted TFP for G6 economies (e.g. Huo et al. (2023), Comin et al. (2023)), but we find these measures are not appropriate for our purposes. On the one hand, the Huo et al. (2023) measure of utilization-adjusted TFP for the United States displays a fairly low correlation (0.42) with the widely-accepted Fernald measure for US TFP, suggesting it is measuring some different notion of technology. Also, most such G6 measures of adjusted TFP can only be constructed at annual frequencies (Huo et al. (2023)) or over a very short a sample period (Comin et al. (2023)), which limits the scope of the analysis. As a result, our benchmark analysis does not include a measure of foreign TFP, but as a robustness exercise we report in the Appendix, we consider alternative specifications where we use G6 Solow residual at quarterly frequency (to maximize data coverage). All of our main results and conclusions remain unchanged.

We estimate the VAR in (1) using four lags and Bayesian methods with a Minnesota prior. This commonly used prior assumes all series are separate random walks and that thus there is no relationship between different variables in Y_t, which is very conservative for our purposes, given that we are looking for a potential connection between the exchange rate and the other macro variables.

[8]Note that these interest rate differentials are not forward discount-implied interest rate differentials, but actual eurodollar rates.

Following the established convention (e.g. Sims et al. (1990), Eichenbaum and Evans (1995)), we estimate the VAR in levels and do not impose ex-ante that there are any specific cointegration relationships. Nevertheless, in Appendix B.2 we show that results remain unchanged if one instead estimates a VECM model that impose the same cointegration relationships as Engel (2016), where the real exchange rate and interest rate differential are assumed stationary. More generally, we have also found the results to be very robust to imposing ex-ante a variety of other potential cointegration relationships.

Our goal is to identify a relationship between the reduced-form residuals, μ_t and some structural disturbances ε_t. Formally, we seek an $A(L)$ such that

$$u_t = A(L)\varepsilon_t \tag{2}$$

where $A(L) \equiv \sum_{-\infty}^{\infty} A_k L^k$ is a potentially two-sided lag polynomial. This structure generalizes more traditional treatments in allowing for the innovations in the VAR (equivalently surprises in agent's information) to depend on past, present, and future structural shocks.

Structural assumptions are needed to identify $A(L)$, and different assumptions lead to identifying different series ε_t and different implied impulse responses. Standard VAR treatments have assumed the true data generating process is invertible, which implies that $A(L) = A_0$. From there, one might assume the shocks have a natural "Choleski ordering" in which some shocks affect the economy before others, so that A_0 is triangular. Or one might impose sign restrictions on either short-term or long-term impacts, which would in turn imply a different restrictions on A_0.

We conduct our analysis in two steps, going from fewer to more structural assumptions. First, we will use a "max-share" approach which imposes $A(L) = A_0$ but otherwise makes minimal structural assumptions about A_0. The results of this analysis then motivate our second step, in which we allow for general form for $A(L)$, but impose stronger economic restrictions to separately identify anticipated TFP shocks and noise shocks to expectations of future TFP.

3 "Max-share" Exchange Rate Shocks

We begin with an agnostic empirical approach that aims to isolate the main driver of real exchange rate fluctuations in the data while imposing minimal ex-ante assumptions on the nature of the underlying structural shocks. To do so, we follow the approach in Uhlig (2003) to extract the shock that explains the biggest share of the variation in the real exchange rate. This approach was recently adopted by Angeletos et al. (2020) to extract a so-called "main business cycle" shock. In parallel to the Angeletos et al.'s (2020) terminology, we refer to the shock we extract here as the "main exchange rate" shock.[9]

To give some intuition first, we note that ultimately, any shock series ε_t that is recovered from (2) is simply a linear combination of the reduced form innovations u_t. Assuming A_0 can be inverted to give $\varepsilon_t = A_0^{-1} u_t$, we can think of different choices of A_0 as selecting different linear combinations of the reduced form residuals u_t. In our version of the Uhlig (2003) max-share approach, we specifically look for the linear combination that has the highest explanatory power for the fluctuations in the (log) *real* exchange rate. The goal is to estimate just the first column of A_0, and thus isolates only the innovation ε_{1t} (the first element of ε_t) which makes the largest contribution to fluctuations in the real exchange rate q_t. This is not a structural shock with a clear economic interpretation – ε_{1t} is potentially a linear combination of several underlying structural shocks. Rather, we view ε_{1t} as a reduced form way of capturing the main component of surprise changes in the exchange rate in the data, whatever its true deep origins might be (which is the topic of the second part of our paper).

The real exchange rate q_t is defined as is standard as the difference between the log nominal exchange rate and the differential in log CPIs, $q_t = s_t + p_t^\star - p_t$, and thus

$$q_t = e_q' Y_t,$$

where $e_q = [1, 0, 0, 0, 0, 0, 0, -1]'$. To apply the max-share procedure, first note that the moving average representation of the VAR in (1) can be written as

$$Y_t = \sum_{k=0}^{\infty} B_k A_0 \varepsilon_{t-k}, \tag{3}$$

where the $\{B_k\}$ correspond to the coefficient in the $MA(\infty)$ representation of $B(L) \equiv$

[9]See also Kurmann and Otrok's (2013), Basu et al. (2021) and Chahrour et al. (2020) as other applications of the Uhlig (2003) max-share approach to macro variables. In a recent paper Miyamoto et al. (2022) also applies this methodology to exchange rates. However, they focus on high frequency movements in the exchange rate, and also consider a VAR expressed in terms of cross-country differentials, which puts the focus on country-specific shocks. Crucially, they do not also then further investigate the specific noisy news to TFP hypothesis as we do for the bulk of our paper.

$(I - C(L))^{-1}$. Then, the h-step ahead forecast error over the real exchange rate is given by

$$q_{t+h} - \mathbb{E}_{t-1}q_{t+h} = e_q' \left[\sum_{\tau=0}^{h-1} B_\tau A_0 \varepsilon_{t+h-\tau} \right]$$

The forecast error variance (FEV) of the real exchange rate, $Var(q_{t+h} - \mathbb{E}_{t-1}(q_{t+h}))$, is a linear combination of the variances of the (orthogonal) elements of the vector ε_t, and in particular, the contribution of the first element of ε_{1t} can be expressed as

$$Var(q_{t+h} - \mathbb{E}_{t-1}q_{t+h} | \varepsilon_{2t} = \varepsilon_{3t} = \cdots = \varepsilon_{8t} = 0) = e_q' \left[\sum_{\tau=0}^{h-1} B_\tau A_0 e_1 e_1' A_0' B_\tau' \right] e_q \tag{4}$$

where e_1 is the selection vector so that $A_0 e_1$ selects the first column of A_0, and $\varepsilon_t^{(k)}$ is the k^{th} shock in the vector ε_t.

We choose the rotation matrix A_0 by maximizing (4). This requires us to specify a horizon h at which the forecast error variance in (4) is computed, and for that we choose $h = 100$ quarters, which effectively gives us the unconditional variance of q_t.[10] This procedure yields a partially identified system, in the sense that the above maximization problem will uniquely determine the first column of A_0 and thus the first element of the shock vector of ε_t (which is what we are interested in), but not the rest.

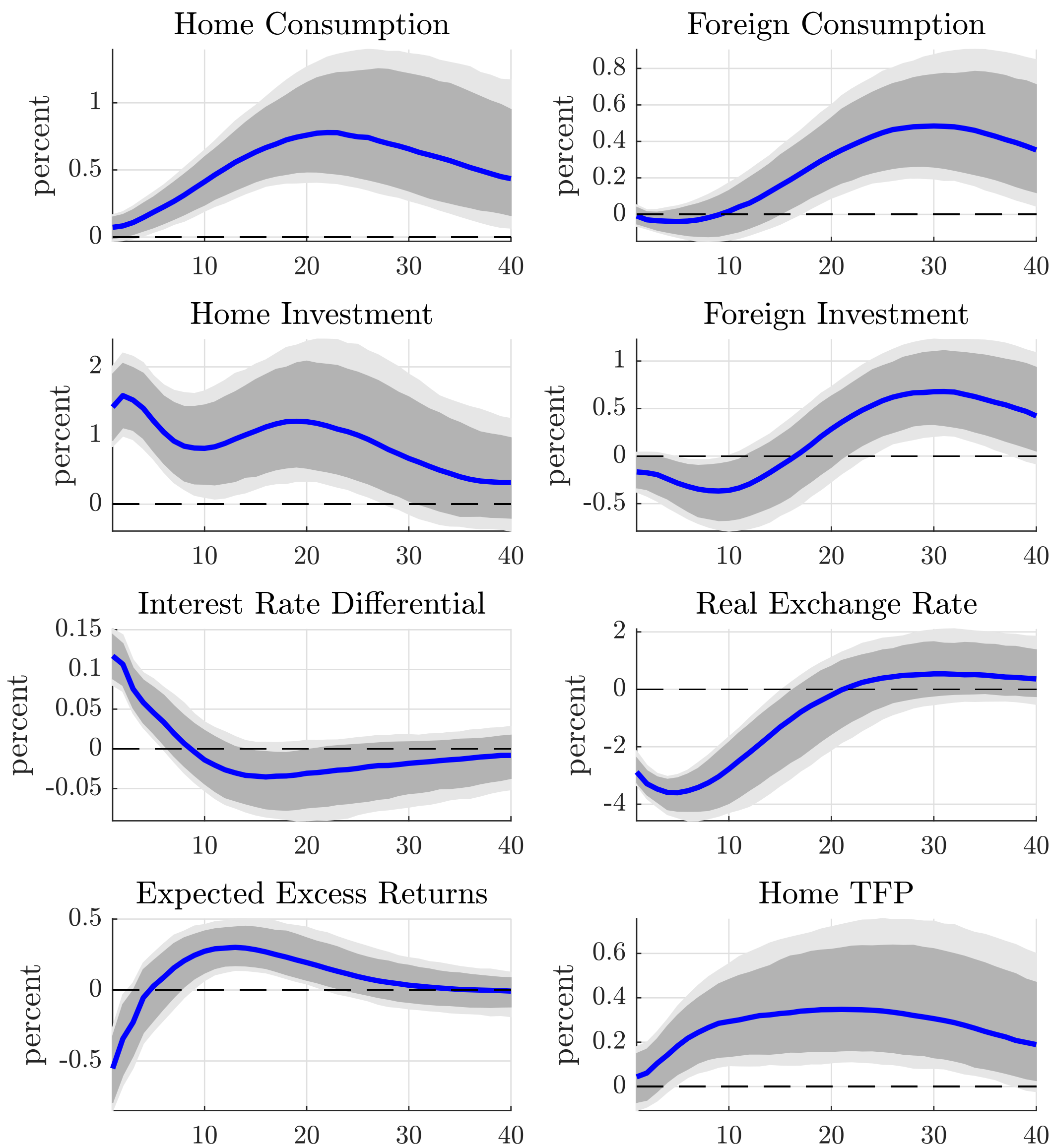
Estimation Results. We find that this "main exchange rate shock" is indeed very important for exchange rate fluctuations – it explains roughly 70% of variance of the real exchange rate, in a variance decomposition sense (see Table 1, row 7). Thus this reduced form innovation captures the bulk of exchange rate fluctuations, and hence for expositional clarity we will refer to the extracted ε_{1t} as the "main exchange rate" (MFX) shock.

To study the typical exchange rate dynamics associated with this innovation, we report the impulse response functions of the exchange rate, and other variables of interest we turn to next, in Figure 1. The median impulse response is plotted with a solid blue line, and the shaded areas denote the 16-84th percentile and the 10-90th percentile bands respectively.

The real exchange rate shows a significant response on impact, appreciating by about 2.5% after a one standard deviation increase in the MFX shock. The exchange rate response also displays persistent hump-shaped dynamics, where it continues to appreciate for another

[10] Our results are robust to choosing a variety of horizons h. Moreover, the same procedure can also be applied in the frequency domain, and the results remain very much the same if we target variation of q_t over specific frequencies instead.

Figure 1: Impulse Response Functions to the Main FX shock (ε_1)



Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Table 1: Share of forecast error variance explained by the Main FX shock (ε_1)

	Forecast Horizon (Quarter)					
	Q1	Q4	Q12	Q24	Q40	Q100
Home TFP	0.03	0.06	0.20	0.37	0.45	0.43
Home Consumption	0.02	0.04	0.21	0.47	0.51	0.40
Foreign Consumption	0.01	0.04	0.06	0.21	0.36	0.30
Home Investment	0.29	0.34	0.32	0.40	0.42	0.41
Foreign Investment	0.06	0.08	0.15	0.22	0.34	0.33
Interest Rate Differential	0.40	0.39	0.30	0.34	0.35	0.39
Real Exchange Rate	0.50	0.69	0.82	0.73	0.70	0.68
Expected Excess Returns	0.47	0.33	0.34	0.44	0.45	0.47
Real Exchange Rate Change	0.50	0.49	0.47	0.49	0.49	0.51

Notes: The table reports the estimated variance shares accounted for by the main exchange rate shock at different horizons.

5 quarters after the initial impact, peaking at a maximum appreciation of about 3.5%, and thereafter it steadily depreciates back to its long-run mean. These persistent non-monotonic dynamics – with a half-life of three years – are similar to the estimates in Steinsson (2008) in the context of an *univariate* reduced form innovation to the exchange rate.[11]

The hump-shaped exchange rate dynamics also underlie a related cyclical pattern in the exhibited deviations from uncovered interest parity, where the MFX shock generates non-monotonic movements in *expected* excess currency returns (bottom left panel of Figure 1). Expected excess currency returns are defined as $\mathbb{E}_t(\lambda_{t+1}) \equiv \mathbb{E}_t(\Delta q_{t+1} + r_t^\star - r_t)$, and computed using VAR-implied expectation. The impulse response of expected excess currency returns reveals that these are negative on impact and remains so up to five quarters after the shock, and then turns significantly positive and remains so for several years afterwards.

We also observe that in response to the MFX shock, the real interest rate differential increases on impact and gradually returns to its long-run mean. As a result, in the immediate aftermath of the shock, the exchange rate response is displaying the classic version of the UIP puzzle where the high interest rate currency (the USD) is earning high returns (Fama, 1984). On the other hand, in the medium run, the direction of the UIP violation reverses, with the USD earning low returns for an extended period of time – and thus the MFX shock

[11]Hump-shaped dynamics also emerge following an identified monetary policy innovation. This "delayed overshooting" result was initially shown by Eichenbaum and Evans (1995).

generates exchange rate dynamics that are consistent with the reversal of UIP violations at longer horizons documented by previous studies such as Engel (2016) and Valchev (2020).

Overall, the results suggest the MFX shock we are isolating is indeed associated with the key features of exchange rate dynamics that the empirical literature has emphasized for decades – high volatility, and persistent dynamics associated with UIP violations that switch direction from short to long horizons. Thus, whatever the ultimate structural source(s) of this reduced form innovation, it is indeed responsible for the most interesting parts of exchange rate fluctuations.

Broader footprint of the MFX shock. The procedure for extracting ε_{1t} imposes very few ex-ante assumptions on the data. The trade-off is that we cannot uniquely label the deep structural origins of the MFX shock we extract. Still, given the prevailing view that exchange rates are disconnected from the broader macroeconomy, it is useful to study whether the main exchange rate shock we find is also associated with significant dynamic impacts on any *other* macro aggregates.

And strikingly, we find that this shock, which was purely identified as an exchange rate innovation, also explains a significant portion of the overall variation of the macro aggregates. Specifically, it accounts for around 40% of the forecast error variance at a horizon of 100 quarters of consumption and investment (both home and foreign), as well as home TFP (see Table 1, rows 1 through 5).

Finding that the main exchange rate shock drives a large amount of the variation in both exchange rates *and* macro aggregates appears, at first glance, surprising given the well-established result that exchange rates appear to be largely disconnected from macro fundamentals (e.g., Meese and Rogoff, 1983 and Engel and West, 2005). The reason is that the effects of our main exchange rate shock materialize at different horizons in exchange rates and macro aggregates – the exchange rate reacts strongly immediately, while most macro aggregates react with a significant lag. These difference in *timing* will result in only a mild correlation between exchange rates and current and past macro aggregates, which is the main type of empirical relationships the previous literature has been interested in.

To see this, examine the impulse responses of macro aggregates in Figure 1. Home consumption only responds in statistically significant terms to the MFX shock after a couple of years, and foreign consumption does not exhibit a significant response until five years after the shock. The effect on home consumption peaks at around 22 quarters after the shock, while foreign consumption's response peaks at around 30 quarters after the shock.

The peak in home consumption (around 0.8%) is about double the size of the peak effect in foreign consumption (around 0.5%). As a result, conditional on the MFX shock we observe the classic violation of the Backus and Smith (1993) condition that $corr(q_t, c_t - c_t^\star) = 1$, where instead the exchange rate appreciates, while the consumption differential rises above its mean.

Similarly, the MFX shock causes no significant impact on US TFP up to five quarters in the future, but productivity eventually displays a significant and prolonged increase at longer horizons. The effect peaks at 0.4% around 20 quarters after the initial impulse. Overall, both consumption and TFP display a significant response in the medium-to-long run, but no response in the immediate aftermath of the shock. The lack of a short-run responses in these core macro series, in contrast to the large immediate response in the exchange rate, imply an apparent contemporaneous disconnect between exchange rates and macro aggregates. While this is consistent with the notion of disconnect emphasized in the previous literature, we want to emphasize that our results suggest the disconnect is in the *timing* – the exchange rate appears to lead the business cycle, not the other way around.

The differences in the timing of the effects of the MFX shock among different variables can also be observed in performing forecast error variance decompositions at different horizons h. In Table 1 (columns 2-6), we compute the share of the h-step ahead forecast error variance of a given variable that is explained by the main exchange rate shock for different horizons h, starting from 1 quarter and going up to 100 quarters. As can be expected given the shape of the IRFs (Figure 1) while this shock is equally important for both short-run and long-run exchange rate fluctuations, it only explains 2% and 1% of the one-quarter-ahead forecast error variance of home and foreign consumption, respectively. At the same time, the MFX shock explains more than 20% of the forecast error at horizons bigger than 3 years for home consumption, and a similar fraction of foreign consumption at longer horizons. And, overall, the shock explains around 40% of the forecast error variance at long horizons in both consumption series.

Takeaways Taken together, this evidence sheds important light on the "exchange rate disconnect puzzle," as broadly construed.

Indeed, the bulk of the variation in the real exchange rate is essentially not related contemporaneously to aggregate consumption or TFP. Rather the exchange rate *leads* these macro aggregates that the prior literature has often tried to connect to the exchange rate. Thus, these results reveal that the canonical finding of a "disconnect" does not emerge because of an actual separation between exchange rate and fundamentals, but rather because of a difference in the timing of the responses these variables.

This a useful statistical summary of the data, however, this empirical procedure cannot sharply label the deep structural origins of the reduced form exchange rate innovation ε_{1t} we have uncovered. Still, the dynamic comovement patterns we uncover between exchange rates, and TFP in particular, suggests the further hypothesis that the MFX is capturing (or at least heavily loading on) the classic notion of a news shock about US TFP. The reason is that macroeconomic quantities such as consumption and TFP itself only rise with a significant delay. However, strongly forward-looking variables such as asset prices (like the exchange rate and the interest rates), and also physical investment, jump on impact, and thus anticipate the increase in TFP.

This is an interesting hypothesis, and challenges the emerging consensus in the literature that the puzzles in exchange rate behavior are generated by financial or risk shocks that are unrelated to macrofundamentals. In order to investigate this hypothesis, further, in the next section we add the minimal amount of structural assumptions needed to generally identify shocks to the expectations about TFP (i.e. "news about TFP"), and evaluate whether they are indeed an important driver of exchange rates.

4 Expectations of future TFP and exchange rates

We adopt a general null hypothesis that some innovations in TFP are forecastable (i.e. there are news of future TFP), but we also allow for the expectations of the future to be noisy (i..e noisy news). Moreover, we will separately identify and account for the "noise" in expectations, by following the recently developed VAR-identification approach of Chahrour and Jurado (2021).

Under our null hypothesis agents see the current realization of TFP and its full history, and in addition to that the agents have advance information about future TFP as summarized by a noisy signal, η_t. The noisy signal can be very general, with minimum restrictions imposed on it, and we simply assume that it be represented as a linear combination of future innovations to TFP plus an orthogonal noise component v_t:

$$\eta_t = \sum_{k=1}^{\infty} \zeta_k \varepsilon^a_{t+k} + v_t, \tag{5}$$

where ε^a_{t+k} are the Wold-representation innovations to the TFP process a_t:

$$a_t = D(L)\varepsilon^a_t. \tag{6}$$

Further assumptions on the particular structure of the TFP process or on the coefficients ζ_k are not necessary. The noise component of the signal is also allowed to have an arbitrary lag structure,

$$v_t = \sum_{k=1}^{\infty} \nu_k \varepsilon^v_{t-k}. \tag{7}$$

with ε^v_t an iid shock.

The assumptions of Chahrour and Jurado's (2021) procedure are that (i) the productivity disturbances ε^a_t are orthogonal to other structural shocks (as is standard) and (ii) the signal-noise innovations ε^v_t are orthogonal to ε^a_t (hence unrelated to actual TFP at all leads and lags). The goal of our empirical analysis is to separately identify the two structural disturbances ε^a_t, a true change in TFP, and ε^v_t, a "noise" shock to expectations of TFP.

To get some intuition of how to do that in practice, consider first the illustrative case where η_t is observed by the econometrician. In that case, the dynamic structure of equations (5)-(7) can be represented as a two-variable VAR in $[a_t, \eta_t]$. In turn, the assumption of orthogonal ε^a_t and ε^v_t, can be restated in terms of placing zeros in the MA representation of that bivariate VAR in the following way:

$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \cdots + \begin{bmatrix} 0 & 0 \\ * & 0 \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t+1} \\ \varepsilon^v_{t+1} \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t} \\ \varepsilon^v_{t} \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t-1} \\ \varepsilon^v_{t-1} \end{bmatrix} + \cdots$$

These are the same number of zero restrictions that the standard Cholesky identification approach would impose as well, but placed in a different way. First, as in a Cholesky approach, we assume that the true productivity innovations ε^a_t only affect TFP after they realize at time t (hence the upper left corner of the coefficient matrices on the leads are zero). But in addition to that, we also assume that ε^v_t does not affect a_t at any leads or lags, and hence the coefficient matrices all have a zero in their upper right corner. Instead, in contrast to the Cholesky approach, we allow for the fact that η_t can be a function of *future* TFP innovations ε^a_{t+k} (that is, the bottom left corner of the lead matrices can be non-zero).

The above illustrative example assumed that the econometrician observes the relevant signal η_t. In practice, this is not true, but the same identification restrictions can be imposed by replacing η_t with forecast of future TFP, $\mathbb{E}_t(a_{t+k})$, implied by our reduced form VAR (equation (1)). The key assumption needed for replacing η_t with $\mathbb{E}_t(a_{t+k})$ is that in equilibrium, endogenous forward-looking variables such as asset prices, interest rates and etc., would reflect any forward information about future TFP agents receive through the signal η_t. And thus, including such variables in our reduced form VAR would make the VAR-implied $\mathbb{E}_t(a_{t+k})$ also a function of the unobserved η_t. If anything, if we have not included sufficient amount of forward looking variables to capture some relevant news agents otherwise have, then our empirical procedure will simply suffer from a lack of statistical power, but this will not introduce a bias rather just make it harder to reject our null.

To implement the procedure in practice we proceed in two steps. First, the usual assumption that TFP disturbances are orthogonal to other structural shocks allows us to directly back out the structural innovations of TFP ε_t^a. Second, to impose the restriction that the informational noise shock ε_t^v is allowed to move expectations of future TFP, but not actual TFP, we orthogonalize the VAR-implied forecast of future TFP $\mathbb{E}_t(a_{t+k})$ to structural innovations at all leads and lags, and the use the resulting residual variation in TFP expectations to estimate the information noise shocks ε_t^v. That, is the series of noise shocks can be written as

$$\{\varepsilon_t^v\}_{t=0}^{T} \equiv \{\mathbb{E}_t(a_{t+k})\}_{t=0}^{T-k} \perp \{\varepsilon_t^a\}_{t=0}^{T}$$

Lastly, we also need to specify a target "horizon" of expectations, for which we decompose the corresponding $\mathbb{E}_t(a_{t+k})$ into a component related to fundamental TFP disturbances ε_t^a and one related to ε_t^v. We choose $k = 20$ to match the peak in the TFP IRF in Figure 1.[12]

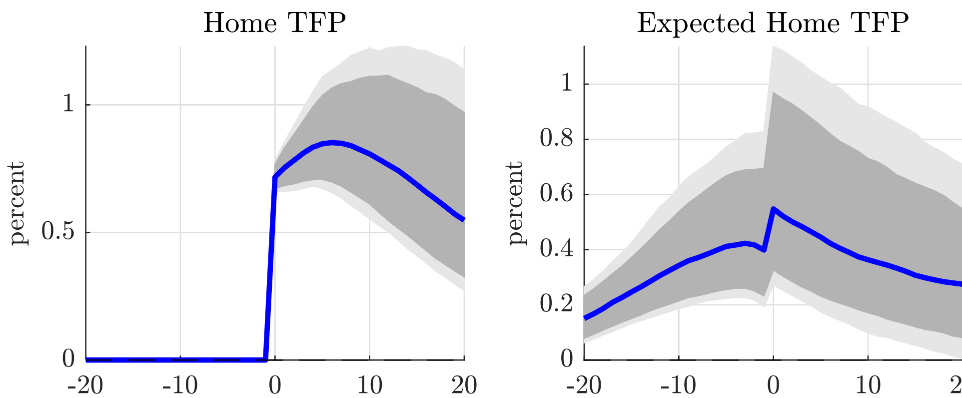
4.1 The dynamic effects of TFP and noise disturbances

We begin by reporting the estimated impulse responses of TFP, a_t, along with the 20-quarter ahead expectation of TFP, $\mathbb{E}_t(a_{t+20})$, in response to the fundamental technological disturbance, ε_t^a in Figures 2 and to the expectational noise disturbance ε_t^v in Figure 3. These two pairs of impulse responses are informative about the basic information structure of the noisy news we identify.

Note that since under our null hypothesis productivity shocks could be anticipated, and

[12] If agents only observe one signal about future TFP, then this horizon is irrelevant, as any choice of h will yield identical estimation results. In practice, we find that the choice of k does not matter much for our findings.

Figure 2: Impulse responses to Technology (ε^a) disturbances



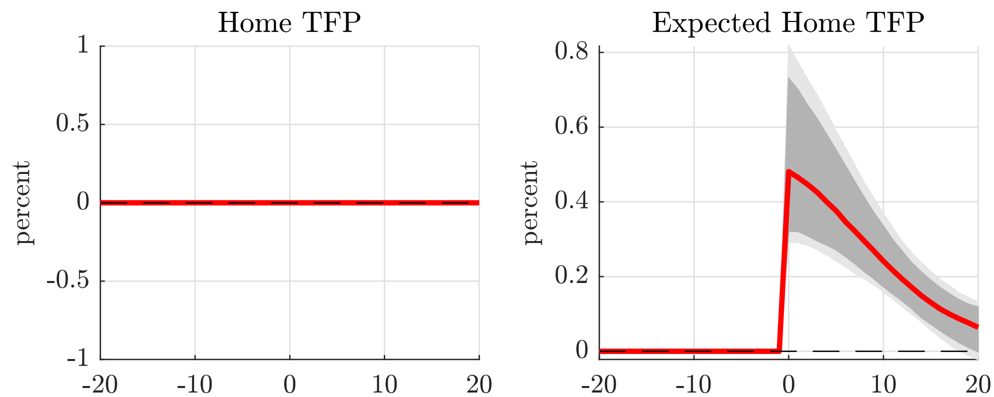
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

hence affect other endogenous variables before the actual change in productivity, we plot each impulse response starting from 20 quarters *before* the actual realization of innovations. Specifically, the X-axis on all impulse response figures in this section is in terms of quarters before and after the shock realization, ranging from -20 to +20, with 0 denoting the period of the shock. The extent to which TFP anticipation plays a role in the data can thus be evaluated by observing whether the estimated IRFs respond significantly to ε_t^a before its actual realization, that is in periods between -20 and -1.

Consider first the response of TFP, a_t, to an ε_t^a increase, plotted in the left panel of Figure 2. As typically found with US TFP data, we estimate that the TFP shocks have very persistent effect. A one standard deviation shock increases the level of TFP by roughly 0.75%, which is the initial impact at time 0, and 20 quarters after the shock the level of TFP is still 0.50% above its long-run mean.

In the right panel of Figure 2 we plot the impulse response of the expectation of TFP 20-quarters ahead, $\mathbb{E}_t(a_{t+20})$. For this and other endogenous variables, we *make no ex-ante assumption* about whether anticipation effects are present. The key result is that indeed this variable is significantly higher than its long-run mean even 20 quarters before the innovation actually realizes (at period 0 in the notation of the Figure), manifesting a significant amount of anticipation. Specifically, 20-quarters before the actual 1-standard deviation TFP improvement, agents expect that future quarter's TFP to be 0.2% higher than average. Thus, we find that roughly about one third of the actual improvement is anticipated 20-quarters ahead of time. We can also see that the expectation is not perfect, of course, by the fact that the impulse response of $\mathbb{E}_t(a_{t+20})$ jumps at time 0, indicating that the actual realization still surprised the agents, and led to adjusting expectations upwards upon observing the actual ε_t^a increase.

Figure 3: Impulse responses to Noise (ε^v) disturbances



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Another way to see that expectations are imperfect, is by considering the impulse response to the pure expectational noise shock ε_t^v, which we plot in Figure 3. In the left panel, we see one of our identification restrictions at play – the expectational noise disturbance has no effect on TFP at any leads or lags. Yet, in the right panel of Figure 3 we see that these shocks indeed moves expectations, as we estimate that a one standard deviation ε_t^v increase (so an "optimistic" revision of future TFP), leads to a 0.5% increase in expected TFP 20-quarters out. This optimism caused by the expectational shock is mean-reverting, which is consistent with the idea that over time agents learn that their initial optimism was misplaced.

Overall, the results in Figure 2 and Figure 3 support the null hypothesis of a noisy-information paradigm, where future movements in TFP are partially anticipated, but expectations are noisy and sometimes move even though is no actual future increase in productivity.

Broader Impacts. We now turn to the impact of these two disturbances on the rest of the endogenous variables in the VAR, with a special attention paid to the response of the exchange rate. In Figure 4 we plot the responses to a TFP innovation, ε_t^a, for the interest rate differential, home consumption, the real exchange rate, foreign consumption and the expected currency returns, $\mathbb{E}_t(\lambda_{t+1})$. We also report the response of the level of TFP again for reference.

We focus on the real exchange rate first. The response exhibits a pronounced V-shape that exhibits significant anticipation effects in the real exchange rate, where the real exchange rate significantly appreciates *before* the actual TFP improvement (at time 0 in the Figure). Also of interest, there is no appreciable jump in the real exchange rate right at time 0, unlike with the expectations of future TFP $\mathbb{E}_t(a_{t+20})$ for example, which suggests that the *surprise* component in the TFP innovation does not matter much for the exchange rate. Instead, after the actual TFP improvement the real exchange rate steadily, and smoothly, depreciates back to its long-run mean. Thus, we uncover that news about future TFP are indeed strongly reflected in the real exchange rate.

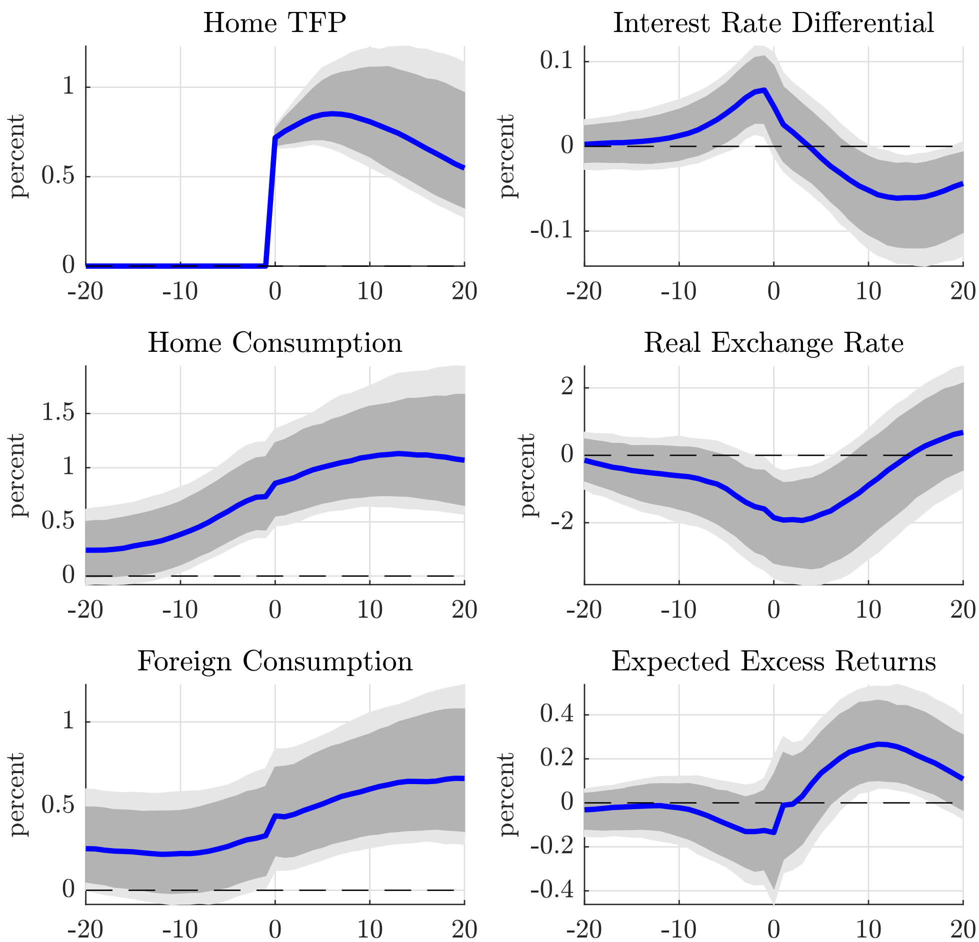
Moving onto the response of real interest rates and consumption, we see that the 3-month real interest rate differential also increases (higher US interest rates) before the TFP innovation, peaking at around 7.5 basis points higher than its long-run mean (which is 0.3% at an annualized basis), just before time 0. The interest rate differential then steadily declines after the TFP increase materializes, and is in fact significantly lower than its mean for a prolonged period of time between 10 and 20 quarters after the TFP improvement. Similarly, there is also a US consumption boom before the actual TFP improvement, and while foreign consumption also increases, that effect is significantly weaker, and the consumption differential is large and positive (not pictured).

In Figure 5 we present the impulse responses of the same set of variables, but in response to an expectational noise shock ε_t^v instead. We see that upon the improvement in expectations (recall that is period 0 on the X-axis), the real exchange rate strongly appreciates. This is consistent with the message from Figure 4, where we saw that the exchange rate appreciates significantly before an actual improvement of TFP, speaking of apparent anticipation effects. We capture those here directly.

The exchange rate response is also fairly persistent, with the exchange rate returning to its long-run mean only after about 12 quarters. The interest rate differential is also consistent with the previous figure, increasing on impact of the optimistic shift in expectations, and subsequently declining.

The response in US consumption is more gradual and delayed, with no significant jump in consumption upon the shift in expectations at time 0, but rather a delayed boom in consumption peaking a full 3 years after the shift in expectations. This suggests that the underlying information structure is one where agents learn slowly, and that the underlying

Figure 4: Impulse responses to Technology (ε^a) disturbances

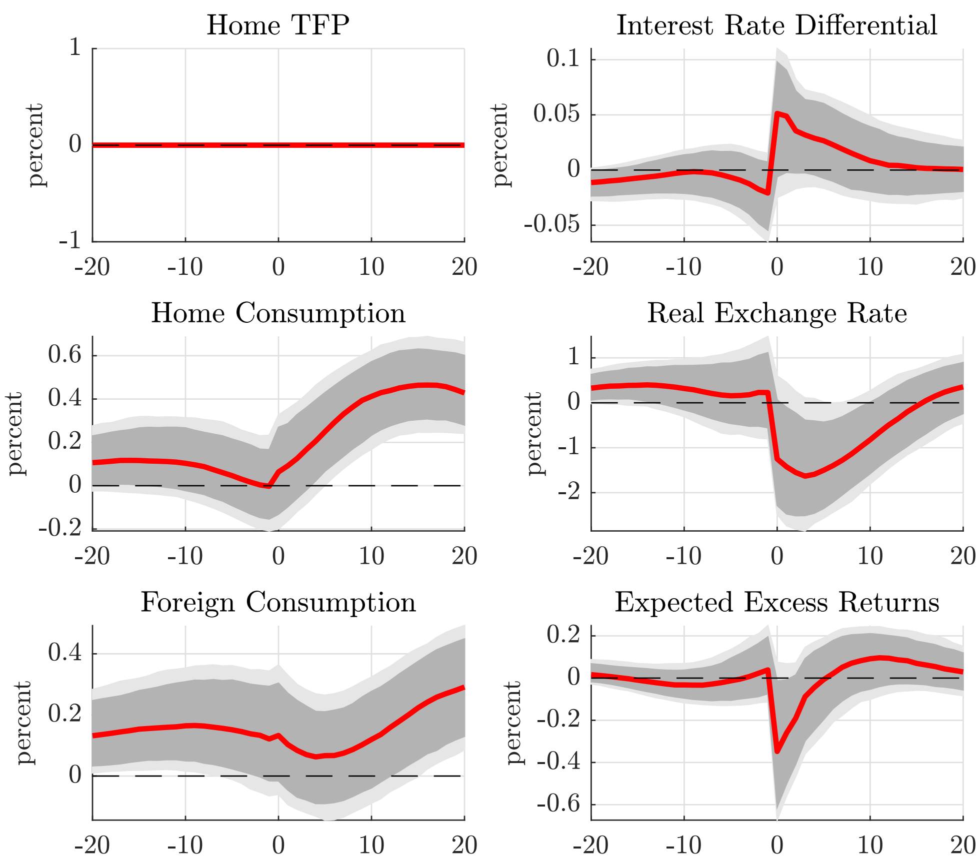


Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

signals that agents receive are about news pretty far into the future. With this kind of information about TFP far into the future, consumption does not respond strongly until the expected TFP improvement becomes closer in time. Lastly, foreign consumption also increases, but weakly so, and thus the consumption differential is positive and significant throughout.

The response to the ε_t^v shock isolate the pure response to news about the future, and we clearly see the differential timing of the impact of news on the exchange rate and consumption, where the exchange rate jumps significantly on impact at time 0, but the response in consumption is delayed. Naturally, this differential timing is also present in the impulse responses in Figure 4, manifesting in the fact that the peak response of the exchange rate is again earlier than that in consumption, but the differential timing is most cleanly observed in the responses to the expectational shock.

Figure 5: Impulse responses to Noise (ε^v) disturbance



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Variance Decomposition To further quantify the effects of TFP and noise disturbances, we consider the respective variance shares of the endogenous variables that these disturbances

Table 2: Variance Decomposition

	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1.00	1.00	0.00	1.00	1.00	0.00
Home Consumption	0.70	0.54	0.16	0.30	0.10	0.20
Foreign Consumption	0.63	0.49	0.14	0.30	0.13	0.17
Home Investment	0.62	0.46	0.15	0.42	0.29	0.13
Foreign Investment	0.68	0.43	0.25	0.45	0.14	0.31
Interest Rate Differential	0.57	0.46	0.11	0.37	0.23	0.14
Real Exchange Rate (q_t)	0.64	0.45	0.20	0.36	0.14	0.22
Expected Excess Returns	0.50	0.35	0.15	0.37	0.19	0.18
Real Exchange Rate Quarterly Growth (Δq_t)	0.30	0.11	0.18	0.28	0.08	0.20

Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances ("Tech"), expectational disturbances ("Noise"), and the combination of both.

explain. Table 2 reports the decomposition of variation over a wide band of frequencies (2-100 quarters) and also the higher-frequency, business cycle variation (6-32 quarters). As per our identification restrictions, the technological disturbance we estimate, ε_t^a, accounts for 100% of the variation in TFP, while the expectational noise disturbance ε_t^v is completely orthogonal to it.

In addition, the estimates indicate that the two disturbances together explain 60-70% of the wide-band (2-100Q) variation in US and G6 real consumption and investments, and also 64% of the real exchange rate – again signifying that there is a strong fundamental connection between exchange rates and real quantities in the data, which manifests through noisy news about future TFP. Similar to these wide-band results, the two noisy-news disturbances we identify are also important at business cycle frequencies (6-32Q), as they explain between 30-45% of business cycles variation in the real macro aggregates and 36% of the business cycles variation in the exchange rate.

The relative impact of the true technological disturbance and the noise disturbance, however, differ across the frequency bands in an interesting way. The true technological disturbance ε_t^a is more important in the lower frequencies, while noise shocks are more important in the higher frequencies. For example, the true technological disturbances generate two-thirds of the explained variance in terms of the exchange rate at the wide-band frequencies (45% of 64% in total), but at business cycle frequencies, the ε_t^a shocks only generate one third of the explained variance (14% vs 36% in total), with the noise shocks ε_t^v being the more important driver at those higher frequencies. A similar switch in the relative importance can also be observed in the variance decompositions of all real quantities.

Lastly, the variance contributions of ε_t^a that we estimate above are due to both movements in anticipation of the actual realization of the shock (the component of the impulse responses before time 0 in the Figure above), and also fluctuations that come after the actual realization in ε_t^a. It is interesting to strip out the pure anticipation effect, which we can formally do by computing the variance contributed by just the leading terms in the impulse responses, i.e. the response of the variables in anticipation of ε_t^a. We find that the anticipation effects are dominant, and for example in terms of the exchange rate, the movements *before* the actual realization of ε_t^a already explain 34% of the wide-band variation in the exchange rate. Thus, non-anticipated changes in TFP indeed have a very small impact on the exchange rate, while anticipation of ε_t^a and expectational shocks ε_t^v contribute up to 55% of the wide-band variation in the real exchange rate.

5 Further Results

5.1 Transmission Mechanism

In this section, we shed some light on the primary channel through which the noisy news about future TFP transmit to the exchange rate. Given the large anticipatory effects on US consumption in response to both noisy-news related shocks we document in the previous section, perhaps one natural hypothesis is that the impact on the exchange rate is primarily due to fluctuations in the expected path of real interest rates. The crux of this hypothesis is that upon receiving good news about the future, US agents experience a large wealth effect, increasing their relative demand for goods, and in turn raising the US interest rate differential (as we also find is true in the data) and appreciating in the real exchange rate.

To evaluate this hypothesis, we start by noting that the real exchange rate can be expressed as the sum of expected future interest rate differentials and currency excess returns:

$$q_t = -\sum_{k=0}^{\infty} \mathbb{E}_t(r_{t+k} - r^*_{t+k}) - \sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1})$$

For expositional purposes, let us denote the first component by $q_t^{uip} \equiv -\sum_{k=0}^{\infty} \mathbb{E}_t(r_{t+k} - r^*_{t+k})$ and the second component by $q_t^{\lambda} \equiv -\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1})$, so that we could write the real exchange rate as the sum of the counter-factual exchange rate that would obtain if there are no deviations from interest parity (q_t^{UIP}) and the contribution of any predictable fluctuations in deviations from interest parity (q_t^{λ}):

$$q_t = q_t^{UIP} + q_t^{\lambda} \tag{8}$$

The key question we want to ask is whether the second component, q_t^{λ}, plays an important role in transmitting our noisy news shocks to the exchange rate or not. In other words, we want to know whether the deviations from interest parity caused by the arrival of noisy news contributes meaningfully to the resulting exchange rate impacts we saw, or if the likely transmission mechanism is rather something the primarily operates in first-order terms, and is related only to fluctuations in real interest rates.

To answer this question we proceed in two steps. First, we observe that using equation (8) the variance of q_t can be expressed as

$$Var(q_t) = Cov(q_t, q_t^{UIP}) + Cov(q_t, q_t^{\lambda})$$

Second, we use our VAR to estimate the two components q_t^{UIP} and q_t^{λ} and their respective impulse response functions to our identified shocks ε_t^a and ε_t^v, and compute the above decomposition when only conditioning the responses on the noisy-news shocks. In that way, we get a decomposition of the fluctuations in q_t that are generate by ε_t^a and ε_t^v as driven by the q_t^{UIP} or the q_t^{λ} component. To be sure, equation (8) is not an orthogonal decomposition, but in practice it turns out that conditional on our shocks, the two components are very close to orthogonal, yielding an informative decomposition we report in Table 3 below.

Table 3: Exchange Rate Covariance Decomposition, conditional on ε_t^a and ε_t^v

	Both shocks		Tech shocks		Noise shocks	
	q_t^{UIP}	q_t^{λ}	q_t^{UIP}	q_t^{λ}	q_t^{UIP}	q_t^{λ}
$\frac{Cov(q_t,q^i)}{Var(q_t)}$	-0.02	1.02	-0.02	1.02	0.05	0.95
$\frac{Cov(\Delta q_t,\Delta q^i)}{Var(\Delta q_t)}$	0.14	0.86	-0.16	1.16	0.43	0.57

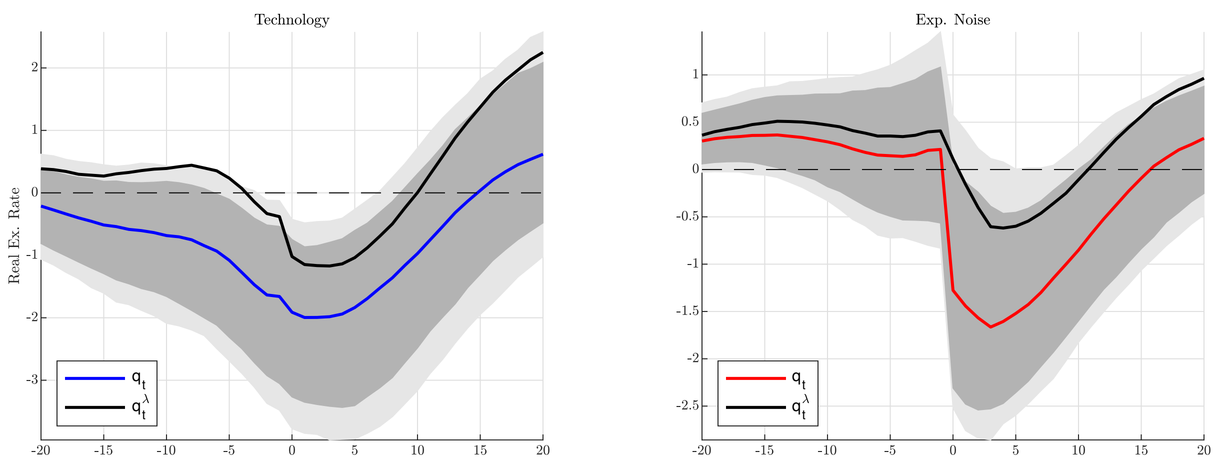
Notes: The table reports decompositions of the fluctuations in the real exchange rate q_t caused by technological disturbances ε_t^a ("Tech"), expectational disturbances ε_t^v ("Noise"), and the combination of both. The table presents covariance decompositions in terms of fluctuations driven by both the path of expected real interest rate differentials q_t^{UIP} and the expected excess returns q_t^{λ}.

The main takeaway is that the noisy-news shocks we uncover primarily transmit to the exchange rate via generating a volatile UIP-wedge and fluctuations in the q_t^{λ} component.

Looking at the first two columns of Table 3, we see that both in terms of the volatility in the level of q_t and the volatility of the quarterly changes Δq_t, the component due to deviations from interest parity explains close to 100% of all fluctuations caused by our two shocks ε_t^a and ε_t^v. This basic decomposition remains the same, with the bulk of the impact on q_t due to fluctuations in q_t^λ when we look at each shock in isolation as well. Although in the case of quarterly fluctuations Δq_t, the noise shock contributes meaningfully through the q_t^{UIP} component as well.

The covariance decompositions can be understood graphically through the impulse responses of q_t and q_t^λ, which we plot in Figure 6 below. As we can see, both the true technology shock and the informational noise shock causes significant fluctuations in q_t^λ, which fluctuations also closely mirror the actual response of q_t.

Figure 6: Impulse responses to Noise (ε^v) disturbance



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Thus, overall we find that fluctuations in the expected currency returns, or the so called "UIP wedge", play an important role in the transmission to the exchange rate of the noisy news shocks we have identified. This implies that in order to understand these empirical results through the lens of equilibrium models, we need to step beyond first-order international macro models where UIP typically holds, and think about models in which the deviations from UIP are significant, endogenous and specifically caused by noisy news of future TFP.

5.2 Common origin in exchange rate "puzzles"

As discussed in the introduction, the exchange rate literature is traditionally organized around the study of various "puzzles" in the empirical behavior of exchange rates. Given the large effect the two identified disturbances play in exchange rate dynamics, it is interesting to consider whether they are also generating some or all of the exchange rate puzzles we outlined at the beginning. And indeed, the answer is yes they do, which will lead us to the conclusion that exchange rate puzzles seemingly have a common, and fundamental origin, in noisy news about TFP.

The UIP Puzzle Clearly, the noisy news disturbances we identify causes significant deviations from interest parity – however, is the nature of these deviations the same as the classic UIP puzzle of Fama (1984), where high interest rate currencies are predicted to make high returns?

Looking at Figure 4, we observe that expected excess currency returns drop marginally just before the realization of the TFP innovation, and then rise significantly and for a prolonged period of time after TFP improves. These movements in $\mathbb{E}_t(\lambda_{t+1})$ are essentially mirrored by the response of the interest rate differential, which is high in the anticipation phase, and then low after realization of ε_t^a.

This speaks to a general negative correlation between currency returns and the interest rate differential, a relationship that is at the heart of the "classic" UIP puzzle that high interest rates predict high currency returns, in the sense that the seminal Fama regression. To test whether the shocks we identify indeed generate the Fama puzzle or not, we consider the so-called UIP regression – main form in which this puzzle has been documented.

Specifically, Fama (1984) estimates the regression

$$\lambda_{t+1} = \alpha + \beta_{UIP}(r_t - r_t^\star) + u_t$$

and the typical finding is an estimated coefficient $\beta_{UIP} < 0$. In our raw data, we also find a significantly negative β_{UIP} of -2.46, in line with previous findings (e.g., Engel, 2014). Next, we compute the resulting β_{UIP} in a counter-factual dataset where only the two disturbances, ε^a and ε^v, are active. To obtain these series, we simulate from our estimated VAR by setting the variance of all other disturbances to zero.

In this counter-factual dataset, we find $\beta_{UIP} = -2.20$, revealing that the combination of disturbances to TFP and to expectations of future TFP qualitatively and quantitatively reproduces the classic UIP Puzzle relationship. Drilling down further, we construct similar counter-factual β_{UIP} based on either only-TFP disturbances (including anticipation effects) and only expectational noise disturbances. The results imply that the TFP disturbances by themselves generate a β_{UIP} of -2.08, while the β_{UIP} based on only expectational disturbances is -2.96, as we also report in Table 4 below. Last ,we find that the two shocks we identify generate 68% of the negative covariance $Cov(\lambda_{t+1}, r_t - r_t^\star)$ which underlies this puzzle unconditionally, hence these TFP-related disturbances are not only generating the right patterns qualitatively, but they are quantitatively important to the puzzle.

Table 4: Exchange Rate Related Puzzles and TFP Expectations

	Technology	Exp. Noise	Both	Unconditional
	Panel A: UIP Puzzle Moments			
Fama β_{UIP}	-2.08	-2.96	-2.20	-2.46
$Cov(\lambda_{t+1}, r_t - r_t^*)$	-0.68	-0.14	-0.82	-1.26
Engel β_Λ	2.33	1.72	2.62	2.53
$Cov(\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}), r_t - r_t^*)$	0.54	0.06	0.60	1.08
$\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$	0.37	0.13	0.25	0.17
autocorr$(r_t - r_t^\star)$	0.99	0.93	0.98	0.95
	Panel B: Backus-Smith Moments			
corr$(\Delta q_t, \Delta(c_t - c_t^\star))$	-0.31	-0.38	-0.35	-0.27
Cov$(\Delta q_t, \Delta(c_t - c_t^\star))$	- 0.12	-0.16	-0.28	-0.7
Cov$(\Delta q_t^\lambda, \Delta(c_t - c_t^\star))$	- 0.13	-0.11	-0.24	-0.49
	Panel C: Excess Volatility and Persistence			
autocorr(Δq_t)	0.90	0.33	0.58	0.29
autocorr(Δq_t^λ)	0.80	0.42	0.60	0.73
$\sigma(\Delta q_t)/\sigma(\Delta c_t)$	3.99	8.14	5.65	6.05
$\sigma(\Delta q_t^\lambda)/\sigma(\Delta c_t)$	5.82	7.74	6.58	7.30

Notes: The table reports the estimated moments conditional on technological disturbances (Technology), expectational disturbances (Exp. Noise), and the sum of both disturbances, along the moments estimated on raw data (Unconditional). The moments in the table are defined in the text.

In addition to this "classic" UIP Puzzle, the conditional responses of the exchange rate to our identified disturbances also exhibit the Engel puzzle that the UIP puzzle essentially "reverses" direction at longer horizons (Engel, 2016). Namely, it has now been established that while the Fama regression finds a negative association between interest rate differentials and one quarter ahead currency excess returns, the correlation between today's interest rate differential and currency excess returns 2+ years into the future is actually *positive*.

We can qualitatively see this pattern in Figure 4, for example, in the fact that the high excess returns in the periods following the realization of the TFP improvement are preceded, a few years beforehand, by high interest rates. Thus, at longer horizons, the correlation between interest rates and excess returns is positive, not negative, in our impulse responses (and this is especially pronounced in the case of the response to ε_t^a).Check for consistency.

As a summary statistic of this phenomenon, we consider the same moment that Engel (2016) emphasizes, which is the coefficient of the following regression

$$\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}) = \alpha_0 + \beta_\Lambda(r_t - r_t^\star) + \varepsilon_t$$

In the raw data, we find $\beta_\Lambda = 2.53$, which together with the previous result of $\beta_{UIP} = -2.46$, implies that there must be at least one horizon $k > 1$ such that $\text{Cov}(\lambda_{t+k+1}, r_t - r_t^\star) > 0$, so as to more than offset the negative covariance at short horizons. In our counter-factual simulation where both of the disturbances we identify are active, we find $\beta_\Lambda = 2.62$, thus these two disturbances can indeed generate the reversal in the UIP puzzle as well. However, the effect of noise in this cases is muted quantitatively, even though it can also generate it on its own qualitatively (see Table 4). In fact, the two disturbances together generate around 60% of the overall $\text{Cov}\left(\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}), r_t - r_t^\star\right)$ in the data, but noise is responsible for only one tenth of this effect.

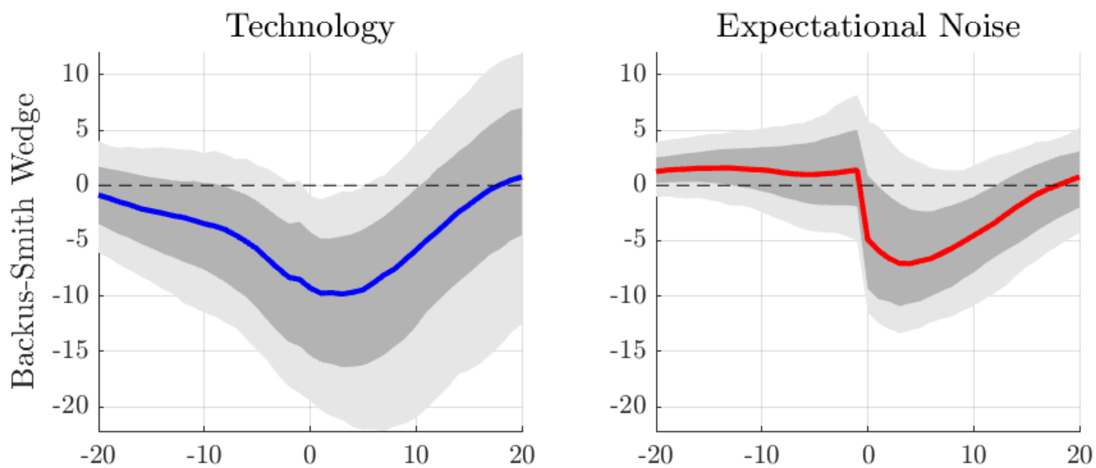
Lastly, our two shocks not only generate empirically relevant regression β's, but the underlying dynamics of the interest rate differentials (the regressor in these UIP regressions) are also very much in line with their unconditional counterpart. This fact can be seen by the $\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$ and $\text{autocorr}(r_t - r_t^\star)$ moments reported in Table 4. Overall, these results suggests that a significant component of the puzzling predictability patterns in excess currency returns documented over the years are originating in noisy news about TFP.

Deviations from the Backus-Smith condition We now turn to the Backus-Smith puzzle, or risk-sharing puzzle. Consider the so-called Backus-Smith "wedge," defined as

$$\text{BS Wedge}_t = q_t - (c_t - c_t^\star)$$

Under the hypothesis of full consumption risk-sharing, in the sense of Backus and Smith

Figure 7: Technology, noise and the Backus-Smith wedge



Notes: The figure displays the Backus-Smith Wedge response to a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

(1993), this variable should be equal to zero in all periods.

The impulse responses of BS Wedge with respect to technological and expectational disturbances are reported in Figure 7. We observe significant deviations from the Backus-Smith condition. In response to the actual TFP disturbance, we again observe a significant anticipation effect: the BS Wedge is significantly negative as early as 10 quarters before the actual TFP improvement. After the realization of the US TFP improvement, the wedge adjusts gradually towards zero. A negative BS Wedge means that in anticipation of a U.S. TFP improvement, the U.S. dollar does not depreciate sufficiently to offset the relative US consumption increase. In fact, from Figure 3 we can see that in anticipation of the US TFP improvement the dollar is in fact *appreciating* even though US consumption is relatively high. The Backus and Smith condition implies an opposite relationship between exchange rate changes and consumption differentials.

The expectational noise disturbance also causes significant fluctuations in the BS Wedge. On impact of heightened expectations of high future productivity, the wedge also moves sharply negative and then converges back to zero over 15-quarters. Thus again, optimistic expectations of future TFP leads to a situation where the exchange rate does not depreciate sufficiently to offset the resulting boom in domestic consumption.

Overall, this shows that the two disturbances we recover with the Chahrour and Jurado's (2021) procedure are responsible for significant and volatile deviations from the perfect risk-sharing condition of Backus and Smith (1993). As a summary statistic that can quantify the contribution of the two shocks we consider, we compute the stylized moment much of the literature works with,

$$\text{corr}(\Delta q_t, \Delta c_t - \Delta c_t^\star),$$

conditional on just our two identified disturbances. We then compare the resulting moment to the unconditional Backus-Smith correlation in the raw data. The results are presented in Table 4. As is well know from previous research the correlation in the raw data is not just far from 1, but is in fact negative, equal to -0.27 in our sample. In the counter-factual sample driven by only the two disturbances we identify, this correlation is very similar and equals -0.35.

We can again also directly decompose the $Cov(\Delta q_t, \Delta c_t - \Delta c_t^\star)$ which underlies the negative correlation, and we find that our two shocks combined explain roughly 40% of this moment in the data. Drilling down further, we can also ask whether the negative covariance generated by our shocks is due to component of exchange rates driven by deviations from interest parity, q_t^λ, and we find that indeed 86% of it is – that is, conditional on our two identified shocks $\frac{Cov(\Delta q_t^\lambda, \Delta c_t - \Delta c_t^\star)}{Cov(\Delta q_t^, \Delta c_t - \Delta c_t^\star)} = 0.86$.

Thus, we find that noisy news to TFP are indeed generating a meaningful portion of the puzzling negative correlation between exchange rates and consumption differential behind the famous Backus-Smith puzzle too. And moreover, these effects are due to the fluctuations in the UIP wedge that are driven by our shocks.

Excess volatility and persistence Another famous "puzzle" are the excess persistence and volatility of the real exchange rate. We therefore ask to what extent the high persistence and volatility found in the data might be accounted for by disturbances to TFP and its expectations.

In Table 4, we consider a few related moments. First, the exchange rate dynamics conditional on the two disturbances we extract are indeed highly persistent. This is well-exemplified by the autocorrelation of the quarterly change in the real exchange rate, which conditional on both of our innovations is 0.58 versus 0.29 in the unconditional data. Thus, our two sets of shocks in fact generate an even higher degree of persistence than the exchange rate exhibits on average, suggesting that all other shocks driving the exchange rate (e.g. monetary shocks) have relatively transitory effects (as is true in standard models). Second, the volatility of the exchange rate generated by our two disturbances is also very high, relative to standard macro aggregates. For example, the ratio of the standard deviation of the quarterly growth in the exchange rate and consumption (conditional only on our noisy news shocks) is 5.65, while the same ratio is 6.05 in the raw data.

Lastly, we also observe that both the high persistence and volatility in the response of the real exchange rate are to a large extend due to the persistent and volatile response of q_t^λ, again highlighting the role of deviations from interest parity in the transmission of the ε_t^a and ε_t^v shocks.

Common and fundamental origin to many exchange rate puzzles Overall, our results imply that a constellation of famous exchange rate puzzles have a *common* and *fundamental* origin in noisy news about future TFP, which news are then transmitted to the exchange rate largely through fluctuations in expected currency returns.

These results have important implications about the development of general equilibrium models of the exchange rate. On the one hand, our results broadly agree with the conclusions of recent theoretical work like Itskhoki and Mukhin (2021) which put volatile UIP wedges at the heart of mechanisms that can jointly explain numerous exchange rate puzzles. Importantly, however, while most of the recent literature in this vein models the volatile UIP wedges as exogenous shocks, our results indicate that they are in fact *endogenously* related to the arrival of noisy news about future TFP. They are not orthogonal to fundamentals, but very much driven by the a quintessential fundamental in macro models – TFP.

Thus, in a way our results also shift the focus back to a long tradition in the literature of developing models of currency premia that are primarily driven by TFP innovations (see, for example, Verdelhan, 2010, Bansal and Shaliastovich, 2012, and Colacito and Croce, 2013). At the same time, contrary to our empirical results, the great majority of such existing models limits their attention to standard information structures where all shocks are pure surprises, and thus there are no anticipation effects, which we find are crucial.

An important exception are the long-run risk models of the exchange rate in the vein of Colacito and Croce (2013), which intuitively share many of the key features of the noisy news shocks we identify. For example, our empirical estimates suggest that the news that are priced in the exchange rate are indeed about relative far into the future, long-run productivity (e.g. we find TFP expectations are significantly elevated a full 5 years before the actual innovation). While not identical, such long-run news are similar in spirit to the very persistent low frequency "long-run" component of TFP that Colacito and Croce (2013) emphasize – an improvement in the long-run growth rate of TFP in their model acts akin to a news shock because most of the resulting TFP improvement accrues in the future (because it consists in a persistent change in the growth rate. Our results offer a sharp estimate of the long-run news of TFP available in the data, and it would be interesting for future research to evaluate existing long-run risk models in regards to that.

That said, we caution that the existing long-run risk models appear to be inconsistent with at least one facet of our empirical results prima facie. While, we find that home consumption is elevated and persistently increasing in expectation of the future TFP improvement, in the log-run risk class of models, home consumption is in fact *depressed* upon an improvement in the long-run growth rate of TFP. This opposite movement in consumption is a characteristic feature of the full risk-sharing setup typical of this class of models where home agents effectively "share" the good news about high future home output with foreign agents by transferring resources abroad today. We thus conclude that there is more work to be done on the modeling front, and our sharp empirical results can be used to guide and discipline future development in theoretical models, and can also be used to estimate and discipline such models.

5.3 Technology, noise and the trade balance

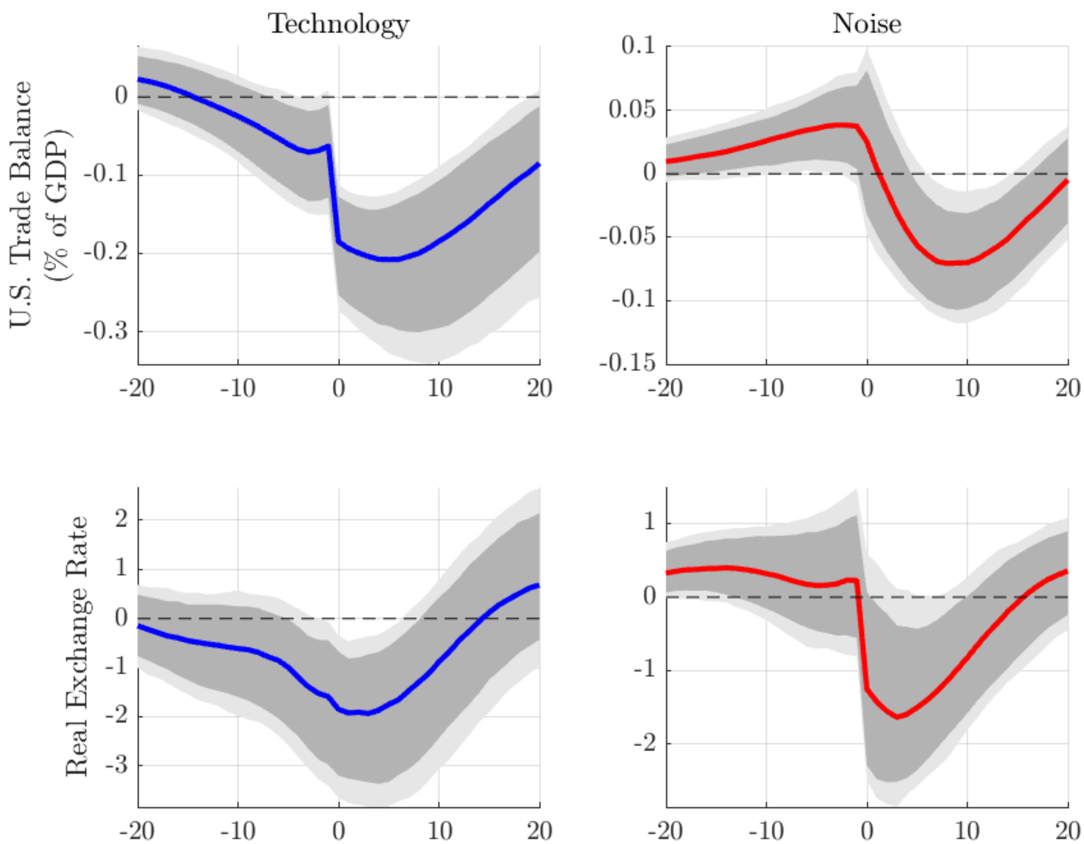
Another long-standing question in the literature concerns the determinants of the trade balance and its comovement with international relative prices such as the real exchange rate (Backus et al., 1994; Corsetti et al., 2008). We thus examine the dynamics of the trade balance in response to TFP and noise disturbances. Figure 8 depicts the dynamic responses of the U.S. trade balance (as a % of U.S. GDP) along with those of the real exchange rate. We find that the U.S. (i.e. home) trade balance deteriorates in anticipation of expected TFP improvements, and it gradually reverts back to its original level when the TFP improvement materializes or when expectations thereof fade away. These dynamics are consistent with the intertemporal approach to the current account by which home households increase their consumption (more than home production) in anticipation of future improvements in the productive capacity of the home economy. This evidence is also consistent with Hoffmann et al.'s (2019) observation that during the 1990s and 2000s, survey expectations of long-run output growth for the U.S. relative to the rest of the world were highly correlated with the US current account.[13]

Moreover, Figure 8 shows that the real exchange rate and the trade balance appear highly positively in their conditional responses. This suggests that the unconditional positive

[13] See also Nam and Wang (2015).

correlation between the real exchange rate and the trade balance documented in the literature (Alessandria and Choi, 2021; Gornemann et al., 2020) emerges as the joint equilibrium response of these variables to technological and noise disturbances.

Figure 8: Technology, Noise and the Trade Balance



Notes: The figure displays the IRF a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The shaded area are the the 16-84th (dark gray) and 5-95th (light gray) percentile bands. Each period is a quarter.

5.4 Discussion

News about long-run TFP growth Our headline result is that exchange rates do indeed share a strong and important relationship with productivity. As this is the quintessential macroeconomic "fundamentals" in most models and empirical studies, it is perhaps surprising that the connection we uncover has gone unnoticed until now. Let us discuss two reasons for this, which discussion can also help shed some more intuition on what are the key features of the data that underlie our identification.

First, many of the previous studies that have tried to find a link between exchange rates and macro fundamentals, and TFP in particular, take as a working hypothesis the standard model formulation where all TFP shocks are pure surprises. From that point of view, one would only look for a relationship between q_t and current and past macro aggregates, and multiple studies in this vein return very low empirical connection between the exchange rate and macro fundamentals. And the reason is, as shown by our results, that the lead-lag relationship is the opposite – it is the exchange rate that leads the macroeconomy.

This lead-lag relationship is the key feature of the data that underlies our VAR identification. To showcase this further, consider the following simple exercise, where we regress the quarterly change in the real exchange rate at time t on leads and lags of the change in TFP. To save on degrees of freedom, we aggregate the TFP leads and lags into annual changes:

$$\Delta q_t = \alpha + \beta_0 \Delta TFP_t + \sum_{k=1}^{h} \beta_{-k}^{lag}(TFP_{t-4(k-1)} - TFP_{t-4k}) + \sum_{k=1}^{h} \beta_k^{lead}(TFP_{t+4k} - TFP_{t+4(k-1)}) + \varepsilon_t \quad (9)$$

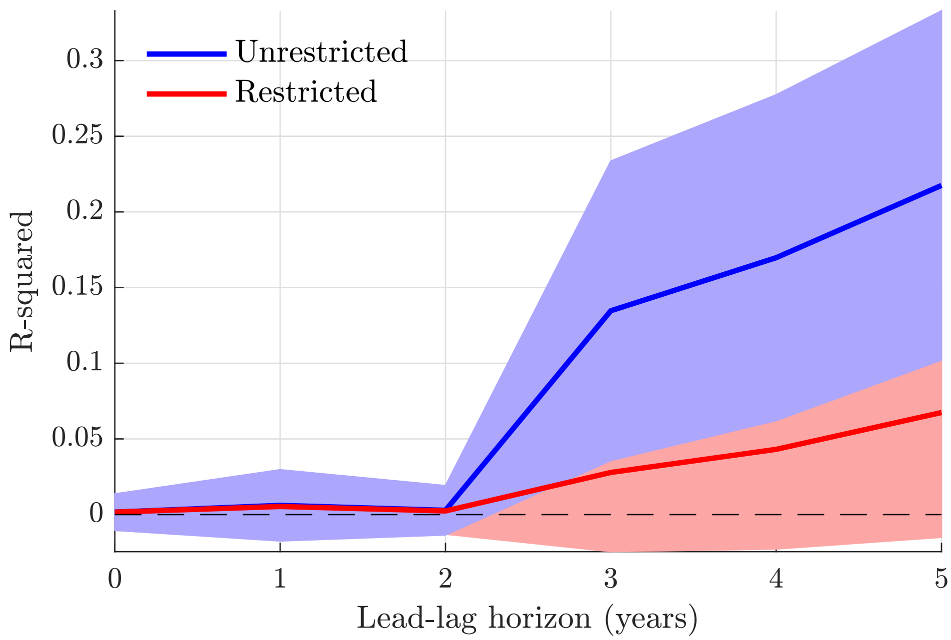
Thus, if we include just the constant and the first term, the regression would estimate the standard relationship between contemporaneous changes in the exchange rate and TFP, which we know from previous research is virtually nil. If in addition we include the first summation term, then we would also consider the additional explanatory power of lagged changes in TFP of up to h-years in the past. Once we include the second summation term, we also consider a potential correlation with *future* TFP changes, of up to h-years forward.

In order to succinctly summarize the lead-lag relationship we find, in Figure 9, we report the resulting R^2 of two versions of the above regression: (i) a "Restricted" backward-looking version that only includes current and lagged TFP growth terms (red line); and (ii) an "Unrestricted" version that includes all terms on the right-hand side (blue line).

The R^2 of the purely backward looking regression is statistically insignificant no matter how many lags of TFP growth we include, embodying the typical "disconnect" result. On the other hand, the message changes substantially once we also include terms capturing *future* TFP growth. The resulting R^2 of this "Unrestricted" regression is plotted with the blue line. The relationship between real exchange rate changes and TFP growth is similarly insignificant if we only include TFP growth of up to 2 years in the future, but becomes increasingly significant as we include TFP growth 3 to 5 years out. Thus, just a simple regression can show us that exchange rates lead TFP improvements.

But more specifically, this evidence shows that the exchange rates contain a substantial

Figure 9: Real exchange rate growth and leads and lags of TFP growth



Notes: The figure reports the R^2 of a regression of exchange rate changes on present and past TFP (Restricted), and the R^2 of a regression of exchange rate changes on present, past and future TFP (Unrestricted). See regression equation (9).

amount of information about future TFP growth in the *medium-run to long-run*. Thus, as we also argued in Section 4.1, the news incorporated in the exchange rate are not about TFP in the next year or so, but are of more long-horizon nature.

This long-horizon nature of news that we uncover can help us understand why papers such as Engel and West (2005) and Sarno and Schmeling (2014), who also make the observation that as a forward-looking asset price the exchange rate ought to lead macroeconomic fundamentals

This long-horizon nature of news that we uncover and relate to the exchange rate is important in the context of the existing literature. A number of papers in the related literature have also made the observation that as a forward looking asset price, the exchange rate ought to lead macroeconomic fundamentals. Yet, this literature generally fails to find a robust evidence of the exchange rate leading the macroeconomic fundamentals. One key difference is that the existing empirical approaches focus on testing relatively short-horizon lead-lag relationships. For example, Engel and West (2005) run a number of Granger-causality type of tests, but only include 1-year lags, while papers like Sarno and Schmeling

(2014) adopt a more non-parametric approach, but still limit their null hypothesis to testing predictive relationships to a maximum of two years ahead. Instead, our results indicate that the news driving the exchange rate are of a low frequency nature that only truly takes form over three to five year horizons.

In addition, our VAR analysis also separately accounts for the noise shock to expectations of future TFP, which also contributes a significant fraction to exchange rate volatility. Our VAR analysis thus allows to capture the effects of both the true TFP innovations (which also come through, in a reduced form way, in Figure 9) and expectational noise.

Relation to other shocks The analysis in sections 4 and 5 relies on the assumption that the technological disturbances ε_t^a are exogenous, that is orthogonal to other structural shocks. One may be concerned that other economic shocks such as shocks to R&D productivity or monetary policy shocks, may lead to changes in TFP through endogenous investment in research and development (R&D). In that case, our identified technological and noise disturbances might be contaminated by other economic shocks.

On the one hand, we view shocks to R&D productivity as a type of "news" shocks about future TFP. In the real world, R&D investment is a small proportion of the overall macroeconomy, so a productivity shock to such a small sector is unlikely to have any direct impacts on the exchange rate itself, and thus our estimates are still correctly picking up that exchange rate variation is to a large extend driven by predictable fluctuations in future aggregate TFP.

On the other hand, if current *contractionary* monetary shocks spur R&D investment and thus future TFP growth, then indeed our identified noisy news innovations might be related to such monetary shocks. We stress that the relationship must be one where contractionary monetary shocks spur R&D investment, since our empirical results show that the exchange rate *appreciates* in anticipation of TFP improvements, and if that appreciations is to be driven by monetary shocks it must be due to monetary tightening.

We see the null hypothesis of contractionary monetary policy spurring R&D as unlikely, but still in what follows we directly test whether our procedure picks up U.S. monetary policy shocks. The measure of U.S. monetary policy shocks we consider is the one identified through the "high frequency approach" by Gertler and Karadi (2015) and recently updated by Jarocinski and Karadi (2020). In Table 5 we report the correlation between our technology and expectational noise shocks, and U.S. monetary policy shocks. We find that both technology and noise disturbances are orthogonal to U.S. monetary policy shocks.

These findings also complement the empirical results of Kim et al. (2017), who find that while the exchange rate responds significantly to monetary policy shocks, the response to these shocks *do not* display any violations of uncovered interest parity. However, the impulse responses of our shocks imply significant deviations from UIP, which is another reason to think that we are picking up something different than monetary policy shocks.

Overall, we should not lose sight of the fact that while TFP innovations and their noisy expectations account for a significant portion of RER variation (up to 66% overall, and roughly a third of the variation of Δq_t and the variation of q_t at business cycle frequencies), our identified shocks still leave a substantial portion of the exchange rate variation unexplained. Certainly a number of other shocks also play an important role in the exchange rate variation in the data, with monetary shocks a prime example of such shocks.

Table 5: Correlation between Technology, Noise and Other Economic Shocks

	Technology	Exp. Noise
U.S. Monetary Policy Shocks	0.09	0.06
	p-value $= 0.46$	*p-value* $= 0.62$

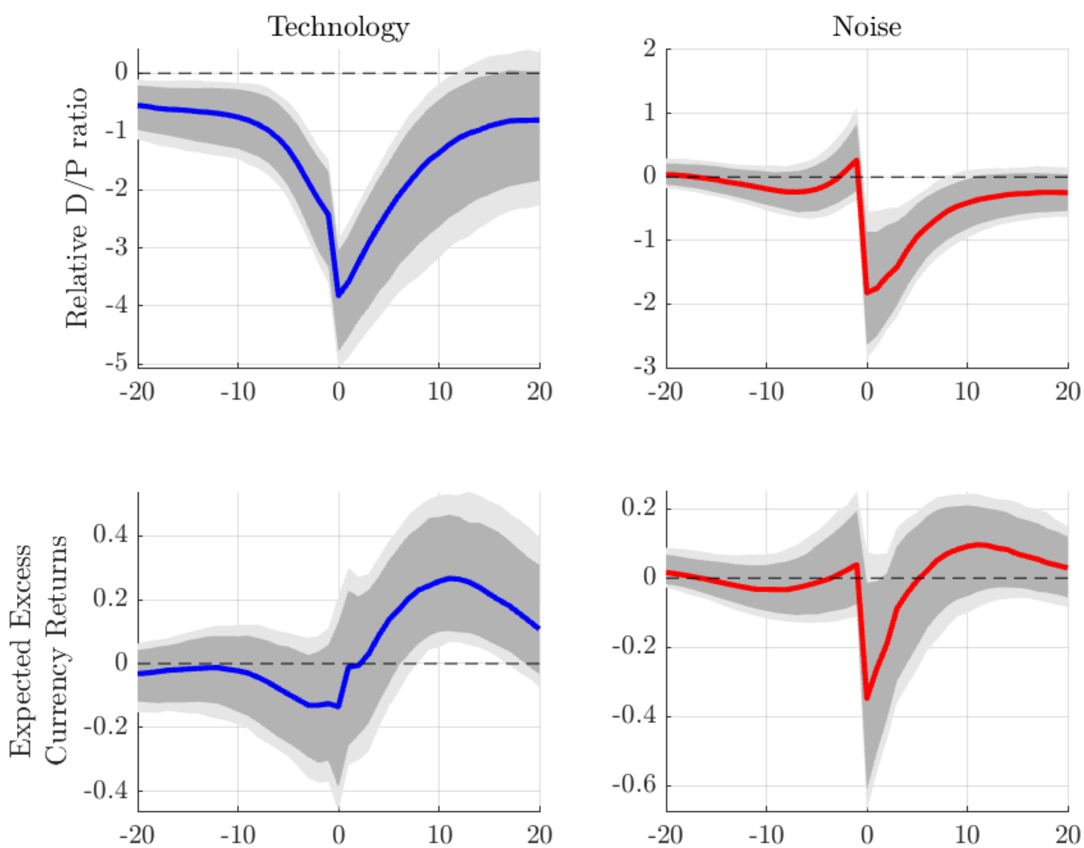
Notes: The table reports the correlation between technological disturbances (Technology) and expectational disturbances (Exp. Noise) with other economic shocks. U.S. monetary policy shocks refer to the series by Gertler and Karadi (2015) and recently updated by Jarocinski and Karadi (2020).

Exchange rates, news, and stock prices As a parting thought, we want to qualitatively link our estimates with the well established results in the asset pricing literature that the cross-section of excess currency returns has a clear factor structure. Lustig et al. (2011) documented that the cross-section of excess currency returns has a clear factor structure, but the literature has also been puzzled by the apparent fact that the estimated currency return factors are *not* related to the factors that explain the prices and returns of other risky assets such as equities (e.g. Burnside, 2011).

Our headline results relate to this literature in two ways. First, as shown above, we find that half of the variation in expected currency returns $\mathbb{E}_t(\lambda_{t+1})$ is driven by just two disturbances ε_t^v and ε_t^a. This speaks to a two-factor structure of currency returns. Moreover, those disturbances are also closely linked to a deep source of macro fluctuations – productivity – and as such we would expect them to affect the price of other risky assets as well.

Indeed, we find that they do. In Figure 10 we plot the impulse response of the relative dividend-to-price ratio (US relative to the G6 average). We see that the pricing of equities

Figure 10: Technology, noise and the relative dividend-to-price ratio



Notes: The figure displays the IRF a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The shaded area are the the 16-84th (dark gray) and 5-95th (light gray) percentile bands. Each period is a quarter.

indeed responds strongly to our shocks, both in anticipation of the actual TFP improvement and in response to a noise shock to expectations.

This suggests that indeed there might a common, fundamental driver to both currency premia and equity premia. However, the TFP innovation and the noise shock seem to generate the *opposite* correlation between stock prices and currency premia. While the TFP innovation pushes towards a negative such correlation, the noise shock implies a *positive* correlation. These opposing forces might explain why the previous literature, which has only looked at unconditional links between equity and currency returns, has found no strong relationship.

Once you isolate the actual TFP innovations and the noise in the expectation of such innovations, the conditional link between equity and currency risk premia seems clear. This calls for richer models, both theoretical and empirical, to further analyze this potential fundamental connection.

6 Conclusions

We have provided empirical evidence that exchange rates are not disconnected from macro aggregates, but that they are indeed tightly linked to fluctuations in noisy expectations of future TFP improvements. This link, however, has been difficult to uncover previously because the anticipation effects, compounded with noise in expectations, make it far from obvious in the raw data. In addition, the two sets of shocks we identify appear to generate a number of famous FX puzzles at the same time, which speaks to a common and fundamental origin of exchange rate puzzles.

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A Data Appendix

A.1 Data sources

In the next lines, we describe the data sources used in the paper.

- Nominal exchange rate
  - Daily bilateral exchange rates, Foreign Currency/USD;

- Source: *Datastream*;
- Quarterly aggregation: period-average.

- Nominal interest rates
  - Daily Eurodollar deposit rates;
  - Source: *Datastream*;
  - Quarterly aggregation: period-average.

- Consumer Price Indexes
  - CPI Index (Chained 2010)
  - Source: *OECD*, https://stats.oecd.org/index.aspx?DataSetCode=PRICES_CPI.

- Consumption
  - Real consumption;
  - Source: *OECD*, Private final consumption expenditure

- Investment
  - Real Investment;
  - Source: *OECD*, Gross Fixed Capital Formation (`GFCF`), Quarterly growth rates, https://data.oecd.org/gdp/investment-gfcf.htm.

- U.S. TFP:
  - U.S. utilization-adjusted TFP as constructed in Fernald (2012);
  - Source: John Fernald's website, https://www.johnfernald.net/TFP (latest available vintage, downloaded on January 2, 2022);

- U.S. R&D:
  - Real R&D expenditure
  - Source: *U.S. Bureau of Economic Analysis*, retrieved from *FRED*, https://fred.stlouisfed.org/series/Y694RX1Q020SBEA

- U.S. trade balance (% of GDP)
  - Shares of gross domestic product: Net exports of goods and services

Table 6: Share of variance explained by the Main FX shock (ε_1); Extended sample 1978:Q3-2018:Q4

	Forecast Horizon (Quarter)					
	Q1	Q4	Q12	Q24	Q40	Q100
Home TFP						
Home Consumption						
Foreign Consumption						
Home Investment						
Foreign Investment						
Interest Rate Differential						
Real Exchange Rate						
Expected Excess Returns						
Real Exchange Rate Change						

Notes: The table reports the estimated variance shares accounted for by the main exchange rate shock at different horizons.

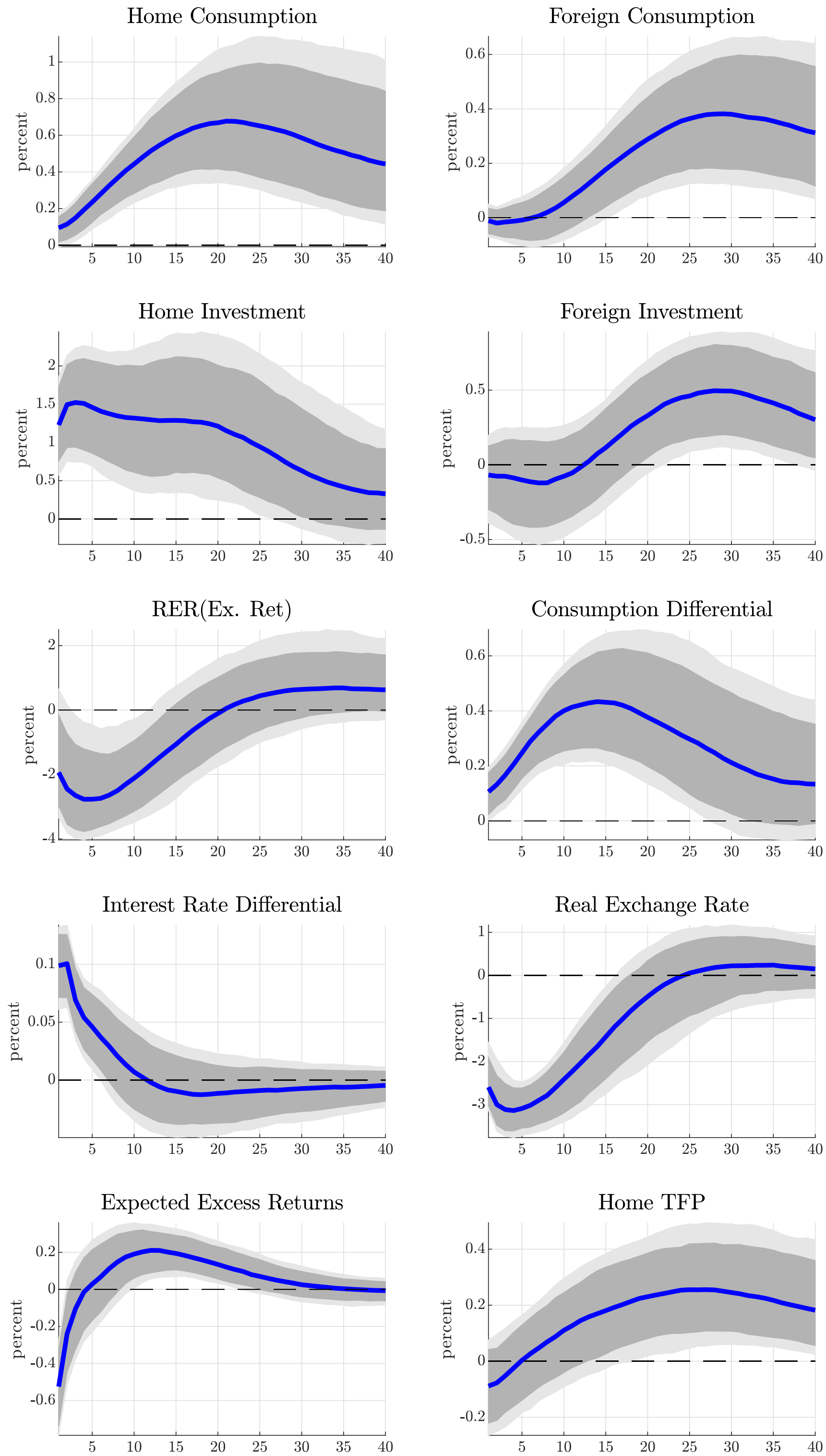
  - Source: *U.S. Bureau of Economic Analysis*, retrieved from *FRED*, https://fred.stlouisfed.org/series/A019RE1Q156NBEA

- Dividend-to-price ratios
  - Constructed following Cochrane (2011), using MSCI price indexes and total returns indexes retrieved from *Datastream*

B Additional tables and figures

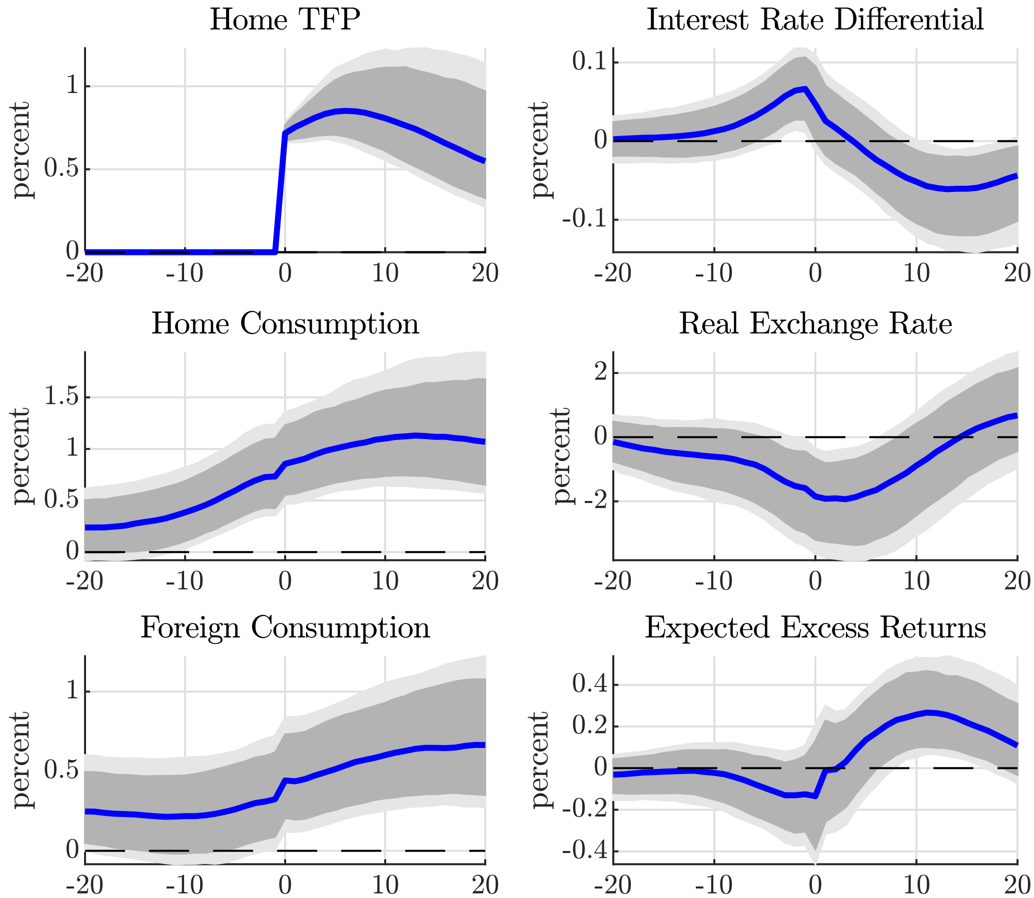
B.1 Extended sample (1978:Q3-2018:Q4)

Figure 11: Impulse Response Functions to the Main FX shock (ε_1), 1978:Q3-2018:Q4



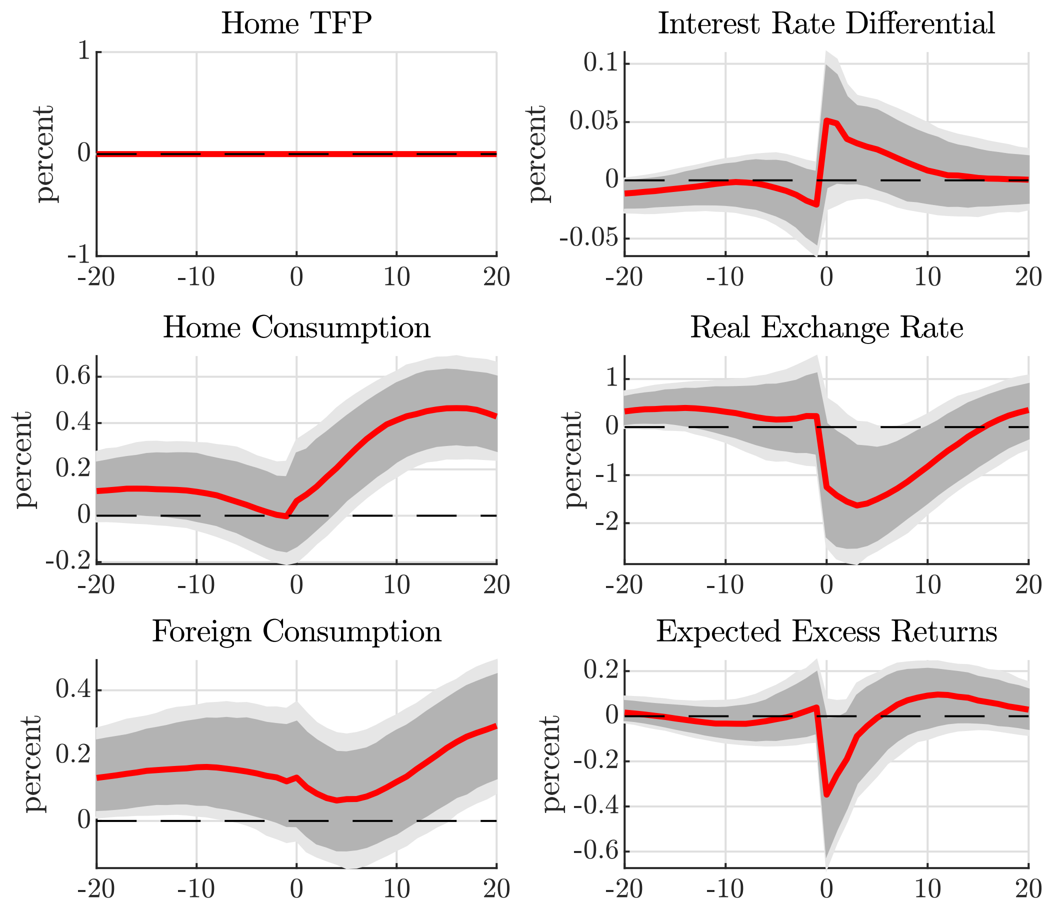
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 12: Impulse responses to Technology (ε^a) disturbances, 1978:Q3-2018:Q4



Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 13: Impulse responses to Noise (ε^v) disturbance, 1978:Q3-2018:Q4



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

B.2 Vector Error-correction Model (VECM)

Table 7: Variance Decomposition; Extended sample 1978:Q32018:Q4

	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1.00	1.00	0.00	1.00	1.00	0.00
Home Consumption	0.67	0.42	0.25	0.33	0.07	0.26
Foreign Consumption	0.47	0.32	0.15	0.18	0.07	0.12
Home Investment	0.56	0.34	0.21	0.27	0.09	0.19
Foreign Investment	0.50	0.25	0.25	0.35	0.08	0.27
Interest Rate Differential	0.41	0.28	0.13	0.30	0.18	0.11
Real Exchange Rate	0.48	0.26	0.22	0.29	0.08	0.20
Expected Excess Returns	0.38	0.22	0.16	0.32	0.16	0.16
Real Exchange Rate Change	0.24	0.06	0.18	0.23	0.05	0.18

Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances ("Tech"), expectational disturbances ("Noise"), and the combination of both.

B.3 Bilateral VARs

Table 8: Share of variance explained by the Main FX shock (ε_1); VECM

	Forecast Horizon (Quarter)					
	Q1	Q4	Q12	Q24	Q40	Q100
Home TFP						
Home Consumption						
Foreign Consumption						
Home Investment						
Foreign Investment						
Interest Rate Differential						
Real Exchange Rate						
Expected Excess Returns						
Real Exchange Rate Change						

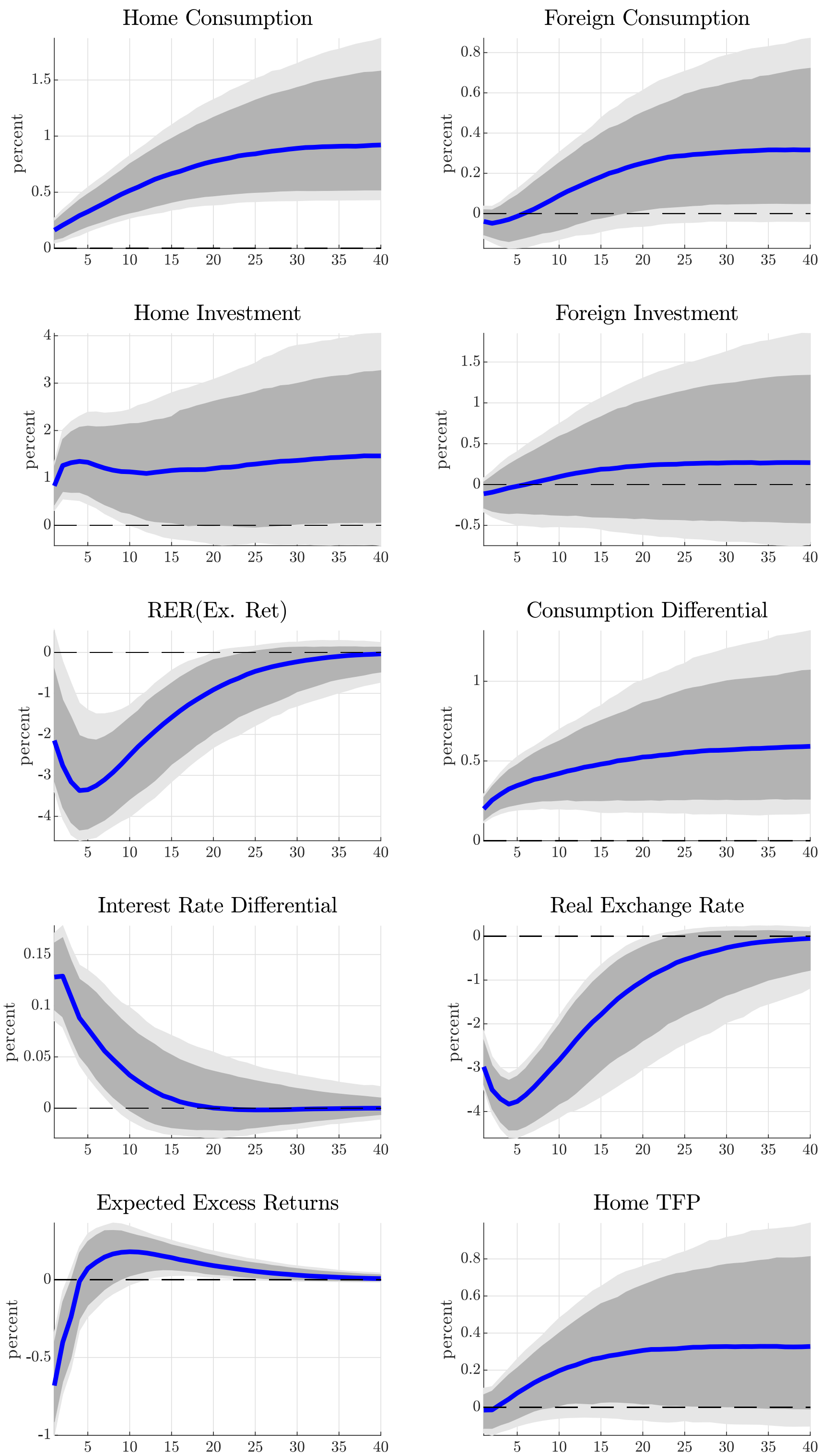
Notes: The table reports the estimated variance shares accounted for by the main exchange rate shock, both unconditionally and at different horizons.

Table 9: Share of variance explained by the Main FX shock (ε_1); Individual Countries (Median across 6 bilateral estimates)

	Forecast Horizon (Quarter)					
	Q1	Q4	Q12	Q24	Q40	Q100
Home TFP						
Home Consumption						
Foreign Consumption						
Home Investment						
Foreign Investment						
Interest Rate Differential						
Real Exchange Rate						
Expected Excess Returns						
Real Exchange Rate Change						

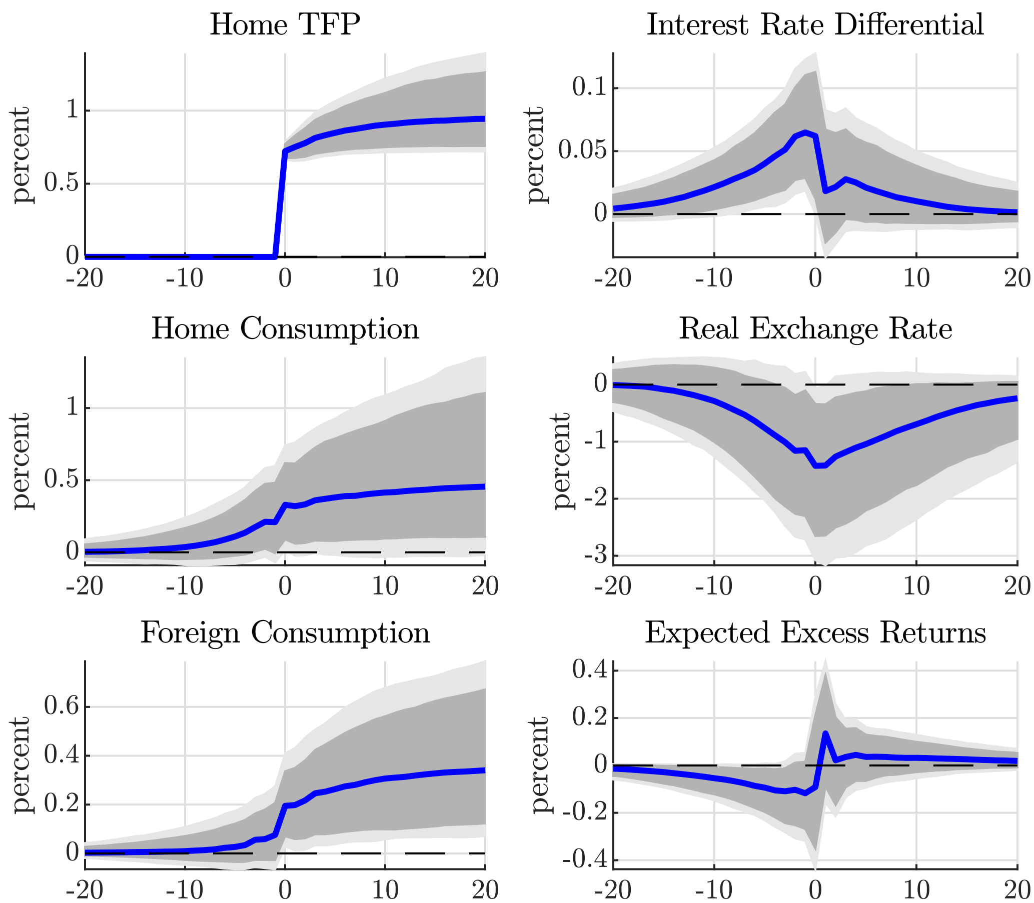
Notes: The table reports the estimated variance shares accounted for by the main exchange rate shock at different horizons.

Figure 14: Impulse Response Functions to the Main FX shock (ε_1), VECM



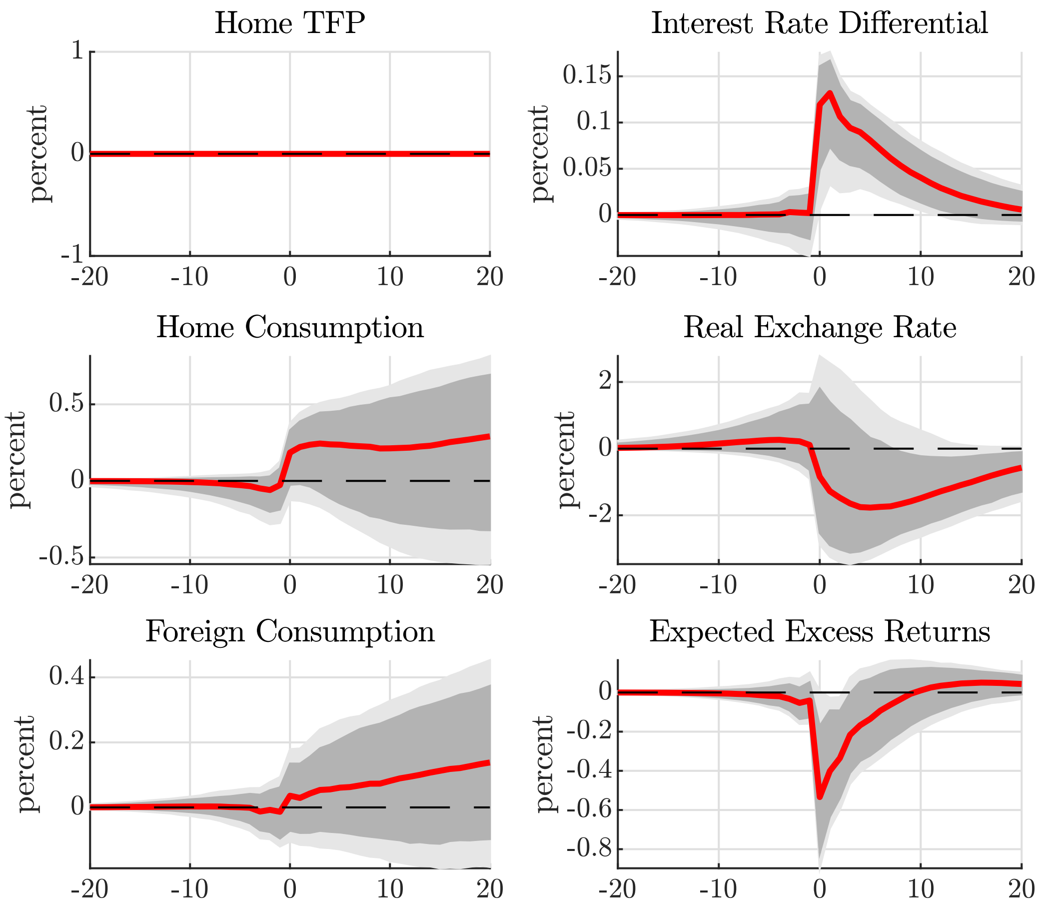
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 15: Impulse responses to Technology (ε^a) disturbances, VECM



Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 16: Impulse responses to Noise (ε^v) disturbance, VECM



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Table 10: Variance Decomposition; VECM

	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1.00	1.00	0.00	1.00	1.00	0.00
Home Consumption	0.28	0.12	0.16	0.25	0.05	0.20
Foreign Consumption	0.24	0.16	0.09	0.15	0.08	0.07
Home Investment	0.29	0.08	0.22	0.40	0.06	0.34
Foreign Investment	0.22	0.08	0.14	0.16	0.04	0.12
Interest Rate Differential	0.66	0.15	0.51	0.62	0.09	0.53
Real Exchange Rate	0.49	0.14	0.35	0.33	0.06	0.27
Expected Excess Returns	0.49	0.13	0.36	0.47	0.09	0.38
Real Exchange Rate Change	0.22	0.04	0.17	0.24	0.04	0.20

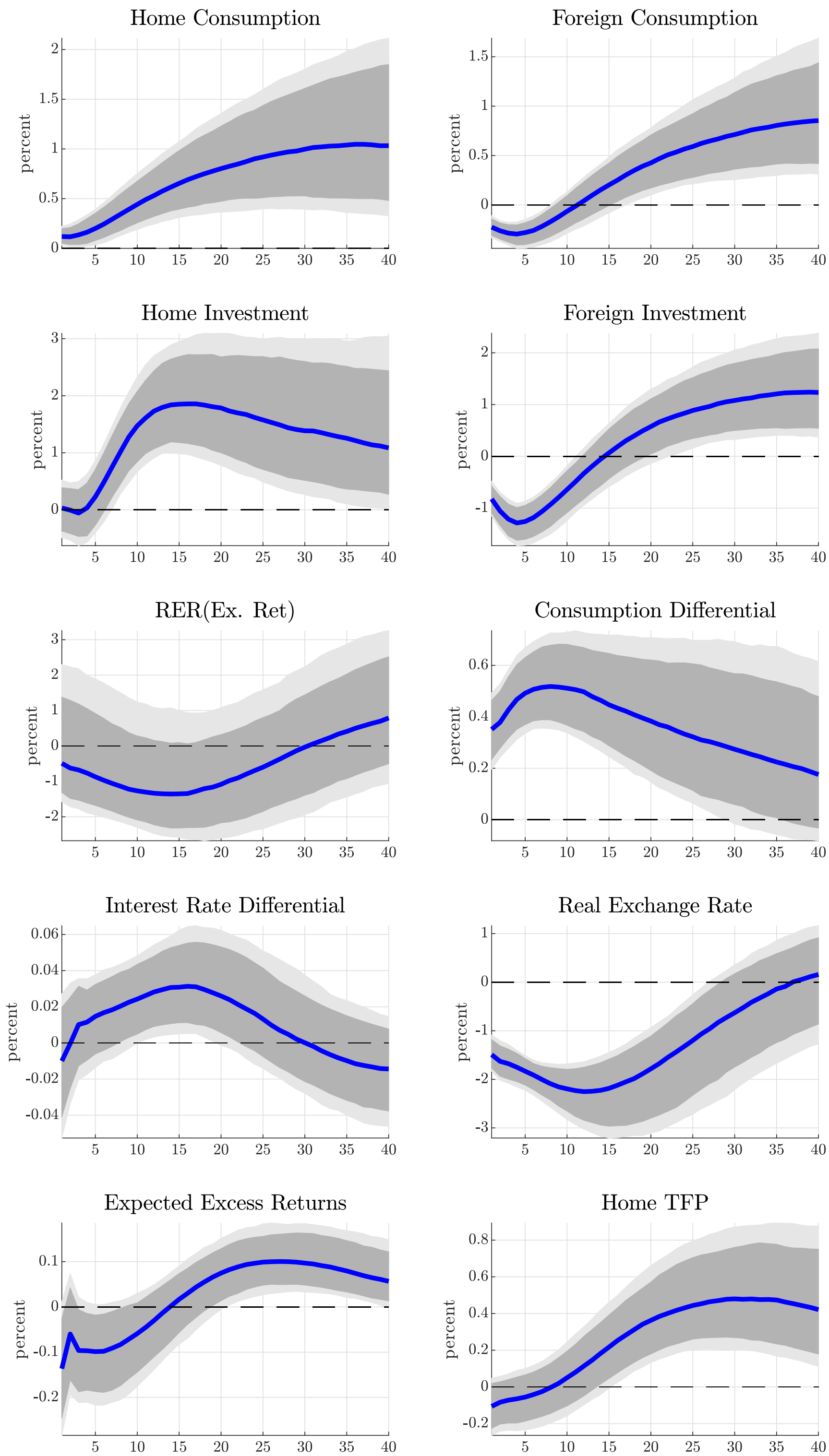
Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

Table 11: Variance Decomposition, Individual countries (Median)

	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1	1	0	1	1	0
Home Consumption	0.69	0.515	0.17	0.34	0.095	0.24
Foreign Consumption	0.54	0.41	0.12	0.29	0.12	0.145
Home Investment	0.62	0.455	0.16	0.375	0.2	0.18
Foreign Investment	0.56	0.43	0.145	0.355	0.105	0.205
Interest Rate Differential	0.395	0.27	0.125	0.245	0.11	0.13
Real Exchange Rate	0.59	0.395	0.195	0.37	0.11	0.245
Expected Excess Returns	0.415	0.25	0.145	0.31	0.13	0.18
Real Exchange Rate Change	0.355	0.095	0.235	0.325	0.06	0.24

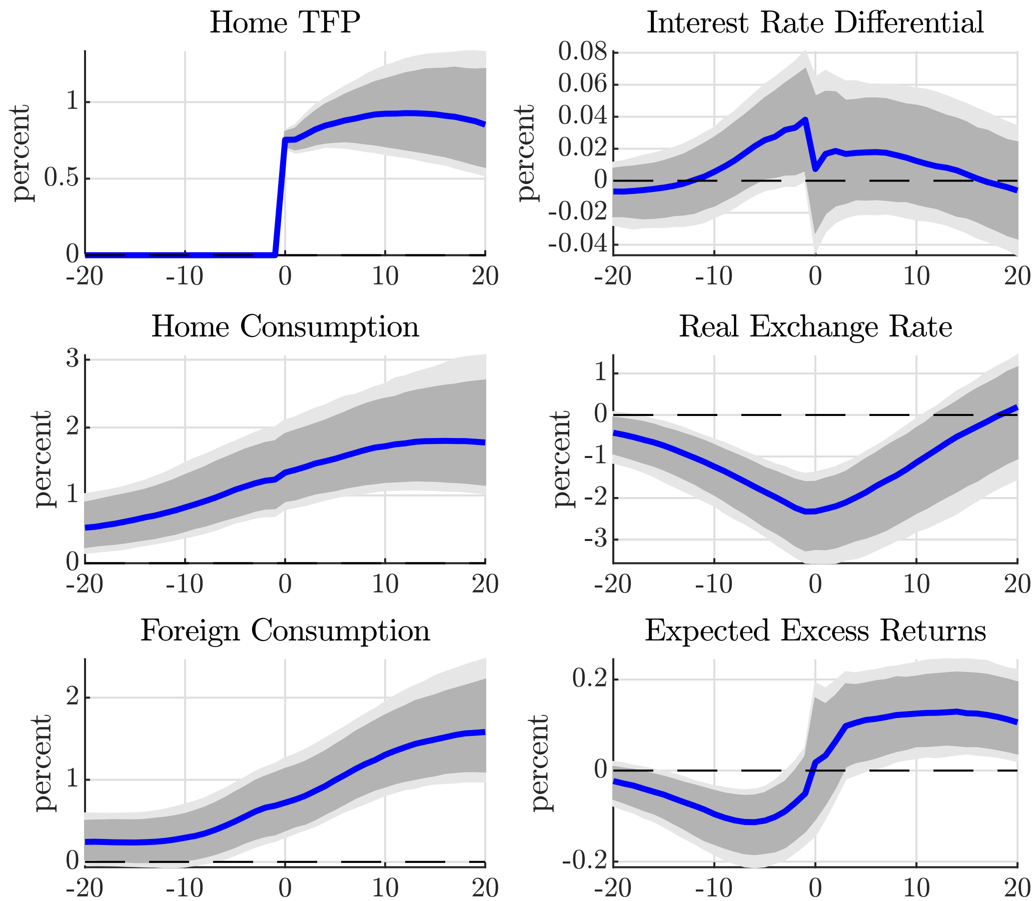
Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

Figure 17: Impulse Response Functions to the Main FX shock (ε_1), Canada



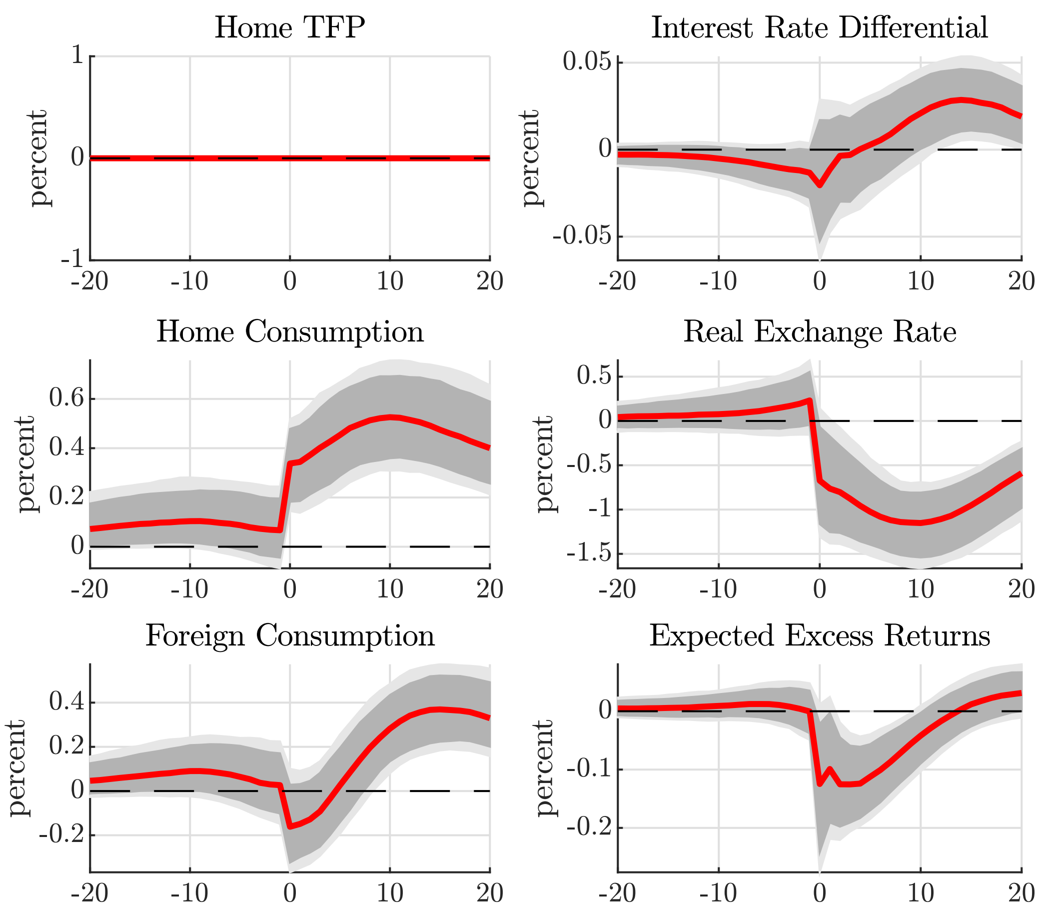
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 18: Impulse responses to Technology (ε^a) disturbances, Canada



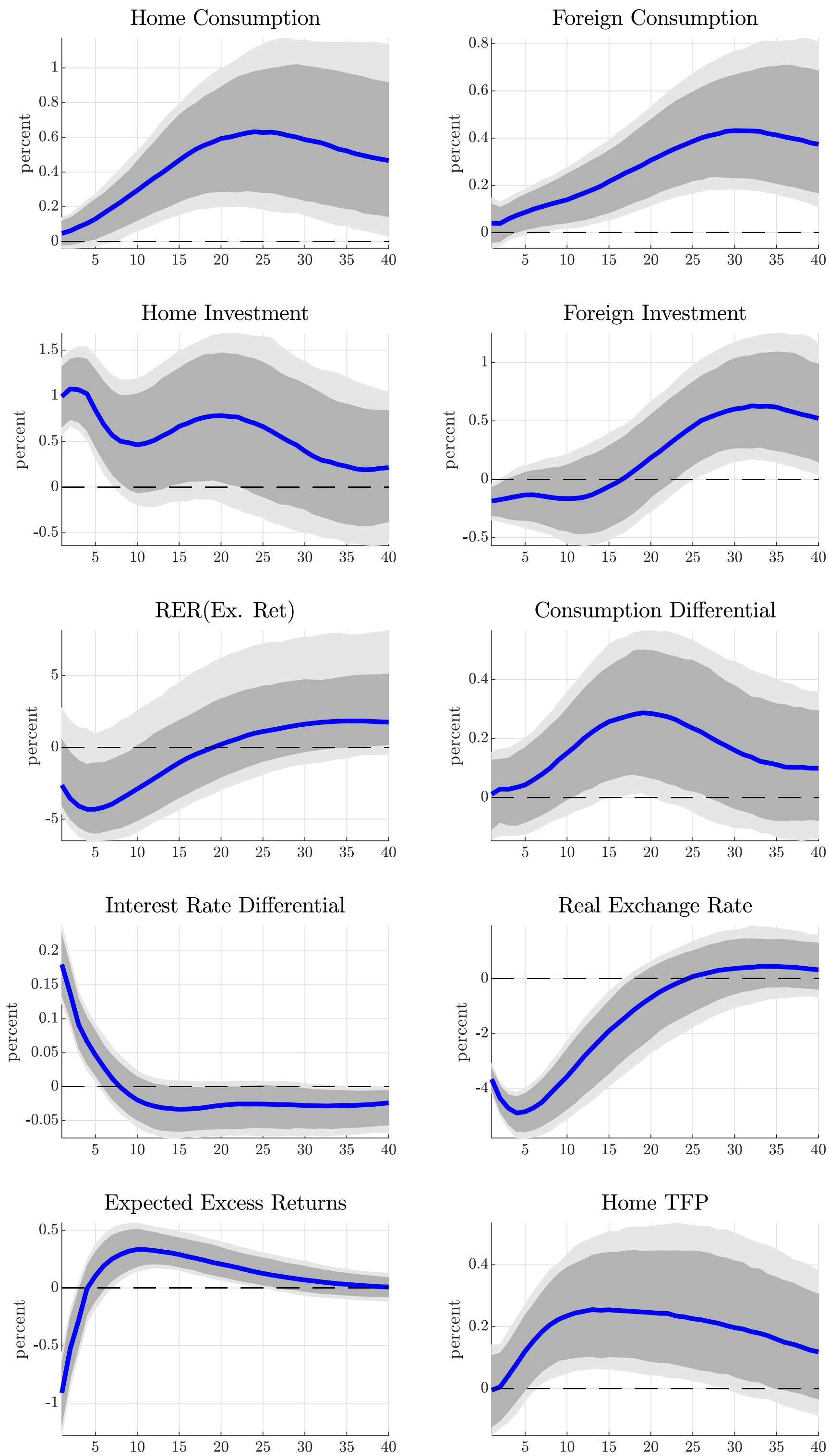
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 19: Impulse responses to Noise (ε^v) disturbance, Canada



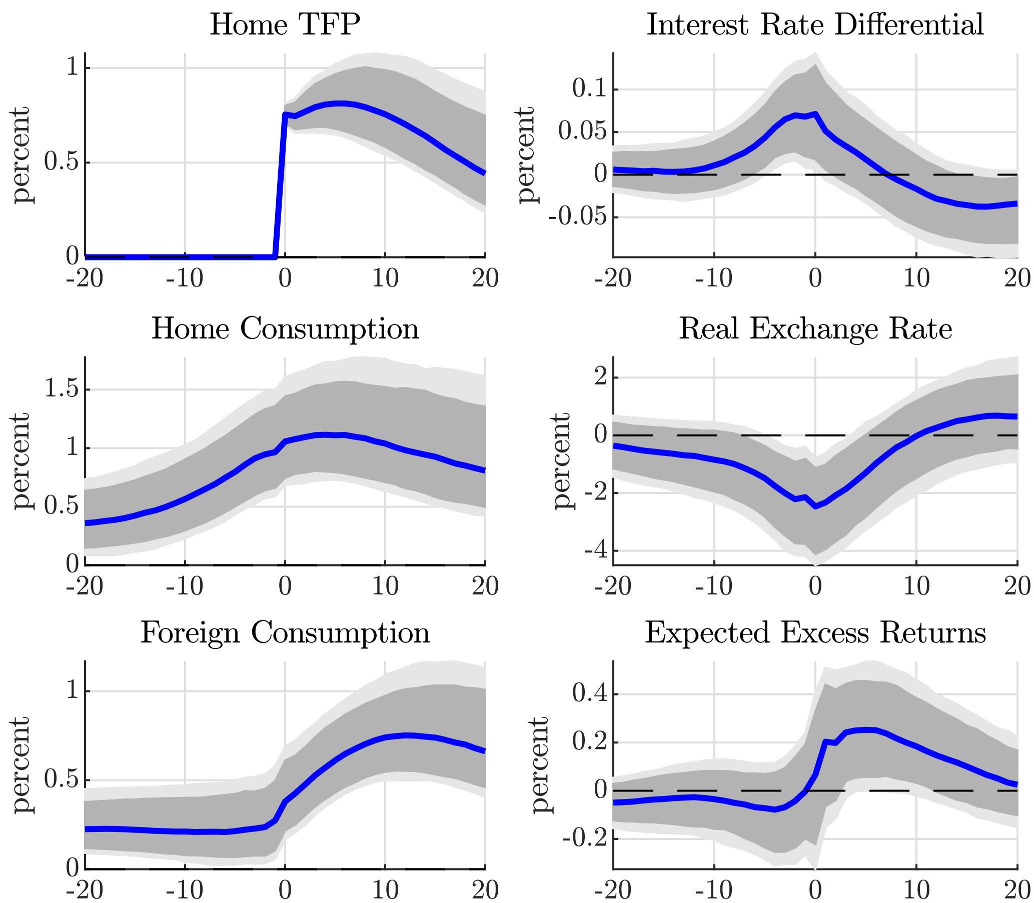
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 20: Impulse Response Functions to the Main FX shock (ε_1), France



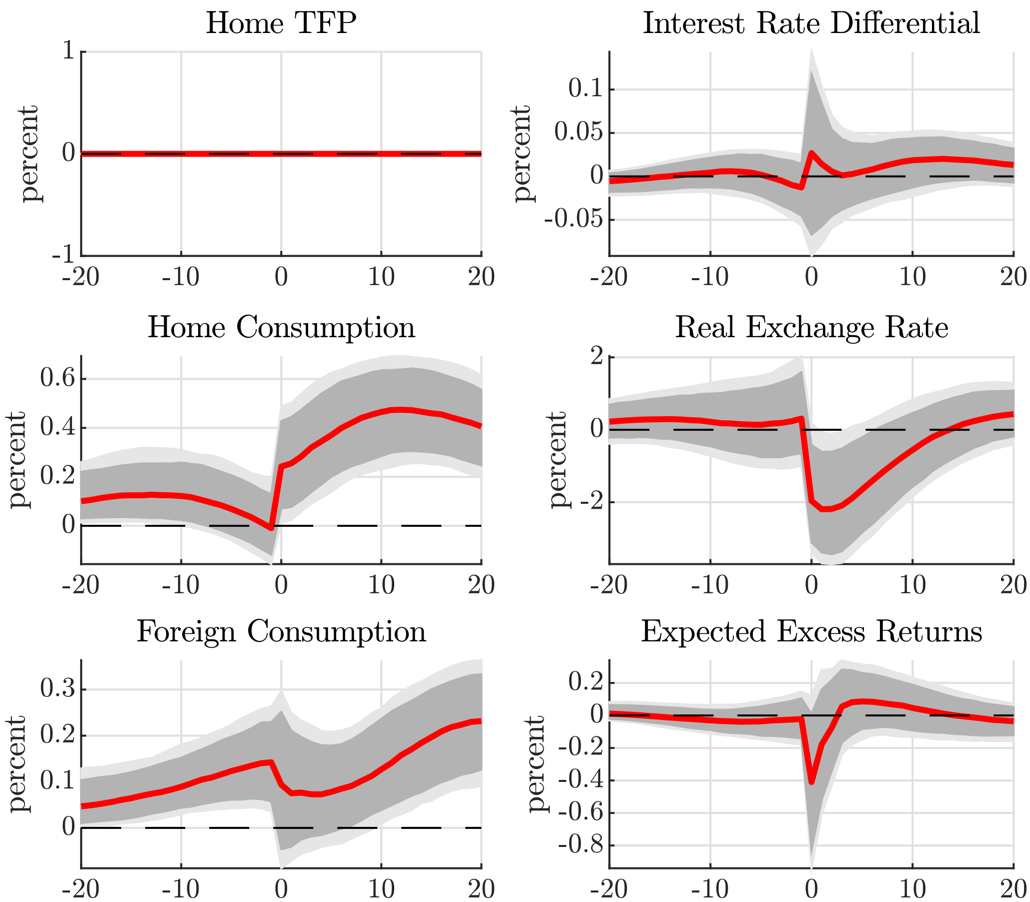
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 21: Impulse responses to Technology (ε^a) disturbances, France



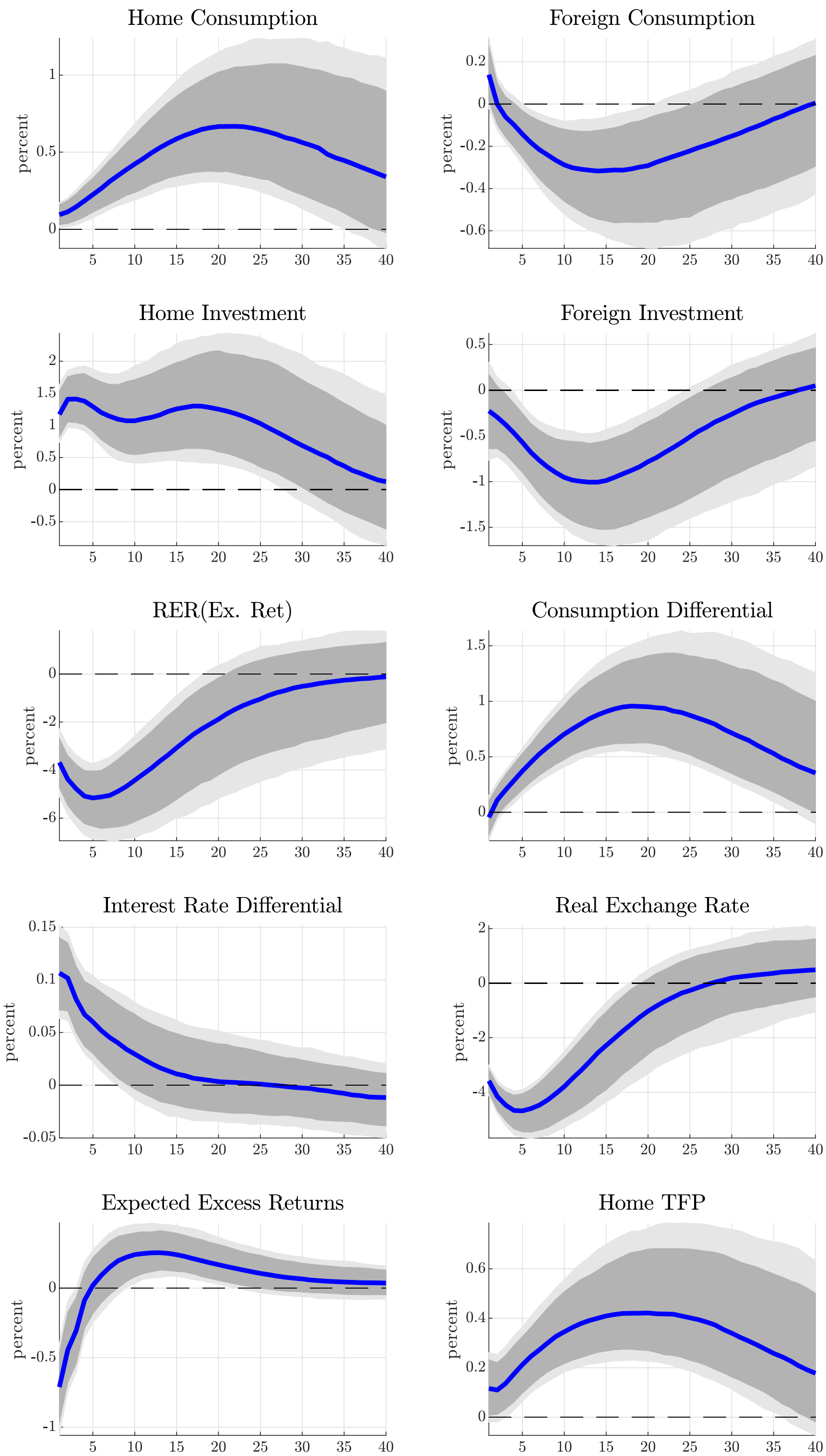
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 22: Impulse responses to Noise (ε^v) disturbance, France



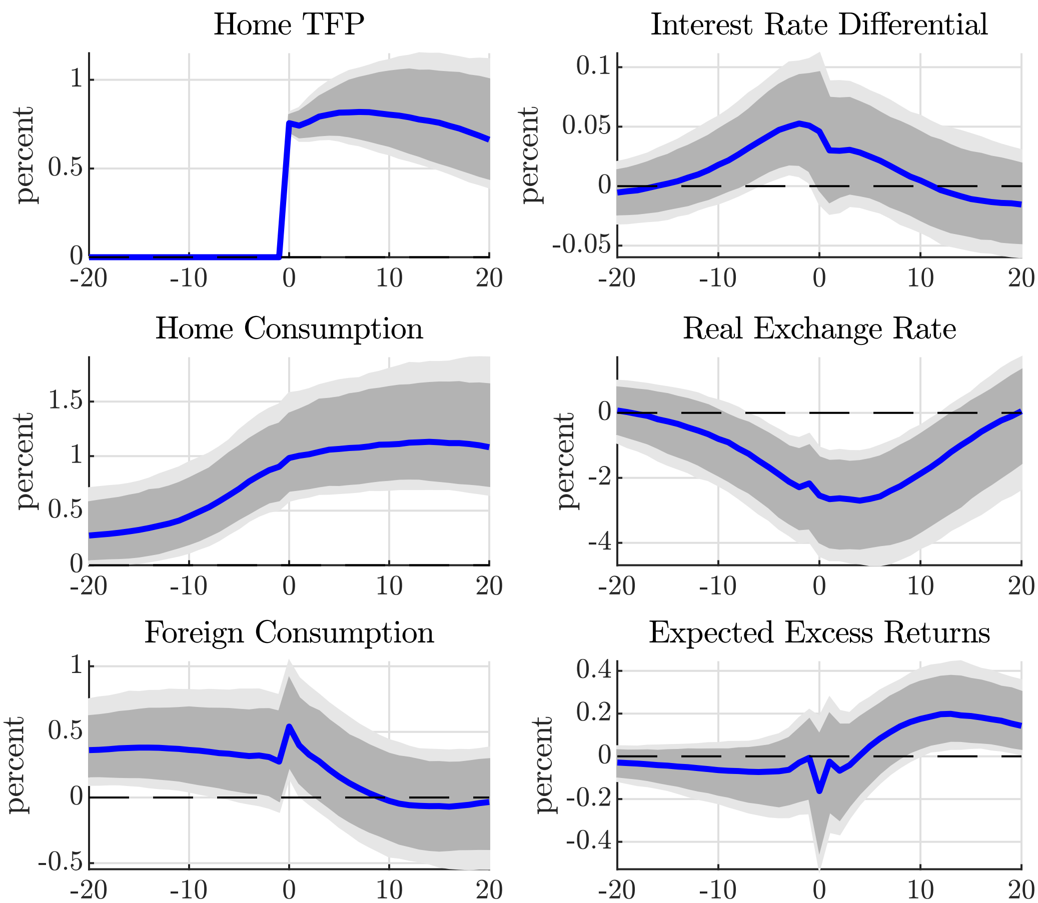
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 23: Impulse Response Functions to the Main FX shock (ε_1), Germany



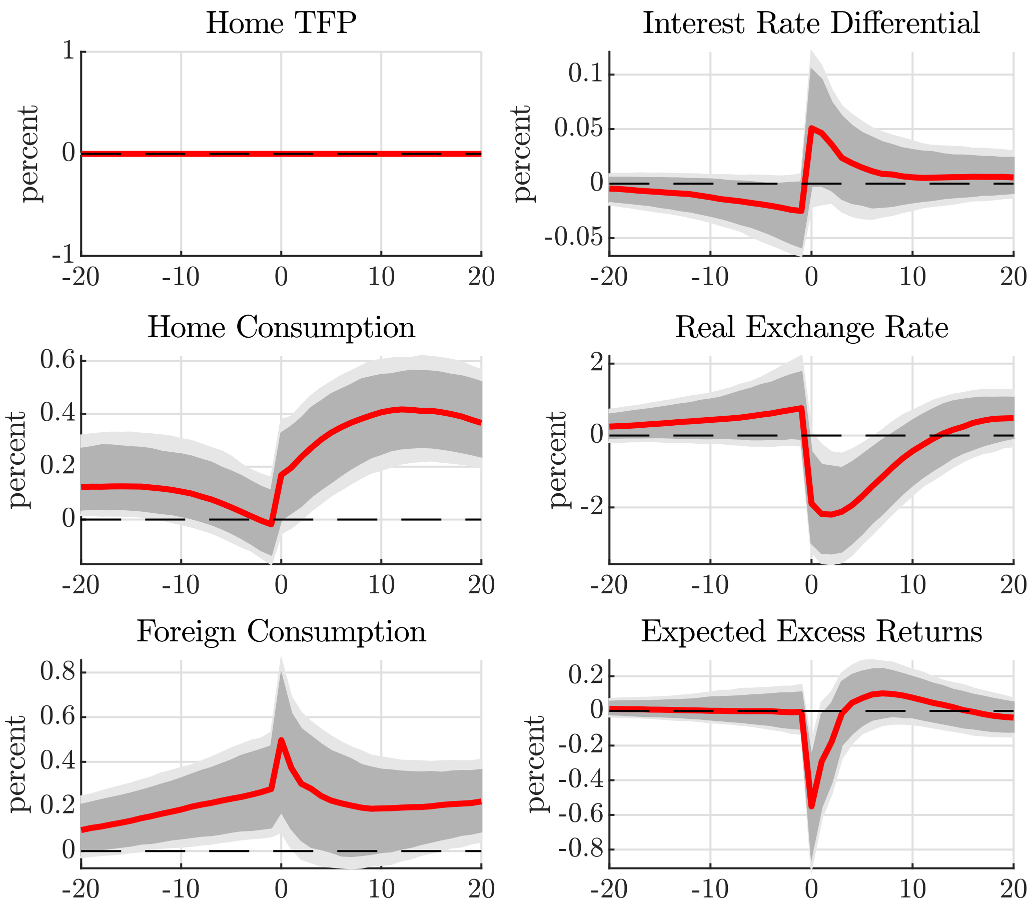
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 24: Impulse responses to Technology (ε^a) disturbances, Germany



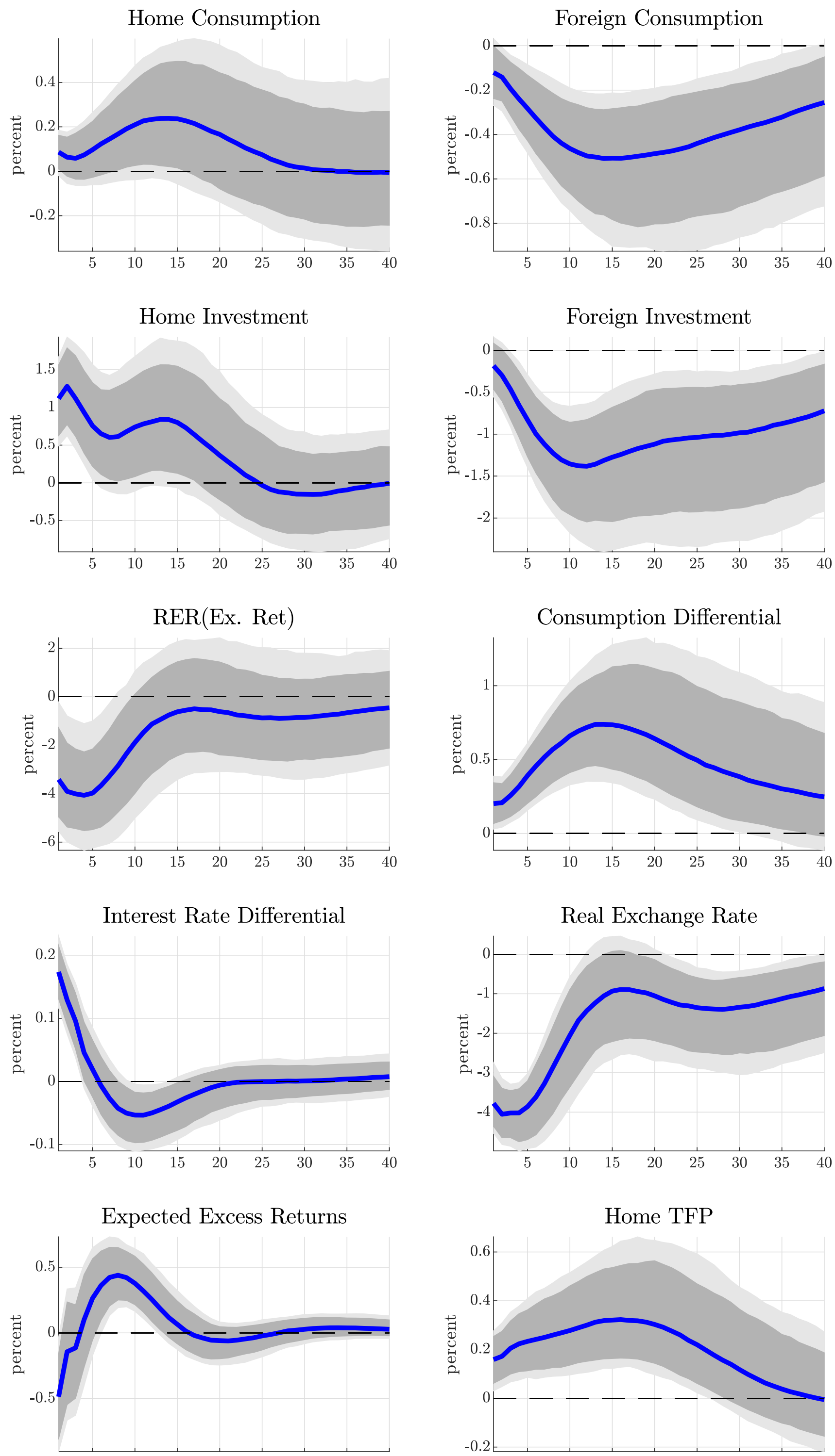
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 25: Impulse responses to Noise (ε^v) disturbance, Germany



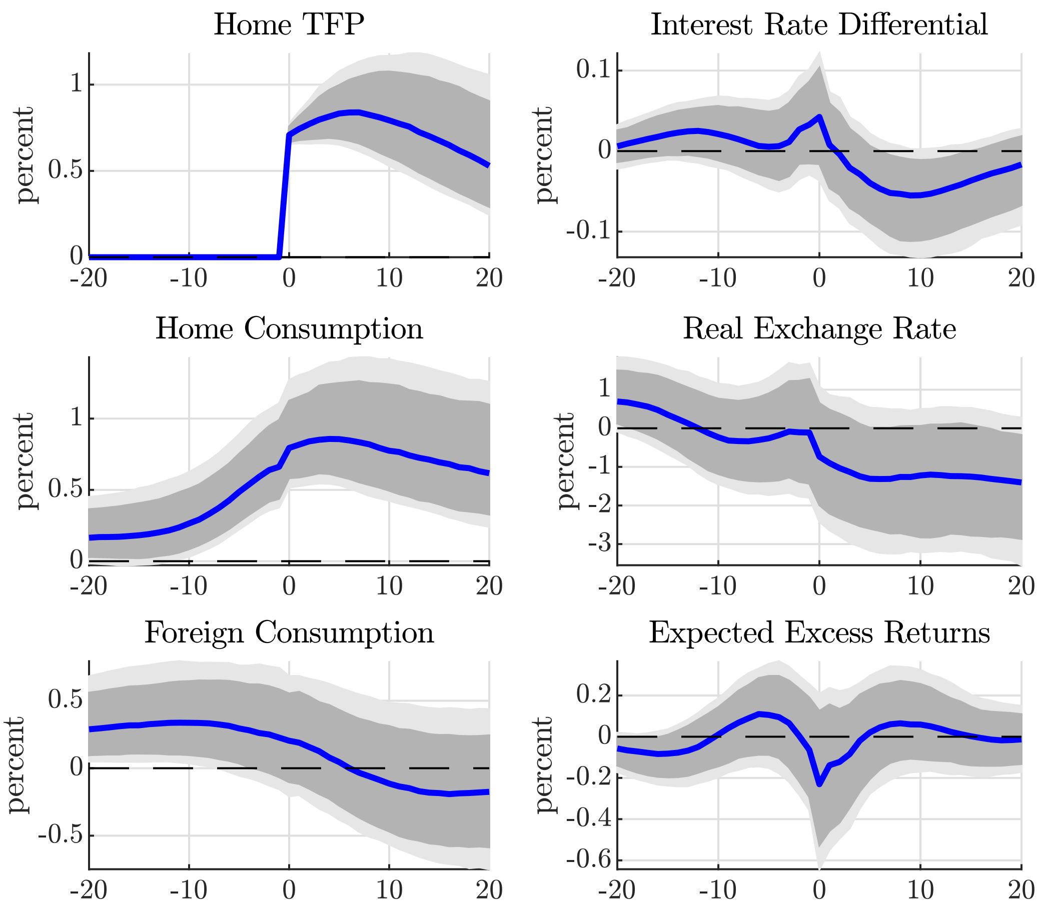
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 26: Impulse Response Functions to the Main FX shock (ε_1), Japan



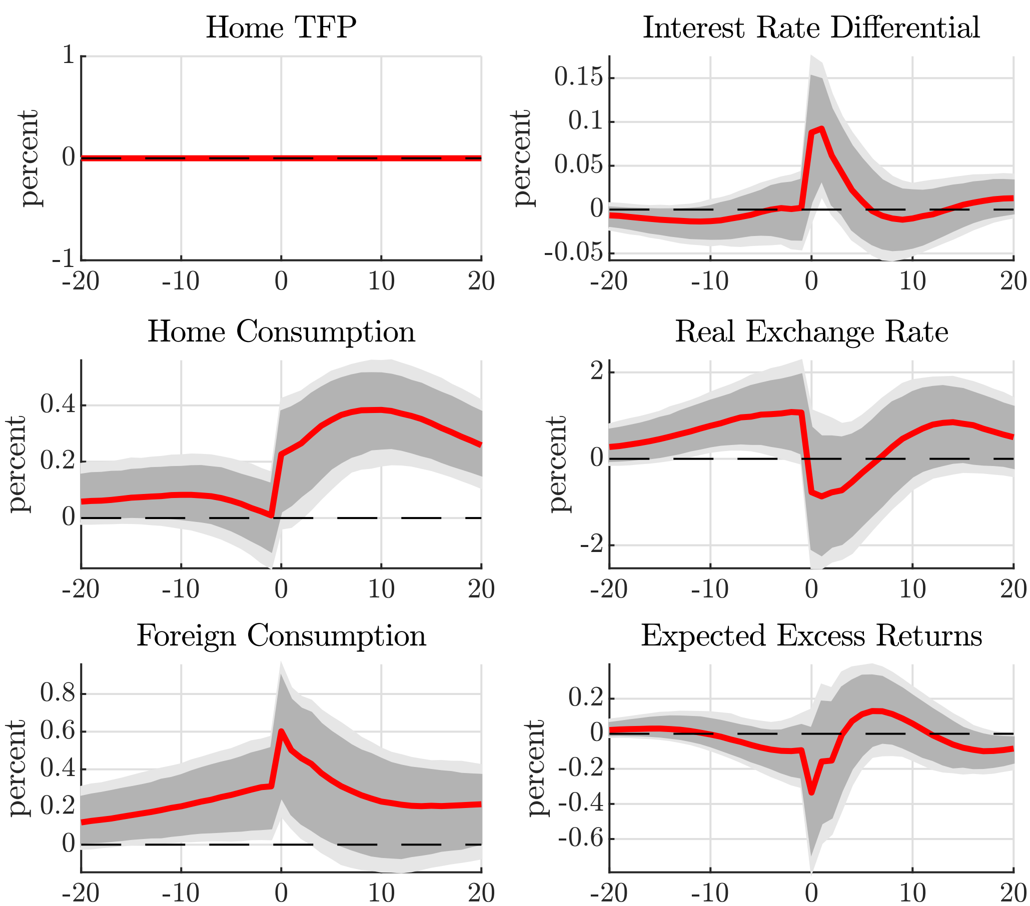
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 27: Impulse responses to Technology (ε^a) disturbances, Japan



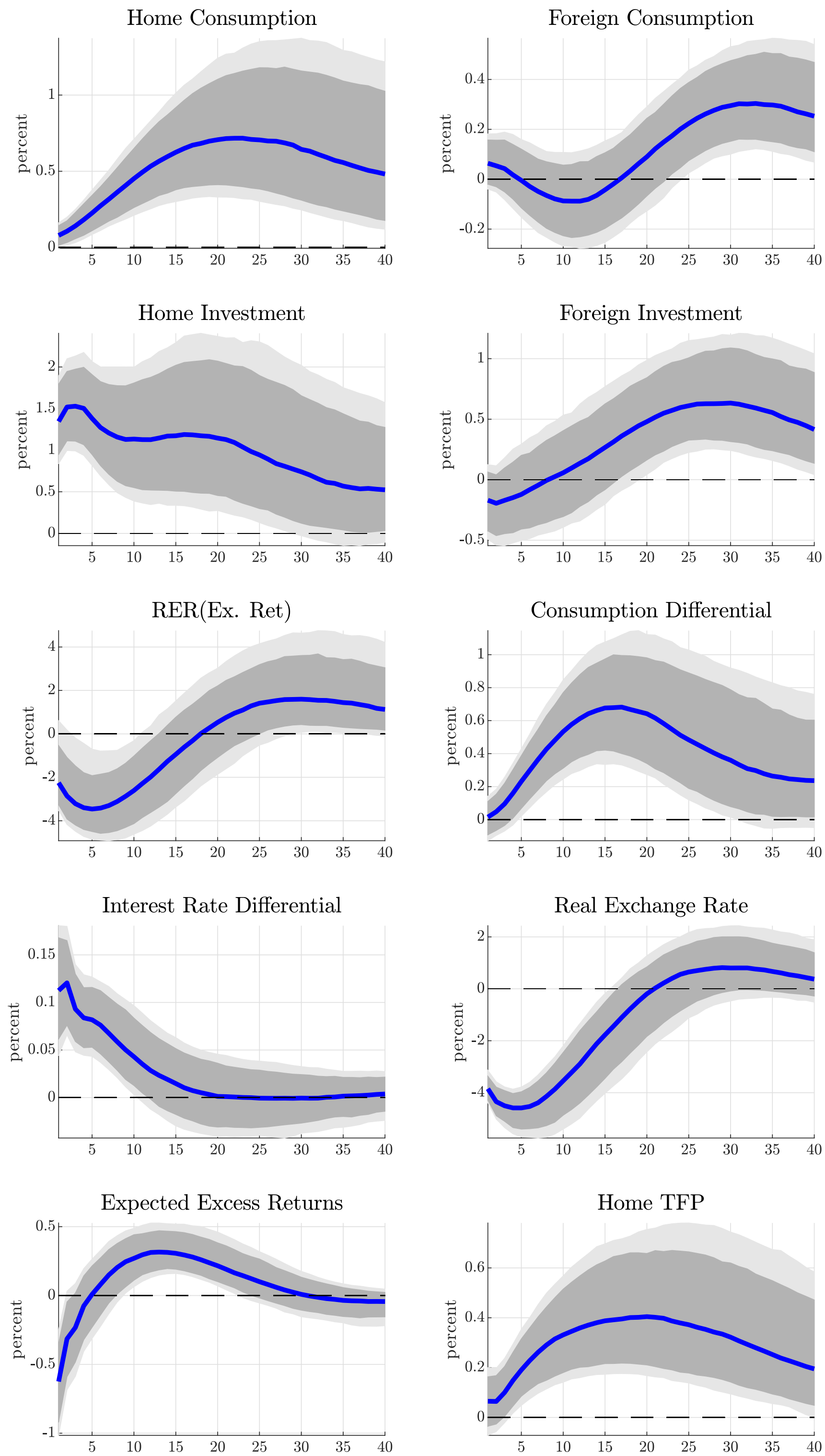
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 28: Impulse responses to Noise (ε^v) disturbance, Japan



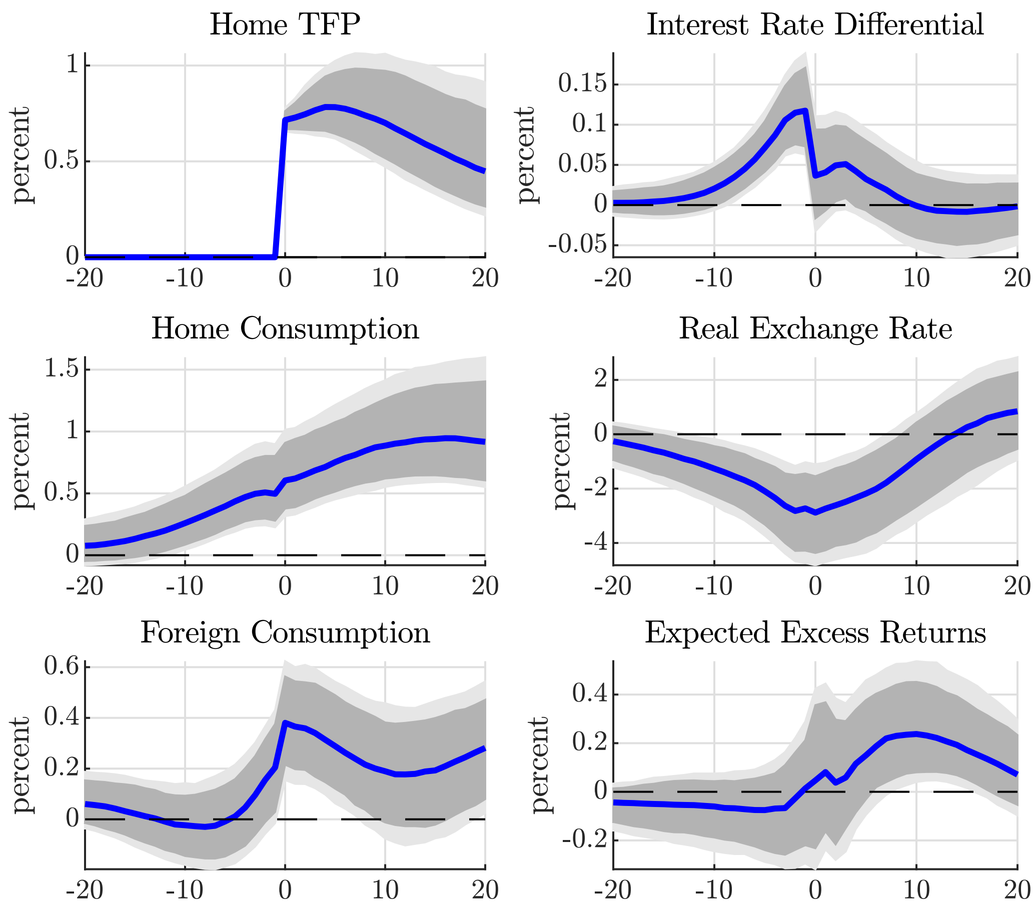
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 29: Impulse Response Functions to the Main FX shock (ε_1), Italy



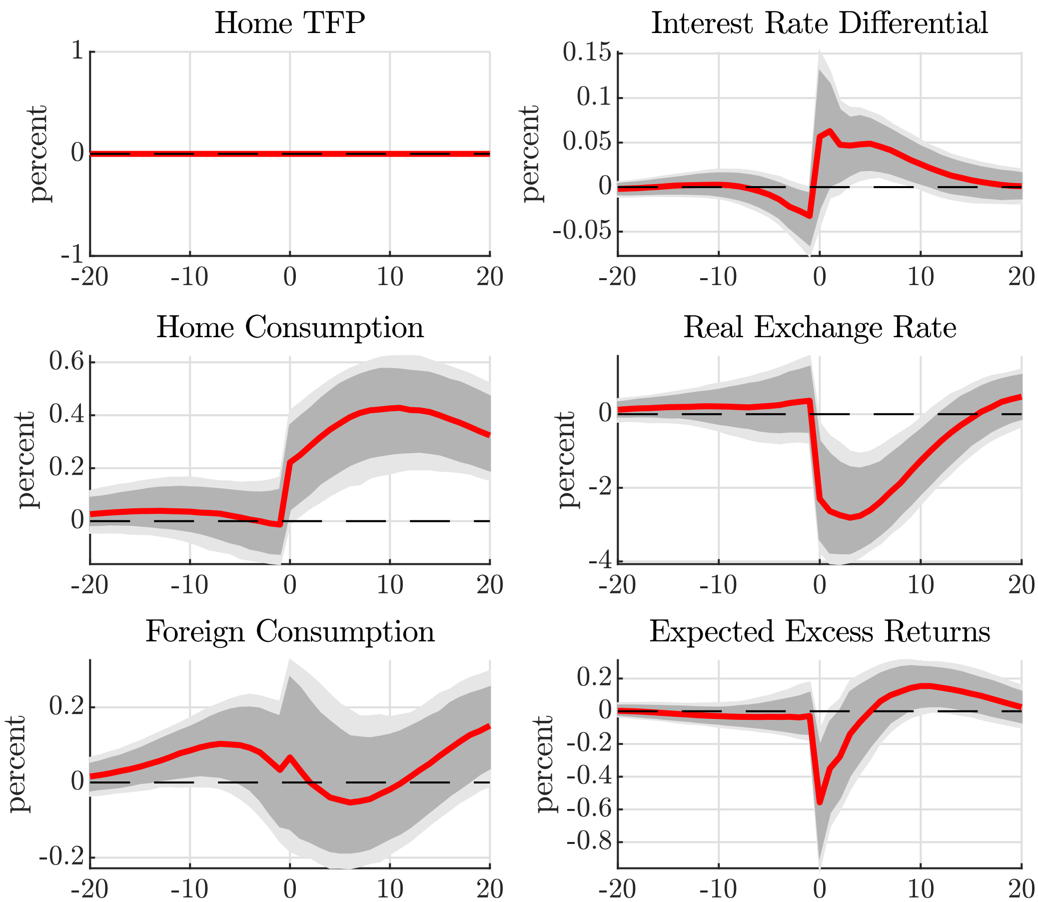
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 30: Impulse responses to Technology (ε^a) disturbances, Italy



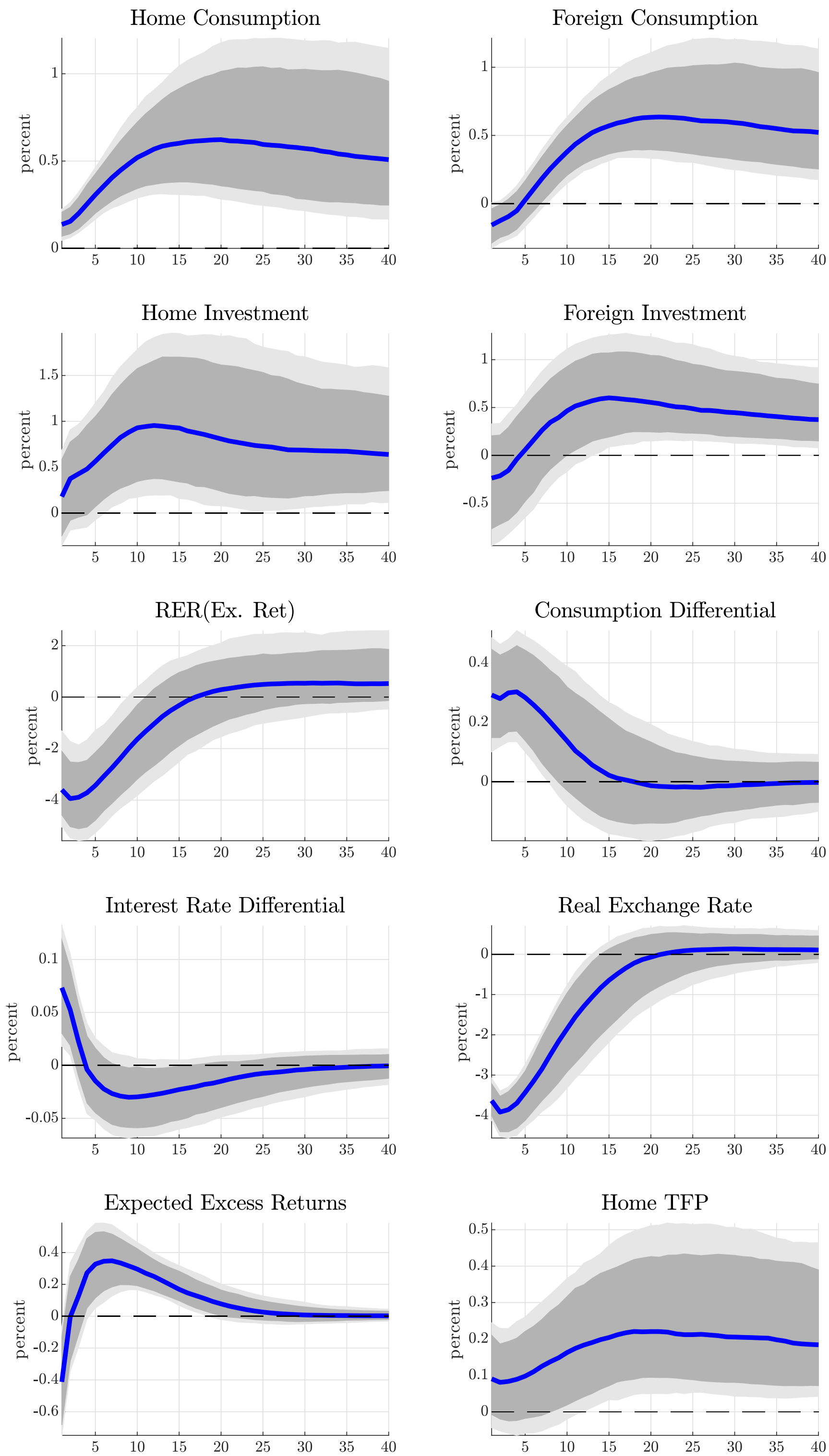
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 31: Impulse responses to Noise (ε^v) disturbance, Italy



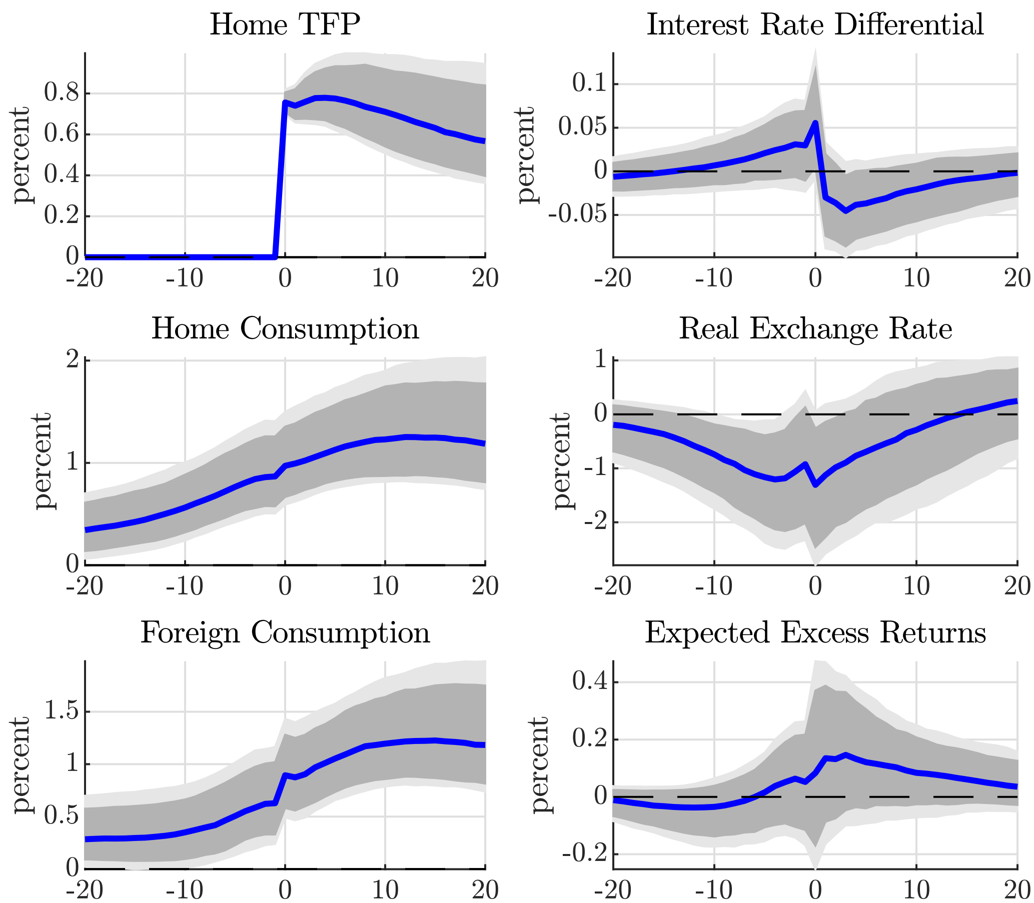
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 32: Impulse Response Functions to the Main FX shock (ε_1), UK



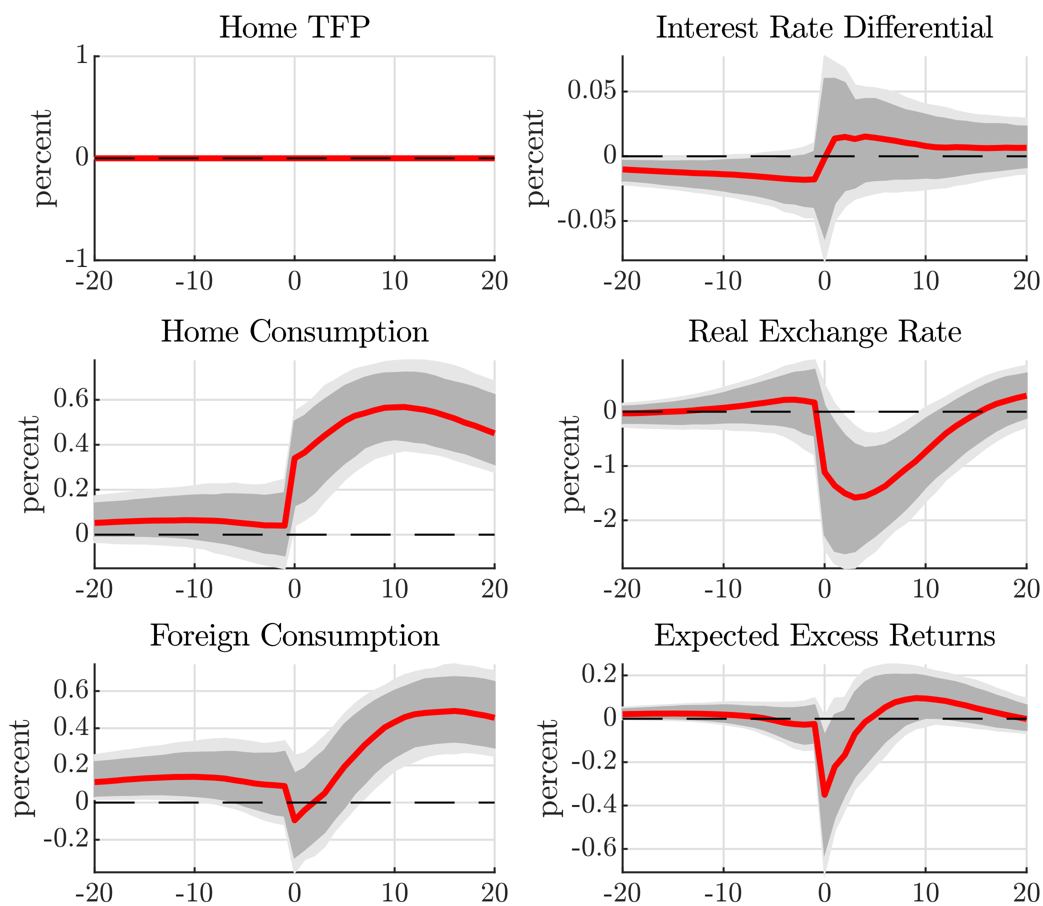
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 33: Impulse responses to Technology (ε^a) disturbances, UK



Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 34: Impulse responses to Noise (ε^v) disturbance, UK



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.