Exchange Rate Disconnect Revisited*

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October 3, 2022

Abstract

We find that variation in expected U.S. productivity explains more than half of G6 exchange rate fluctuations vis-a-vis the USD. Both correctly-anticipated changes in productivity and expectational "noise", which influences expected productivity but never its realization, play an important role in driving exchange rates. Together, these disturbances account for many unconditional exchange rate patterns, including predictable excess returns, low Backus-Smith correlations, and excess volatility. Our findings suggest these famous puzzles share a common empirical origin, one that is very much connected to (expected) fundamentals.

JEL Codes: D8, F3, G1
Keywords: Exchange Rate Disconnect, TFP News, Excess Returns, Excess Volatility

*We thank Gurdip Bakshi, Max Croce, Charles Engel, Tarek Hassan, Oleg Itskhoki, Dmitry Mukhin, Francesco Pappadà, Mikkel Plagborg-Møller, Stephanie Schmitt-Grohé, and seminar and conference participants at Boston College, UC Berkeley, UT Austin, University of Florida, University of Wisconsin, IMF, CEPR ESSIM 2021, NBER IFM Spring 2022, 2021 International Finance and Macro Conference at BFI, T2M 2022, VSFX 2021, 2021 Workshop on Exchange Rates at Swiss National Bank, 2021 Workshop on Macroeconomic Dynamics at Università Cattolica for helpful comments. This paper previously circulated under "Exchange Rate Disconnect Redux".
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1 Introduction

The study of exchange rates is suffused with empirical "puzzles" that suggest a disconnect between exchange rates and macroeconomic fundamentals. In particular, there is a surprising lack of connection between a variety of macroeconomic aggregates (output, consumption, etc.) and exchange rates, both contemporaneously and in a forecasting sense – a set of results the literature broadly refers to as the "exchange rate determination" puzzle.[1] Another puzzling pattern is the lack of correlation between current interest rate differentials and subsequent exchange rate changes, which results in forecastable excess returns and violations of the Uncovered Interest Parity (UIP) condition.[2] A third puzzle emphasizes the low correlation between real exchange rates and consumption differentials across countries, which violates the so-called Backus and Smith (1993) risk-sharing condition that appears in a large class of models. The literature has explored a variety of potential mechanisms that could be behind these patterns, with an emerging consensus that exchange rates and macro aggregates are driven by separate sets of shocks. Importantly, this literature and emerging conclusions are almost entirely based on structural model analysis.

In this paper, we seek to uncover the main drivers of exchange rate fluctuations in the data in a model-free way. We find that there are two disturbances, both related to expectations of productivity growth, which account for more than half of real exchange rate variation. Moreover, the implied conditional exchange rate dynamics exhibit the seminal failures of risk-sharing and UIP conditions referenced above. And these disturbances also explain a large portion of fluctuations in macroeconomic quantities such as consumption, while still implying that the exchange rate appears "disconnected" according to standard metrics. These two disturbances, which we separately identify, consist of (i) a fundamental disturbance to technology, which people partially anticipate; and (ii) an expectational "noise" disturbance, which drives changes in expected technology *that never materialize.* We stress that the responses to noise that we recover are consistent with a rational agent who has access to noisy (but unbiased) information about future, unproven technologies. Overall, our empirical results suggest that the three major exchanges rate "puzzles" result, to a large extent, from a common mechanism – noisy information about future productivity.

Our analysis proceeds in two steps. First, we seek a purely "agnostic" description of

[1] See for example Meese and Rogoff (1983) and Engel and West (2005) among others.

[2] The UIP puzzle has been central to the exchange rate literature since the seminal work of Fama (1984), see Engel (2014) for an excellent survey.

the comovement patterns associated with surprise changes in exchange rates. To do this, we follow the VAR identification procedure of Uhlig (2003), and recover a set of orthogonal shocks ordered by their respective importance in explaining exchange rate variation. We find that the "first" shock (i.e. the one most important to exchange rate dynamics) explains two-thirds of exchange rate variation, and around 40% of the variation in macro aggregates. The shock also generates all three celebrated exchange rate puzzles described above. Our first key observation is that, while this shock immediately impacts the exchange rate, its effect on macroeconomic quantities are generally delayed. Thus, it only generates a correlation between exchange rates and *future* macro aggregates, but leaves exchange rates effectively "disconnected" from contemporaneous macroeconomic quantities.

This first step of our analysis intuitively suggests that exchange rates – a forward-looking asset price – are reacting to the arrival of "news" about future fundamentals. However, this agnostic procedure cannot tell us what, specifically, those news are about. One obvious hypothesis, that is often emphasized in the broader macro literature, is the possibility of news about future TFP. To explore this question further, we regress quarterly exchange rate growth on current, lagged and *future* TFP growth and indeed find that while contemporaneous and past TFP growth shows no relationship with exchange rates, TFP growth four and five years *in the future* explains roughly one fifth of exchange rate variation.

While this is a remarkable result, given the classic findings of exchange rate "disconnect," the exercise itself is quite limited in scope because future realizations are a very imperfect measure of expected TFP. Realistically, it is unlikely that markets have perfect advance information. In other words, the world is likely to be characterized by *noisy* expectations of future TFP, where some expectations simply do not come true. Think, for example, about the uncertainty in forecasting the productivity impact of new technologies such as the internet in the 1990s. Some expectations were eventually disappointed, but the associated (temporary) optimism — for example regarding *pets.com* — certainly affected asset prices in the short-run. In order to examine the hypothesis of noisy TFP expectations, we turn to the structural identification approach of Chahrour and Jurado (2021), which is specifically designed to distinguish and separately identify true technological disturbances that eventually change TFP and disturbances that influence expectations of productivity, but are unrelated to any eventual change in productivity.

Implementing this approach in our baseline VAR, we find that both of these types of disturbances, actual TFP changes and "noise" in TFP expectations, play an important role in driving exchange rates and in generating the three puzzles summarized above. First, the two disturbances together account for more than 60% of the variation in the real exchange rate. Second, the Impulse Response Functions (IRFs) to both disturbances display significant fluctuations in expected currency returns, in line with both the classic UIP puzzle of high interest rates forecasting domestic currency profits and the newly documented "reversal" in this forecastability pattern at longer horizons. Both sets of disturbances also cause conditional movements in exchange rates and (delayed) movements in aggregates that generate the Backus-Smith puzzle, and the exchange rate determination puzzle more broadly.

Importantly, the expectational ("noise") disturbances we identify are *unpredictable* expectational mistakes, and hence are not evidence of a behavioral bias. Moreover, this noise disturbance is conceptually different from exogenous disturbances in the demand for foreign currency bonds, which is the typical way the previous literature has modeled "noise" in exchange rate. Thus, our results show that exchange rates, and three of their major associated puzzles, are indeed tightly connected to fundamentals, and in particular to noisy expectations of future productivity.

Thus, our results suggest that the theoretical literature's traditional focus on building models of exchange rate puzzles that are driven by TFP shocks is generally warranted. However, these models are still counter-factual in that they typically assume TFP innovations are pure surprises, which is in stark contrast with our headline results, which suggests that the bulk of the exchange rate variation is due to *noisy expectations of future* TFP innovations. Hence, our result call for developing new exchange rate models which leverage imperfect information about future TFP.

Related literature This paper is related to several different strands of the international and macro literatures. On the empirical side, we speak to the exchange rate determination puzzle which refers to 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). 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).

We find that there is a connection between exchange rates and macroeconomic fundamentals, but one that runs between current exchange rates and future fundamentals. This is the opposite of the forecasting relationship between current and past macro variables and 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 standard exchange rate models do not imply that exchange rate changes should be predictable using current fundamentals, or even necessarily strongly correlated with contemporaneous changes in fundamentals. Instead, they show that a testable hypothesis of the models is that the news that is incorporated in exchange rates should help the exchange rate forecast future macroeconomic variables. Our results contribute to this discussion, by showing that the link between current exchange rates and future fundamentals runs specifically through *imperfect* foresight regarding future productivity. In addition, we argue that the noise in expectations that we uncover can act as an omitted variable in previous empirical approaches, contributing the weak finding of exchange rates Granger-causing macroeconomic aggregates. (Engel and West, 2005; Sarno and Schmeling, 2014).[3]

A related 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, and one that is especially important for the portion of the exchange rate driven by expected future currency returns. Our definition of "news" is different, as we specifically identify disturbances to beliefs about *future* US TFP *changes*, as opposed to revision of beliefs about *past* endogenous variables such as output. Hence we document the importance of the arrival of information about *future* productivity developments is a significant driver of exchange rates and currency returns.

Relative to the papers discussed above, our results also specifically show a link between the imperfect information about the future and two seminal exchange rate puzzles – the UIP (Fama, 1984; Engel, 2014) and the Backus-Smith puzzles (Backus and Smith, 1993). Both puzzles have received extensive theoretical attention, and numerous potential mechanisms have been proposed as resolution of one or the other.[4] Such models, however, have typically

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

[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.

relied on the standard assumption that agents have full information on current and past innovations to the exogenous shocks driving the economy, but no information on their future innovations. As a result, while the models are consistent with the pricing puzzles, they often run counter to the exchange rate "disconnect," since shocks drive contemporaneous changes in both exchange rates and other macroeconomic quantities.

To confront this challenge, a new strand of the literature has analyzed mechanisms that can generate the exchange rate pricing puzzles based on exchange-rate-market specific "noise trader" shocks that have only a muted effect on the broader macroeconomy (Eichenbaum et al., 2020; Itskhoki and Mukhin, 2021). Indeed, given the exchange rate disconnect fact, shocks to the UIP wedge appear a convenient and powerful way of generating empirically realistic exchange rate dynamics (Devereux and Engel, 2002; Jeanne and Rose, 2002; Kollmann, 2005; Bacchetta and van Wincoop, 2006; Farhi and Werning, 2012).[5] Most notably, Itskhoki and Mukhin (2021) show such that shocks to the UIP wedge can generate not only the UIP puzzle, but also the general disconnect and the Backus-Smith puzzle.

Relative to this recent literature emphasizing the role of exogenous shocks to the UIP wedge, our empirical results suggest that another promising avenue is to examine models with imperfect information about future productivity. While both paradigms feature a notion of "noise", the two are conceptually different. In the existing literature, the "noise shock" is an exogenous shift in the demand for one currency relative to another, with no structural interpretation or connection to macroeconomic fundamentals. Our results, instead, provide evidence of a disturbance that creates noise in the expectations of future fundamentals. Hence, while our notion of noise is also orthogonal to fundamentals, agents do not know this in real time and react to it as if it carries information about future productivity. In that sense, it is both a disturbance about fundamentals, and one that is perceived as such by the agents.

Overall, our results suggest a mechanism that provides a comprehensive explanation of empirical exchange rate dynamics should be able to generate all major exchange rate puzzles conditional on the *same* disturbances related to imperfect foresight of future productivity. Models that can generate multiple exchange rate puzzles out of TFP disturbances are rare. Notably, Colacito and Croce (2013) develop model driven by long-run risk shocks, albeit without pure anticipation effects of future productivity, generate both the UIP puzzle and the Backus-Smith puzzle. By tracing out the effects of TFP news on exchange rates and

[5]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

macro aggregates, we put forward new evidence on the conditional relationship between consumption and TFP as well as a broader set of puzzle. As we discuss in the paper, modifying the long-run risk paradigm to take into account our rich empirical results appears a promising way forward.

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 of comovement between macro aggregates across countries, contrary to previous evidence by Beaudry and Portier (2014).[6] Perhaps most closely related to us is the work of Nam and Wang (2015), who use a Barsky and Sims (2011) approach to identifying news-to-TFP shocks, and find that they are indeed an important driver of exchange rates in the data. In contrast to us, however, they do not consider the effect of the shocks on exchange rate puzzles and also do not separately identify the effects of fundamental disturbances from those driven by expectations disturbances that are orthogonal to fundamentals. Moreover, their news identification procedure is less general and can only detect news about *idiosyncratic* movements in US and foreign TFP, while our results speak to both global and local shocks. Gornemann et al. (2020), instead, develop an international model of endogenous TFP growth, and show that it can account very well for the low frequency movements in real exchange rates, which speaks, in another way, to the importance of predictable TFP growth to exchange rate volatility and persistence.

2 Initial empirical analysis

We begin with an empirical exercise that aims to uncover the basic statistical properties of the main empirical driver of exchange rate fluctuations, while keeping structural identification restrictions to a minimum. To do so, we follow the approach in Uhlig (2003), which was also recently used by Angeletos et al. (2020) to identify what they call the "main business cycle" shock. In parallel to the Angeletos et al. (2020) terminology, we will call the shock we identify here the "main exchange rate" shock.[7]

[6]Corsetti et al. (2014) identify US manufacturing productivity shocks using a sign-restriction approach. However, they do not separately identify technological and noise disturbances.

[7]See also Kurmann and Otrok (2013).

Specifically, we start by estimating the VAR

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

where the vector Y_t contains data on the US and a trade-weighted aggregate for the other G6 countries. The endogenous variables are (i) the nominal exchange rate S_t expressed in units USD per foreign currency, (ii) Fernald's (2012) series on utilization-adjusted U.S. TFP, (iii) US real consumption and investment, (iv) foreign real consumption and investment, (v) the interest rate differential, (vi) and the CPI price level differential vis-a-vis the US:

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

For our benchmark results, we use quarterly data for the time period 1976:Q1-2008:Q2 for the G7 countries. The sample stops in 2008 to guard against a possible structural break in the aftermath of the financial crisis, as argued by Baillie and Cho (2014) and Du et al. (2018). As robustness, we also consider estimates on the longest sample we have data for – 1976:Q1-2018:Q4 – and the results remain very similar. Those robustness results can be found in the Appendix.

We describe the data and their sources in Appendix A. The exchange rate is the average of the daily exchange rates within a quarter, obtained from Datastream. The interest rate differential is similarly the quarterly average of daily Eurodollar rates obtained from Datastream (note, these are not forward discount-implied interest rate differentials, but actual eurodollar rates). The CPI indices and the consumption and investment series are from the OECD database. Lastly, the US TFP is from John Fernald's website.

The foreign variables in Y_t are trade-weighted G6 averages, e.g. the exchange rate is the trade-weighted exchange rate of the US vis-a-vis the other G6 countries, C_t^* is the trade-weighted consumption of the other G6 countries, and etc.[8] In the Appendix we also report separate estimation results for bilateral VARs between the US and each of the other six G7 countries, and the outcome remains the same. We use the G6 average as a convenient way to summarize the results, but note that the relationships we identify here are consistent across the cross-section of individual countries.

We include four lags, and estimate the VAR via Bayesian methods using Minnesota priors. Following the established convention (e.g. Sims et al. (1990), Eichenbaum and

[8]We use the trade-weights as in Engel (2016).

Evans (1995)), we estimate the VAR in levels and do not impose ex-ante that there are any specific cointegration relationships, but as robustness checks in the Appendix we also show that results remain unchanged if we instead estimate a VECM model and impose the same cointegrating relationships as Engel (2016) (who assumes the real exchange rate and interest rate differential are stationary). Alternative cointegration relationships and VECM specifications make little difference as well.

As is standard in VAR analyses, any "shocks" estimated by our analysis are a linear combination of the VAR innovations u_t. But instead of picking a linear combination based on some "ordering" of the sequence in which shocks affect variables (e.g. Cholesky identification) or sign restrictions, we follow Uhlig (2003) and look for the linear combination that has the highest explanatory power for the fluctuations in the *real* exchange rate. The (log) real exchange rate q_t, defined as usual to be the log ratio of the nominal exchange rate and CPI differentials

$$q_t = s_t + p_t^* - p_t,$$

And while it is not included in the VAR ex-ante, it is a linear combination of the variables in our VAR, hence it is straightforward to apply the Uhlig (2003) procedure as follows.

Denote by $Y_t = B(L)u_t$ the reduced-form moving average representation of the VAR in equation (1). Let the relationship between reduced-form innovations and structural shocks be given by

$$u_t = A_0\varepsilon_t, \tag{2}$$

which implies the following structural moving average representation:

$$Y_t = B(L)A_0\varepsilon_t. \tag{3}$$

We assume that the structural shocks are orthogonal with unitary variance. Therefore, the impact matrix A_0 has to satisfy the condition $A_0A_0' = \Sigma$, where $\Sigma = \text{Var}(u_t)$ is the variance-covariance matrix of innovations. This restriction is not sufficient to identify the matrix A_0. In fact, for any matrix A_0 there exists an alternative matrix $\tilde{A}_0$ such that $\tilde{A}_0D = A_0$, where D is an orthonormal matrix, thus $\tilde{A}_0$ also satisfies $\tilde{A}_0\tilde{A}_0{}' = \Sigma$. Therefore, fixing a matrix $\tilde{A}_0$ satisfying $\tilde{A}_0\tilde{A}_0{}' = \Sigma$ (e.g., the Cholesky decomposition of Σ is a convenient choice), identification boils down to choosing an orthonormal matrix D.

Denote the h-step ahead forecast error of the i-th variable $y_{i,t}$ in Y_t by

$$y_{i,t+h} - \mathbb{E}_{t-1} y_{i,t+h} = e_i' \left[\sum_{\tau=0}^{h-1} B_\tau \tilde{A}_0 D \varepsilon_{t+h-\tau} \right]$$

where e_i is a column vector with 1 in the i-th position and zeros elsewhere, and B_τ is the matrix of moving average coefficients at horizon τ.

The Uhlig (2003) approach consists of finding the column of D that isolates the shock explaining most of the forecast error variance of a specific variable y_i. Formally, we solve

$$d_1^* = \underset{d_1}{\operatorname{argmax}} \quad e_i' \left[\sum_{\tau=0}^{H-1} B_\tau \tilde{A}_0 d_1 d_1' \tilde{A}_0' B_\tau' \right] e_i \tag{4}$$

subject to $d_1' d_1 = 1$, where d_1 is the first column of D. The problem is analogous to find the eigenvector associated with the largest eigenvalue of the appropriately rearranged objective function. As mentioned above, the variable over which we want to maximize explanatory power is the real exchange rate q_t, hence the selector vector is $e_i = [1, 0, 0, 0, 0, 0, 0, -1]$. The procedure involves a choice of forecast horizon H, which we set to 100 to effectively capture the unconditional variance of the real exchange rate.

Overall, this procedure is agnostic to the structural interpretation of the extracted "shock", however the results are still quite informative about the basic structure of dynamic comovements that are associated with surprise changes in the exchange rate.

Extracting this "main exchange rate shock" $\varepsilon_{1,t}$, as defined by d_1^* in equation (4) above, we find that it is indeed very important for exchange rate fluctuations as it explains roughly 70% of variance of the real exchange rate. This large share attributable to just one innovation means that the data implies there is a large degree of commonality in the dynamic patterns that emerge following a surprise change in the real exchange rate. Most interestingly, we also find that this shock explains a significant portion of the variation of the main macro aggregates included in our VAR – specifically it also accounts for around 40% of the forecast error variance at a horizon of 100 quarters, $\text{Var}(x_{t+100} - \mathbb{E}_t(x_t))$, of consumption and investment (both home and foreign), and US TFP. For the macro aggregates we turn to a decomposition of the FEV, because they are non-stationary, but we choose a very large horizon to effectively capture both short, medium and long-run fluctuations. In terms of the real exchange rate, the FEV decomposition at 100-quarters is identical to that emerging from the decomposition of the unconditional variance.

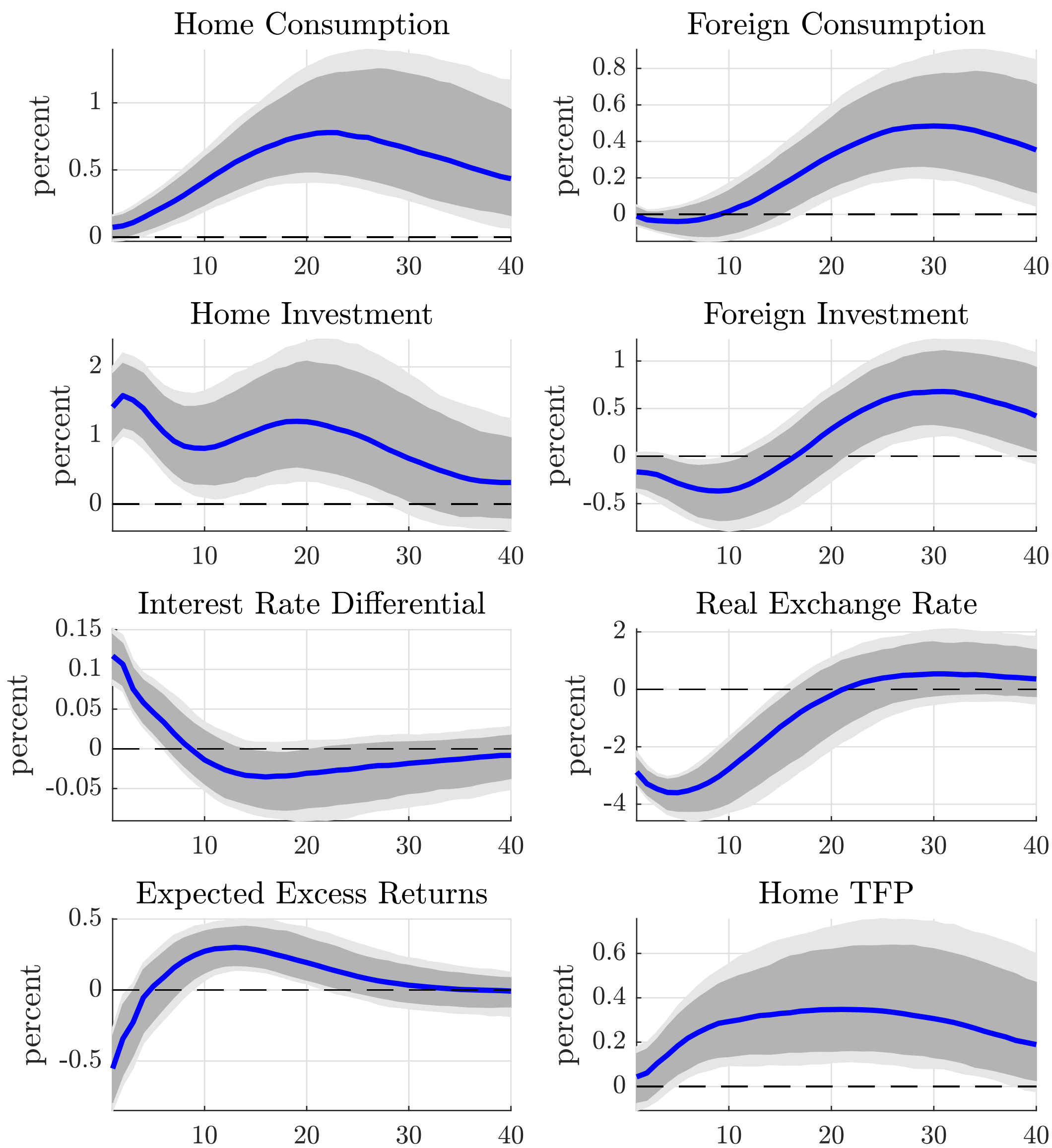
The fact that the main exchange rate shock drives a significant amount of the variation in both exchange rates and macro aggregates is, at first blush, surprising given the well-established result that exhange rates appear to be largely disconnected from macro fundamentals (e.g. Engel, 1999 and Engel and West, 2005). Our results (and dataset), are in fact consitent with these previous results, and the reason is that there is a difference in the *timing* of the response of exchange rates and the macro aggregates to the shock we extract, with the exchange rate responding significantly on impact, while aggregate quantities only react with a lag. In contrast, the seminal results on exchange rate disconnect largely focus on the *contemporaneous* unconditional correlation between exchange rates and macro aggregates. Our results, instead, indicate that there is indeed a common driver behind exchange rates and macro aggregates (and thus a fundamental connection between the two), but the effects materialize at different horizons in exchange rates and macro quantities, respectively.

To showcase this, in Figure 1, we plot the impulse response functions of several variables of interest from our VAR to this "main exchange rate shock" (MFX). The median impulse response is plotted with a solid blue line, and the shaded areas around it are the 16-84th percentile and the 10-90th percentile bands respectively.

A number of notable results emerge. First, 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 the characteristic "delayed" overshooting dynamics, where it continues to appreciate for another 5 quarters after the shock, peaking at a maximum appreciation of about 3.5%, and thereafter the exchange rate steadily depreciates back to its long-run mean. The non-monotonic dynamics we recover are similar to the ones previously emphasized by Eichenbaum and Evans (1995) and Steinsson (2008), and this results in a dynamic response that is very persistent – with a half life of three to three-and-a-half years – in line with the "excess persistence" puzzle documented by previous studies.

Importantly, these exchange rate patterns of initial appreciation, and then strong depreciation, are also underlying a "reversing" or "cyclical" pattern in the deviations from uncovered interest parity. Specifically, the MFX shock causes non-monotonic movements in the *expected* excess currency return, defined as usual as $\mathbb{E}_t(\lambda_{t+1}) \equiv \mathbb{E}_t(\Delta q_{t+1} + r_t^* - r_t)$, with the expectation as implied by our VAR estimates. We plot the IRF of $\mathbb{E}_t(\lambda_{t+1})$ in the bottom left panel of Figure 1, and we see that it is negative on impact and remains so up to six quarters after the shock, and then turns significantly positive and remains so for several years afterwards. Such predictable variation in the expected excess returns is a violation of the uncovered interest parity (UIP) condition.

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.

Note also that the MFX shock leads to a monotonic impulse response in the interest rate differential, which 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, while in the medium run the direction of the UIP violation reverses, with the dollar earning low returns for an extended period of time. Thus, the MFX shock generates exchange rate dynamics that are consistent with the reversal of UIP violations at longer horizons documented by previous studies like Engel (2016) and Valchev (2020).

Overall, the results suggest that our empirical procedure is indeed picking up not just a shock that is responsible for a large fraction of exchange rate fluctuations, but also generates several important and familiar exchange rate "puzzles".

Turning to the responses of macro aggregates, the MFX shock we identify induces no short-run movements in consumption; home consumption only responds in statistically significant terms to the 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 is also about double the size of the peak effect on foreign consumption, with home consumption peaking at an increase of about 0.8%, while foreign consumption peaks at 0.5%.

The impulse response of TFP shows a similar delay, with the shock having an insignificant impact on productivity up to 5 quarters in the future, and productivity eventually displaying a significant and prolonged increase at longer horizons, with the effect peaking at 0.4% at about 20 quarters after the shock. Thus, 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 response 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. This is consistent with the notion of disconnect emphasized in the previous literature, but we want to emphasize that our results suggest the disconnect is just one of timing – the exchange rate is indeed significantly related to *future* macro aggregates.

The response of the TFP series is reminiscent of a "news" shock, as it implies that the eventual increase is essentially predictable at time t. Given such anticipation, standard models would imply that home investment should increase immediately — and indeed, this is precisely what we observe in the impulse response of home investment. Similarly, foreign

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.

investment only rises with a significant delay, which is also consistent with the notion of a news shock, as standard models would imply that in the short run capital is shifted towards the economy with higher anticipated productivity growth.

To showcase the differences in the timing of effects in the different series in an alternative way, in Table 1 columns 2 through 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 in Figure 1, while this shock is equally important for both short-run and long-run exchange rate fluctuations, it only explains 2% and 1%, respectively, of the one-quarter-ahead forecast error variance of US and G6 consumption. 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 MFX explains more than 40% of the FEV a long horizons in both consumption series.

Takeaways

Taken together, this evidence sheds important light on the "exchange rate disconnect puzzle," as broadly construed. First, bulk of the variation in the real exchange rate (68%

of the total) is essentially not related contemporaneously to aggregate consumption or TFP, but rather the exchange rate *leads* these two macro aggregates that the prior literature has often tried to connect to the exchange rate. Thus, our results suggest that the canonical finding of a "disconnect" does not emerge because of a genuine separation between FX and fundamentals, but rather because of a difference in the timing of the responses of exchange rates and macro aggregates to the same macroeconomic surprise(s).

Second, in addition this basic disconnect puzzle, the dynamic responses to the MFX shock display a number of other famous and well-established exchange rate puzzles. On the one hand, we have already discussed the high persistence of the real exchange rate implied by the IRFs, and also how the short-run and long-run patterns of UIP violations conditional on the shock correspond to previous, unconditional results. On the other hand, IRFs in Figure 1 also exhibit the classic violation of the Backus et al. (1993) condition that $corr(q_t, c_t - c_t^*) = 1$. In contrast to this risk-sharing condition, conditional on the MFX shock the exchange rate appreciates, and rather than falling, the consumption differential also rises above its mean. Thus, the MFX generates not only a lack of contemporaneous correlation between exchange rates and macro aggregates, but it specifically generates exchange rate dynamics that violate a number of standard model-implied conditions.

Third, the dynamic response patterns are consistent with the 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, seemingly in anticipation of the increase in TFP.

3 Expectations of future TFP and exchange rates

Our results so far indicate that anticipation of future TFP might hold the key to a fundamental connection between exchange rates and macro aggregates, while at the same time generating many of the classic exchange rate puzzles. This is an interesting hypothesis, especially given the emerging consensus in the literature that the plethora of puzzles in exchange rate behavior are generated by financial or risk shocks that are unrelated to macrofundamentals. However, our results so far are only suggestive, as the MFX shock has no direct structural interpretation. So, next we turn to directly testing the hypothesis that disturbances to anticipated TFP are indeed affecting the exchange rate.

Anticipated TFP has a rich modeling tradition in macroeconomics, both on the theory side and in the data, and previous empirical studies have suggested that news or anticipation about TFP potentially plays an important role in business cycle fluctuations of the main macro aggregates (e.g. Beaudry and Portier, 2006 and Chahrour and Jurado, 2021). But the empirical content of TFP expectations vis-a-vis exchange rates is less explored. The only paper we are aware of studying the impact of such news shocks on the real exchange rate is Nam and Wang (2015), and in their study they completely abstract from the potential impact of the shocks they identify on exchange rate puzzles such as UIP deviations. However, whether or not news shocks are behind the famous exchange rate puzzles is crucial to know for informing theoretical models.

Let us spell out our null hypothesis. It is well understood in the literature that exchange rates are asset prices, and are thus forward looking. As such, they can be expressed as the sum of future expected interest rate differentials and excess returns (e.g. Engel (2016)):

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

To the extent that agents' expectations about future interest rates and risk-premia are associated with agents' expectations of future TFP, we would expect that shocks to TFP expectations will also materially (and immediately) impact the exchange rate.

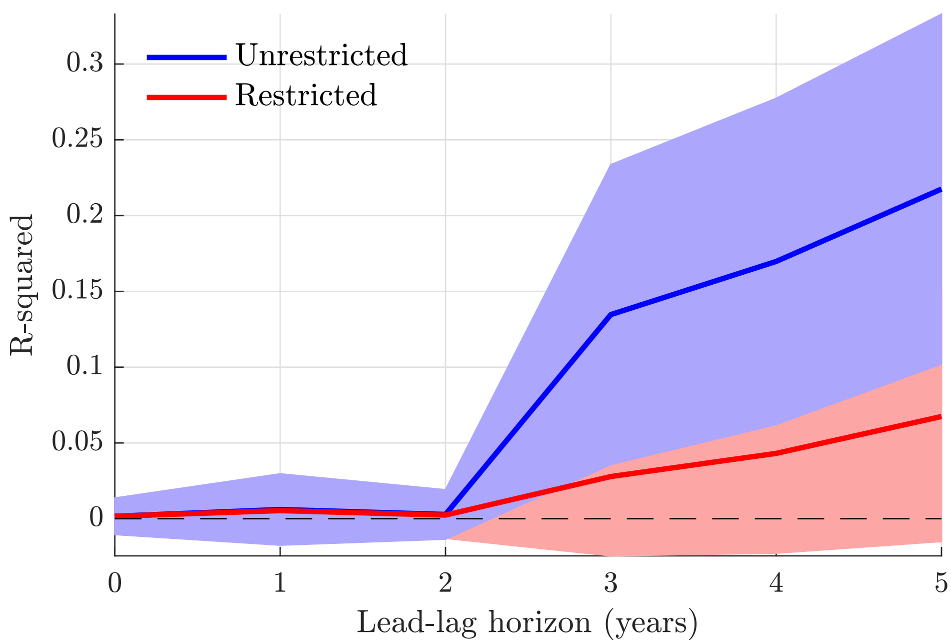
As a first step in evaluating this hypothesis, we consider a simple exercise, where we regress the change in the real exchange rate at time t on leads and lags of the change in TFP. To save on degrees of freedom, we aggregate the leads and lags into annual TFP changes:

$$\Delta q_t = \alpha + \beta_0 \Delta TFP_t + \sum_{k=1}^{h} \beta_{-k}^{lag}(TFP_{t-4(k-1)} - TFP_{t-4k}) + \sum_{k=1}^{h} \beta_k^{lead}(TFP_{t+4k} - TFP_{t+4(k-1)}) + \varepsilon_t \quad (5)$$

Thus, if we include just the first two terms, we have a regression estimating the standard relationship between contemporaneous changes in the exchange rate and TFP, which we know from previous research is virtually nil. If we include the first summation term, then we also consider the additional (potential) explanatory power of lagged changes in TFP of up to h-years in the past. Lastly, once we include the second summation term, we also consider a potential correlation with *future* TFP changes, of up to h-years forward. The coefficients β_k^{lead} might be non-zero if the marginal foreign exchange investor has some information on likely future developments to TFP (e.g. some advance notice of the likely productivity of new technologies).

In Figure 2 we report the resulting R^2 of two versions of the above regression – a "Restricted" backward-looking version that only includes current and lagged TFP growth terms and an "Unrestricted" version that includes all terms on the right-hand side. The first version captures the typical direction of the relationship between TFP and exchange rates that the previous literature has focused on, and its resulting R^2 (and its associated 90% confidence interval) are plotted with the red line and bands. The R^2 of this purely backward looking regression is statistically insignificant no matter how many lags of TFP growth we include, embodying the typical "disconnect" result.

Figure 2: 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 (5).

On the other hand, the result 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 FX 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, the evidence speaks to the fact that exchange rates contain a substantial amount of information about future TFP growth in the medium-run to long-run.

While suggestive, this exercise has limited power to capture the full extent of the effects of TFP expectations, because realized values of future TFP are likely imperfect proxies for investors' actual expectations of future TFP. That is, expectations are likely to be noisy, in the sense that sometimes they are overly optimistic, and other times they are overly pessimistic. However, investors cannot know in real time what part of their expectation is a forecast error, and which part is correctly anticipating actual future changes in TFP.

As such, the noise in expectations acts as an omitted variable bias in the above regression. That is expectations often vary over time, even when there are no actual fundamental changes in the future, purely due to the inherent noisiness of forecasting the future. This variation in expectations, however, is by definition orthogonal to actual future productivity changes and hence is missing from the regression. Intuitively, we would expect that correcting for this bias could uncover an even stronger link between TFP expectations and current exchange rates. Think, for example, about the uncertainty in forecasting the productivity impact of new technologies such as the internet in the 1990s. Some expectations were eventually disappointed, but the associated (temporary) optimism — for example regarding *pets.com* — certainly affected asset prices in the short-run.

One indication that noise in expectations might be playing an important role is that the maximal R^2 we achieve in regression (5) is in the neighborhood of 0.2, while the MFX shock explains 55% of $\mathrm{Var}(\Delta q_t)$ as per Table 1. Would accounting for the expectational noise bring us closer?

In order to separately identify and account for the "noise" in expectations, we follow the recently developed VAR-identification approach of Chahrour and Jurado (2021). This approach is specifically designed to independently identify the "fundamental" disturbances driving realized changes in productivity and expectational "noise" disturbances, which drive changes in productivity forecasts that are never realized. It is important to realize from the onset that responses to "noise" recovered this way are not indicators of a predictable bias in expectations, but the consequences of errors made under rational expectations. Thus, our eventual finding of a significant identified noise component in expectations is evidence of imperfect forward information, information that rational agents should respond to in real time even though they may later learn that some of that information was incorrect.

In contrast, other "news shock" identification schemes, such as Barsky and Sims (2011), do not separately identify the noise component of expectations. Moreover, Chahrour and Jurado (2021) avoids the assumption that the underlying structural data generating process has an invertible representation, which is often violated in models of economic foresight

(Blanchard et al., 2013). Finally, as we discuss below, this procedure allows for an arbitrary structure for the fundamental process and a very general signal thereof, so that we need make essentially no assumptions about what aspects of productivity people learn about, or when they do so.[9]

To fix ideas, we present a simplified discussion of the Chahrour and Jurado (2021) procedure here. The null hypothesis is that agents in the economy have advance information about future TFP as summarized by a general noisy signal η_t, which can be represented as a linear combination of future innovations to TFP plus an orthogonal noise component v_t:

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

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

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

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

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

The assumptions of the Chahrour and Jurado (2021) procedure are that (i) the productivity disturbances ε^a_t are exogenous (orthogonal to other structural shocks) and (ii) the signal-noise innovations ε^v_t are orthogonal to TFP at all leads and lags. To get some intuition, consider a two-variable VAR in just $[a_t, \eta_t]$. In this case, the restrictions we impose amount to placing zeros in the MA representation of the data in the following way:

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

In words, we are assuming the productivity disturbances are equivalent to the "shocks" in its univariate Wold representation, and only affect productivity once they realize – i.e. a_t is

[9] From a broad perspective, the results are qualitatively similar when following a Barsky and Sims (2011) procedure.

a function of the history of ε_t^a up to and including time t. In addition, we assume the signal η_t contains information about future productivity disturbances, ε_{t+k}^a, while the signal noise disturbances ε_t^v are orthogonal to productivity at all leads and lags. This gives us enough restrictions to uniquely identify the two shocks ε_t^a and ε_t^v.

Intuitively, the VAR-forecast $\mathbb{E}_t(a_{t+k})$ is a function of both the history of TFP a^t, because it is a persistent process, and also the signals η^t because they contain advance information of future TFP innovations. In turn, we decompose the VAR-implied forecast $\mathbb{E}_t(a_{t+k})$ into a component that is correlated with ε_{t+k}^a, thus giving us the component of expectations that is "correct", and a component that is orthogonal to this future TFP innovation, and thus is driven by the noise terms ε_t^v – i.e. the expectational error.

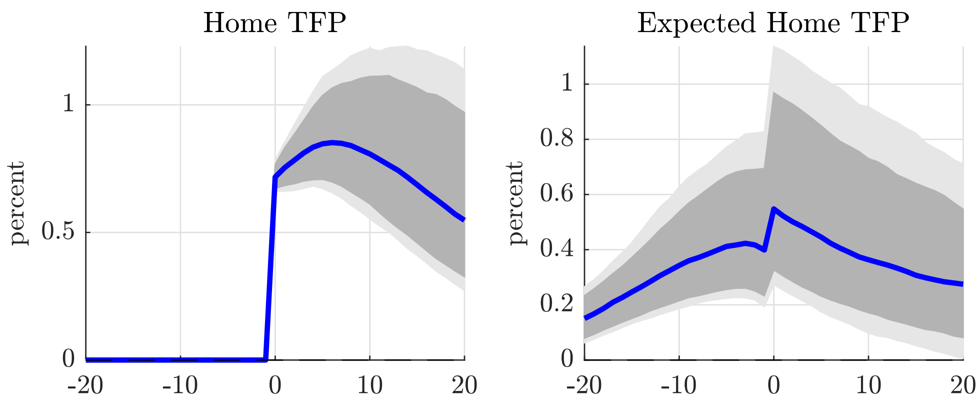
This strategy thus allows us to estimate the separate impulse responses of any variable of interest to both the fundamental disturbances, ε_{t+k}^a, and the "noise" component of expectations, v_t. By examining the responses of economic variables, like the exchange rate, q_t, to the "fundamental" disturbance ε_{t+k}^a, we can therefore see an indication of whether (and how) fundamental disturbances are anticipated. By examining responses to the second type of disturbance, ε_t^v we learn how much of economic fluctuations are associated with movements in expectations that are completely orthogonal to productivity – e.g. misplaced optimism or pessimism (but again in the form of a rational mistake, not a behavioral bias).

The above illustrative example assumed we observe the relevant signal η_t, but in practice, our implementation simply assumes that the TFP forecast of our baseline VAR in equation (1) contains sufficient forward-looking variables to span the economy's information of future TFP innovations. Thus, the implicit assumption here is that the endogenous variables we include (exchange rate, interest rates, consumption, investment and price levels) incorporate the marginal agent's beliefs about future TFP, and thus correctly captures the expectation $\mathbb{E}_t(a_{t+k})$. In multivariate settings, we also need to specify a target "horizon" of expectations, for which we decompose the corresponding $\mathbb{E}_t(a_{t+h})$ into a component related to ε_{t+h}^a and one related to ε_t^v. We choose $h = 20$ to match the peak in the TFP IRF in Figure 1.[10]

Under these auxiliary assumptions, we can identify the fundamental and noise disturbances without making further assumptions about the information structure in the economy, and expectations of any variables in the system can be backed-out using the dynamics implied by the VAR.

[10]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 it does not matter much for our findings.

Figure 3: 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.

3.1 Conditional dynamics

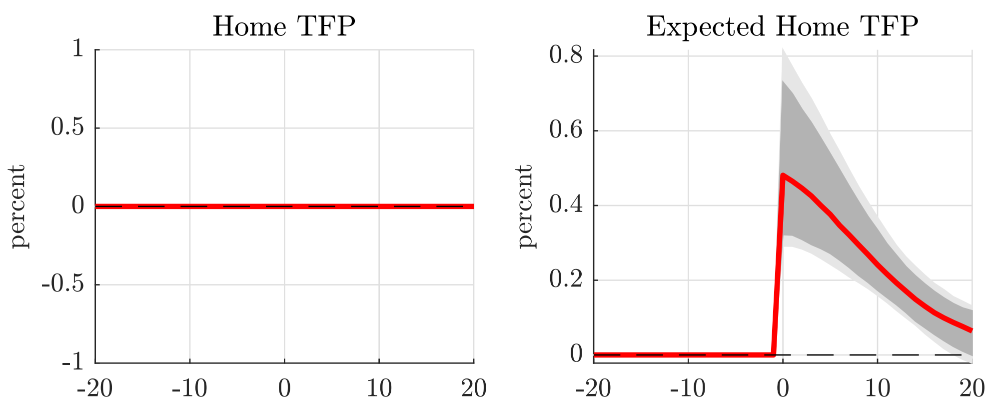
We begin by plotting the estimated impulse responses of TFP (a_t) and the 20-quarter ahead expectation of TFP ($\mathbb{E}_t(a_{t+20})$), in respect to the fundamental technological disturbance ε_t^a in Figures 3 and to the expectational noise disturbance ε_t^v in Figure 4. These would be informative about the basic structure of the information set and agent's ability to anticipate TFP that we estimate.

Since anticipated productivity shocks can influence endogenous variables before the actual change in productivity, we plot each figure from 20 quarters *before* the respective innovation (either ε_t^a or ε_t^v) realizes. The extent to which TFP anticipation plays a role in the data can be evaluated by seeing whether the estimated IRFs respond significantly to ε_t^a before its actual realization. In our figure, we plot the X-axis in terms of the quarters before and after the realization of the TFP increase, with 0 denoting the period of realization. Hence, anticipation effects are equivalent to statistically significant IRFs in periods between -20 and -1. Lastly, we stress that whether or not the endogenous variables respond before productivity actually moves is not assumed but *estimated.* If the estimates show no significant early response of these variables, this would constitute evidence against the hypothesis of expectational effects of productivity.

Consider the response of TFP (a_t) to a ε_t^a shock, plotted in the left panel of Figure 3. Naturally, the level of TFP does not change until the innovation ε_0^a is actually realized (at time 0), and then TFP exhibits fairly persistent, dynamics while returning to its long-run mean.

On the other hand, in the right panel we plot the impulse response of the expectation of TFP 20-quarters ahead, $\mathbb{E}_t(a_{t+20})$, and we see that this variable is significantly higher than its long-run mean even a full 20 quarters before the innovation actually realizes, manifesting a significant amount of anticipation. Specifically, 20-quarters before the actual 1-standard deviation TFP improvement, which is roughly 0.6%, agents expect that quarter's TFP to be roughly 0.2% higher than average. Thus, TFP expectations anticipate about one third of the actual improvement in TFP a full 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 upward upon observing the actual ε_t^a innovation.

Figure 4: 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 disturbance ε_t^v, which we plot in Figure 4. In the left panel, we essentially see one of our identification restrictions at play – the expectational noise disturbance has no effect on TFP at any leads or lags. On the other hand, in the right panel we see that the expectational noise shock indeed moves expectations, where a one standard deviation positive ε_0^v (so an "optimistic" shock), leads to a 0.5% increase in expected TFP 20-quarters out. This impulse response then converges back down to its long-run mean, which signifies that agents learn, over time, that their initial optimism was misplaced.

Thus, taking the results in Figure 3 and Figure 4 together, we conclude that our estimates indeed strongly support a noisy-information paradigm, where agents do have some advance information and thus *partially* anticipate future movements in TFP, yet that information is noisy hence expectations sometimes move even though there is no actual future increase in productivity.

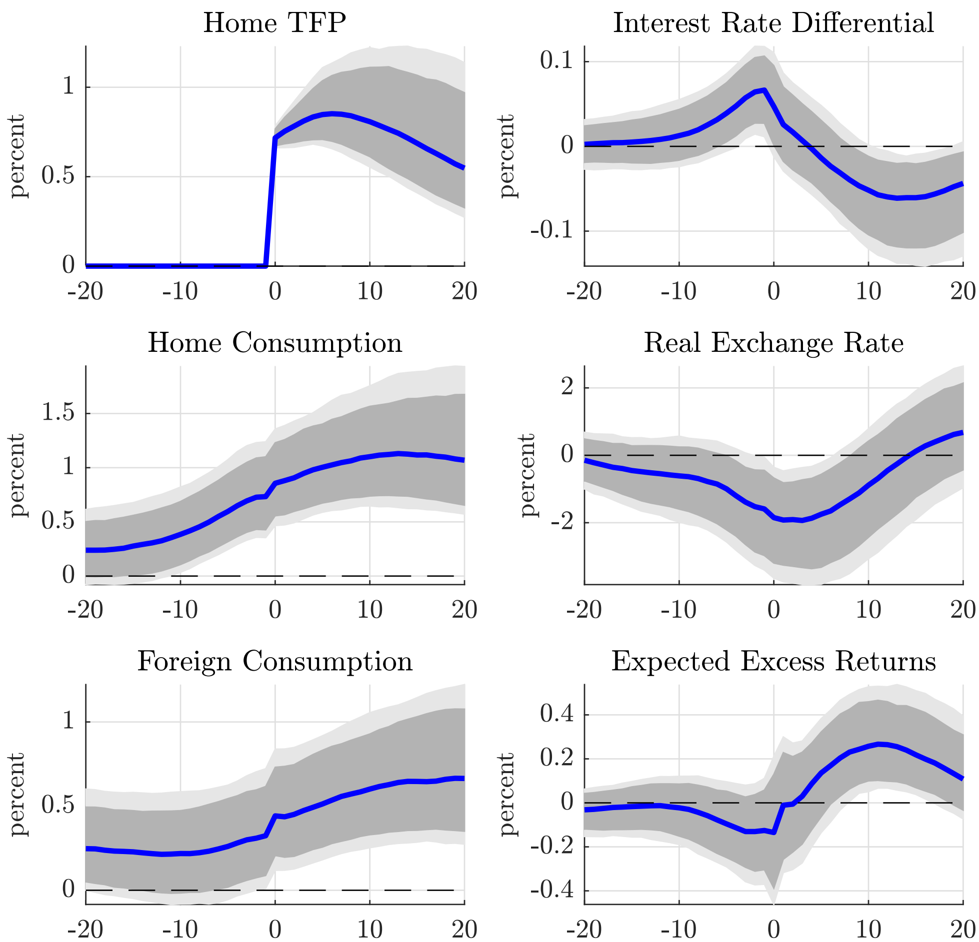
Now let us turn to the impact of these two types of disturbances on the rest of the endogenous variables in our VAR, with a special attention played to the response of the exchange rate. In Figure 5 we plot the responses to a TFP innovation ε_t^a, for the interest rate differential, home consumption, the real exchange rate, foreign consumption and the expected currency returns ($\mathbb{E}_t(\lambda_{t+1})$, with the expectation based on the estimated VAR), together with the response of the TFP level again for reference.

We focus on the real exchange rate first, which is presented in the middle row, right panel. The response exhibits a pronounced V-shape, which peaks right around the time at which the TFP innovation actually realizes. That is to say, the real exchange rate significantly appreciates *before* the actual TFP improvement, showcasing that the TFP anticipation effects we estimated above are indeed priced into the exchange rate. The maximum appreciation of about 2% occurs right around period-0, and the exchange rate then steadily depreciates after TFP improves. Tentatively, this suggests a mechanism where the higher expected US productivity generates a boom in US consumption, driving the relative price of US goods higher, which price appreciation is then reversed once productivity actually improves, and the resource constraint of the economy is loosened.

This basic hypothesis is consistent with the responses of the interest rate differential and relative consumption as well. The 3-month dollar interest rate increases before the TFP innovation, peaking at around 7.5 basis points higher than its long-run mean (or 0.3% at an annualized basis), which could signify increased borrowing desire in the US in the face of higher expected permanent income. The interest rate differential then steadily depreciates after the TFP innovation 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 a US consumption boom before the TFP improvement, and while foreign consumption also increases, the consumption differential is still large and positive (not pictured). Thus, indeed there is a US consumption boom even relative to foreign consumption in anticipation of the US productivity gain.

In Figure 6 we present the impulse responses of the same set of variables, but in response to an expectational noise shock ε_t^v instead. Starting with the exchange rate again, we see that upon the improvement in expectations (recall that is period 0 on the X-axis), the real

Figure 5: Impulse responses to Technology (ε^a) disturbances



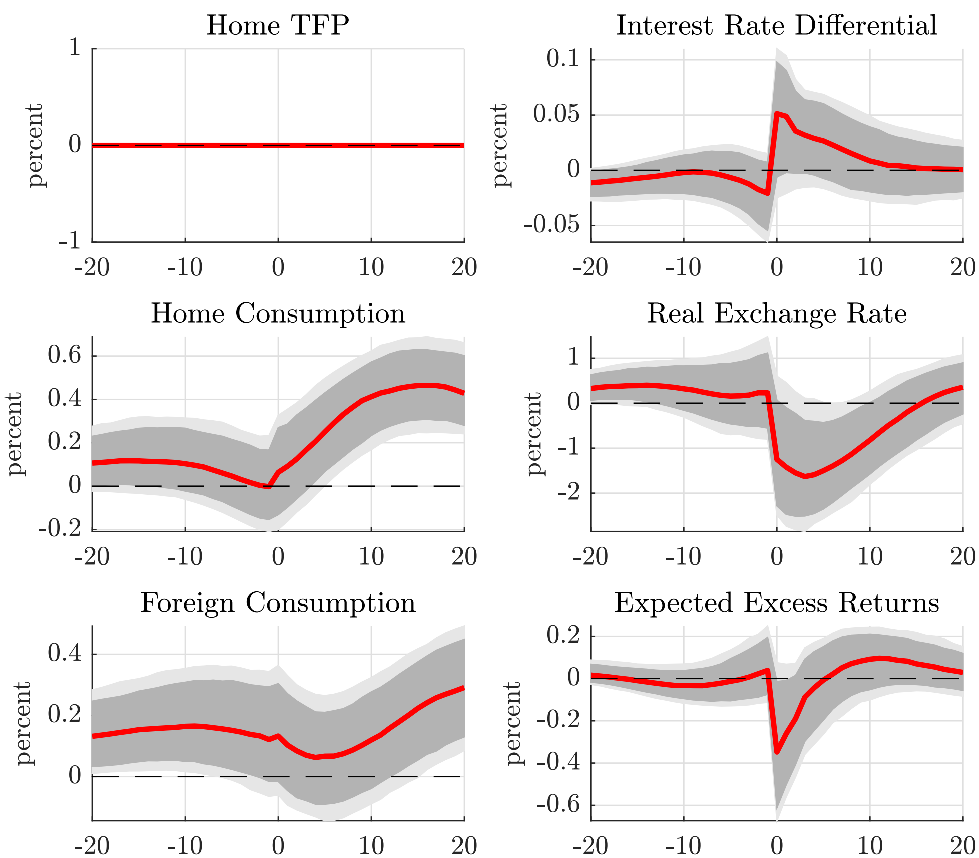
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

exchange rate strongly appreciates. This is consistent with the message from Figure 5, 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 then declining.

The response in consumption is more gradual and delayed, but there is indeed again a US consumption boom following an increase in expected future US TFP. The fact that the boom is a little bit delayed suggests that the underlying information structure is one of low frequency news. That is, our findings indicate that the underlying signals that agents receive are about news pretty far into the future. We can see this from the fact that the expectational noise raises TFP expectations for TFP fairly far in the future, peak impact is at 20 quarters in the future. With this kind of very far in advance information, consumption does not respond strongly until the expected TFP improvement becomes closer in time.

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.

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	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 Change	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.

3.2 Variance decomposition

To further quantify the effects, we consider the respective variance shares of the endogenous variables that the two disturbances explain. The results are reported in Table 2. The table reports decomposition of variation over a wide band of frequencies (2-100 quarters) and also the higher frequency, business cycle variation (6-32 quarters).

By our identification restrictions, the technological disturbance we estimate, ε^a, accounts for 100% of the variation in TFP, while the expectational noise disturbance is completely orthogonal to it.

In addition, the estimates indicate that the combination of the two shocks explain 70% (30%) of the wide-band (business cycle) variation in US consumptions, and 63% (30%) of the wide-band (business cycle) variation in foreign (G6) consumption. The two shocks also account for 62% (42%) of the wide-band (business cycle) variation in US investment, and 68% (45%) of the wide-band (business cycle) variation in foreign (G6) investment. Thus, the disturbances to TFP and its expectation are indeed significant drivers of macro aggregates, both at high and low frequencies.

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 is more important in the lower frequencies, while noise shocks are more important in the higher frequencies. For example, the true technological disturbances explain 54% (10%) of the wide-band (business cycle) variation in US consumptions, and 49% (13%) of the wide-band (business cycle) variation in foreign (G6) consumption, while the expectational noise disturbance explains 16% (20%) of the wide-band (business cycle) variation in US consumption and about 14% (17%) of the wide-band (business cycle) variation in foreign consumption. Thus, consumption is not driven only by the actual productivity disturbance, but also by disturbances to the expectations of future TFP, and these noisy expectation shocks are relatively more important at high frequencies.[11] This showcases that endogenous variables are impacted by noise, but at the same time the noise effect is more transitory than the actual TFP improvement, as agents eventually learn expectations were wrong.

Intuitively, one would expect this latter expectational effect to also have an impact on asset prices. And indeed, Table 2 reveals the shares of the variation in exchange rate (the international asset price of key interest to this study) that are driven by those two disturbances. The disturbances to productivity explain 45% (14%) of its wide-band (business-cycle) frequency fluctuations, while we see that expectational noise disturbances are also quantitatively important, explaining another 20% (22%) of the exchange rate variation. Thus, together two types of shocks we identify account for 64% (36%) of the wide-band (business cycle) frequencies variation of the exchange rate. We find a similar split in the importance of the two disturbances for the interest rate differential, with actual productivity disturbances explaining 46% (23%) and the expectational noise disturbances explaining 11% (14%) of the interest rate differential fluctuations.

Moreover, these disturbances together explain roughly half of the wide-band variation in expected currency returns, 35% due to TFP disturbances and another 15% by disturbances to TFP expectations. Thus, these two shocks are affecting the exchange rate not just through variation in interest rate differential, but also by affecting expected currency returns, which we know to be quite volatile and important to understand.

Lastly, we close this section by also quantifying the overall role of TFP expectations, in terms of both the correctly anticipated part of ε_t^a and the noise ε_t^v. This effectively amounts to stripping away variation in endogenous variables due to current and past TFP innovations, i.e. the hisotry $\varepsilon^{a,t}$. To do so, we examine how much of the wide-band variation in the exchange rate that our two disturbances can generate (64%) is accounted for by the combination of (i) correct anticipation of future TFP disturbances and (ii) expectational

[11] Our results about the macro aggregates are very similar to the ones reported in Chahrour and Jurado (2021), where they identify the two disturbances based on domestic US data only.

noise disturbances. We use the VAR to simulate an economy with technology and noise disturbances only and compute the $1 - R^2$ after regressing the change in exchange rate on present and past technological disturbances. We find that 85% of the exchange rate variation due to our two types of shocks is generated by anticipation of future outcomes (both accurate and in error), and only about 15% of our results (or just 4.5% of the overall variation in Δq_t) can be attributed to current and past productivity disturbances.

4 Technology, noise and exchange rate puzzles

Given the large effect our two identified disturbances play in exchange rate dynamics, it is interesting to consider whether the disturbances are also driving some or all of the exchange rate puzzles we outlined in the beginning. Namely, (i) the UIP puzzle and its reversal, (ii) the Backus-Smith puzzle, (iii) excess volatility and persistence, and also (iv) the general disconnect of exchange rates and macro aggregates.

We present a number of moments related to these puzzles in Table 3, and we discuss each in detail below.

Deviations from Uncovered Interest Parity Starting with the classic UIP puzzle, note that as reported in the last row of Table 2, the news and noise shocks about TFP that we identify explain half of the variation in the predictable excess currency return $E_t(\lambda_{t+1})$. This suggests that the shocks to TFP and its expectation are significant drivers of the observed deviations from uncovered interest parity in the data.

Looking at Figures 5 (bottom right panel), we see that the currency excess return drops marginally just before the realization of the TFP innovation, and then rises significantly and for a prolongued 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 (1984) UIP regression. To test the hypothesis that the shocks we identify indeed generate the puzzling results the previous literature has documented, we consider the so-called UIP regression that is the main form in which this puzzle has been documented.

Specifically, the seminal paper by Fama (1984) estimates the regression

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

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 we identified, ε^a and ε^v, are active. To obtain this, we simulate our estimated VAR by setting the variance of all other disturbances to zero.

In this counter-factual dataset, we find $\beta_{UIP} = -2.2$, 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 3 below. Lastly ,we find that the two shocks we identify generate 68% of the unconditional covariance $Cov(\lambda_{t+1}, r_t - r_t^*)$ which underlies this puzzle, hence these TFP-related disturbances are not only generating the right patterns qualitatively, but they are quantitatively important to the puzzle.

Table 3: Exchange Rate Related Puzzles and TFP Expectations

	Technology	Exp. Noise	Both	Unconditional
Fama β_{UIP}	-2.08	-2.96	-2.20	-2.46
Engel β_{Λ}	2.33	1.72	2.62	2.53
$\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$	0.37	0.13	0.25	0.17
autocorr$(r_t - r_t^\star)$	0.99	0.93	0.98	0.95
corr$(\Delta q_t, \Delta(c_t - c_t^\star))$	-0.31	-0.38	-0.35	-0.27
autocorr(Δq_t)	0.90	0.33	0.58	0.29
autocorr(q_t)	0.99	0.97	0.99	0.98
$\sigma(\Delta q_t)/\sigma(\Delta c_t)$	3.99	8.14	5.65	6.05

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 (2016) puzzle that the UIP puzzle essentially "reverses" direction at longer horizons. Namely, it has now been established that while the Fama (1984) 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 5, for example, in the fact that the high excess returns in the period 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).

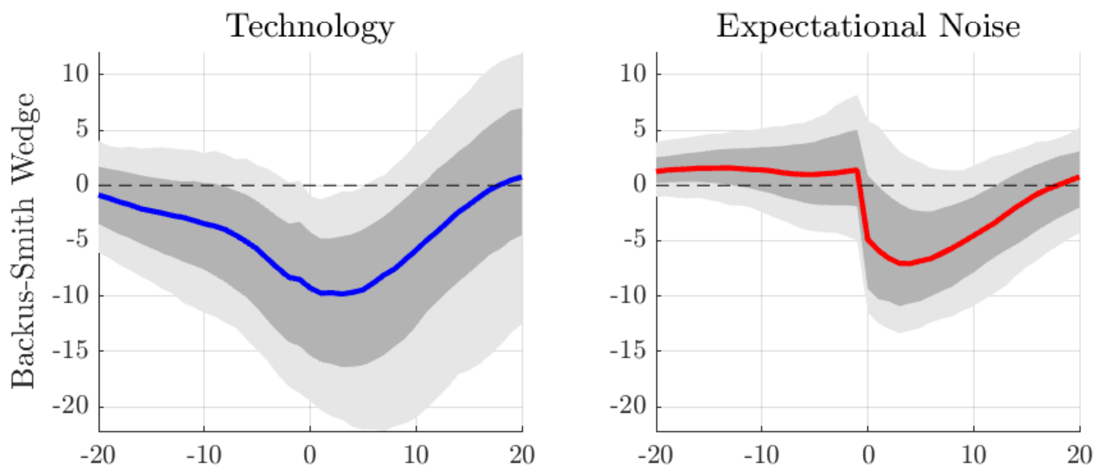
As a summary statistic of this phenomenon, we consider the same moment that Engel (2016) emphasizes, which is the coefficient of the following regression

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

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 many horizons $k > 1$ such that $\text{Cov}(\lambda_{t+k+1}, r_t - r_t^*) > 0$, 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 the noise shock in this cases is muted quantitatively (even though it can also generate it on its own qualitatively, as we can see in he second column) – the two shocks together generate 60% of the overall $\text{Cov}\left(\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}), r_t - r_t^*\right)$ in the data, but the noise shock is responsible for only one tenth of this effect.

It is also worth nothing that these two disturbances 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 the raw data, as seen by the $\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$ and $\text{autocorr}(r_t - r_t^\star)$ moments reported in the Table. Hence, obtaining UIP regression coefficients of the same magnitude as in the raw data indeed suggests that the puzzling predictability patterns in excess currency returns that have been identified over the years are largely driven by disturbances to TFP and its expectations.

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



Notes: The figure displays the Backus-Smith Wedge responds 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.

Risk-sharing Puzzle Next we turn to the Backus-Smith risk-sharing puzzle. As a first step we consider the IRF of the Backus-Smith "wedge" defined as

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

Under the null hypothesis of full consumption risk-sharing, in the sense of Backus et al. (1993), this variable should be equal to zero in all periods.

The impulse responses with respect to a technological and an expectational disturbance are both reported in Figure 7. We can again see a significant anticipation effect in response to the actual TFP disturbance, with the wedge being significantly negative as early as 10 quarters before the actual TFP improvement. The fact that the wedge is negative, means that in anticipation of a US TFP improvement, the dollar does not depreciate sufficiently to offset the relative US consumption boom. This same phenomenon can also be inferred from Figure 4, where we see that in anticipation of the US TFP improvement the dollar is in fact *appreciating* even though US consumption is high – the opposite of the Backus-Smith implied relation. After the realization of the US TFP improvement, the wedge adjusts gradually towards zero.

The expectational noise disturbance also causes significant effects on 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 (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 benchmark Backus-Smith Puzzle moment much of the literature works with,

$$\mathrm{corr}(\Delta q_t, \Delta c_t - \Delta c_t^*),$$

in the counter-factual simulations based on the two identified disturbances.We then compare the resulting moment to the Backus-Smith correlation in the raw data. The results are presented in Table 3.

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. Thus, the disturbances to TFP and its expectations tend to drive a similarly puzzling, negative correlation between exchange rate growth rates and the growth rate in relative consumption.

Excess Volatility and Persistence Lastly, another set of exchange rate features that are commonly emphasized as “puzzling” are the excess persistence and volatility of the real exchange rate. In both cases, the puzzle is that standard models do not deliver exchange rates that are nearly persistent or volatile enough to match the data. Thus, we are next interested to what extent the high persistence and volatility found in the data might be accounted for by the disturbances to TFP and its expectations that we have identified.

In Table 3, we consider three related moments: First, the autocorrelation of quarterly exchange rate change; second, the autocorrelation of the level of the exchange rate; and third, the ratio of the standard deviation of quarterly FX changes and consumption growth. The first result is that the exchange rate dynamics conditional on the two disturbances we extract are indeed highly persistent. In the counter-factual simulation with both disturbances active, the autocorrelation of the exchange rate is 0.99 as compared to 0.98 unconditionally, and the autocorrelation of the first difference of q_t is 0.58 versus 0.29 in the unconditional data.

Thus, our two sets of shocks are in fact generating 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). Lastly, while both the actual TFP disturbance and the expectational noise disturbance generate high persistence in the level of the exchange rate, the persistence in the growth rate of the exchange rate is primarily driven by the TFP disturbances themselves.

Lastly, we find that exchange rate growth is indeed highly volatile relative to consumption growth – that ratio is around 6 conditional on the two disturbances we identify as well as in the raw data. This volatility appears to be mostly driven by expectational disturbances, which generate a ratio of around 8.

FX Determination Puzzle We now consider the so called determination or disconnect puzzle that we started with originally. This has been documented in many different ways, with no single summary statistic emerging form previous work. Here, we will just focus on the link between two key macro aggregates, home consumption (as a basic measure of the business cycle) and home TFP (as the quintessential driver of standard models), and the real exchange rate. And as is standard in the previous literature, we will compute the contemporaneous correlation between the macro aggregates and exchange rate changes.

Unconditionally, in our data $\text{corr}(\Delta q_t, \Delta c_t) = -0.1$ and $\text{corr}(\Delta q_t, \Delta a_t) = -0.07$, showcasing the typical result that exchange rates are not closely related to macro aggregates contemporaneously. A similar result appears when we consider the above correlation conditional on just the two sets of shocks ε_t^a and ε_t^v. When both shocks are active, we have $\text{corr}(\Delta q_t, \Delta c_t) = -0.07$ and $\text{corr}(\Delta q_t, \Delta a_t) = -0.12$, thus the relationship is similarly low.

There are two channels behind this low correlation. One, is the fact that conditional on a ε_t^a shock the effects of the innovation on macro aggregates and the exchange rate appear at different times, with the exchange rate reacting in anticipation of the TPF improvement. We have already explained the basic intuition behind this channel.

However, there is also another channel, which has to do with the fact that we estimate agent's expectations to be quite *noisy*. As such, often the exchange rate effectively reacts in anticipation of a TFP improvement that never actually materializes. And in fact, in terms of the volatility of Δq_t noise is relatively more important than the actual TFP innovations (11% vs 18% in Table 2). Thus, the noise channel we uncover thanks to our identification procedure plays an important role that would have been otherwise been overlooked.

Technology, noise and the trade balance Another long-standing question in the literature concerns the driver 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). For this reason, we now examine the response of the trade balance to the disturbances we identify. Figure 8 reports the response of the U.S. trade balance (as a % of U.S. GDP) to technological and noise disturbances. We find that the U.S. (i.e. home) trade balance deteriorates in anticipation of possible future TFP improvements, and it 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 consistent with Hoffmann et al.'s (2019) fact 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.[12] Moreover, Figure 8 reveals that the real exchange rate and the U.S. trade balance are highly positively correlated in response to both fundamental disturbances. This suggests that the unconditional positive correlation between the real exchange rate and the trade balance documented in the literature (Alessandria and Choi, 2021; Gornemann et al., 2020) can be understood as the joint equilibrium response of these variables to technological and noise disturbances.

4.1 Implications

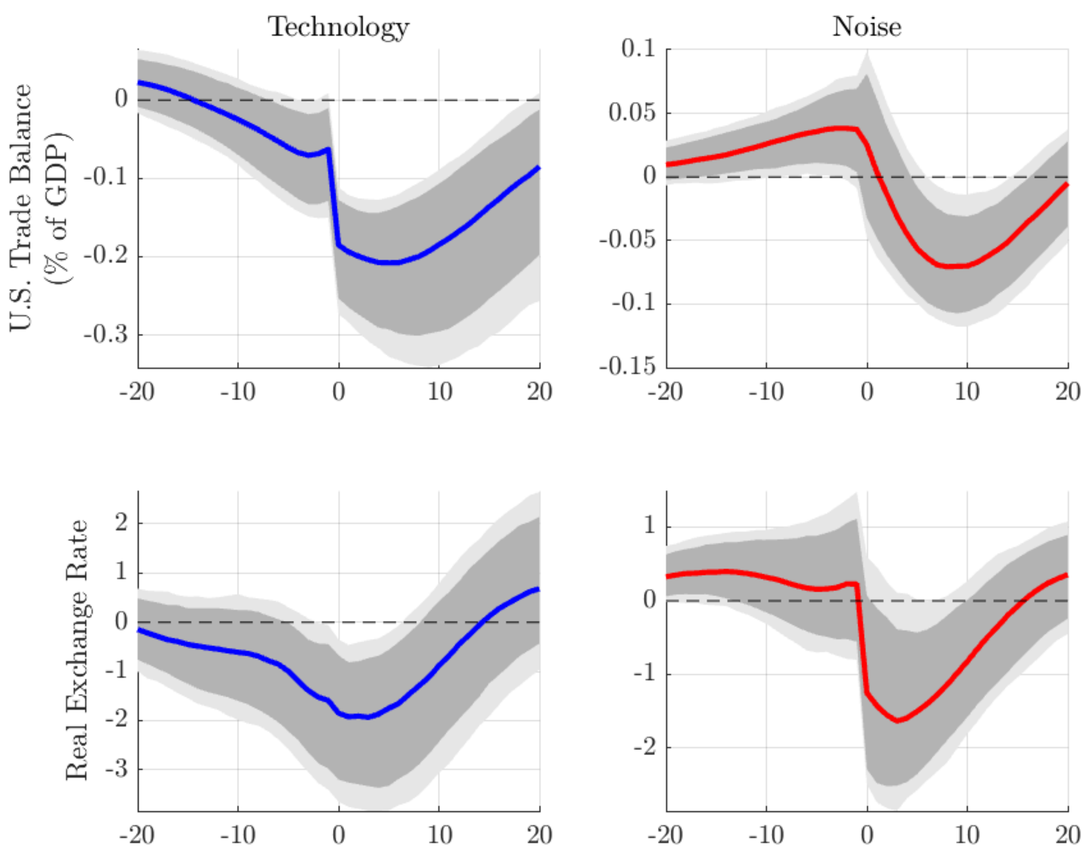
Let us take stock of the results and their broader implications.

Fundamental connection Our first main conclusion is that exchange rates do indeed share a strong and important relationship with productivity – the quintessential macro "fundamentals" in most models. However, this connection is not immediately obvious for two reasons.

First, many of the previous studies that have tried to find a link between exchange rates and macro fundamentals, and TFP in particular, had taken as a null 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. As our discussion in Section 3 indicates, however, the link with current and past TFP innovations

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

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.

$\varepsilon^{t,a}$ is very weak, and accounts for only 3-4% of the variation in Δq_t. Instead, as we have shown extensively, the first-order link between exchange rates and TFP runs through noisy expectations of *future* TFP innovations. This will be missed by empirical approaches that focus on the link with the history of current and past macro fundamentals.

Second, we are of course not the first to recognize that exchange rates are forward-looking asset prices, and should thus be expected to predict and correlate with future macro fundamentals. A seminal paper that formulates and examines exactly this hypothesis is Engel and West (2005). However, its results are at best mixed, with some weak supportive evidence of this leading relationship. How come our results apparently speak to a much stronger relation?

Engel and West (2005) examine the hypothesis that exchange rates lead macro aggregates with a Granger causality test of the form

$$f_t = \alpha + A(L)f_{t-1} + B(L)q_t \tag{7}$$

where f_t is some macro fundamental of interest. The follow-up literature has examined many different potential fundamentals, such as output, consumption, TFP and many others. This literature has also considered many formulations of this Granger Causality test (first-differences vs levels). And in general, the results have been relatively weak, to the point that no strong consensus of this potential leading relationship has emerged.

Our results shed some light on why the Granger causality methodology has not yielded more convincing results. It has to do with our result that *noise* in expectations ε_t^v plays an important role in the variation of q_t. In fact, expectational noise would act akin to measurement error in the right-hand-side variable of the Granger causality regression equation (7). It thus attenuates the coefficient on q_t and the estimated explanatory power of current and lagged q_t over f_t in any finite sample.

Lastly, a different strand of the literature that tests the hypothesis that current exchange rates leads macro aggregates, such a Sarno and Schmeling (2014), adopts a more non-parametric approach leveraging the cross-sectional variation in the data. However, papers in this literature limit their attention to a potential connection between current exchange rates and macro fundamentals up to only one or two years in the future. Yet, 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.

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. Whether the other shocks that drive q_t in the data also generate a disconnect or not is an interesting topic for future analysis.

Common origin to many FX puzzles One important aspect of the two shocks we identify is that the resulting conditional dynamics of the exchange rate exhibit many famous exchange rate puzzles. This suggests that these puzzles, which are often documented and analyzed in isolation, in fact share a common origin in TFP fluctuations and their noisy expectations.

It is particularly striking that the two sets of shocks we identify account for about 50% of $\mathrm{Var}\left(\mathbb{E}_t(\lambda_{t+1})\right)$, and for roughly two-thirds of the covariances that are behind seminal results in the literature such as the regressions of Fama (1984) and Engel (2016). Thus, TFP disturbances and their noisy expectations indeed play a very important role in understanding the puzzlingly volatile currency returns and their complex dynamics.

These estimates are significant for two reasons. First, the apparent importance in productivity fluctuations as drivers of exchange rate puzzles validates a very long tradition in the theoretical literature of building models of exchange rate puzzles that are indeed primarily driven by TFP innovations (see, for example, Verdelhan, 2010, Bansal and Shaliastovich, 2012, and Colacito and Croce, 2013). Our results also complement the empirical results of Kim et al. (2017). They find that while exchange rates respond also monetary policy shocks, these shocks do *do not* display any violations of uncovered interest parity. So the study of exchange rate puzzles appear rightly focused on using TFP as a source of fluctuations, while monetary policy shocks are important in their own right, but are often studied instead in terms of their impact on the international transmission of business cycles within first-order models (see, for example, Clarida et al., 2002).

Second, it is important to realize that existing models of exchange rate puzzles are still insufficient, given our results, and more work needs to be done to bring models closer to the novel features of the data we uncover. On the one hand, our empirical results suggest that *noisy expectations* of future TFP innovations play a crucial role in both exchange rate fluctuations and in puzzles such at the deviations from UIP and the Backus-Smith condition. Existing models, instead, rely heavily on information structures where all productivity shocks are pure surprises. Moreover, many of the existing models address only one of the UIP (e.g. Verdelhan, 2010) and Backus-Smith puzzles (e.g. Corsetti et al., 2008), but not these two together. Our results, instead, show that conditional on the shocks to TFP and their noisy expectations, the dynamic responses of the exchange rates generate both types of deviations. So we need models where both puzzles arise at the same time, as jointly driven by noisy expectations of TFP.

Among the existing class of models, it would seem like long-run risk models in the vein of Colacito and Croce (2013) are the most promising ones. Those are not models of noisy expectations of future TFP per-se, but they are still a mid-point between a framework where TFP innovations are pure surprises and where there is significant noisy anticipation of future TFP. Moreover, those models have also been shown to be able to account for both the UIP and the Backus-Smith puzzles at the same time.

That said, we caution that this paradigm still needs to be further refined to match the full extent of our empirical results, even though it shares some of the qualitative intuition behind our estimates. Specifically, we find that the 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 (which acts akin to a news shock because most of its TFP improvement effects accrue in the future, due to it being a persistent change in the growth rate). This opposite movement in consumption is a characteristic feature of the full risk-sharing setup in this class of models – home agents are effectively "sharing" their good news about high future home output with foreign agents by transferring resources abroad today.

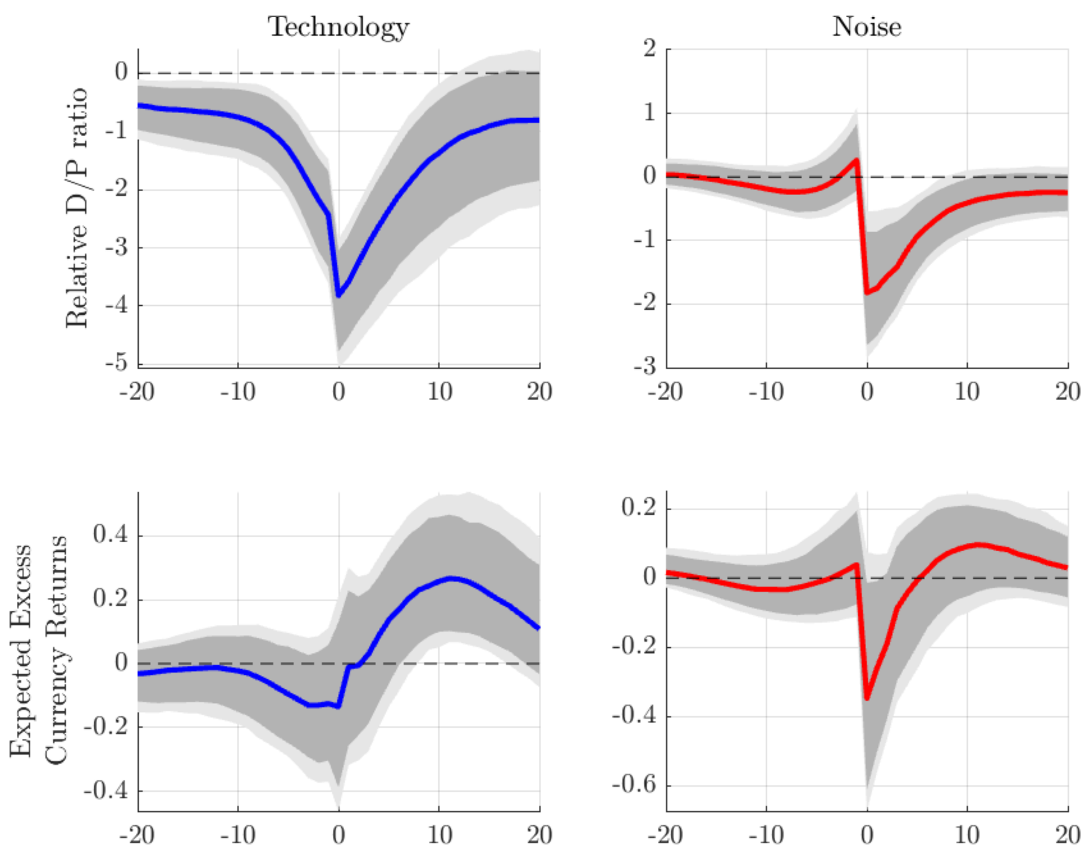
So there is more work to be done on the modeling front, and this discussion highlights how our rich empirical results can be used to inform the needed improvements in theoretical models, and can also be used to estimate and discipline such models. Perhaps one interesting avenue for future research is to merge the incomplete markets setup of Corsetti et al. (2008) with the Epstein-Zin utility and non-linear solutions of Colacito and Croce (2013), and then use our estimates to discipline the information structure and dynamics of the forcing process.

Factor structure in currency excess returns 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 9 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 is indeed responding strongly to our shocks, both in anticipation of the actual TFP improvement and in response to a noise shock to expectations.

Figure 9: 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.

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 in future work.

5 Robustness analysis

Identified disturbances and endogenous TFP The analysis in sections 3 and 4 relies on the assumption that the technological disturbances ε_t^a are exogenous (orthogonal to other structural shocks). However, one may be concerned that other economic shocks, such as monetary policy shocks, may lead to changes in TFP via endogenous investment in research and development (R&D). In that case, identified technological and noise disturbances might be contaminated by other economic shocks.

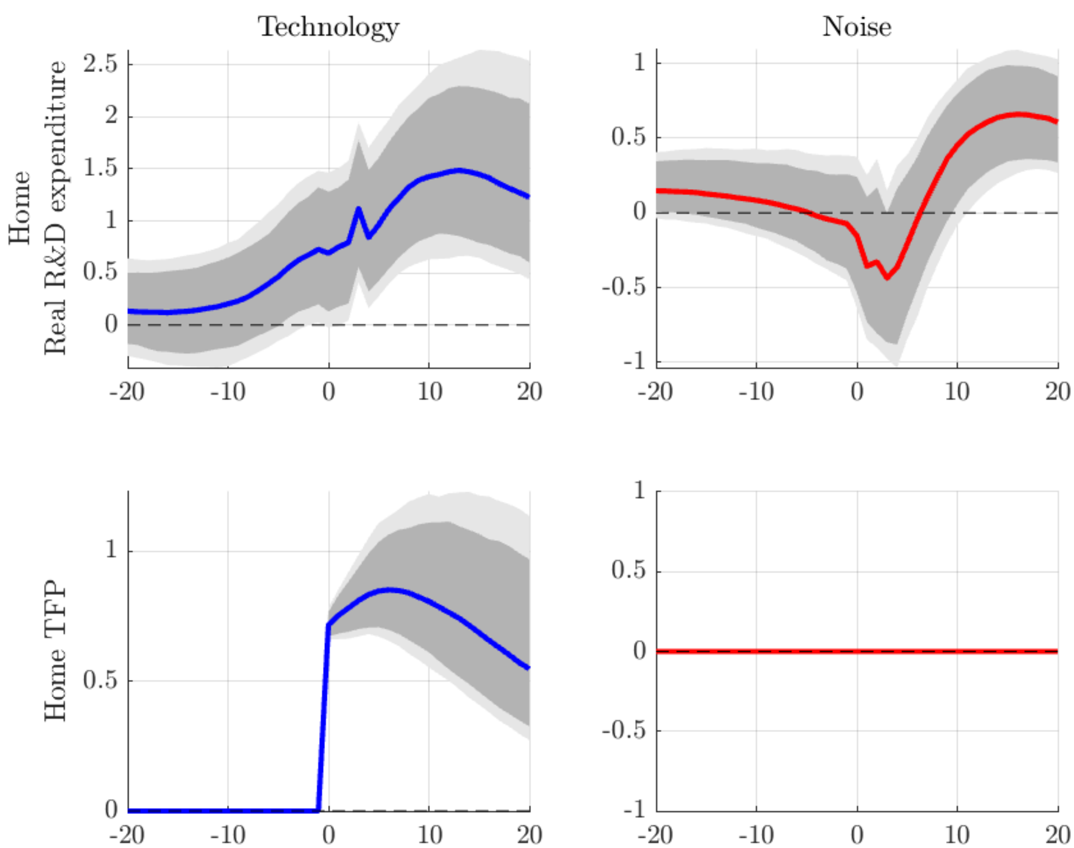
To address this concern, we first study the response of R&D to identified technological and noise disturbances. Figure 10 reveals that while real R&D expenditure responds significantly to both identified disturbances, its largest increase occurs *after* the TFP improvement has materialized. Also, R&D expenditures increase after an increase in the noise component of TFP expectations and thus it is not followed by an actual increase in TFP. This appears in contrast with a view in which TFP changes are predominantly caused by preceding R&D investment. In these models, R&D leads TFP we should observe R&D to peak before TFP and R&D to be orthogonal to noise.

To study whether our identified disturbances are contaminated by other economic shocks, we study whether technological and noise disturbances are orthogonal to other identified shocks. In particular, we examine whether our procedure is picking 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 4 we report the correlation between technology, noise and U.S. monetary policy shocks. We can't reject the hypothesis that both technology and noise disturbances are orthogonal to U.S. monetary policy shocks.

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

Figure 10: Technology, noise and research and development expenditures



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.

Table 4: Correlation between Technology, Noise and Other Economic Shocks

	Technology	Exp. Noise
U.S. Monetary Policy Shocks	0.09	0.06
	$p\text{-}value = 0.46$	$p\text{-}value = 0.62$

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).

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

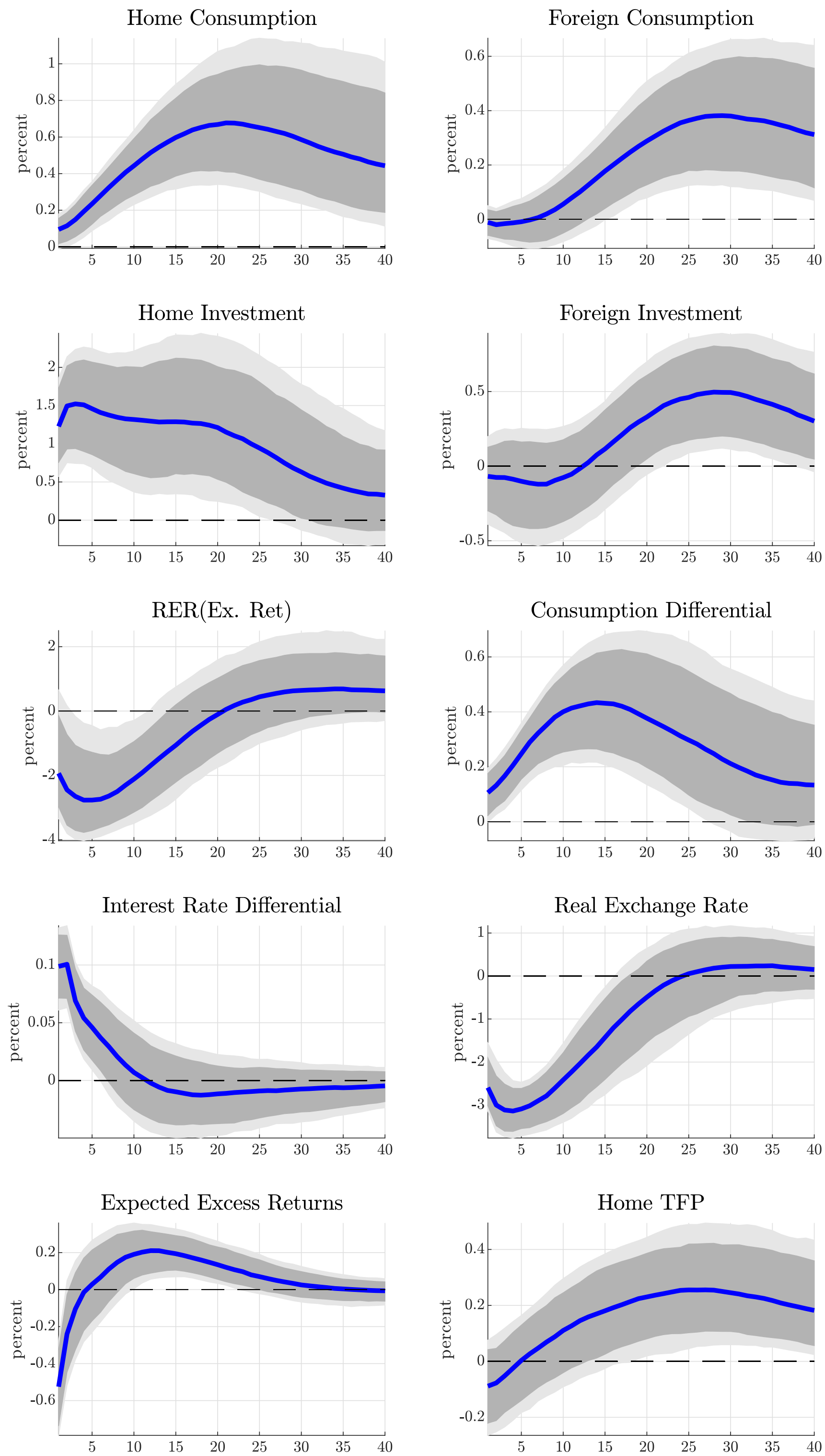
- Nominal exchange rate
  - Daily bilateral exchange rates, Foreign Currency/USD;
  - Source: *Datastream*;
  - Quarterly aggregation: period-average.
- Nominal interest rates
  - Daily Eurodollar deposit rates;
  - Source: *Datastream*;
  - Quarterly aggregation: period-average.

- Consumer Price Indexes
  - CPI Index (Chained 2010)
  - Source: *OECD*, https://stats.oecd.org/index.aspx?DataSetCode=PRICES_CPI.
- Consumption
  - Real consumption;
  - Source: *OECD*, `LNBQRSA`: National currency, chained volume estimates, national reference year, quarterly levels, seasonally adjusted.
- 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
  - 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

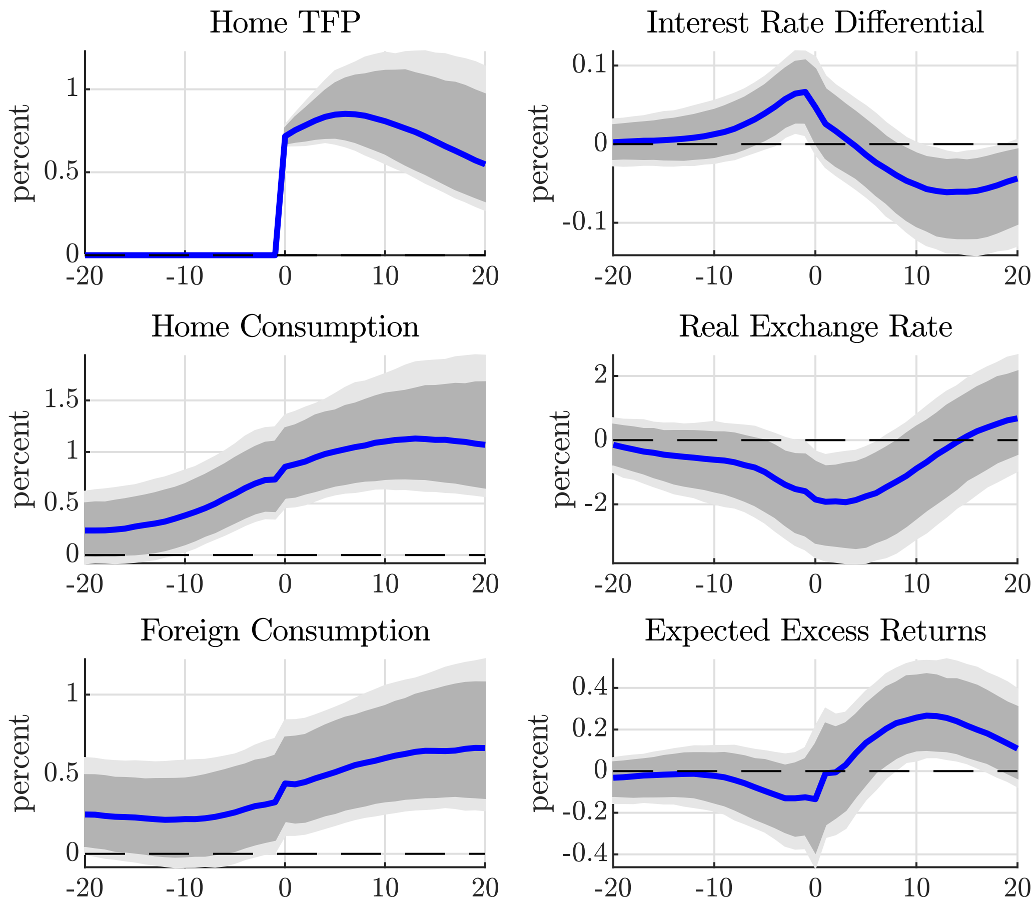
B.1 Extended sample (1976:Q1-2018:Q4)

Figure 11: Impulse Response Functions to the Main FX shock (ε_1), 1976:Q1-2018: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, 1976:Q1-2018: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.

Table 5: Share of variance explained by the Main FX shock (ε_1); Extended sample 1976:Q1-2018: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.

Table 6: Variance Decomposition; Extended sample 1976:Q12018:Q4

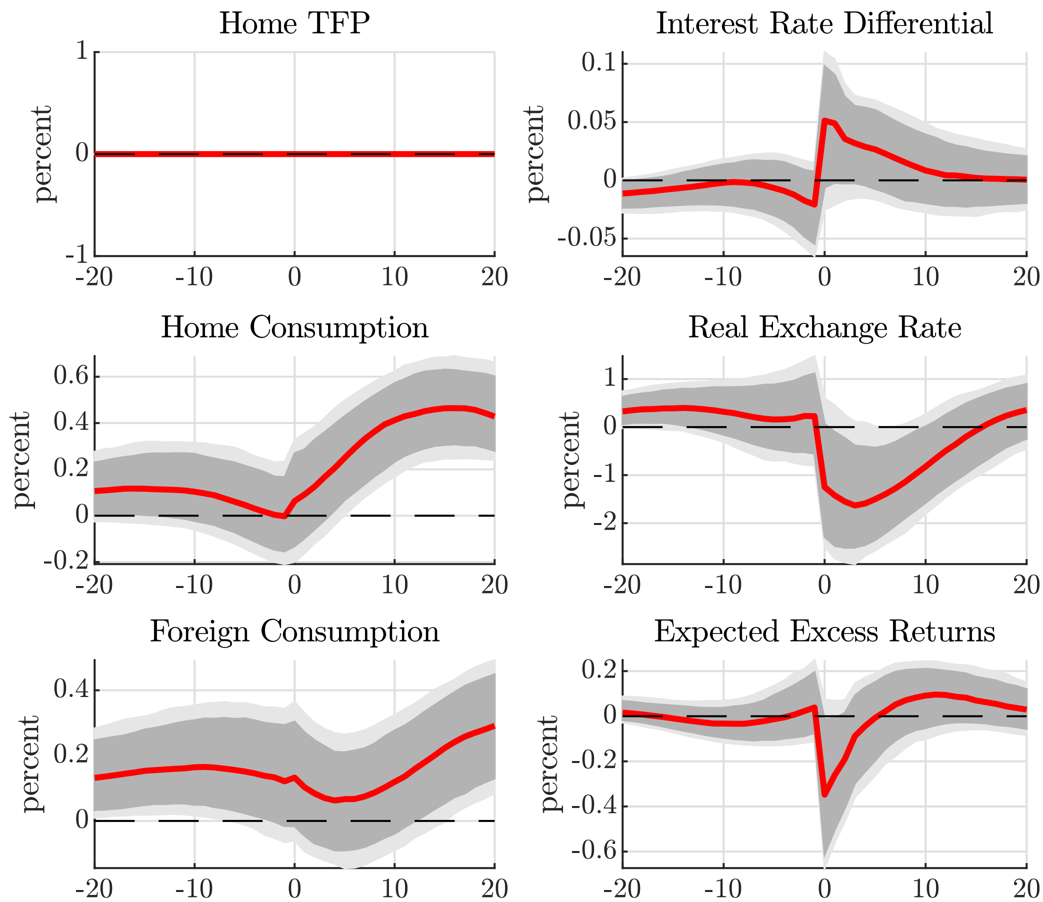
	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1.00	1.00	0.00	1.00	1.00	0.00
Home Consumption	0.67	0.42	0.25	0.33	0.07	0.26
Foreign Consumption	0.47	0.32	0.15	0.18	0.07	0.12
Home Investment	0.56	0.34	0.21	0.27	0.09	0.19
Foreign Investment	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.2 Vector Error-correction Model (VECM)

The procedure consists in running a Bayesian VAR including the first difference of all the baseline variables except for the nominal exchange rate and the nominal interest rate

Figure 13: Impulse responses to Noise (ε^v) disturbance, 1976:Q1-2018: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.

differential. We replace the nominal exchange rate with the real exchange.Then, we impose hard zero priors on the 4th lag loadings on the first differenced variables, a prior of 1 on the first self lag of the real exchange rate and the interest rate differential, and 0 otherwise, with variance parameter γ equal to 0.2 as in the baseline. The restricted VAR(4) is equivalent to a VECM(3) that assumes the real exchange rate and the nominal interest rate differential to be stationary as in Engel (2016).

Table 7: 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.

B.3 Bilateral VARs

Table 8: 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						

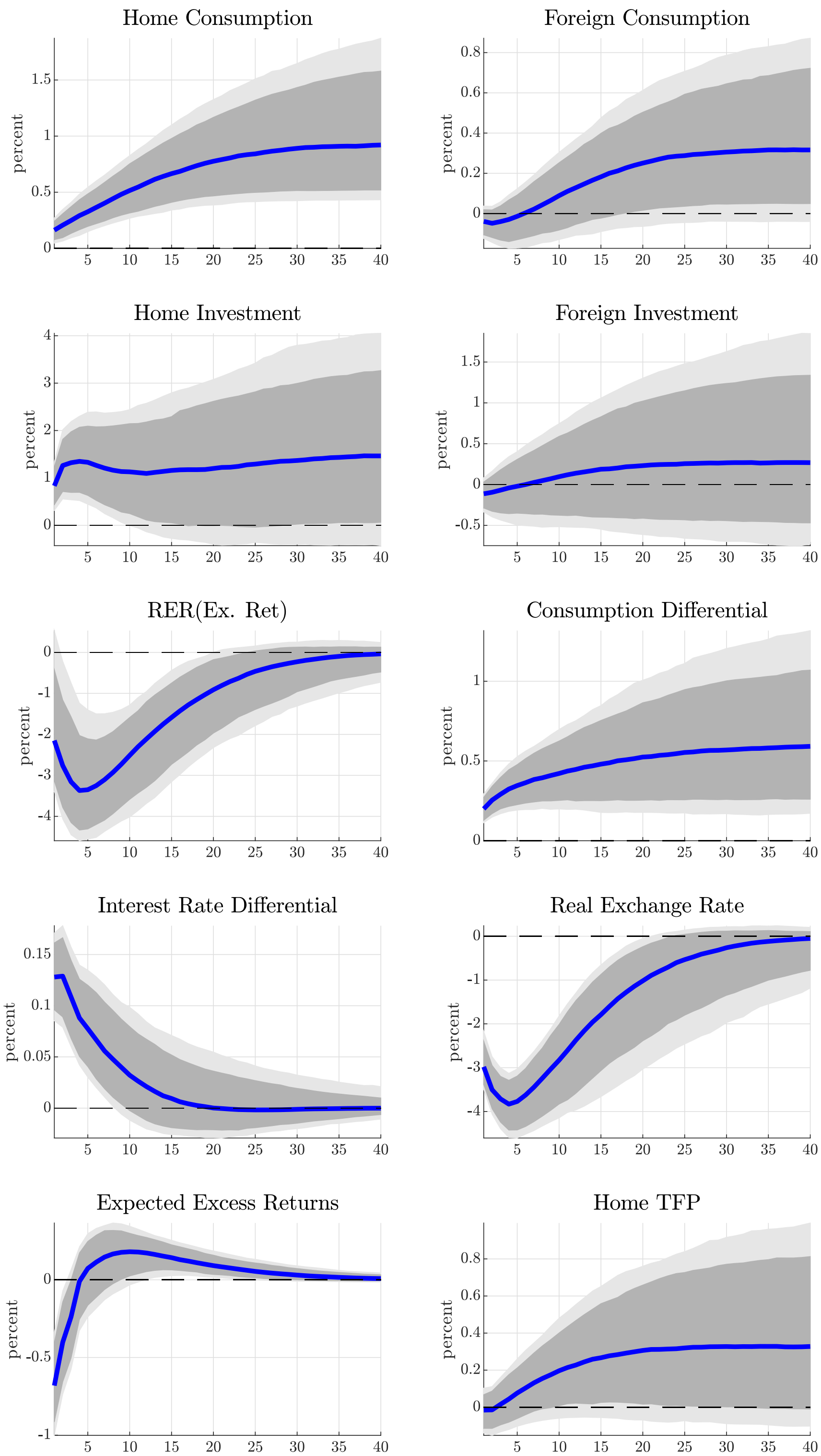
Notes: The table reports the estimated variance shares accounted for by the main exchange rate shock at different horizons.

Table 9: 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

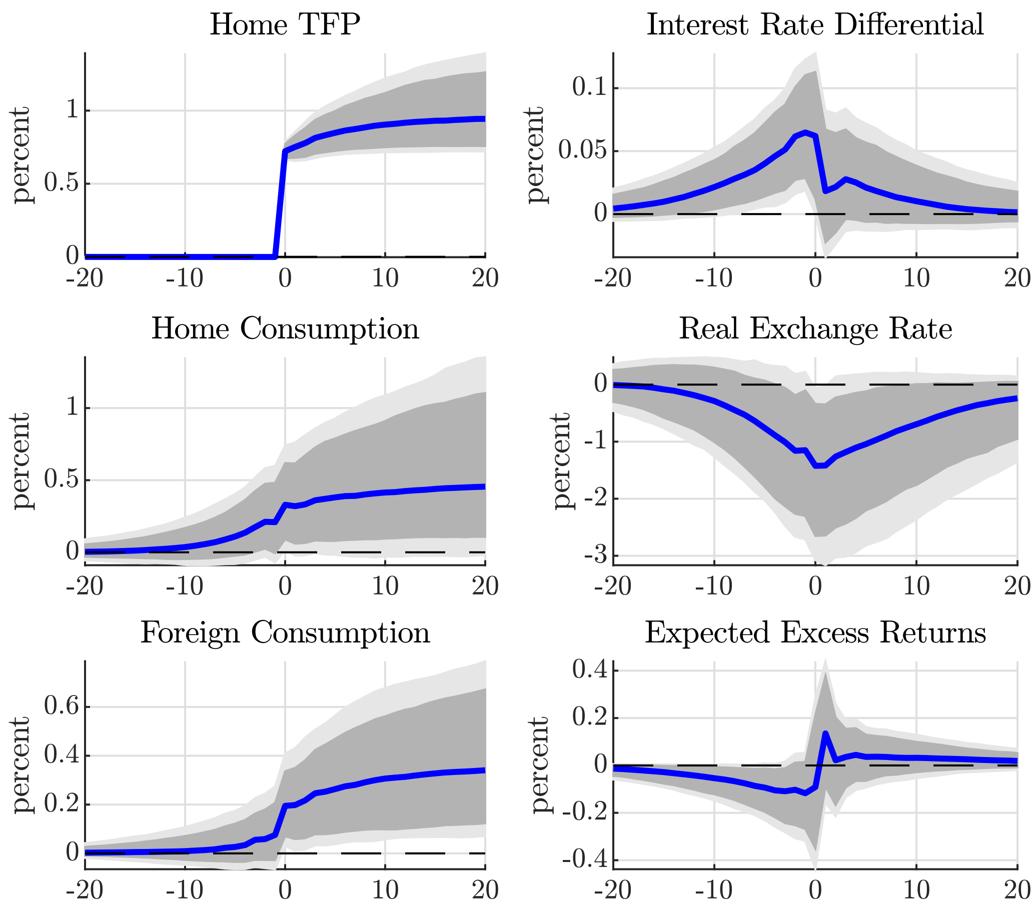
Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

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



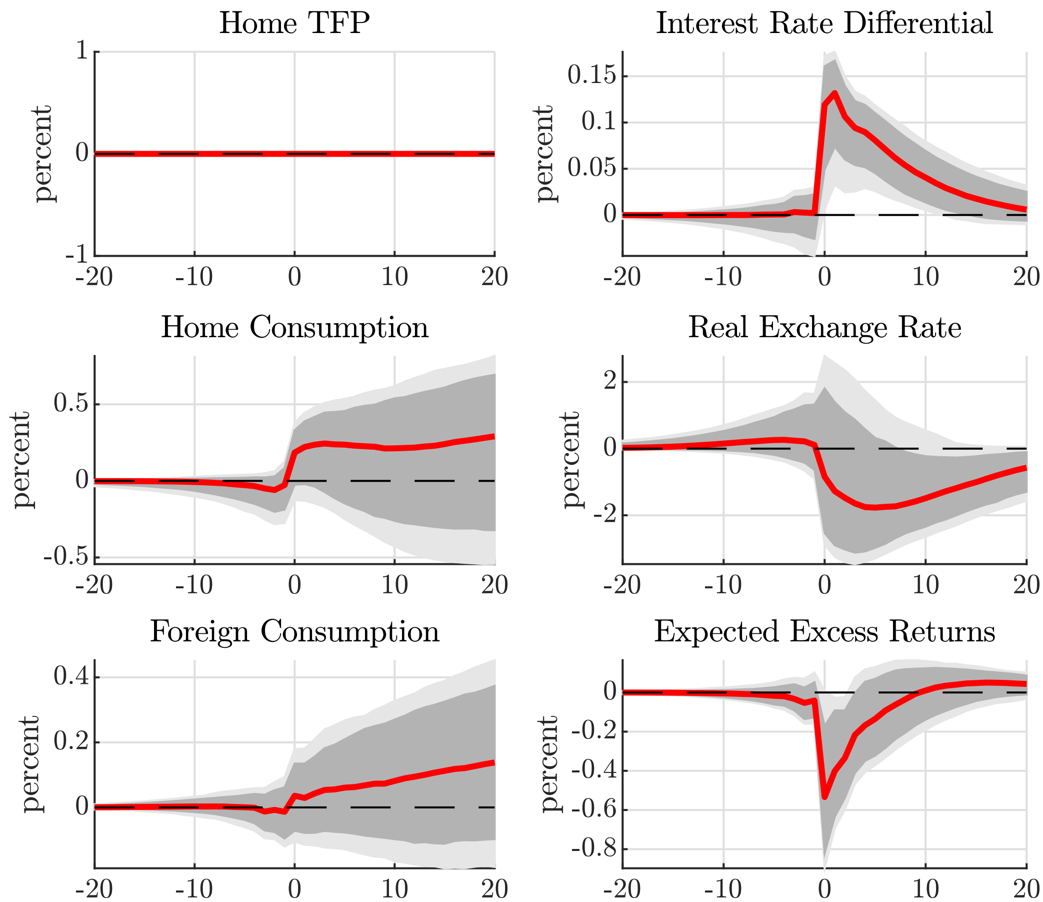
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



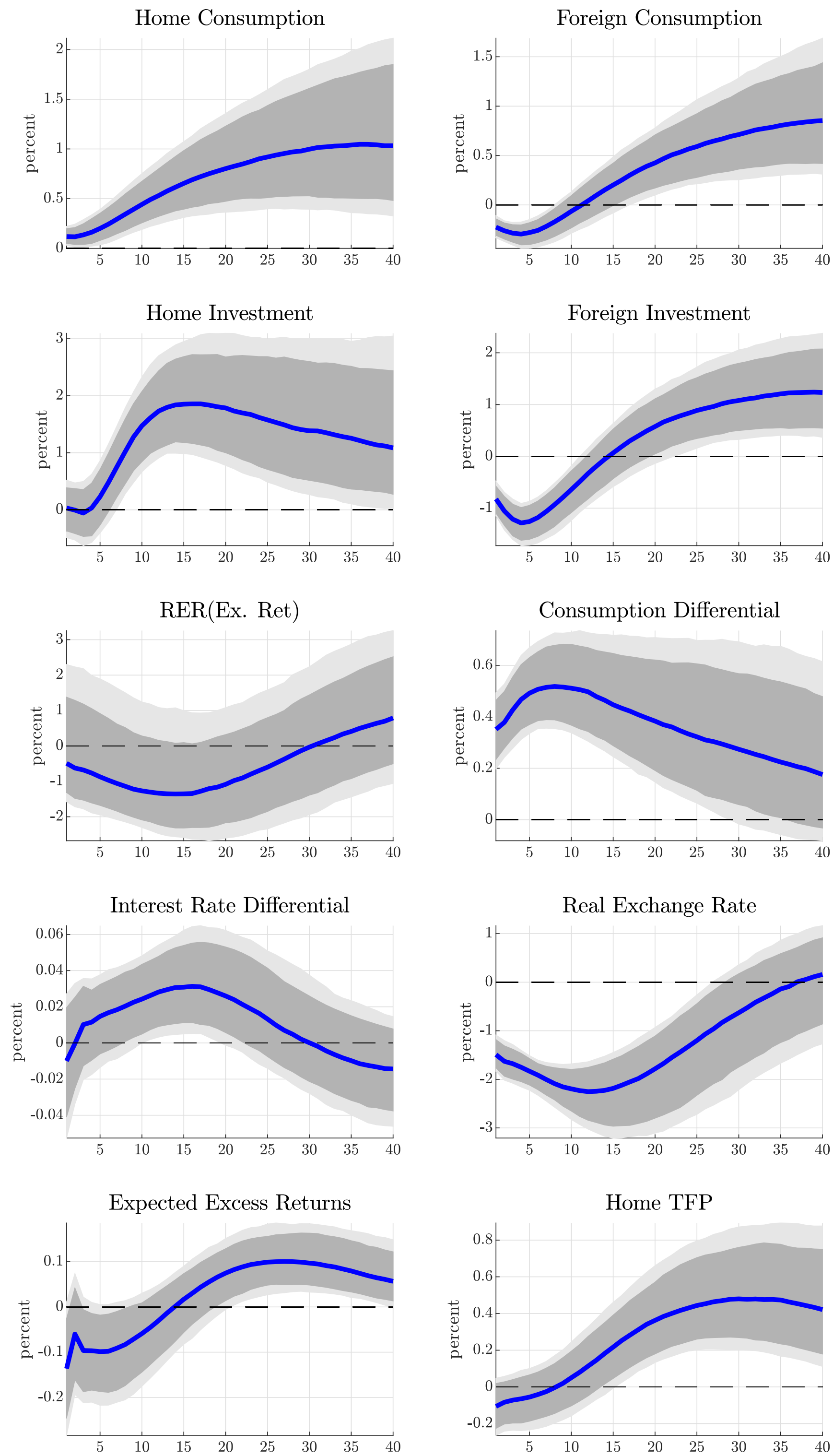
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Table 10: Variance Decomposition, 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

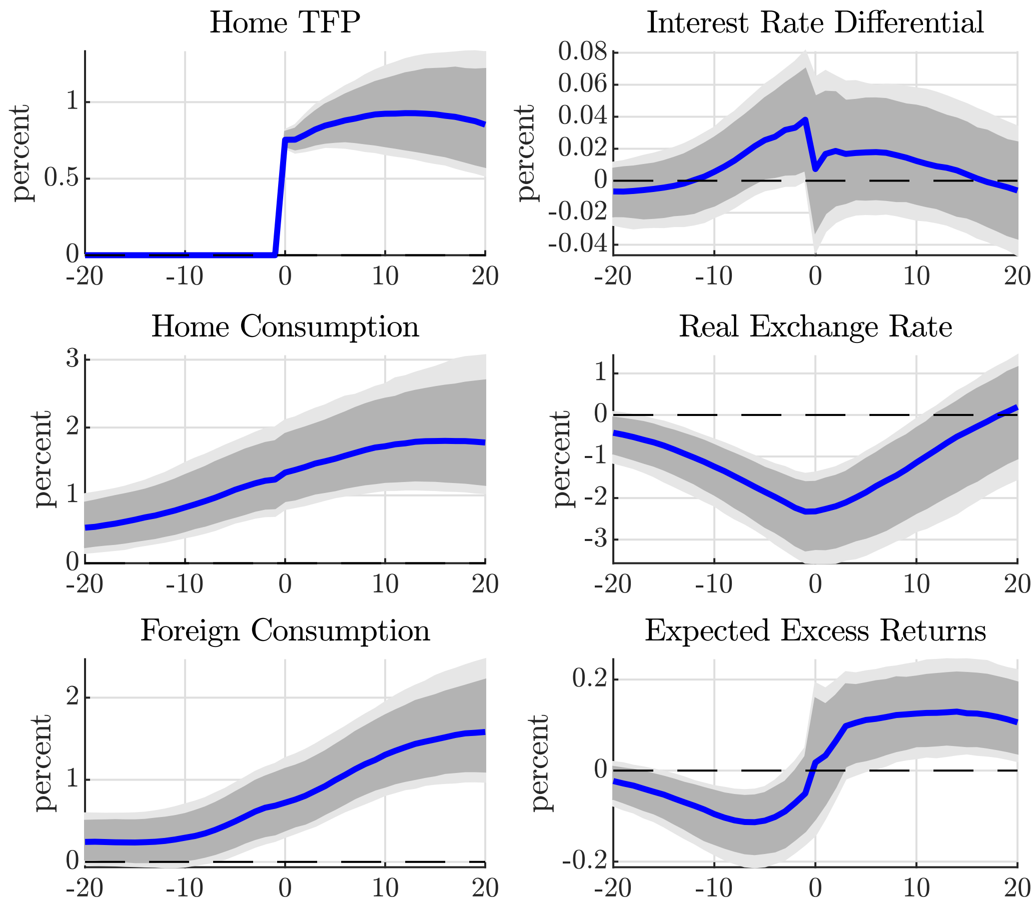
Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances ("Tech"), expectational disturbances ("Noise"), and the combination of both.

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



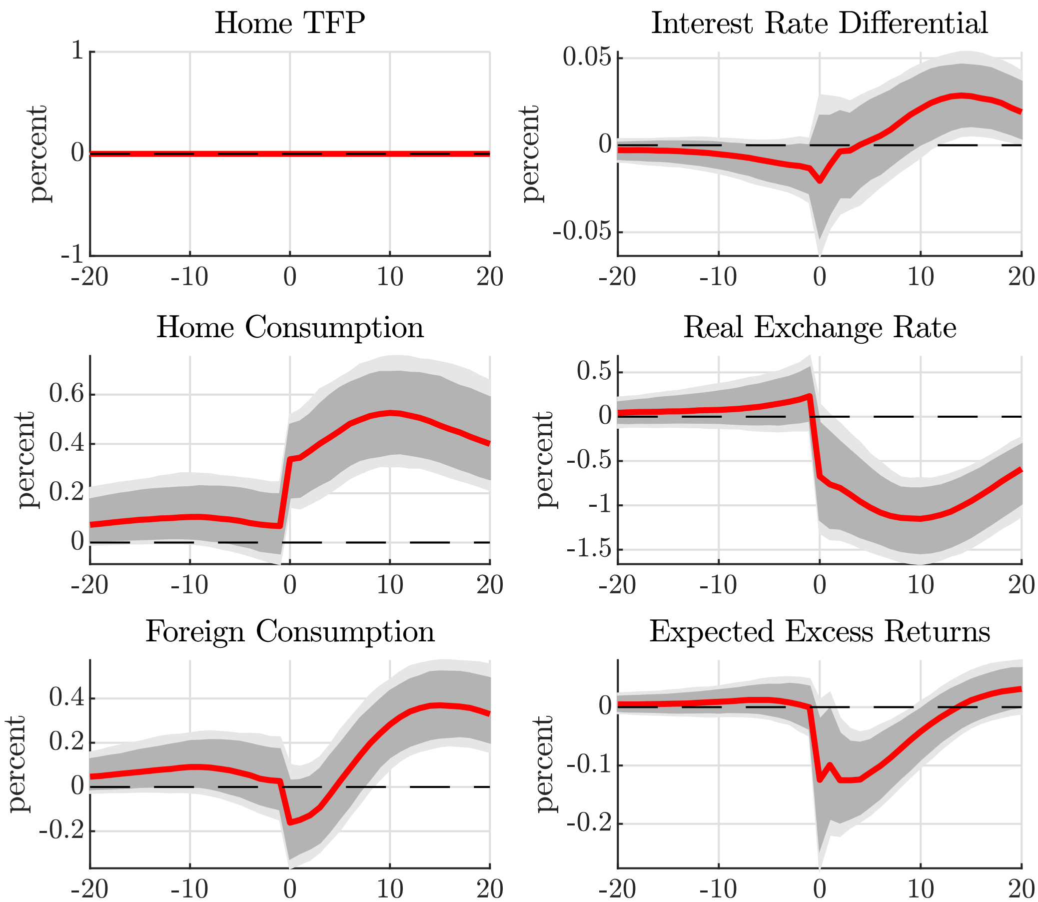
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



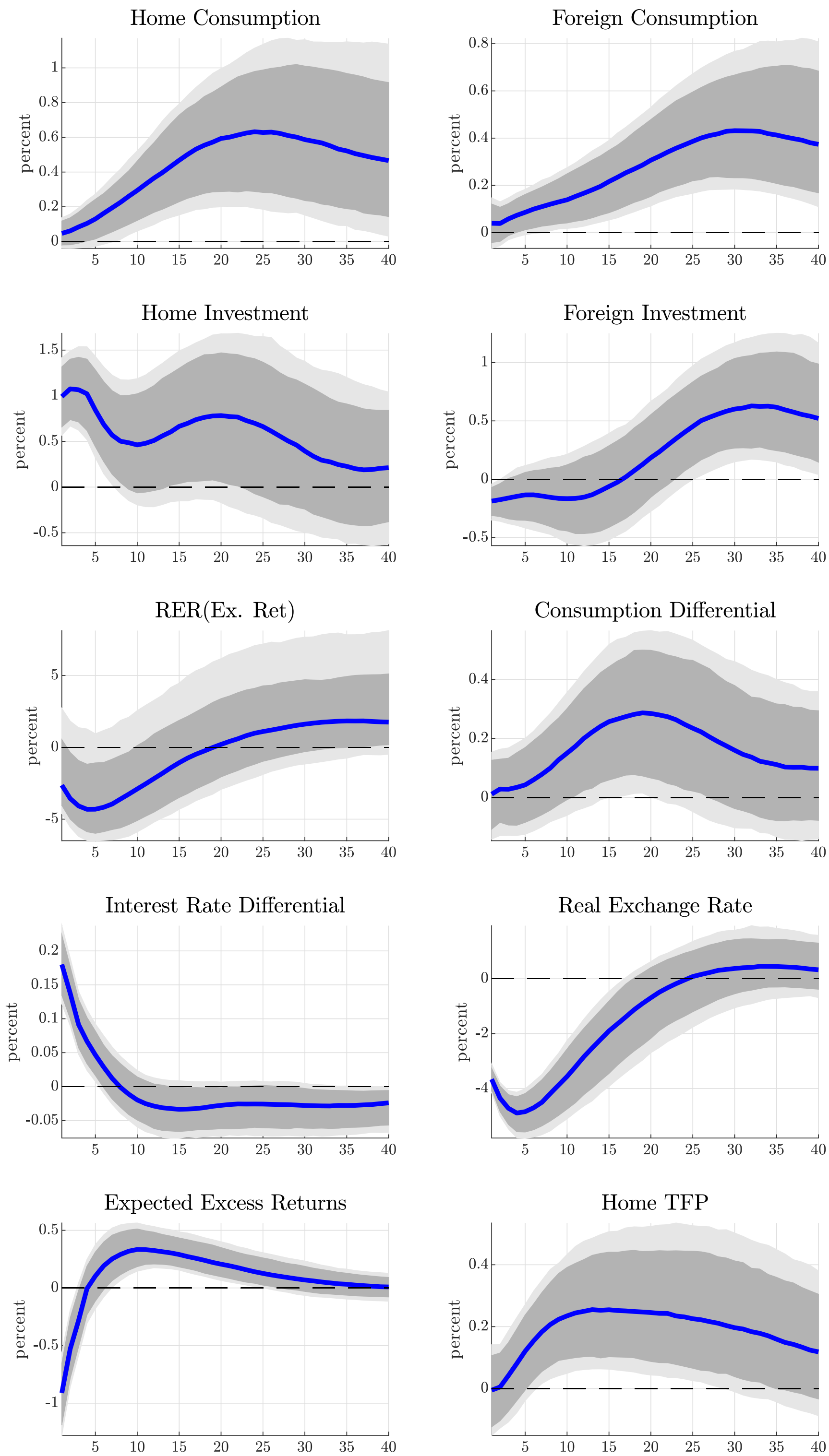
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

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



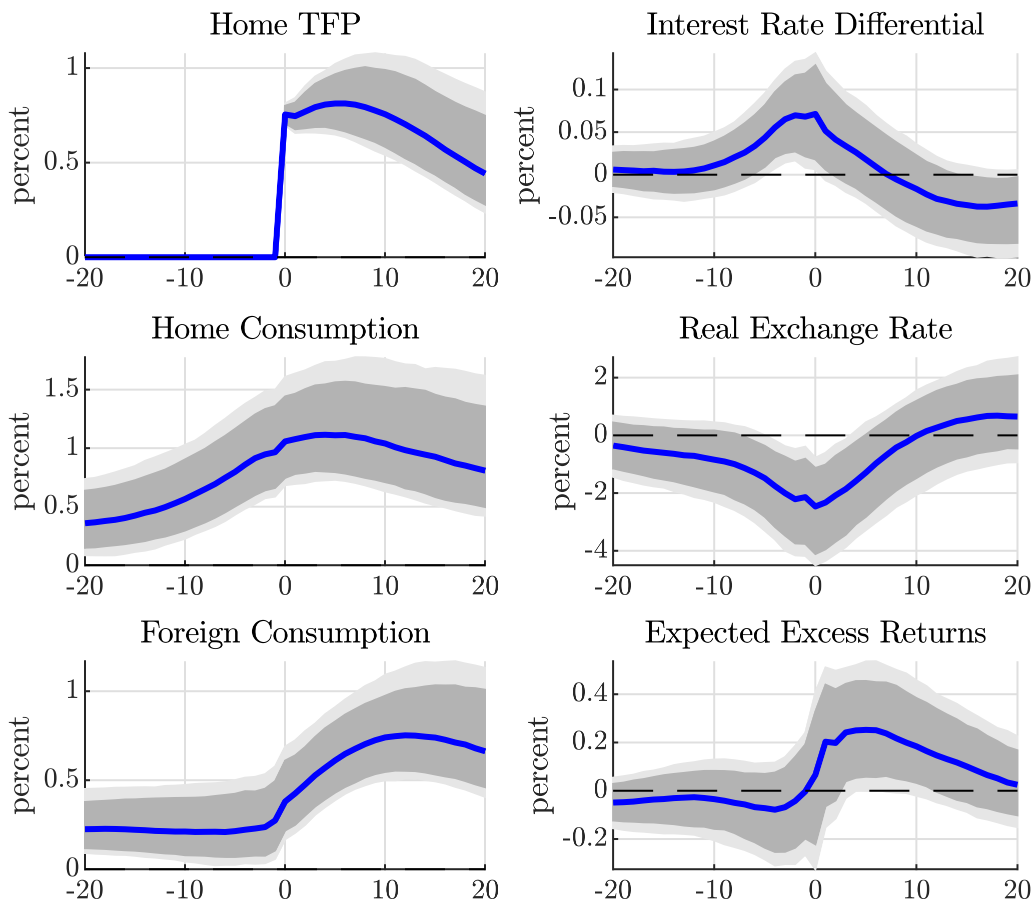
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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



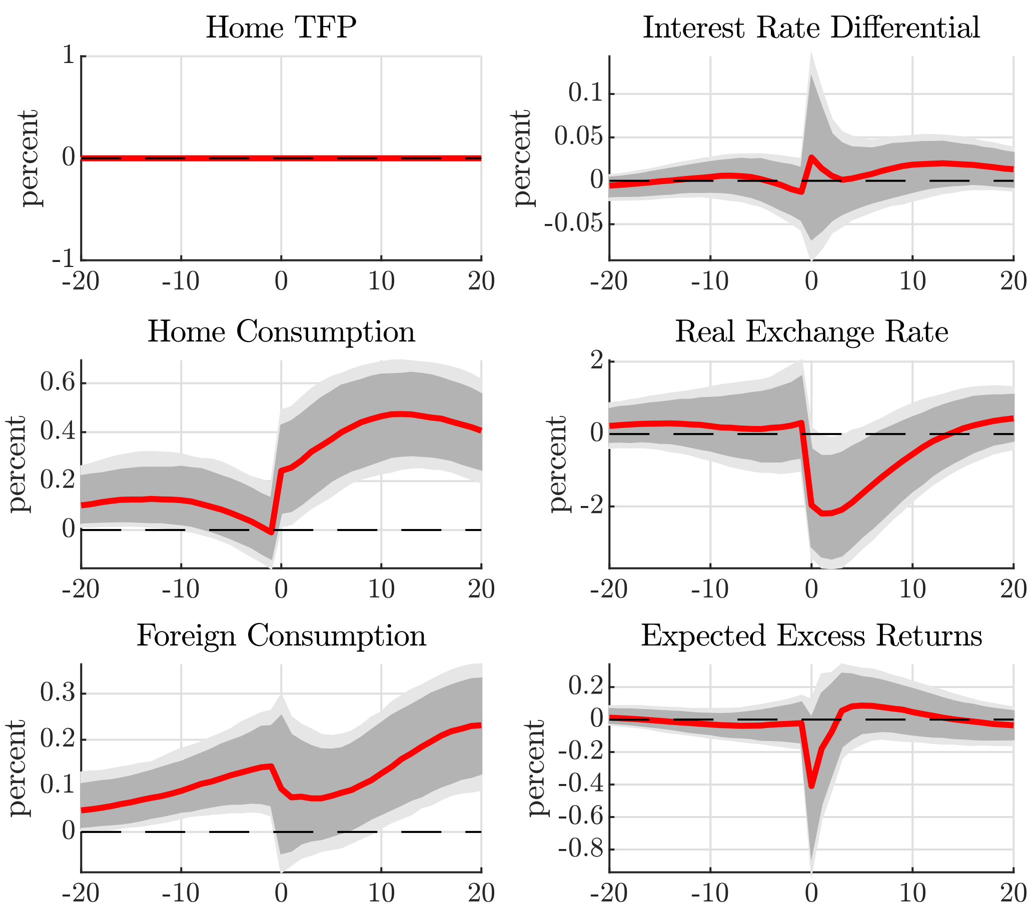
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



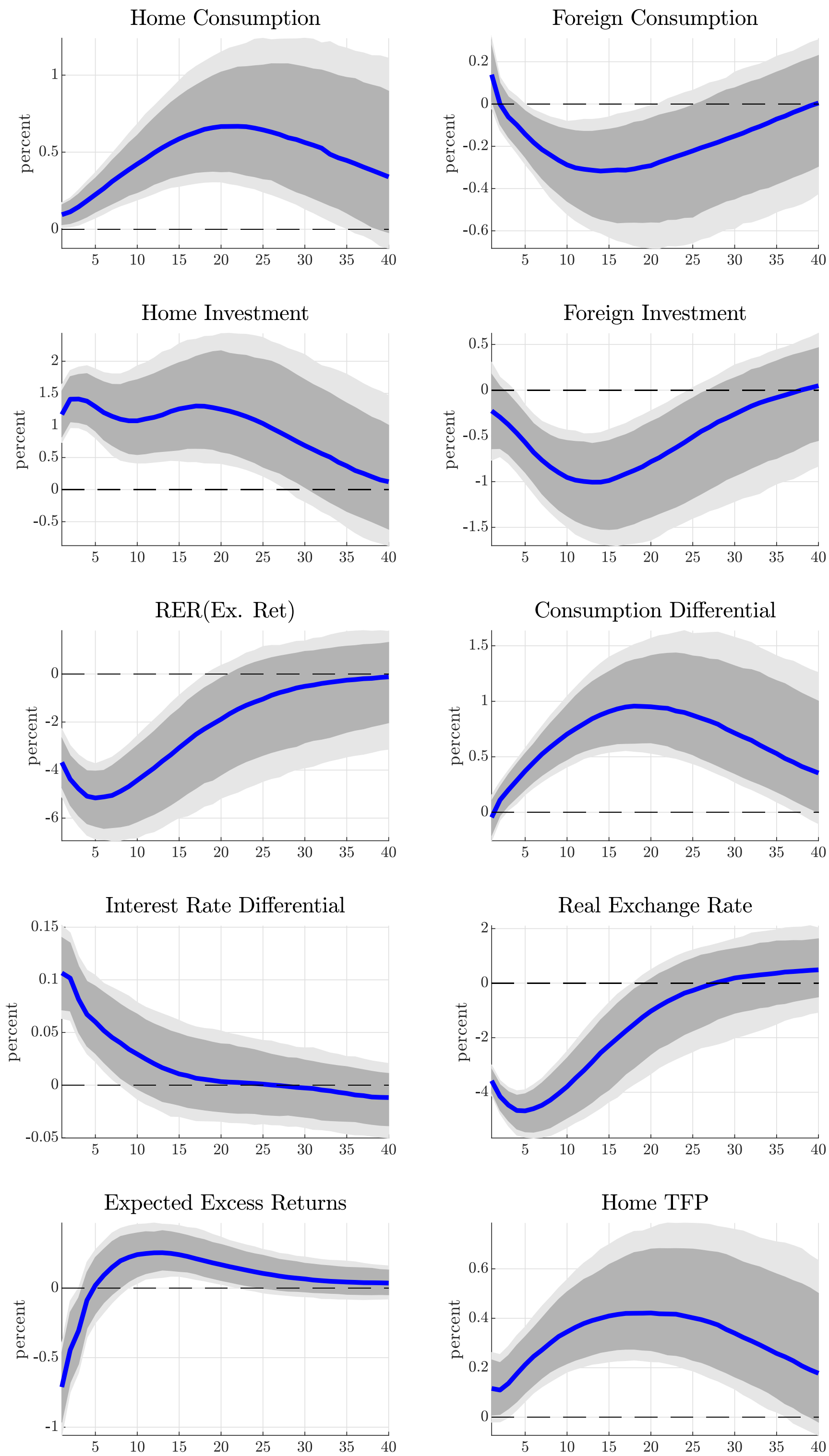
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

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



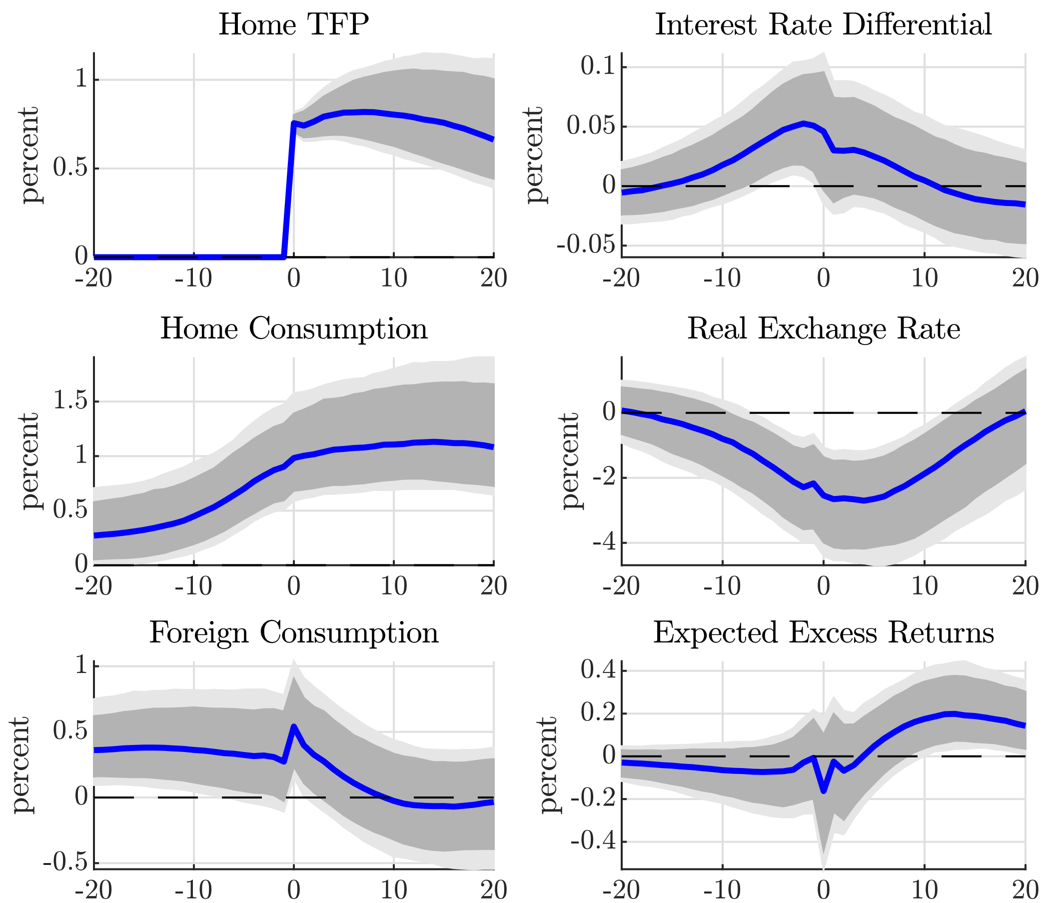
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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



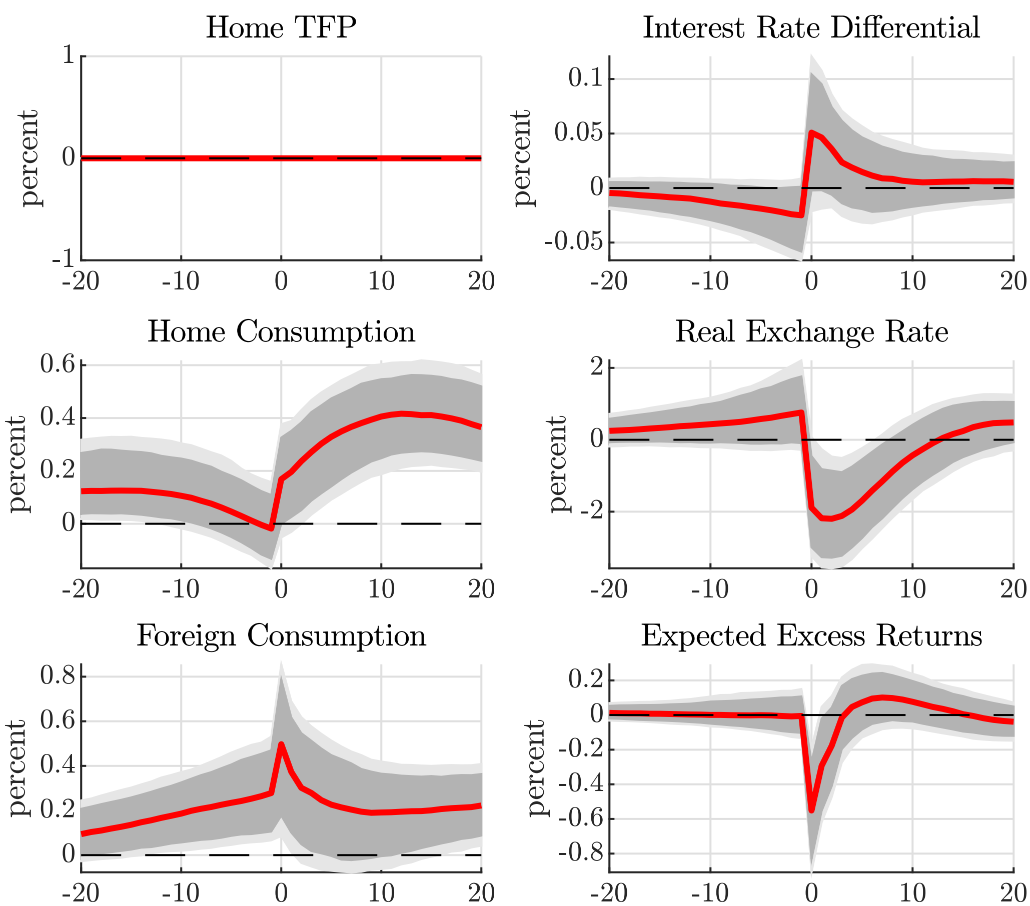
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



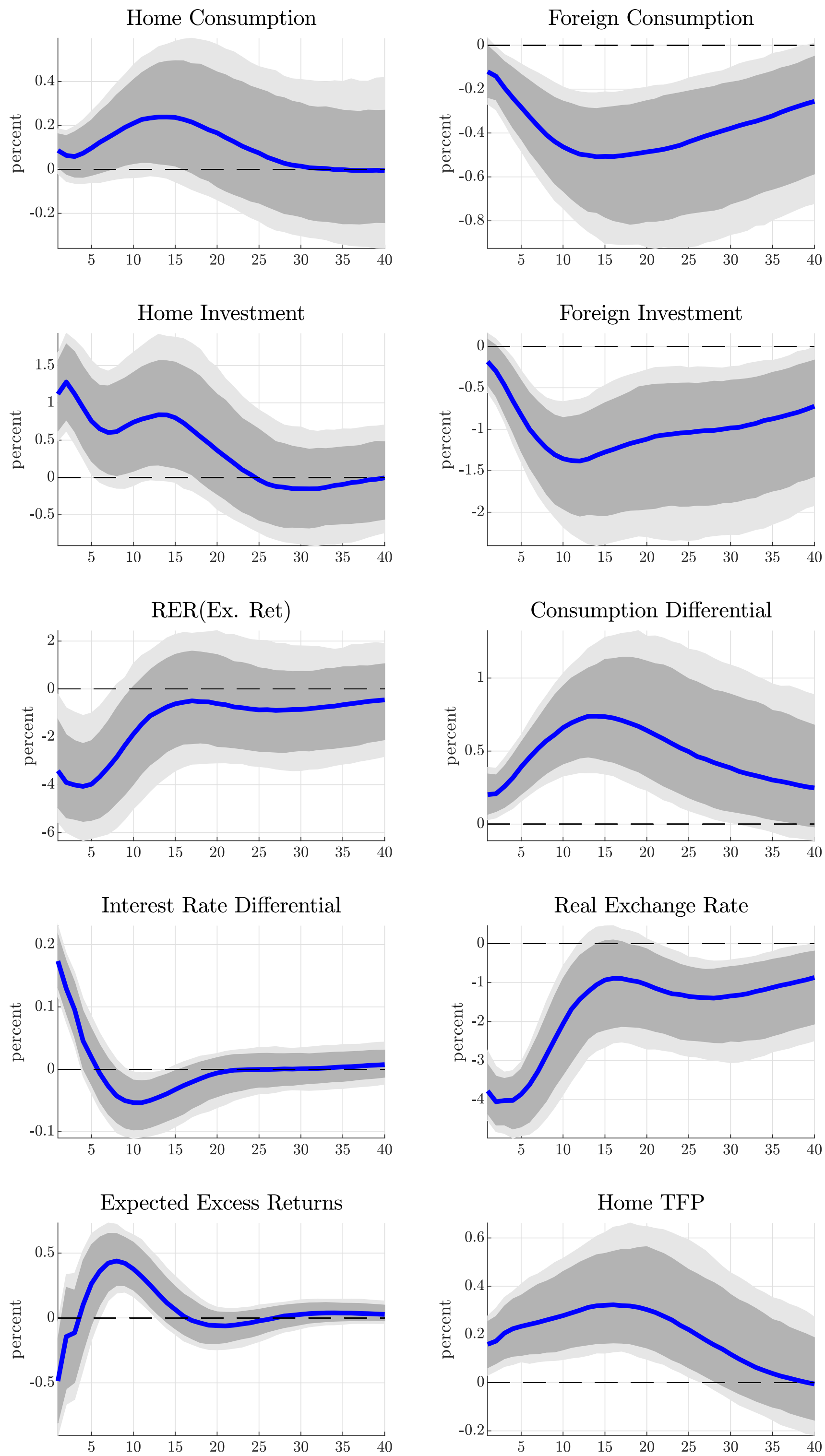
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

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



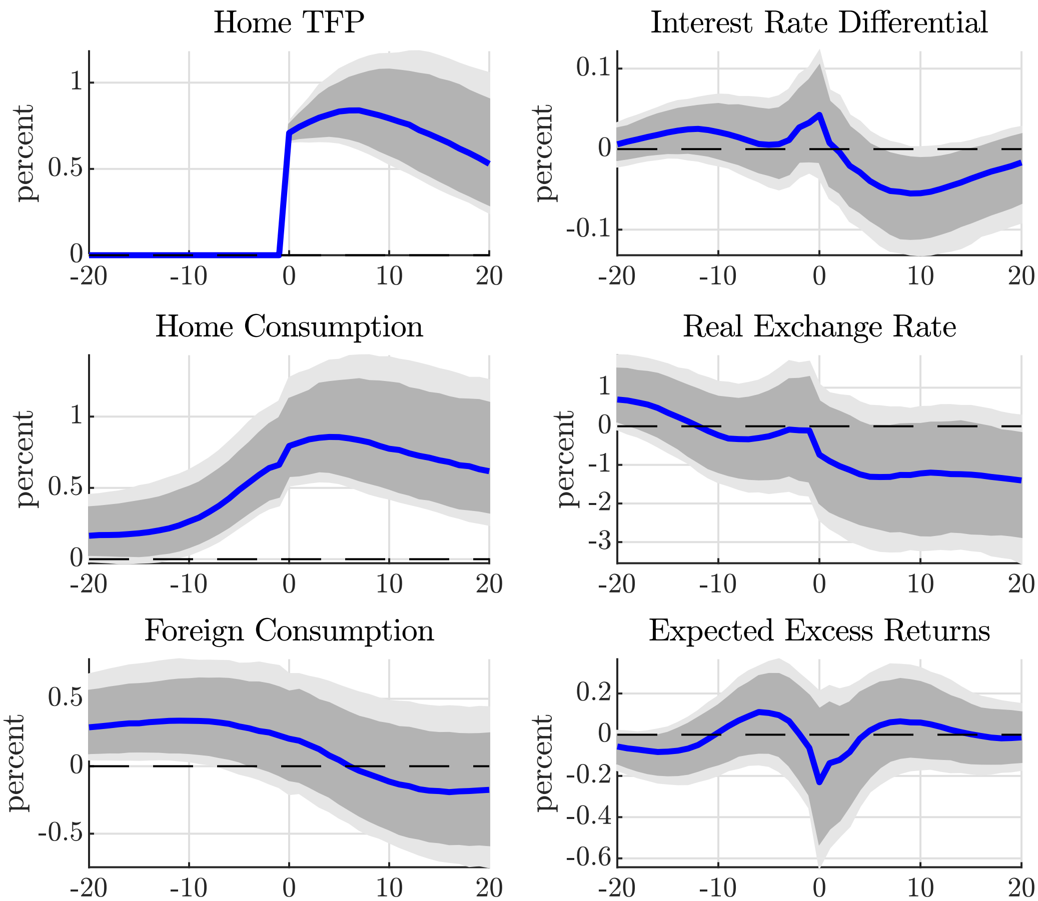
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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



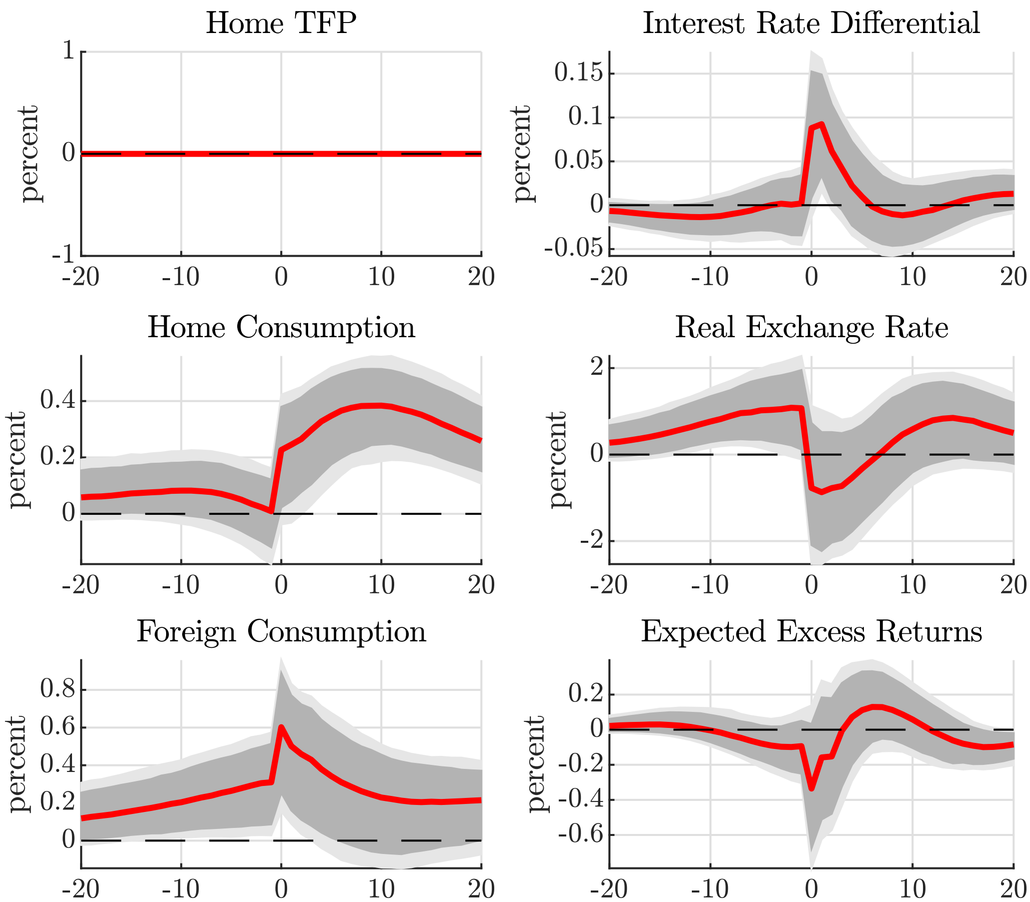
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



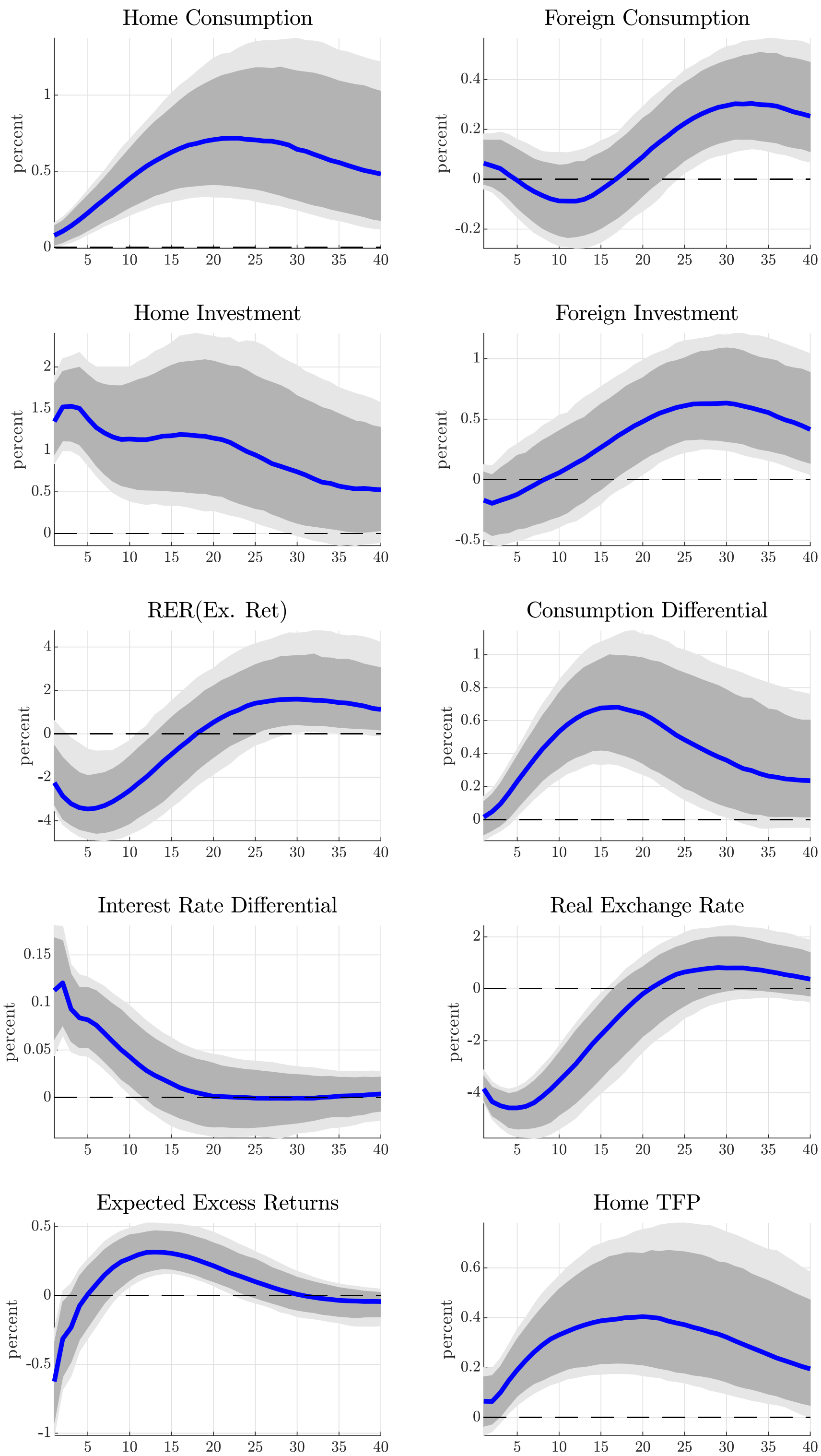
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

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



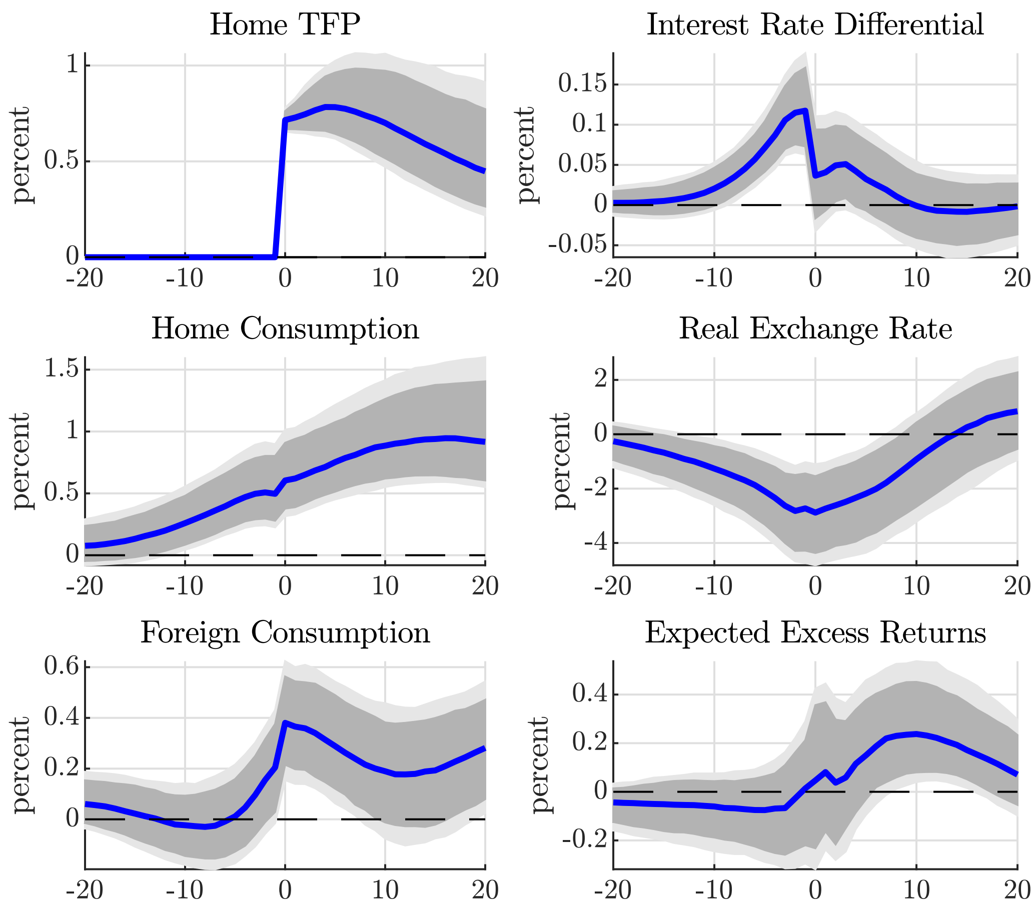
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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



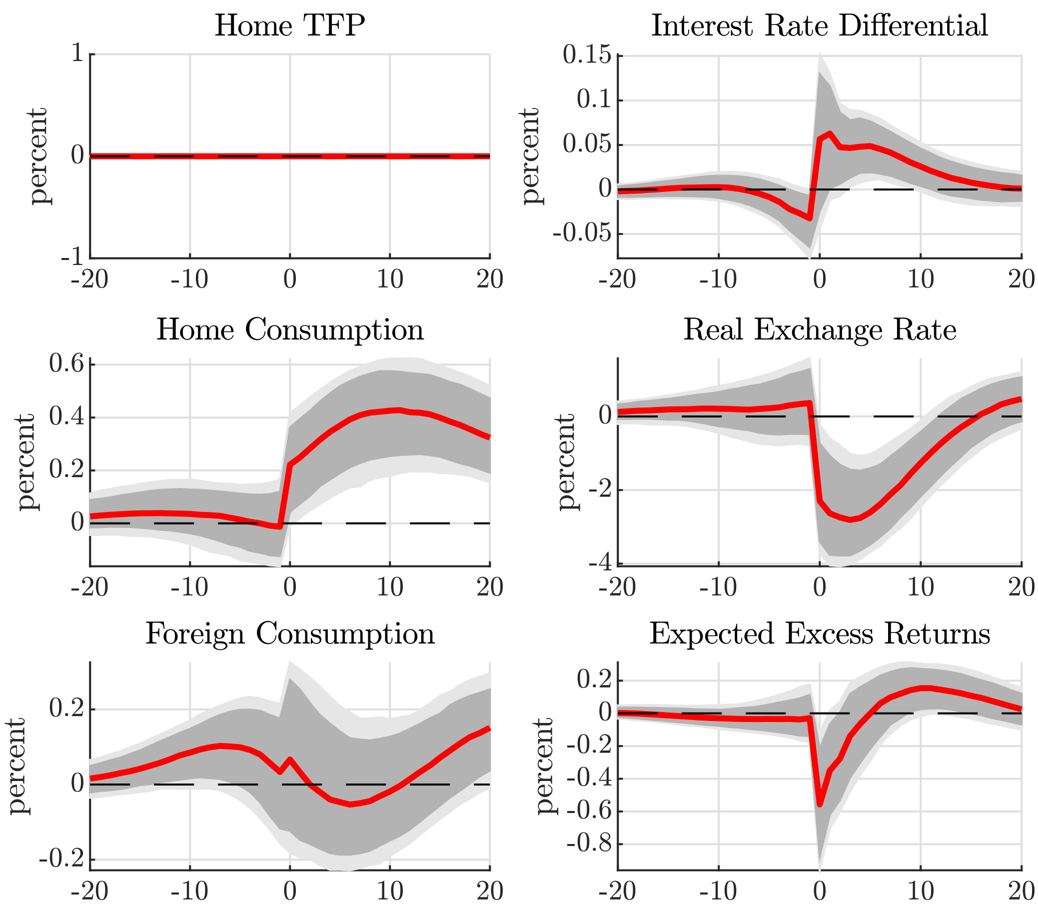
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



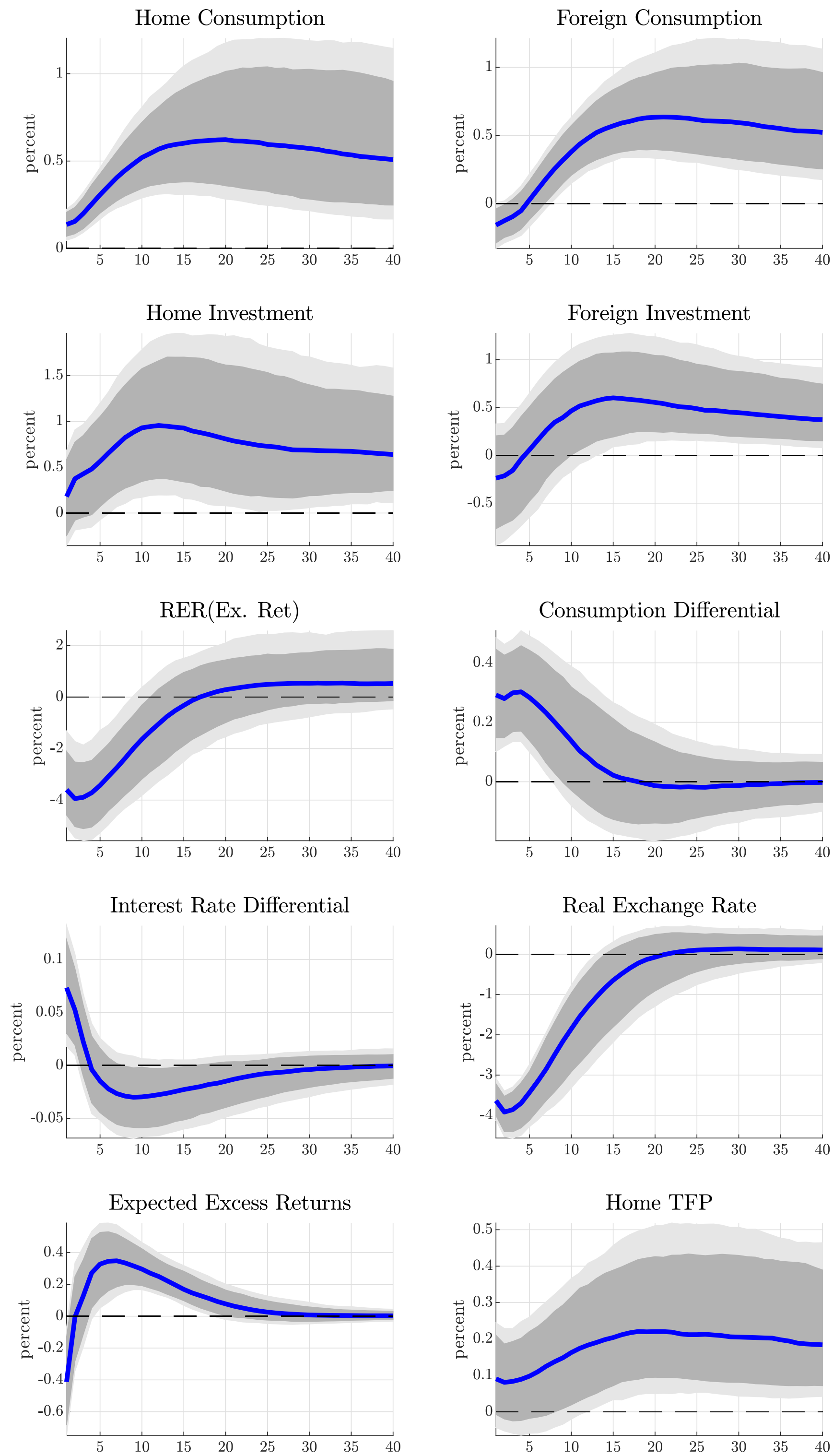
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

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



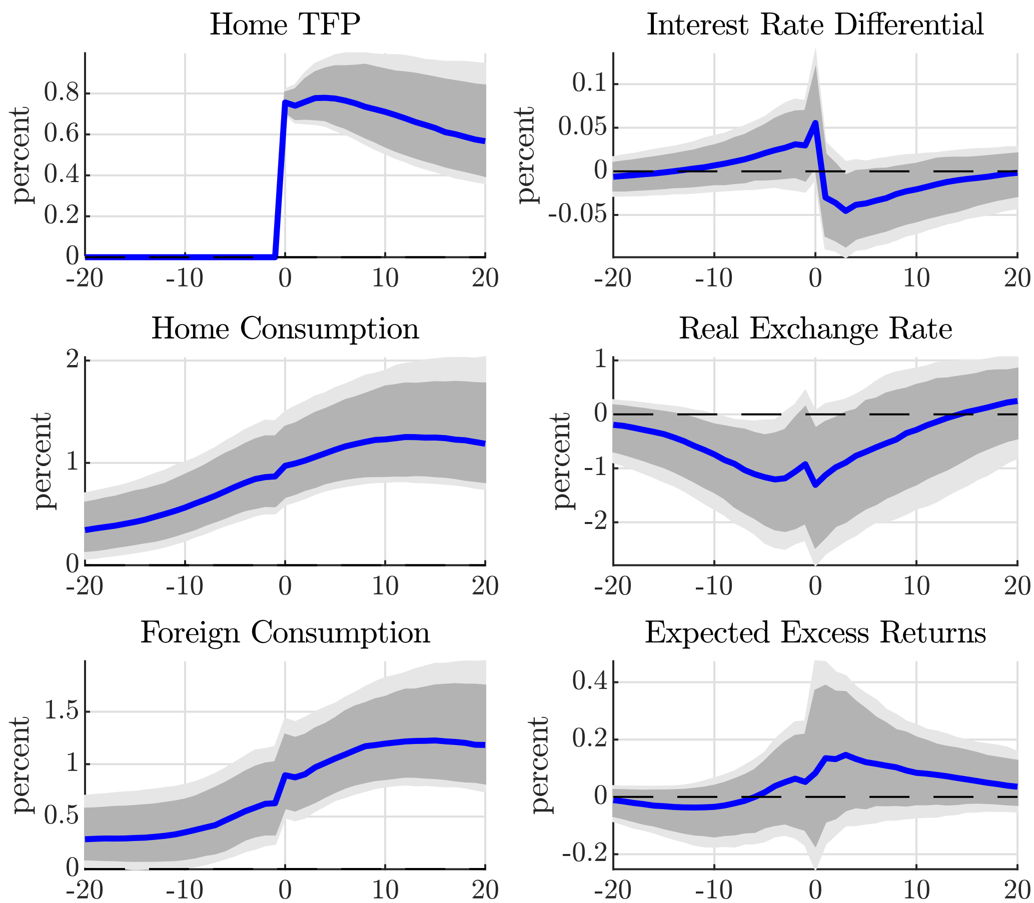
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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



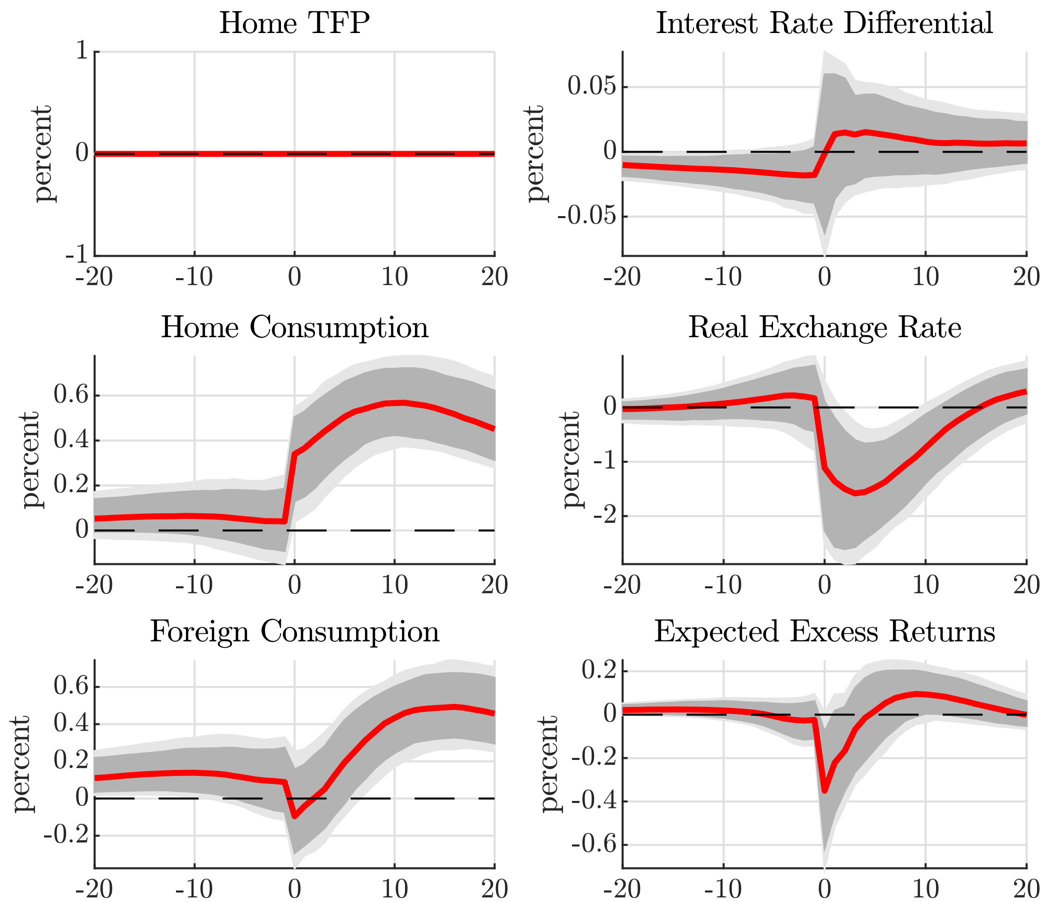
Notes: The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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.