

# Exchange Rate Disconnect Revisited\*

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## Abstract

We find that variation in expected U.S. productivity explains over half of G6 exchange rate fluctuations vis-a-vis the USD. Both correctly-anticipated changes in productivity and expectational “noise,” which influences expectations of productivity but not the actual realization, have significant effects on exchange rates. Together, these two types of disturbances explain many unconditional exchange rate patterns, including predictable excess returns, low [Backus-Smith](#) correlations, and excess volatility. Our findings suggest these well-known puzzles have a common empirical origin, which is linked to (expected) productivity. We also discuss how noise in expectations has obscured the relationship between exchange rates and fundamentals in the empirical approaches undertaken in prior work.

**JEL Codes:** D8, F3, G1

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# 1 Introduction

In most international models, the real exchange rate, which is the relative price of consumption across countries, plays a crucial role in clearing international markets in both real goods and financial assets. As a result, models typically imply that exchange rates are tightly linked to cross-country differentials in macroeconomic quantities, real interest rates and also other asset prices in the economy. However, in the data exchange rates turn out to be largely “disconnected” from a variety of such macro fundamentals, with in particular a distinct lack of correlation between current and past macro quantities (e.g. consumption, [Backus and Smith \(1993\)](#)) and interest rates (e.g. [Fama \(1984\)](#)) on one hand, and exchange rates on the other. There has been a tremendous amount of work focused on resolving the many empirical exchange rate “puzzles” that have been documented, however the bulk of this research is almost entirely based on structural model analysis, without direct, model-free empirical evidence on what might be driving this disconnect in the data.

Contrary to the standard, model-based approach, in this paper, we seek to uncover the main empirical drivers of exchange rate fluctuations only using minimal structural assumptions. Our key finding is that exchange rates are indeed connected to macro fundamentals, however, the link runs between current real exchange rates and *future* macro fundamentals. Specifically, we find that two disturbances, related to future TFP growth and its expectations, account for more than half of the variation in both real exchange rates and also other macro variables like consumption and real interest rates. We separately identify the two disturbances as (i) actual changes in future productivity which are (partially) anticipated; and (ii) an expectational “noise” disturbance, which drives changes in expected productivity *that never materialize in terms of actual productivity changes*.

Another important finding is that while the exchange rate reacts immediately upon the arrival of noisy news of future TFP, other macroeconomic fundamentals generally respond with a lag, and these differential dynamic responses explain the “disconnect” we see in the data unconditionally (i.e. on average). Moreover, the conditional responses to the shocks we identify also generate numerous well-known anomalies like the [Backus et al. \(1993\)](#) and [Fama \(1984\)](#) puzzles, which suggests that a number of major exchange rate puzzles share a common, fundamental source, in noisy information about future TFP. This has important implications for theoretical models and likely propagation mechanisms, as we discuss in some detail.

Our analysis proceeds in two steps. First, we seek a purely “agnostic” description of 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 – the one most important to exchange rate dynamics – explains two-thirds of exchange rate variation *and* around 40% of the variation in macro aggregates. This is essentially a reduced form shock, and while we cannot label its deep structural origins, it is informative to consider how the dynamic responses of the exchange rate and the macro variables differ from one another. We make two key observations. First, the shock immediately impacts the exchange rate, but 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 macro aggregates. Second, we find that the shock has, in particular, no impact on Fernald’s utilization adjusted TFP on impact, but leads to a significant improvement in TFP 3-5 years in the future, and ultimately explains more than 40% of the variation in TFP.

These results intuitively suggest that what we are uncovering with the above reduced form shock is that exchange rates – a forward-looking asset price – react to the arrival of “news” about future changes in technology. With this hypothesis in mind, we turn to the second step of our analysis, in which we specifically identify and isolate shocks to the expectations of future US TFP, and then estimate the implied impulse responses of real exchange rates and other macro variables to these shocks.

We do so in a general way, and among other things allow for the expectations of future TFP to be noisy – for example, our approach would allow for a model in which agents receive a very general form of noisy news about future TFP improvements. To accomplish this, we follow the structural identification approach of Chahrour and Jurado (2021), which allows us to separately identify shocks to TFP that are partially correctly anticipated and also expectational “noise” shocks that influence the expectations of future productivity, but are themselves not related to actual changes in productivity at any lead or lag. Intuitively, this identification approach is designed to separately identify the “signal” from the “noise” component in the underlying noisy news about the future. And the basic idea is to exploit the fact that as econometricians we can look at the data ex-post, and thus decompose the estimated TFP expectations in a component that does eventually materialize, and a component that turns out to be pure noise, unrelated to any actual changes in productivity.

Implementing this approach in our baseline VAR, we find that both of these types of disturbances, anticipated actual future TFP changes and “noise” in TFP expectations, play an

important role in driving exchange rates and in generating the well-known 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 (Fama, 1984) and the recently documented “reversal” in this forecastability pattern at longer horizons (Engel, 2016; Valchev, 2020). Both sets of disturbances also cause conditional movements in exchange rates and (delayed) movements in aggregates that generate the Backus and Smith (1993) puzzle, and the exchange rate determination puzzle more broadly. We also study the impulse responses of a number of other variables of interest, such as the trade balance and stock prices, and similarly find the intuitive results that the US current account deteriorates and US stock prices rise in anticipation of an improvement of future productivity.

Ultimately, our results essentially speak to three main points. First, forecastable fluctuations in future productivity are indeed reflected in current exchange rates, as we would naturally expect under an asset view of exchange rates. On the other hand, we find that the unforecastable component of TFP changes has little to no impact on exchange rates. Taken together, these two empirical findings can help us understand why previous empirical analysis much of which has focused on evaluating the relationship between exchange rates and current and lagged TFP (and other macro variables), has failed to find a robust relationship.

Second, our findings indicate that the exchange rate also reflects the fact that while TFP is partially forecastable, the forecasts are noisy, and the corresponding expectational noise is also priced into the exchange rate. This can help us understand why previous studies that, similar to us, have emphasized the forward-looking nature of exchange rates, have also failed to find a robust relationship between exchange rates and future TFP (and macro variables more broadly). The bulk of such studies utilized *unconditional* Granger-causality type of analysis (e.g. Engel and West (2005)), by regressing current TFP on lags of the exchange rate. In this kind of unconditional regressions, where the real exchange rates is on the right hand side, the expectational noise we find acts as a classical measurement error and biases the coefficients downward. In small samples, which exchange rate data often suffers from, this could weaken and obfuscate the relationship between lagged exchange rates and future TFP. In our *conditional* analysis, we separately identify both the TFP innovation itself and the noise in the TFP expectations, and this helps us uncover a much stronger and robust empirical relationship.

Third, we find that the two shocks we uncover transmit to the exchange rate almost

exclusively through imparting significant fluctuations in the so called UIP wedge – that is by causing time-variation in expected currency returns. At a basic level, this means that the UIP wedge and currency returns are largely endogenous to shocks to noisy expectations of future TFP. Thus, our findings speak in favor of theoretical models where there is a mechanism through which UIP violations are endogenous, and not driven by separate, exogenous sets of shocks. In particular, our findings intuitively speak in favor of long-run risk type of models (e.g. [Colacito and Croce \(2013\)](#)), where the partial forecastability of TFP far in the future plays an important role in currency returns. However, as we discuss in detail later, much work remains to be done, as existing models do not align perfectly with the specific details of our findings. Still, we share the conclusion that fluctuations in expectations of long-run TFP plays a vital role, through its impact on deviations from interest parity.

Lastly, let us stress that the expectational (“noise”) disturbances we identify are best understood as rational expectations error, akin to the noise component in a noisy signal about future TFP. This noise disturbance is conceptually different from the notion of exogenous disturbances in the demand for foreign currency bonds, which the previous literature has often labeled as “noise” in exchange rates. Our noise shock is a component of the statistically optimal forecast of future TFP, and thus is tightly linked to macroeconomic fundamentals. It is quantitatively important on its own, contributing to about 20% of the variation in exchange rates in levels, and being even more important for the fluctuations of exchange rates in first differences, and high frequencies more generally.

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

Contrary to this literature, we find that there is indeed a connection between exchange rates and macroeconomic fundamentals, but one that relates 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 Stavrageva, 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 by or strongly correlated with current fundamentals, but is rather forward looking and incorporates news about 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* and *noisy* foresight of future productivity. Failing to account for the noise contributes to the previous weak finding of exchange rates Granger-causing macroeconomic aggregates (Engel and West, 2005; Sarno and Schmeling, 2014).<sup>1</sup>

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 reflecting expected future currency returns. Our definition of “news” is different, as we specifically identify disturbances to the forecast of *future U.S. TFP* changes, as opposed to revision of beliefs about *past* endogenous variables such as output.

Relative to the papers discussed above, our results also specifically show a link between imperfect information about the future and the emergence of two seminal exchange rate puzzles – the UIP puzzle (Fama, 1984; Engel, 2014) and the Backus-Smith puzzle (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.<sup>2</sup> Such models, however, have typically 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” as shocks cause contemporaneous changes in both exchange rates and other macroeconomic quantities.

To confront this challenge, a new strand of the literature has analyzed mechanisms that

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<sup>1</sup>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.

<sup>2</sup>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.

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).<sup>3</sup> Most notably, Itskhoki and Mukhin (2021) show such that shocks to the UIP wedge can generate not only the exchange rate disconnect, but also the UIP puzzle and the Backus-Smith puzzle.

Our evidence echoes a key insight of Itskhoki and Mukhin (2021): resolving the broad exchange rate disconnect requires shocks that move exchange rate today but without a contemporaneous movement in the real resource constraint. We emphasize that this is a distinctive feature of models with imperfect information about future productivity. Our evidence thus support news-type shocks as promising alternative to models with *exogenous* shocks to the UIP wedge. 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, and causes *endogenous* fluctuations in the UIP wedge. 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.<sup>4</sup>

Overall, our results indicate that candidate mechanisms of 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 a 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 macro aggregates, we put forward new

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<sup>3</sup>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

<sup>4</sup>Models in which investors have dispersed information about future fundamentals and learn from equilibrium exchange rate movements, as in Bacchetta and van Wincoop (2006) appear as an interesting middle ground. In these models, the exchange rate acts as a public signal for future fundamentals and “noise-trader shocks” act as the noise in this (public) signal. This framework thus equates the two notions of noise. Our evidence quantifies the relative contribution of signal and noise in equilibrium exchange rate movements.

evidence on the conditional relationship between consumption and TFP as well as a broader set of puzzle. As we discuss further below, 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 \(2014\)](#).<sup>5</sup> Perhaps most closely related to us is the work of [Nam and Wang \(2015\)](#), who use [Barsky and Sims’ \(2011\)](#) approach to identifying news-to-TFP shocks, and find that they indeed have a statistically significant impact on exchange rates in the data. In contrast to us, however, they do not separately identify the effects of fundamental disturbances from those driven by expectational disturbances that are orthogonal to fundamentals, and do not consider the effect of the shocks on exchange rate puzzles. 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 The nature of exchange rate surprises

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 \(2003\)](#) to extract the shock that explains most of the variation in the real exchange rate. This approach was recently adopted by [Angeletos et al. \(2020\)](#) to extract the so-called “main business cycle” shock. In parallel to the [Angeletos et al.’s \(2020\)](#) terminology, we refer to the shock we extract as the “main exchange rate” shock.<sup>6</sup>

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<sup>5</sup>[Corsetti et al. \(2014\)](#) identify US manufacturing productivity shocks using a sign-restriction approach. However, they do not separately identify technological and noise disturbances.

<sup>6</sup>See also [Kurmman and Otrok’s \(2013\)](#), [Basu et al. \(2021\)](#) and [Chahrour et al. \(2020\)](#) as other applications of the [Uhlig \(2003\)](#) max-share approach to macro variables. More specifically, the recent paper by [Miyamoto](#)

## 2.1 Econometric procedure

We start by estimating the VAR

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

where the vector  $Y_t$  contains data on the U.S. and a trade-weighted aggregate for the other G6 economies. Hereinafter, we will refer to the U.S. and the G6 economies as the “home” and “foreign” economies, respectively. The endogenous variables are the nominal exchange rate  $S_t$  expressed in units of USD per foreign currency, Fernald’s (2012) series on utilization-adjusted U.S. TFP, U.S. real consumption and investment, foreign real consumption and investment, the interest rate differential, and the CPI price level differential between the U.S. :

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

For our benchmark results, we use quarterly data for the time period 1978:Q3-2008:Q1 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, in the Appendix we conduct our analysis on the longest sample we have data for (1978:Q3-2018:Q1) and the results remain very similar.

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 the average of daily Eurodollar rates within a quarter, obtained from Datastream.<sup>7</sup> The CPI indices and the consumption and investment series are from the OECD database. Lastly, the US TFP is from John Fernald’s website. Some authors have proposed approaches to overcome the data limitation and construct utilization-adjusted TFP for G6 economies. However, we find these measures unreliable for our purposes. When these approaches are used to construct utilization-adjusted TFP for the United States, they display a low correlation (between 20% and 40%) with the widely-accepted Fernald’s measure. Also, some of the proposed measures can only be constructed at annual frequencies or for short

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et al. (2022), similar to us, applies this methodology to exchange rates. However, they focus on high frequency movements in the exchange rate, and also consider a VAR expressed in terms of cross-country differentials, which puts the focus on country-specific shocks.

<sup>7</sup>Note that these interest rate differentials are not forward discount-implied interest rate differentials, but actual eurodollar rates.

sample periods.

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, etc.<sup>8</sup> 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. In the Appendix we also report separate results obtained when estimated bilateral VARs between the US and each of the other six G7 economies, and results are substantially similar.

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 Evans (1995)), we estimate the VAR in levels and do not impose ex-ante that there are any specific cointegration relationships. In the Appendix we show that results remain unchanged if one instead estimates a VECM model that impose the same cointegration relationships as Engel (2016), where the real exchange rate and interest rate differential are assumed stationary. 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  $q_t$  is commonly defined as the log ratio of the nominal exchange rate and CPI differentials,  $q_t = s_t + p_t^* - p_t$ . Note that while it is not explicitly included in the VAR, the real exchange rate is a linear combination of the variables in the VAR. Thus, 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:

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

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<sup>8</sup>We use the same trade-weights as utilized in Engel (2016).

We assume that the structural shocks,  $\varepsilon_t$ , are orthogonal with unitary variance. Therefore, the impact matrix  $A_0$  has to satisfy the condition  $A_0 A_0' = \Sigma$ , 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  $\tilde{A}_0 D = A_0$ , where  $D$  is an orthonormal matrix, and 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  $\Sigma$  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 0 elsewhere, and  $B_\tau$  is the matrix of moving average coefficients at horizon  $\tau$ .

Uhlig's (2003) approach consists of finding the column of  $D$  that isolates the shock that explains most of the forecast error variance of a specific variable  $y_i$  up to a forecast horizon  $H$ . Formally, we solve

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

subject to  $d_1' d_1 = 1$ , where  $d_1$  is the first column of  $D$ . The problem is analogous to finding 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,  $e_i$ , 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 can be informative of the basic structure of dynamic comovements associated with surprise changes in the exchange rate.

## 2.2 The broader footprint of a typical exchange rate surprise

We find that it the ‘‘main exchange rate shock’’ is indeed very important for exchange rate fluctuations as it explains roughly 70% of variance of the real exchange rate (see Table 1, column 1). This result indicates that the data imply there is a large degree of commonality

in the dynamic patterns that emerge along with a surprise change in the real exchange rate. More interestingly, we also find that this shock explains a significant portion of the variation of the macro aggregates included in the VAR. Specifically, it accounts for around 40% of the forecast error variance at a horizon of 100 quarters of consumption and investment (both home and foreign), as well as home TFP.<sup>9</sup> For the macro aggregates we turn to a decomposition of the forecast error variance, 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 forecast error variance decomposition at 100-quarters is identical to that emerging from the decomposition of the unconditional variance.

The finding that the main exchange rate shock drives a large amount of the variation in both exchange rates *and* macro aggregates appears, at first glance, surprising given the well-established result that exchange rates appear to be largely disconnected from macro fundamentals (e.g., [Meese and Rogoff, 1983](#) and [Engel and West, 2005](#)).

Yet, we will show that these two results can be easily reconciled. The seminal results on the exchange rate disconnect primarily focus on the *contemporaneous* unconditional correlation between exchange rates and macro aggregates. To the contrary, we find that the effects of the main exchange rate shock materialize at different horizons in exchange rates and macro aggregates. Conditional on a main exchange rate shock, the exchange rate moves immediately, while macro aggregates largely react with a significant lag. These difference in *timing* will result in a mild *contemporaneous* correlation between exchange rates and macro aggregates.

To show this result, we report the impulse response functions of several variables of interest to the “main exchange rate shock” (MFX) in [Figure 1](#). The median impulse response is plotted with a solid blue line, and the shaded areas denote the 16-84th percentile and the 10-90th percentile bands respectively.

A number of 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 hump-shaped dynamics, where it continues to appreciate for another 5 quarters after the initial appreciation, peaking at a maximum appreciation of about 3.5%, and thereafter it steadily depreciates back to its long-run mean. The non-monotonic dynamics we recover are similar to the ones previously emphasized [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”

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<sup>9</sup>The forecast error variance at a horizon of 100 quarters is formally defined as  $\text{Var}(x_{t+100} - \mathbb{E}_t(x_t))$ .

Table 1: Share of forecast error variance explained by the Main FX shock ( $\varepsilon_1$ )

	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.

puzzle documented by previous studies.<sup>10</sup>

Importantly, the hump-shaped exchange rate patterns characterized by initial appreciation and subsequent depreciation underlie a related “cyclical” pattern in the deviations from uncovered interest parity. Specifically, the MFX shock generates non-monotonic movements in *expected* excess currency returns. Expected excess currency returns are defined as  $\mathbb{E}_t(\lambda_{t+1}) \equiv \mathbb{E}_t(\Delta q_{t+1} + r_t^* - r_t)$ , and computed using VAR-implied expectation. The impulse response of expected excess currency returns reveals that these are negative on impact and remains so up to five quarters after the shock, and then turns significantly positive and remains so for several years afterwards. Such predictable variation in the expected excess returns is a violation of the uncovered interest parity (UIP) condition.

We observe that the MFX shock spurs a monotonic 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 (Fama, 1984). In the medium run, the direction of the UIP violation reverses, with the USD earning low returns for an extended period of time. Thus, the main exchange rate shock generates exchange rate dynamics that are consistent with the reversal of UIP viola-

<sup>10</sup>Hump-shaped dynamics also emerge following an identified monetary policy innovation. This result was initially shown by Eichenbaum and Evans (1995) and it is commonly referred to as “delayed overshooting.”

tions at longer horizons documented by previous studies such as Engel (2016) and Valchev (2020).

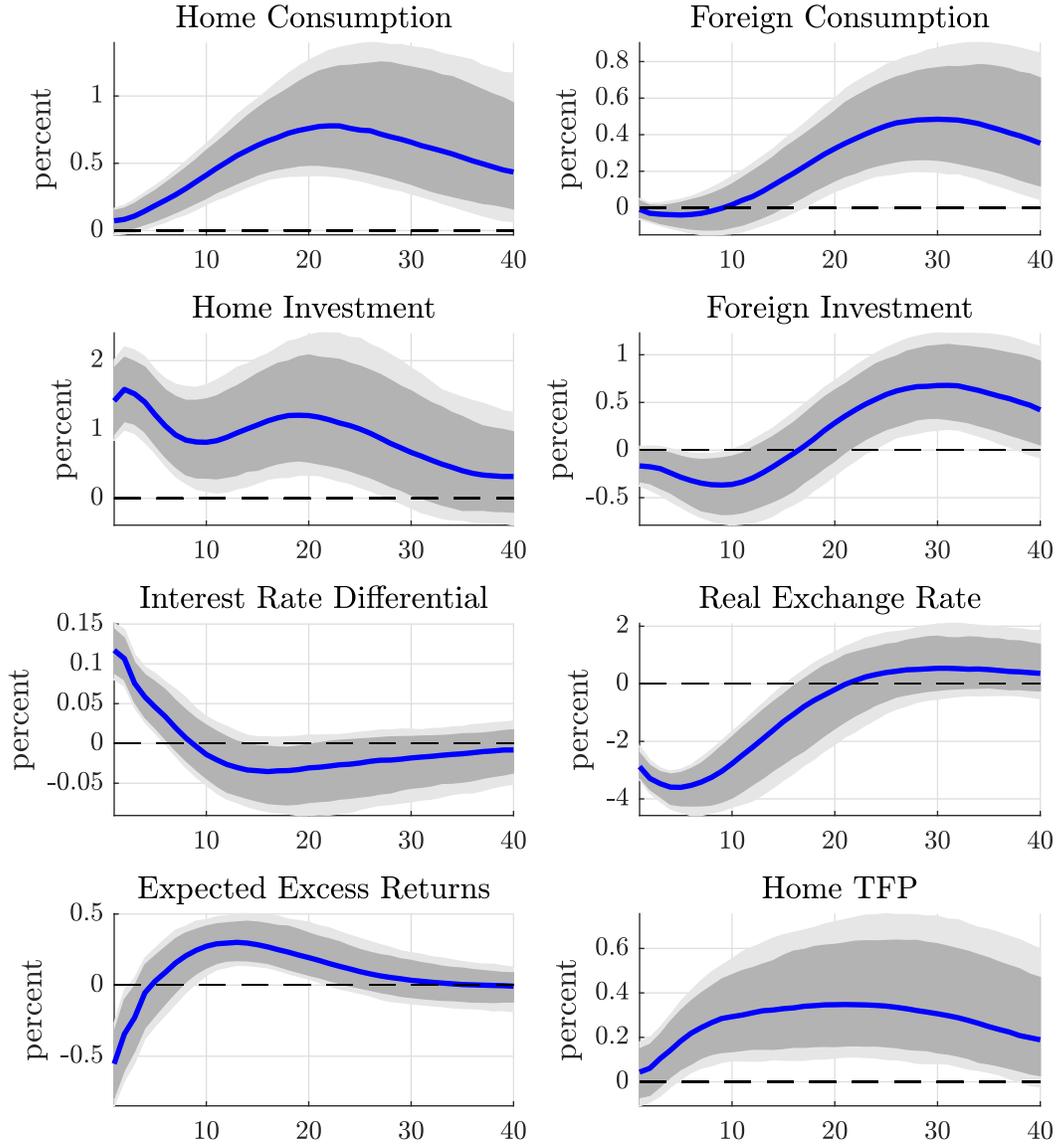
Overall, the results suggest that our empirical procedure is indeed picking up not just a shock that is responsible for a large fraction of exchange rate fluctuations, but also generates several important and familiar exchange rate “puzzles.”

We now turn to the dynamics of macro aggregates related to the main exchange rate shock. First, we note that the MFX shock 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 (around 0.8%) is about double the size of the peak effect in foreign consumption (around 0.5%). As a result, we observe the classic violation of the Backus and Smith (1993) condition that  $corr(q_t, c_t - c_t^*) = 1$ . In fact, in contrast to this risk-sharing condition, the exchange rate appreciates, while the consumption differential rises above its mean, rather than falling.

We observe that the impulse response of TFP shows a similar delay. The MFX shock causes no significant impact on productivity up to five quarters in the future, while productivity eventually displays a significant and prolonged increase at longer horizons. The effect peaks at 0.4% around 20 quarters after the initial impulse. Overall, both consumption and TFP display a significant response in the medium-to-long run, but no response in the immediate aftermath of the shock. The lack of a short-run responses in these core macro series, in contrast to the large immediate response in the exchange rate, imply an apparent contemporaneous disconnect between exchange rates and macro aggregates. While this is consistent with the notion of disconnect emphasized in the previous literature, we want to emphasize that our results suggest the disconnect is in the *timing*. The exchange rate is indeed significantly related to *future* macro aggregates.

We note that the response of the TFP series is reminiscent of a “news” shock, as it implies that the eventual increase is essentially predictable in advance. Given such anticipation, standard models would imply that home investment should increase immediately. This is precisely what we observe in the impulse response of home investment. Similarly, foreign 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 (Backus et al., 1992, 1994).

Figure 1: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ )



*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.

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

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

First, the bulk of the variation in the real exchange rate (68% of the total) is essentially not related contemporaneously to aggregate consumption or TFP. Rather the exchange rate *leads* these macro aggregates that the prior literature has often tried to connect to the exchange rate. Thus, these results reveal that the canonical finding of a “disconnect” does not emerge because of an actual separation between exchange rate and fundamentals, but rather because of a difference in the timing of the responses these variables to the same macroeconomic surprise(s).

Second, in addition to this basic disconnect puzzle, the dynamic responses to the MFX shock display a number of other well-established exchange rate puzzles. We have discussed above that the MFX shock causes a dynamic comovement consistent with the high persistence of the real exchange rate, its short-run and long-run patterns of UIP violations, as well the classic violation of the [Backus and Smith](#) condition that  $corr(q_t, c_t - c_t^*) = 1$ . 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 comovement 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 main exchange rate shock has no direct structural interpretation. So, next we turn to directly testing the hypothesis that disturbances to anticipated TFP indeed affect 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 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 their expectations of future TFP, we would expect that shocks to TFP expectations will also materially (and immediately) influence the exchange rate.

### 3.1 Identifying TFP and noise disturbances

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 expectations 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 noise component in expectations is evidence of imperfect advance 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 (see, e.g., [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.<sup>11</sup>

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

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

where  $\varepsilon_{t+k}^a$  are the Wold-representation innovations to the TFP process  $a_t$ :

$$a_t = A(L)\varepsilon_t^a. \tag{5}$$

Further assumptions on the particular structure of the TFP process or on the coefficients  $\zeta_k$  are not necessary. Moreover, the noise component of the signal is also very general, and

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<sup>11</sup>From a broad perspective, the results are qualitatively similar when using [Barsky and Sims’s \(2011\)](#) procedure.

allowed to have an arbitrary lag structure:

$$v_t = \sum_{k=1}^{\infty} \nu_k \varepsilon_{t-k}^v.$$

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

$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \dots + \begin{bmatrix} 0 & 0 \\ * & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1}^a \\ \varepsilon_{t+1}^v \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_t^a \\ \varepsilon_t^v \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_{t-1}^a \\ \varepsilon_{t-1}^v \end{bmatrix} + \dots$$

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; that is,  $a_t$  is a function of the history of  $\varepsilon_t^a$  up to and including time  $t$ . In addition, we assume the signal  $\eta_t$  contains information about future productivity disturbances,  $\varepsilon_{t+k}^a$ , while the signal noise disturbances  $\varepsilon_t^v$  are orthogonal to productivity at all leads and lags. This gives us enough restrictions to uniquely identify the two disturbances,  $\varepsilon_t^a$  and  $\varepsilon_t^v$ .

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,  $\eta^t$ , 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  $\varepsilon_{t+k}^a$ , 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,  $\varepsilon_t^v$ , 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,  $\varepsilon_{t+k}^a$ , 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  $\varepsilon_{t+k}^a$ , we can therefore see an indication of whether (and how) fundamental disturbances are anticipated. By examining responses to the second type of disturbance,  $\varepsilon_t^v$  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 that we observe the relevant signal  $\eta_t$ . In prac-

tice, however, 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 capture 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  $\varepsilon_{t+h}^a$  and one related to  $\varepsilon_t^v$ . We choose  $h = 20$  to match the peak in the TFP IRF in Figure 1.<sup>12</sup>

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.

### 3.2 The dynamic effects of TFP and noise disturbances

We begin by reporting the estimated impulse responses of TFP,  $a_t$ , along with the 20-quarter ahead expectation of TFP,  $\mathbb{E}_t(a_{t+20})$ , in response to the fundamental technological disturbance,  $\varepsilon_t^a$  in Figures 2 and to the expectational noise disturbance  $\varepsilon_t^v$  in Figure 3. These would be informative about the basic structure of the estimated information set and agent’s ability to anticipate TFP.

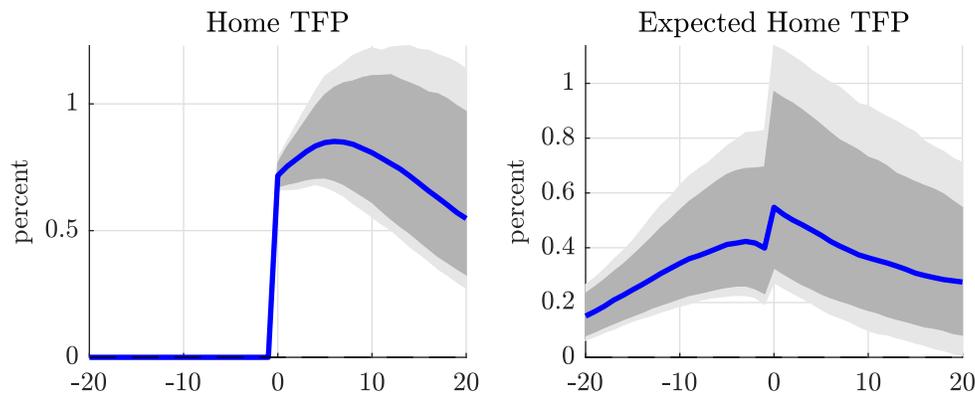
Since anticipated productivity shocks can influence endogenous variables before the actual change in productivity, we plot each figure from 20 quarters *before* the respective innovation (either  $\varepsilon_t^a$  or  $\varepsilon_t^v$ ) materializes. The extent to which TFP anticipation plays a role in the data can be evaluated by observing whether the estimated IRFs respond significantly to  $\varepsilon_t^a$  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  $-1$ . 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  $\varepsilon_t^a$  increase, plotted in the left panel of Figure 2.

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<sup>12</sup>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 2: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances



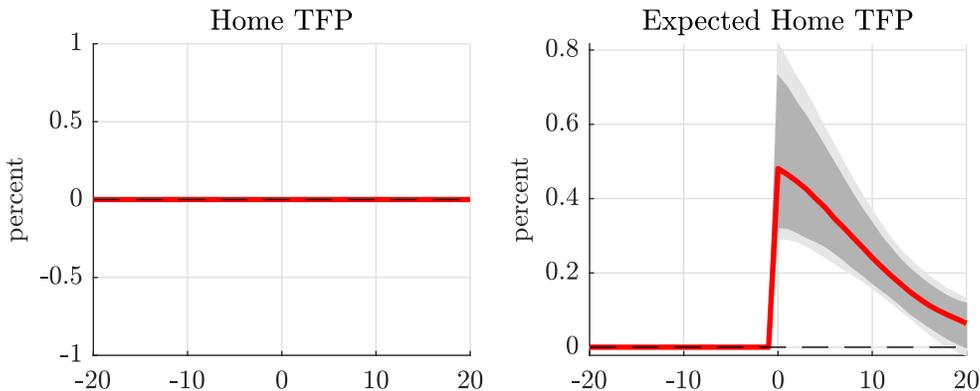
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Naturally, the level of TFP does not change until the disturbance  $\varepsilon_0^a$  is actually realized (at time 0), and then TFP exhibits fairly persistent dynamics while returning to its long-run mean.

In the right panel of Figure 2 we plot the impulse response of the expectation of TFP 20-quarters ahead,  $\mathbb{E}_t(a_{t+20})$ . We observe that this variable is significantly higher than its long-run mean even 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 20-quarters ahead of time. We can also see that the expectation is not perfect, of course, by the fact that the impulse response of  $\mathbb{E}_t(a_{t+20})$  jumps at time 0, indicating that the actual realization still surprised the agents, and led to adjusting expectations upwards upon observing the actual  $\varepsilon_t^a$  increase.

Another way to see that expectations are imperfect, is by considering the impulse response to the pure expectational noise disturbance  $\varepsilon_t^v$ , which we plot in Figure 3. 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 of Figure 3 we see that the expectational noise shock indeed moves expectations, where a one standard deviation  $\varepsilon_0^v$  increase (so an “optimistic” revision of future TFP), leads to a 0.5% increase in expected TFP 20-quarters out. This impulse response then converges back

Figure 3: Impulse responses to Noise ( $\varepsilon^v$ ) 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.

down to its long-run mean, which signifies that agents learn, over time, that their initial optimism was misplaced.

The results in Figure 2 and Figure 3 together, thus, reveal 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.

We now turn to the impact of these two types of disturbances on the rest of the endogenous variables in the VAR, with a special attention played to the response of the exchange rate. In Figure 4 we plot the responses to a TFP innovation,  $\varepsilon_t^a$ , 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. We also report the response of the level of TFP again for reference.

We focus on the real exchange rate first. The response exhibits a pronounced V-shape, which peaks right around the time at which the TFP increase actually materializes. That is to say, the real exchange rate significantly appreciates *before* the actual TFP improvement, revealing that the TFP anticipation effects are indeed priced into the exchange rate. The maximum appreciation of about 2% occurs right around period-0, after which the exchange rate then steadily depreciates. 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.

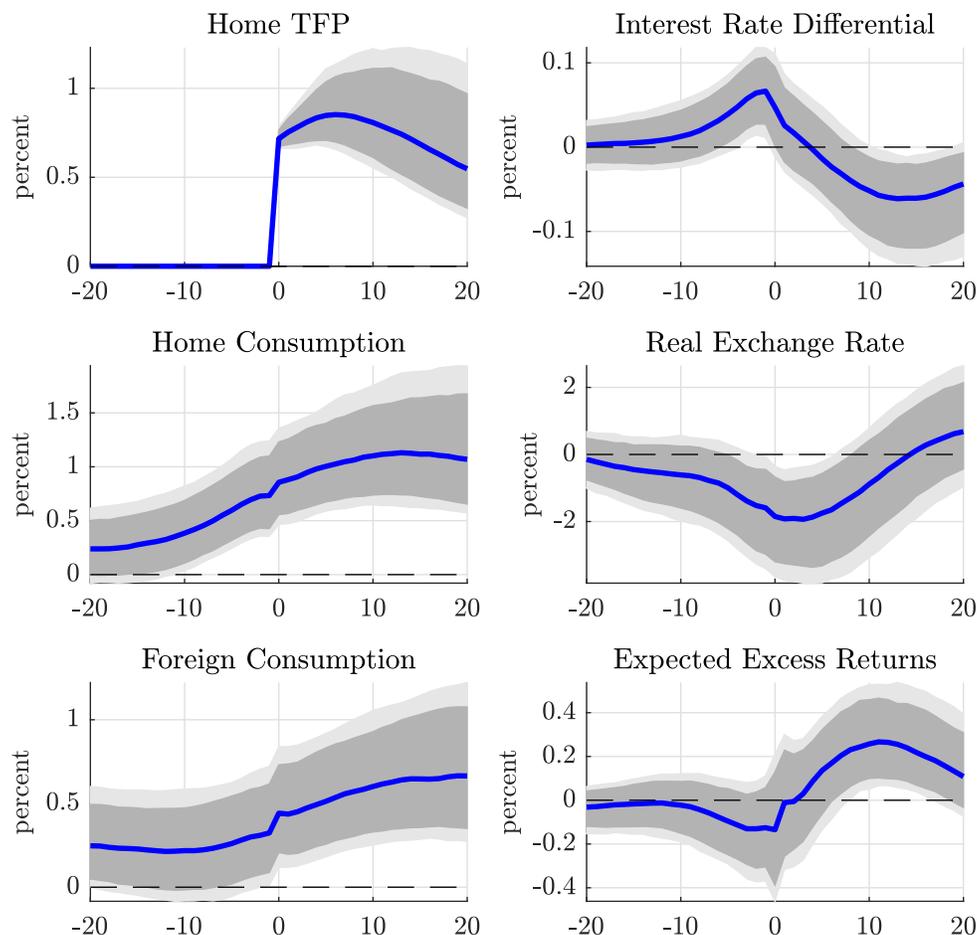
This basic hypothesis is consistent with the responses of the interest rate differential and relative consumption as well. The 3-month dollar interest rate increases before the TFP innovation, peaking at around 7.5 basis points higher than its long-run mean (or 0.3% at an annualized basis), which could 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 increase materializes, and is in fact significantly lower than its mean for a prolonged period of time between 10 and 20 quarters after the TFP improvement. Similarly, there is 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 5 we present the impulse responses of the same set of variables, but in response to an expectational noise shock  $\varepsilon_t^v$  instead. We see that upon the improvement in expectations (recall that is period 0 on the  $X$ -axis), the real exchange rate strongly appreciates. This is consistent with the message from Figure 4, where we saw that the exchange rate appreciates significantly before an actual improvement of TFP, speaking of apparent anticipation effects. We capture those here directly.

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

The response in consumption is more gradual and delayed, but there is indeed again an increase in US consumption following an increase in expected future US TFP. The fact that the consumption increase is 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 4: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances



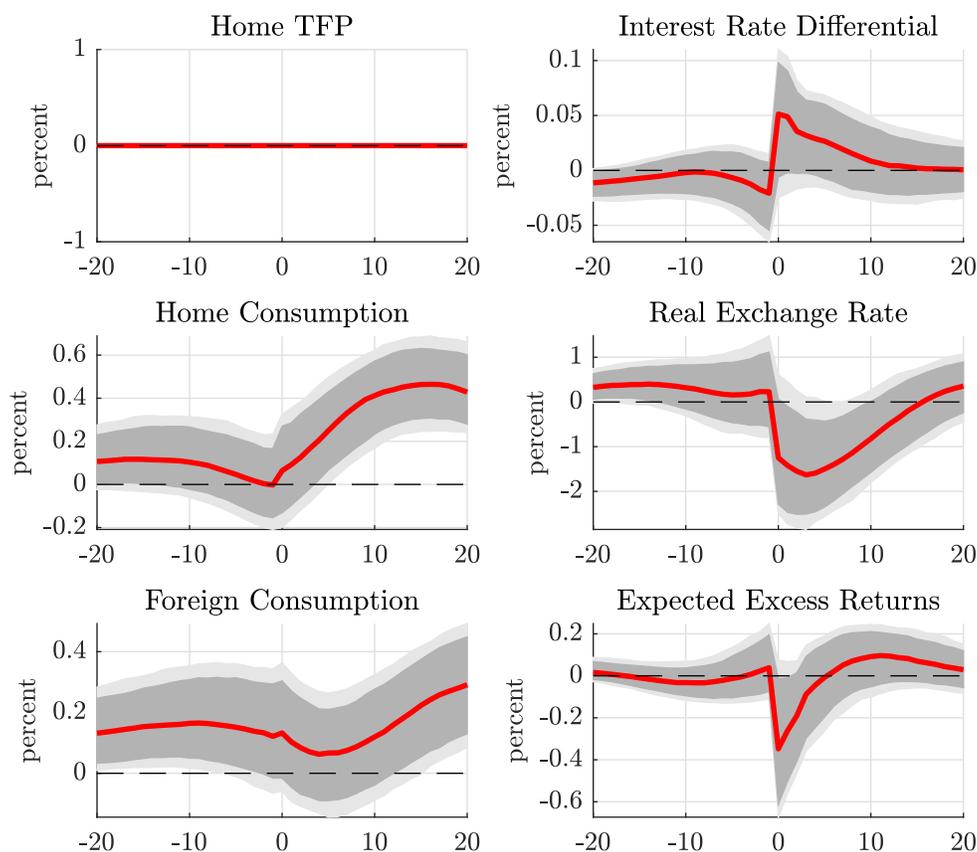
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

### 3.3 The importance of TFP and noise disturbances

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

By our identification restrictions, the technological disturbance we estimate,  $\varepsilon^a$ , accounts

Figure 5: Impulse responses to Noise ( $\varepsilon^v$ ) 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.

for 100% of the variation in TFP, while the expectational noise disturbance is completely orthogonal to it.

In addition, the estimates indicate that the two disturbances together 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 low and high frequencies.

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.

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 higher frequencies.<sup>13</sup> 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. Indeed, Table 2 reports 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

<sup>13</sup>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.

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 for exchange rate fluctuations.

We close this section by also quantifying the overall role of TFP expectations, in terms of both the correctly anticipated part of  $\varepsilon_t^a$  and the noise  $\varepsilon_t^v$ . This effectively amounts to stripping away variation in endogenous variables due to current and past TFP innovations, i.e. the history  $\varepsilon^{a,t}$ . 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 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 the two disturbances 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  $q_t$ ) can be attributed to current and past productivity disturbances.

## 4 Technology, noise and exchange rate puzzles

Given the large effect the two identified disturbances play in exchange rate dynamics, it is interesting to consider whether they are also generating some or all of the exchange rate puzzles we outlined at the beginning.

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** First, recall that TFP and noise disturbances explain half of the variation in the predictable excess currency return,  $E_t(\lambda_{t+1})$  (Table 2). This suggests that the shocks to TFP and expectations thereof are significant drivers of the observed deviations from uncovered interest parity in the data.

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

This speaks to a general negative correlation between currency returns and the interest rate differential, a relationship that is at the heart of the “classic” UIP puzzle that high interest rates predict high currency returns, in the sense that the seminal Fama regression. To test the hypothesis that the shocks we identify indeed generate the Fama puzzle, we consider the so-called UIP regression – main form in which this puzzle has been documented.

Specifically, Fama (1984) estimates the regression

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

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

In this counter-factual dataset, we find  $\beta_{UIP} = -2.20$ , revealing that the combination of disturbances to TFP and to expectations of future TFP qualitatively and quantitatively reproduces the classic UIP Puzzle relationship. Drilling down further, we construct similar counter-factual  $\beta_{UIP}$  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  $\beta_{UIP}$  of  $-2.08$ , while the  $\beta_{UIP}$  based on only expectational disturbances is  $-2.96$ , as we also report in Table 3 below. Last, 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.

In addition to this “classic” UIP Puzzle, the conditional responses of the exchange rate to our identified disturbances also exhibit the Engel puzzle that the UIP puzzle essentially

Table 3: Exchange Rate Related Puzzles and TFP Expectations

	Technology	Exp. Noise	Both	Unconditional
Fama $\beta_{UIP}$	-2.08	-2.96	-2.20	-2.46
Engel $\beta_\Lambda$	2.33	1.72	2.62	2.53
$\sigma(r_t - r_t^*)/\sigma(\Delta q_t)$	0.37	0.13	0.25	0.17
$\text{autocorr}(r_t - r_t^*)$	0.99	0.93	0.98	0.95
$\text{corr}(\Delta q_t, \Delta(c_t - c_t^*))$	-0.31	-0.38	-0.35	-0.27
$\text{autocorr}(\Delta q_t)$	0.90	0.33	0.58	0.29
$\text{autocorr}(q_t)$	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.

“reverses” direction at longer horizons (Engel, 2016). Namely, it has now been established that while the Fama regression finds a negative association between interest rate differentials and one quarter ahead currency excess returns, the correlation between today’s interest rate differential and currency excess returns 2+ years into the future is actually *positive*.

We can qualitatively see this pattern in Figure 4, for example, in the fact that the high excess returns in the 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  $\varepsilon_t^a$ ).

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 at least one horizon  $k > 1$  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 noise in this cases is muted quantitatively, even though it can also generate it on

its own qualitatively (see Table 3). In fact, the two disturbances together generate around 60% of the overall  $\text{Cov}(\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}), r_t - r_t^*)$  in the data, but noise is responsible for only one tenth of this effect.

It is also worth noting that these two disturbances not only generate empirically relevant regression  $\beta$ 's, but the underlying dynamics of the interest rate differentials (the regressor in these UIP regressions) are also very much in line with their unconditional counterpart. This fact can be seen by the  $\sigma(r_t - r_t^*)/\sigma(\Delta q_t)$  and  $\text{autocorr}(r_t - r_t^*)$  moments reported in Table 3. Overall, these results suggest that the puzzling predictability patterns in excess currency returns documented over the years are largely originating from disturbances to TFP and its expectations.

**Deviations from the Backus-Smith condition** We now turn to the [Backus-Smith](#) puzzle, or risk-sharing puzzle. We first consider the so-called [Backus-Smith](#) “wedge,” defined as

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

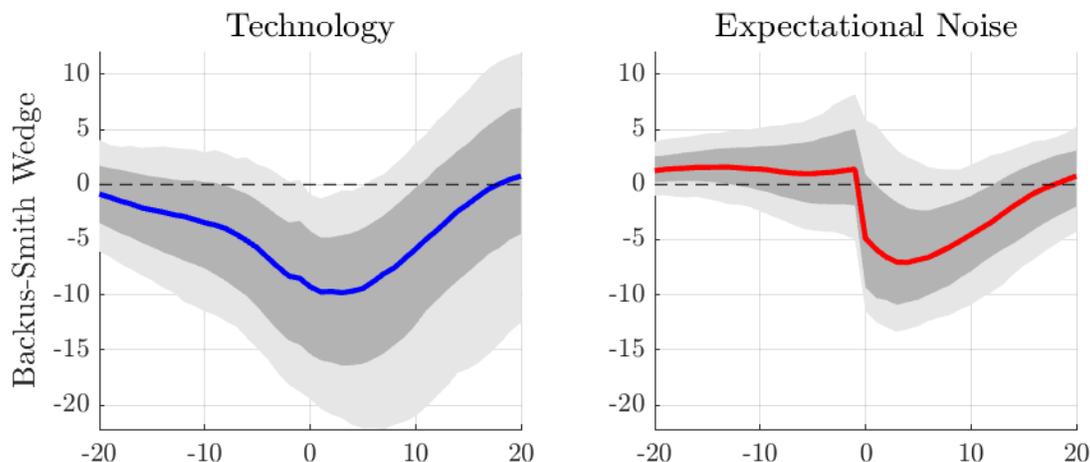
Under the null hypothesis of full consumption risk-sharing, in the sense of [Backus and Smith \(1993\)](#), this variable should be equal to zero in all periods.

The impulse responses of BS Wedge with respect to technological and expectational disturbances are reported in Figure 6. We observe significant deviations from the [Backus-Smith](#) condition. In response to the actual TFP disturbance, we again observe a significant anticipation effect: the BS Wedge is significantly negative as early as 10 quarters before the actual TFP improvement. After the realization of the US TFP improvement, the wedge adjusts gradually towards zero. A negative BS Wedge means that in anticipation of a U.S. TFP improvement, the U.S. dollar does not depreciate sufficiently to offset the relative US consumption increase. This same phenomenon can also be inferred from Figure 3, where we see that in anticipation of the US TFP improvement the dollar is in fact *appreciating* even though US consumption is relatively high. The [Backus and Smith](#) condition implies an opposite relationship between exchange rate changes and consumption differentials.

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

Overall, this shows that the two disturbances we recover with the [Chahrour and Jurado's](#)

Figure 6: 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.

(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,

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

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** 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. We therefore ask to what extent the high persistence and volatility found in the data might be accounted for by disturbances to TFP and its expectations.

In Table 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 exchange rate 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 in fact generate an even higher degree of persistence than the exchange rate exhibits on average, suggesting that all other shocks driving the exchange rate (e.g. monetary shocks) have relatively transitory effects (as is true in standard models). It's worth noting that 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.

Besides, we find that exchange rate changes are highly volatile relative to consumption changes. 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. In fact, expectational disturbances alone generate a relative volatility of around 8.

**FX Determination Puzzle** Let us now consider the so-called determination or disconnect puzzle (Meese and Rogoff, 1983). This puzzle has been documented in many different ways, and no single summary statistic emerges from 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 fundamental of standard models), and the real exchange rate. 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  $\text{corr}(\Delta q_t, \Delta a_t) = -0.07$ , reflecting the typical evidence 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  $\varepsilon_t^a$  and  $\varepsilon_t^v$ . 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.

We point to two reasons behind low contemporaneous correlations. First, conditional on a TFP improvement fluctuations of macro aggregates and the exchange rate appear at different times. In fact, the exchange rate reacts in anticipation of the TFP improvement.<sup>14</sup> Second, we estimate agent’s expectations to be quite *noisy*. As a result, the exchange rate often reacts in anticipation of expected TFP improvements that never actually materialize. In fact, noise contributes to a larger fraction of the volatility of  $\Delta q_t$  (11%) relative to actual TFP changes (18%, see Table 2). Therefore, this noise channel we uncover thanks to our identification procedure plays an important role that would have otherwise been overlooked.

**Technology, noise and the trade balance** Another long-standing question in the literature concerns the determinants of the trade balance and its comovement with international relative prices such as the real exchange rate (Backus et al., 1994; Corsetti et al., 2008). We thus examine the dynamics of the trade balance in response to TFP and noise disturbances. Figure 7 depicts the dynamic responses of the U.S. trade balance (as a % of U.S. GDP) along with those of the real exchange rate. We find that the U.S. (i.e. home) trade balance deteriorates in anticipation of expected TFP improvements, and it gradually reverts back to its original level when the TFP improvement materializes or when expectations thereof fade away. These dynamics are consistent with the intertemporal approach to the current account by which home households increase their consumption (more than home production) in anticipation of future improvements in the productive capacity of the home economy. This evidence is also consistent with Hoffmann et al.’s (2019) observation that during the 1990s and 2000s, survey expectations of long-run output growth for the U.S. relative to the rest of the world were highly correlated with the US current account.<sup>15</sup>

Moreover, Figure 7 shows that the real exchange rate and the trade balance appear highly positively in their conditional responses. 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) emerges as the joint equilibrium response of these variables to technological and noise disturbances.

## 4.1 Implications

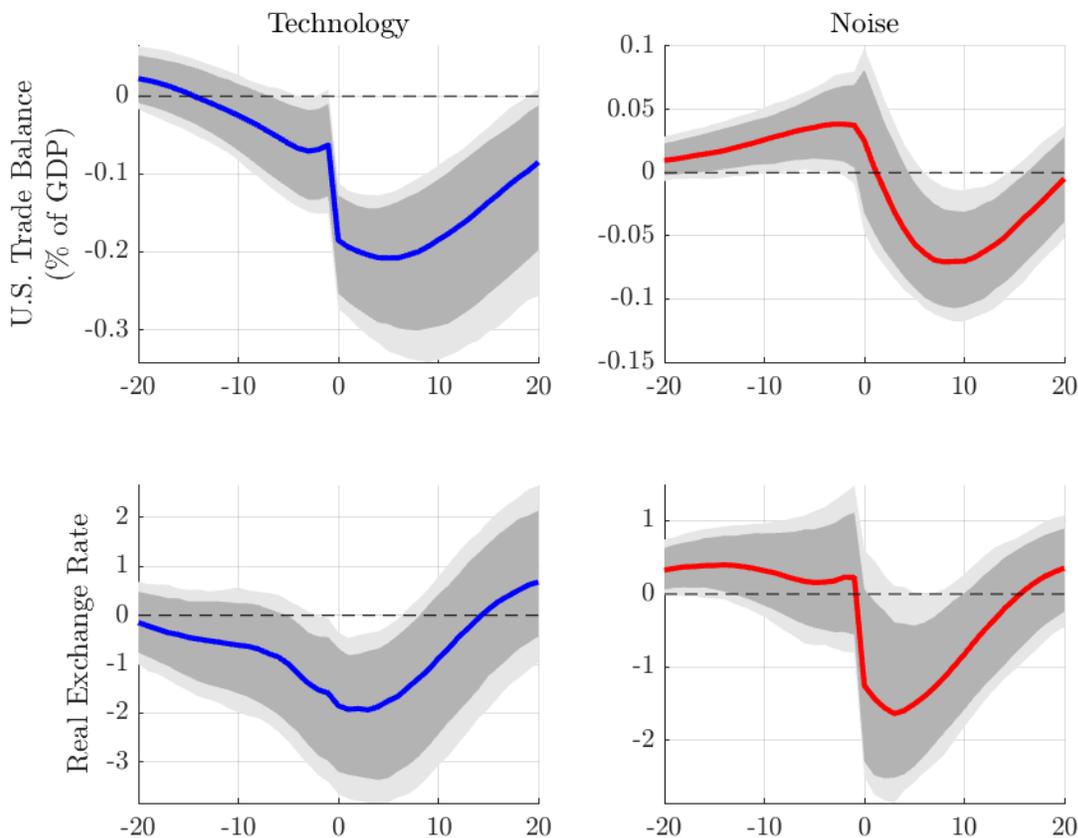
Let us take stock of the results and their broader implications.

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<sup>14</sup>We explain the intuition for the different timing in responses in Section 3

<sup>15</sup>See also Nam and Wang (2015).

Figure 7: 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.

**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, take 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 discussed in Section 3, however, the link with current and past TFP innovations  $\varepsilon^{t,a}$  is very weak,

and accounts for only 3-4% of the variation in  $\Delta q_t$ . Instead, as we have shown extensively, the first-order link between exchange rates and TFP emerges through noisy expectations of *future* TFP innovations. This link will be missed by empirical approaches that focus on the link with the history of current and past macro fundamentals.

Let us then 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:

$$\Delta q_t = \alpha + \beta_0 \Delta TFP_t + \sum_{k=1}^h \beta_{-k}^{lag} (TFP_{t-4(k-1)} - TFP_{t-4k}) + \sum_{k=1}^h \beta_k^{lead} (TFP_{t+4k} - TFP_{t+4(k-1)}) + \varepsilon_t \quad (6)$$

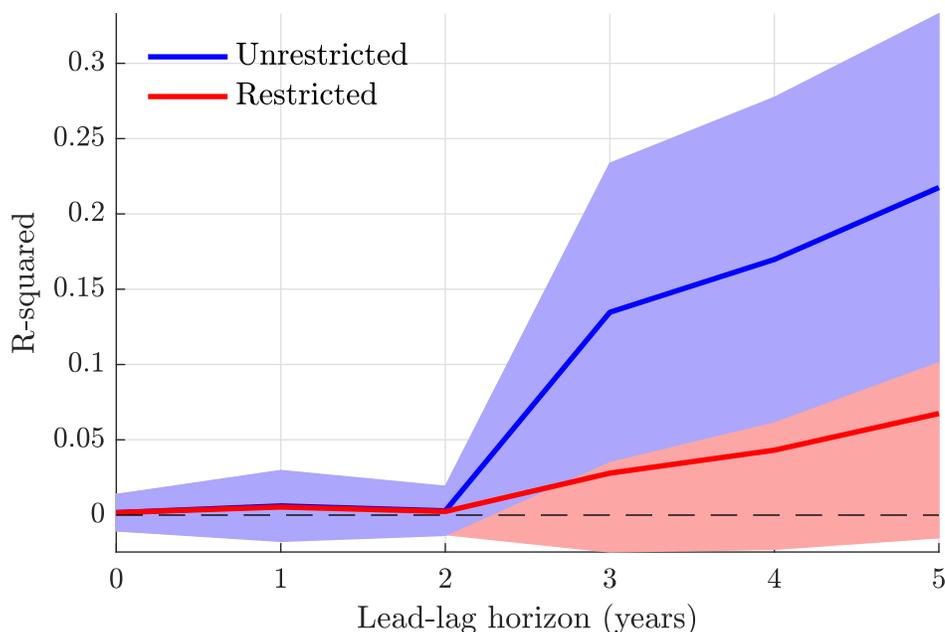
Thus, if we include just the first two terms, the regression would estimate the standard relationship between contemporaneous changes in the exchange rate and TFP, which we know from previous research is virtually nil. If we include the first summation term, then we would also consider the additional explanatory power of lagged changes in TFP of up to  $h$ -years in the past. Once we include the second summation term, we also consider a potential correlation with *future* TFP changes, of up to  $h$ -years forward. The coefficients  $\beta_k^{lead}$  can be non-zero if the marginal foreign exchange investor has some information on likely future developments to TFP.

In Figure 8 we report the resulting  $R^2$  of two versions of the above regression: (i) a “Restricted” backward-looking version that only includes current and lagged TFP growth terms; and (ii) 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. Its resulting  $R^2$  (and 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.

On the other hand, the message changes substantially once we also include terms capturing *future* TFP growth. The resulting  $R^2$  of this “Unrestricted” regression is plotted with the blue line. The relationship between real exchange rate changes and TFP growth is similarly insignificant if we only include TFP growth of up to 2 years in the future, but becomes increasingly significant as we include TFP growth 3 to 5 years out. This 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, in line with the results emerging from the analyses above.

Second, we are of course not the first to recognize that exchange rates are forward-looking

Figure 8: 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 (6).

asset prices, and thus should predict and correlate with future macro fundamentals. A seminal paper that formulates and examines exactly this hypothesis is [Engel and West \(2005\)](#). However, its empirical results are fairly mixed, with some weak supportive evidence of this leading relationship. Why do our results apparently speak to a much stronger relationship?

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

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

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 (e.g., first-differences vs levels). 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. In particular, we observe that *noise* in expectations  $\varepsilon_t^v$  plays an important role in the variation of  $q_t$ . That is, expectations of TFP 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 in (7). In fact, expectational noise would act akin to measurement error in the right-hand-side variable of the Granger-causality regression equation (7). It would thus attenuate the coefficients  $B$ s on  $q_t$  and the estimated explanatory power of current and lagged  $q_t$  over  $f_t$  in any finite sample.

Moreover, a different strand of the literature that tests the hypothesis that the current exchange rate leads macro aggregates, such as [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.<sup>16</sup>

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  $\Delta q_t$  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 exchange rate puzzles** One important property of TFP and noise disturbances is that the resulting conditional dynamics of the exchange rate exhibit many famous exchange rate puzzles. This result 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 the variance of expected excess currency returns,  $\text{Var}(\mathbb{E}_t(\lambda_{t+1}))$ , and for roughly two-thirds of the covariances that underlies seminal results in the literature such as the regressions of [Fama \(1984\)](#) and [Engel \(2016\)](#).

These estimates are significant for two reasons. First, the apparent importance in pro-

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<sup>16</sup>This point can also be noted from Figure 6.

ductivity 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 TFP as a source of fluctuations.

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 as 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 TFP and noise disturbances generate conditional responses of the exchange rates that exhibit both types of deviations. This evidence calls for models where both puzzles emerge at the same time, as jointly driven by noisy expectations of TFP.

Among the existing class of models, it appears that 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 home consumption is elevated and persistently increasing in expectation of the future TFP improvement. In the long-run risk class of models, home consumption is in fact *depressed* upon an improvement in the long-run growth rate of TFP.<sup>17</sup> This opposite movement in consumption is a characteristic feature of the full risk-

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<sup>17</sup>An improvement in the long-run growth rate of TFP acts akin to a news shock because most of the resulting TFP improvement accrues in the future (because it consists in a persistent change in the growth rate).

sharing setup typical of this class of models where home agents effectively “share” the good news about high future home output with foreign agents by transferring resources abroad today.

We thus argue that 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.

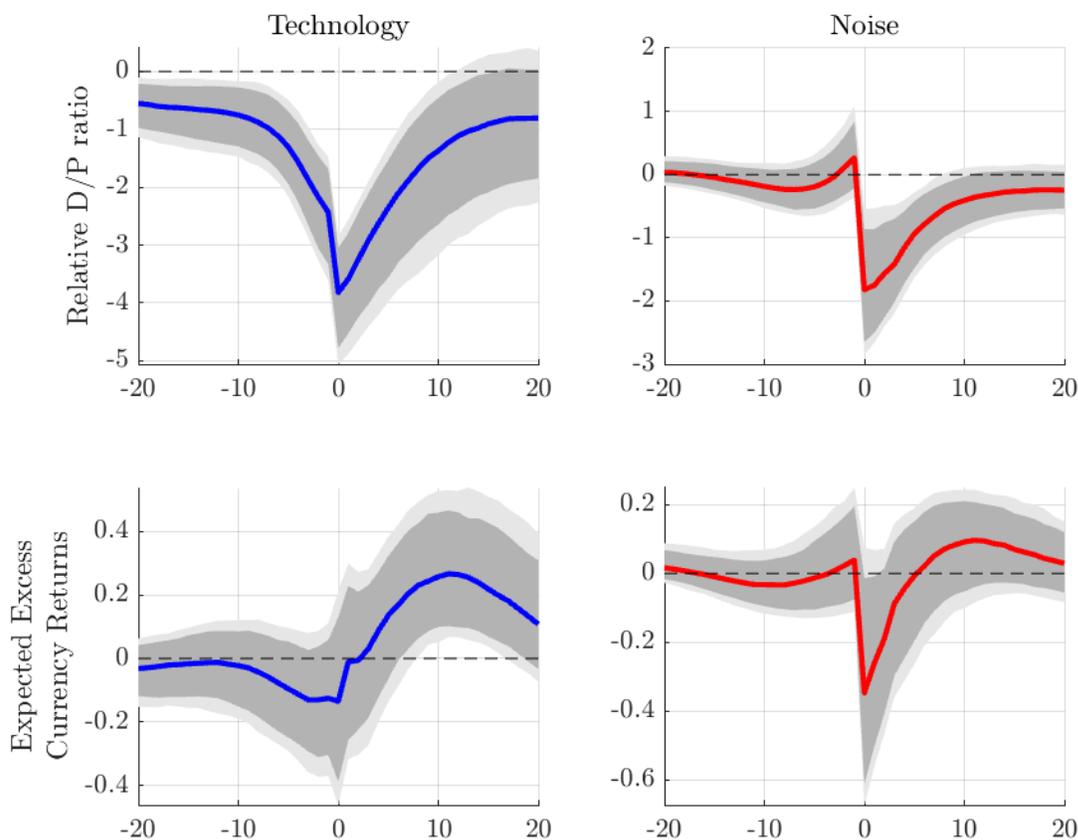
**Factor structure in currency excess returns** As a parting thought, we want to qualitatively link our estimates with the well established results in the asset pricing literature that the cross-section of excess currency returns has a clear factor structure. [Lustig et al. \(2011\)](#) documented that 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  $\varepsilon_t^v$  and  $\varepsilon_t^a$ . 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 indeed responds strongly to our shocks, both in anticipation of the actual TFP improvement and in response to a noise shock to expectations.

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

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.

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.

## 5 Robustness analysis

**Identified disturbances and endogenous TFP** The analysis in sections 3 and 4 relies on the assumption that the technological disturbances  $\varepsilon_t^a$  are exogenous (orthogonal to other

structural shocks). One may be concerned that other economic shocks, such as monetary policy shocks, may lead to changes in TFP through 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 real R&D expenditure responds significantly to both identified disturbances. However, its largest increase occurs *after* the TFP improvement has materialized. Also, R&D expenditures increase also conditional on the noise component of TFP expectations, and thus sometimes R&D expenditures are not followed by an actual TFP improvement. Overall, this evidence appears in contrast with a view that posits that TFP changes are predominantly caused by preceding R&D investment. According to this view, R&D should always lead TFP, and we should have observed R&D to peak before TFP and R&D to be orthogonal to noise.

To study whether TFP and noise 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 picks up U.S. monetary policy shocks. The measure of U.S. monetary policy shocks we consider is the one identified through the “high frequency approach” by Gertler and Karadi (2015) and recently updated by Jarocinski and Karadi (2020). In Table 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.

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

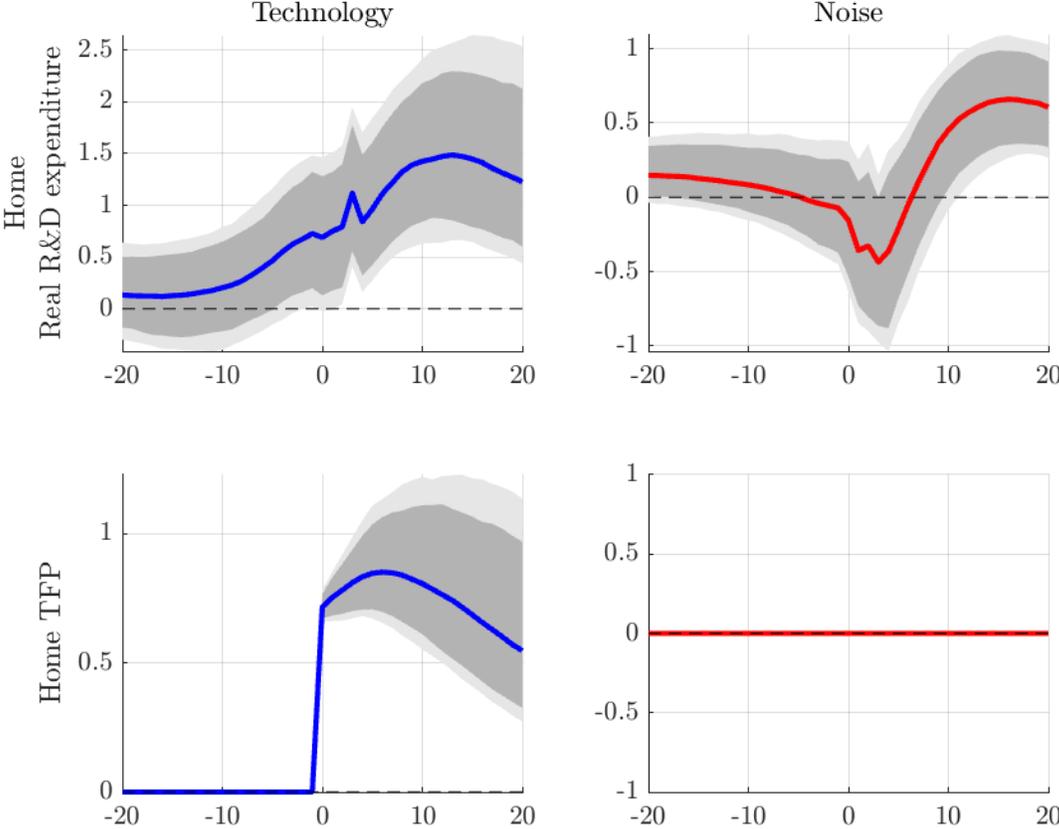
	Technology	Exp. Noise
U.S. Monetary Policy Shocks	0.09	0.06
	<i>p-value</i> = 0.46	<i>p-value</i> = 0.62

*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).

## 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

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.

future TFP improvements. This link, however, has been difficult to uncover previously because the anticipation effects, compounded with noise in expectations, make it far from obvious in the raw data. In addition, the two sets of shocks we identify appear to generate a number of famous FX puzzles at the same time, which speaks to a common and fundamental origin of exchange rate puzzles.

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## A Data Appendix

- 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](https://stats.oecd.org/index.aspx?DataSetCode=PRICES_CPI).
- Consumption
  - Real consumption;
  - Source: *OECD*, Private final consumption expenditure
- Investment
  - Real Investment;
  - Source: *OECD*, Gross Fixed Capital Formation (GFCF), Quarterly growth rates, <https://data.oecd.org/gdp/investment-gfcf.htm>.
- U.S. TFP:
  - U.S. utilization-adjusted TFP as constructed in [Fernald \(2012\)](#);
  - Source: John Fernald’s website, <https://www.johnfernald.net/TFP> (latest available vintage, downloaded on January 2, 2022);
- U.S. R&D:
  - Real R&D expenditure
  - Source: *U.S. Bureau of Economic Analysis*, retrieved from *FRED*, <https://fred.stlouisfed.org/series/Y694RX1Q020SBEA>
- U.S. trade balance (% of GDP)
  - Shares of gross domestic product: Net exports of goods and services
  - 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*

Table 5: Share of variance explained by the Main FX shock ( $\varepsilon_1$ ); Extended sample 1978:Q3-2018:Q4

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

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

## B Additional tables and figures

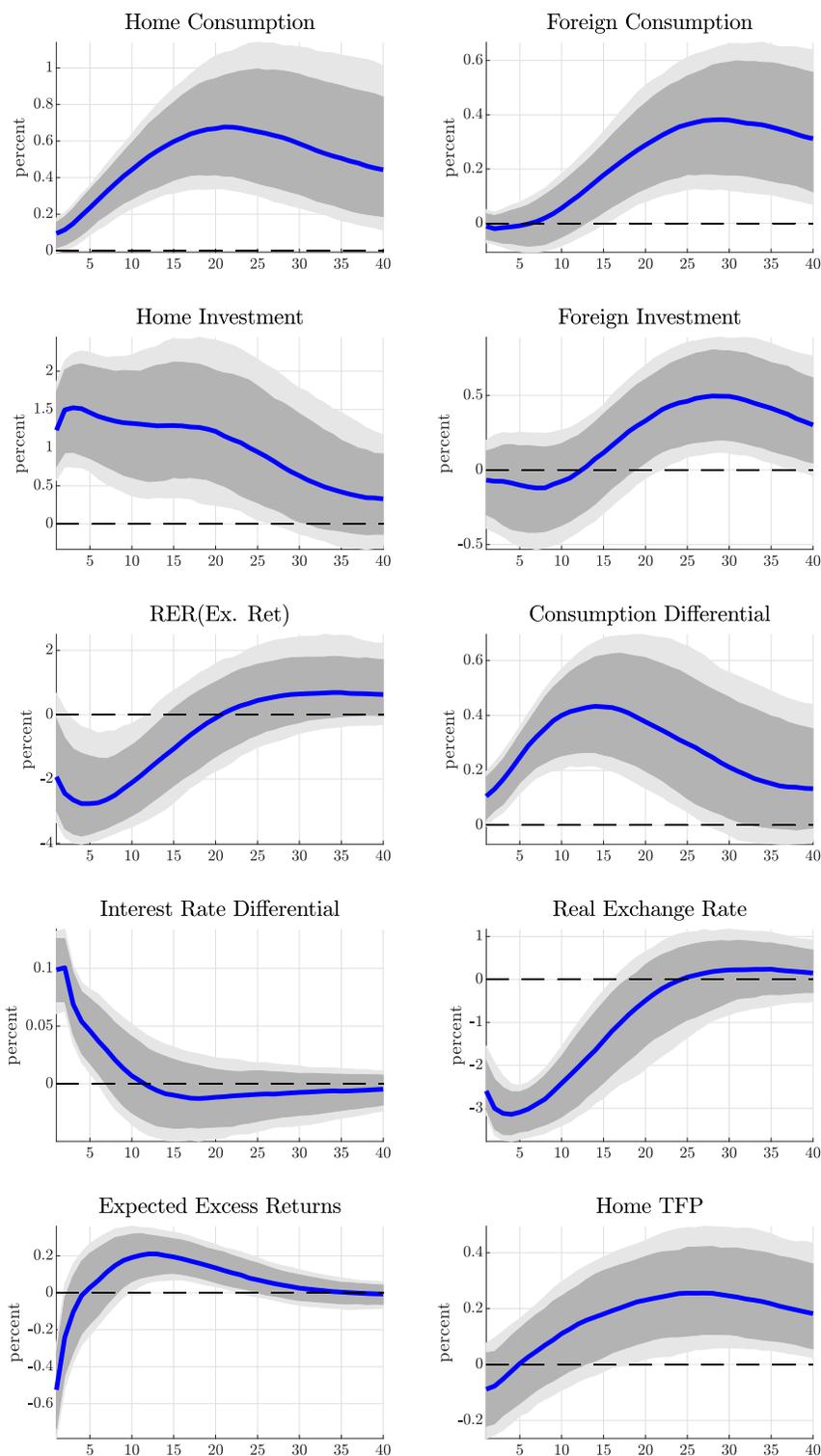
### B.1 Extended sample (1978:Q3-2018:Q4)

Table 6: Variance Decomposition; Extended sample 1978:Q3-2018: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

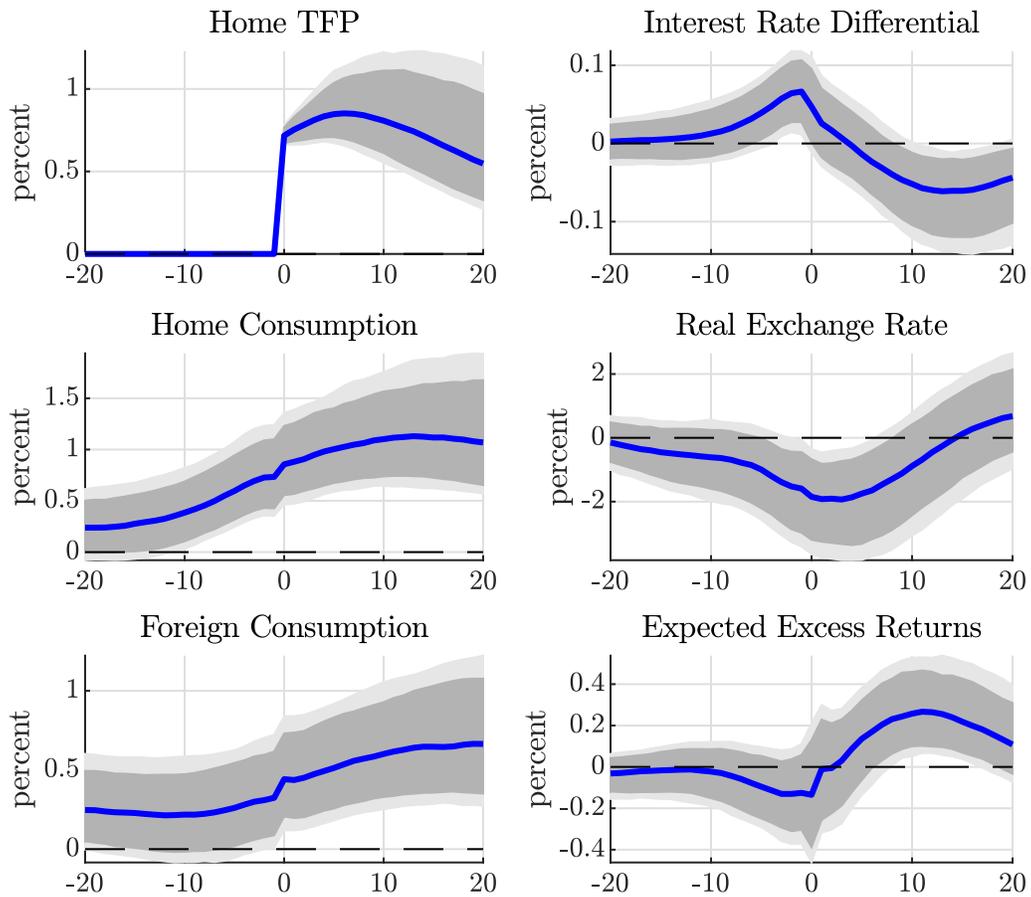
*Notes:* The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

Figure 11: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), 1978:Q3-2018:Q4



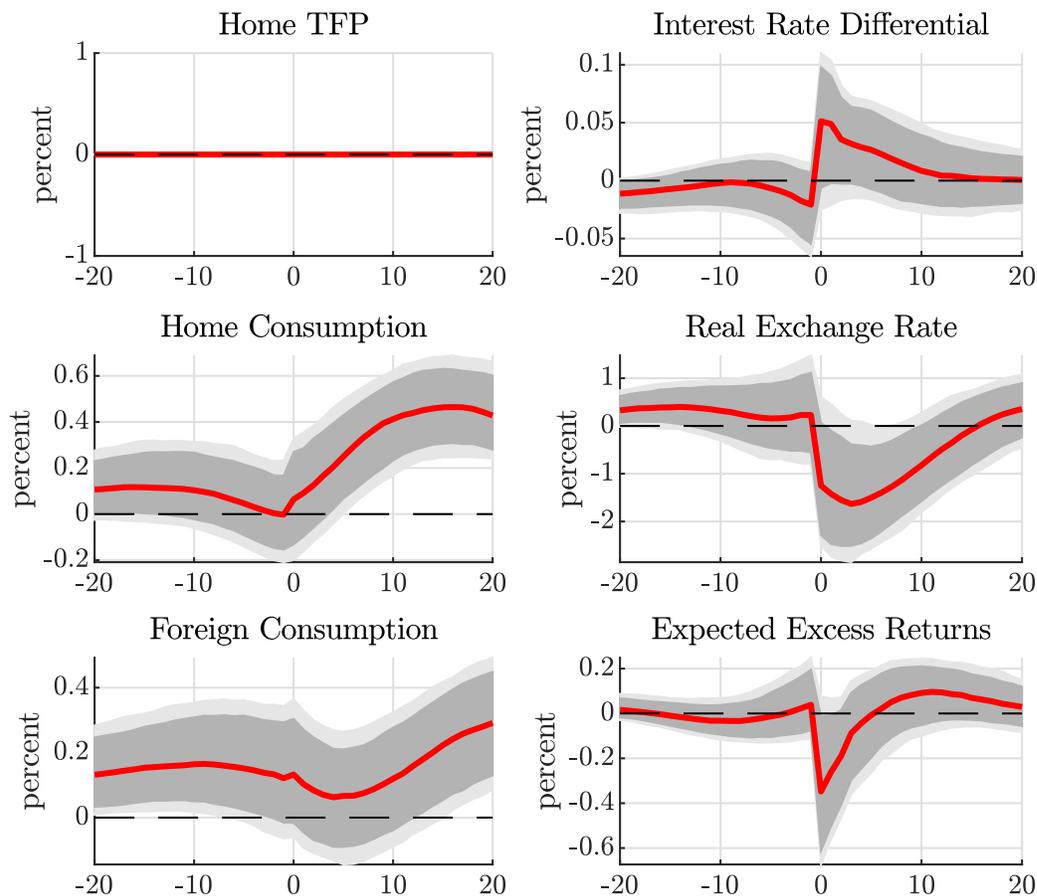
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

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



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

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



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

## B.2 Vector Error-correction Model (VECM)

Table 7: Share of variance explained by the Main FX shock ( $\varepsilon_1$ ); 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 ( $\varepsilon_1$ ); 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						

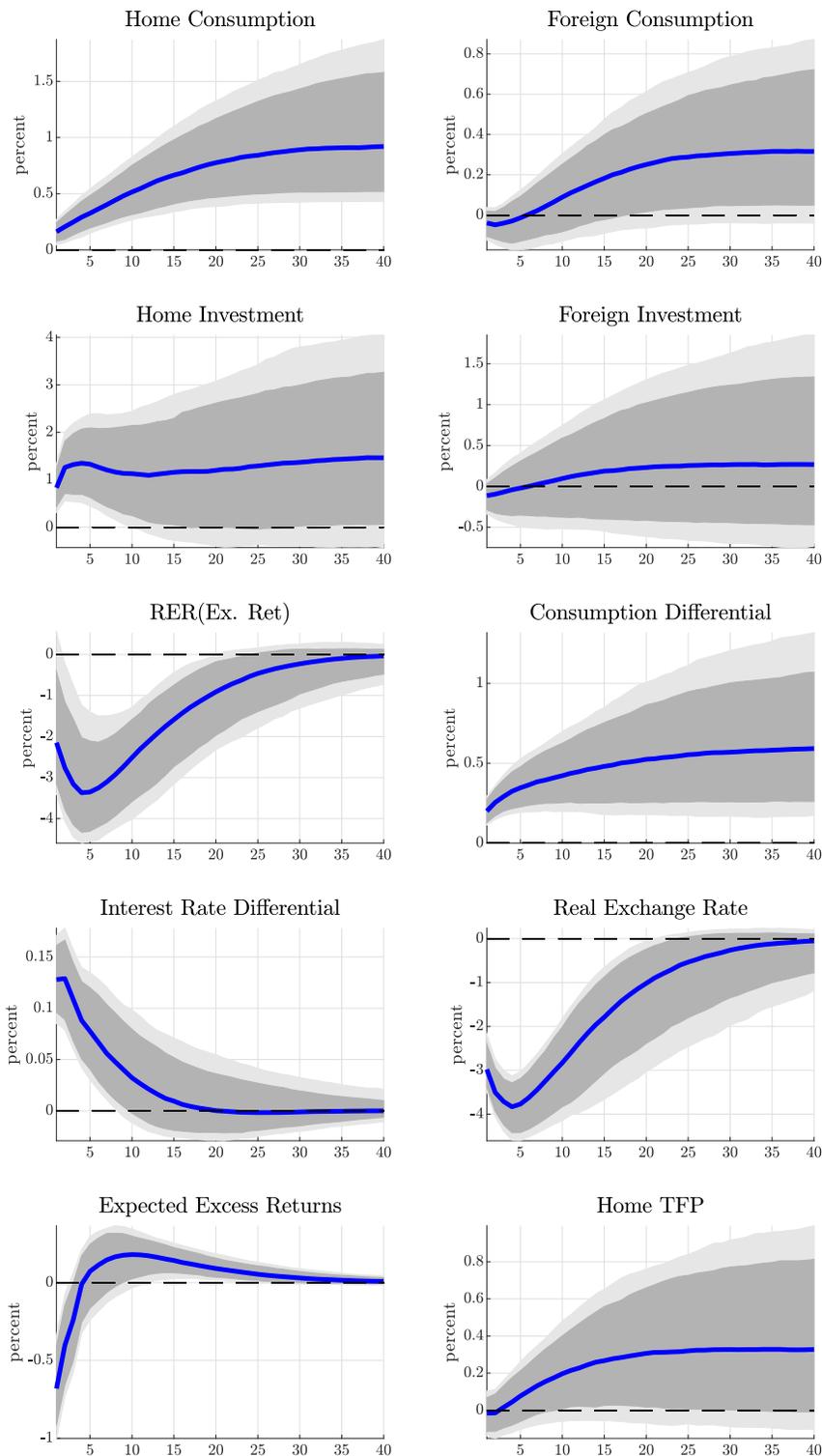
*Notes:* The table reports the estimated variance shares accounted for by the main exchange rate shock at different horizons.

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

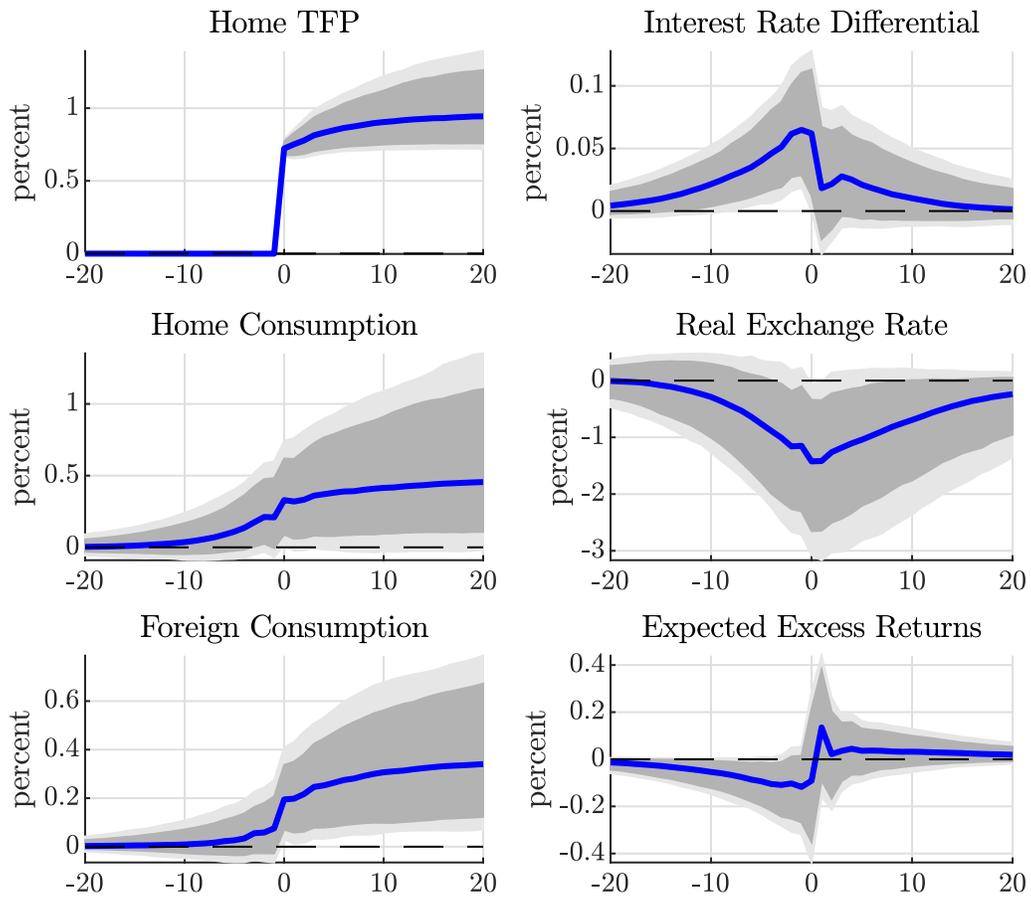
*Notes:* The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

Figure 14: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), VECM



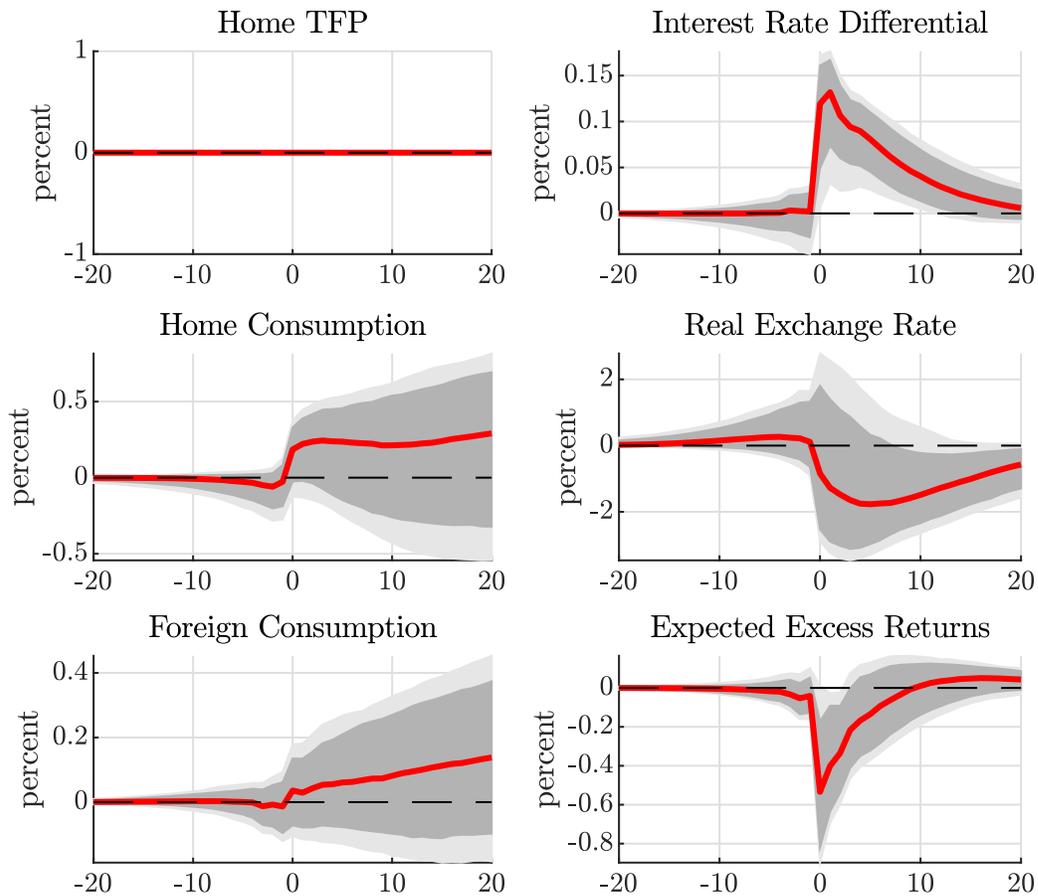
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 15: Impulse responses to Technology ( $\varepsilon^a$ ) 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 ( $\varepsilon^v$ ) disturbance, VECM



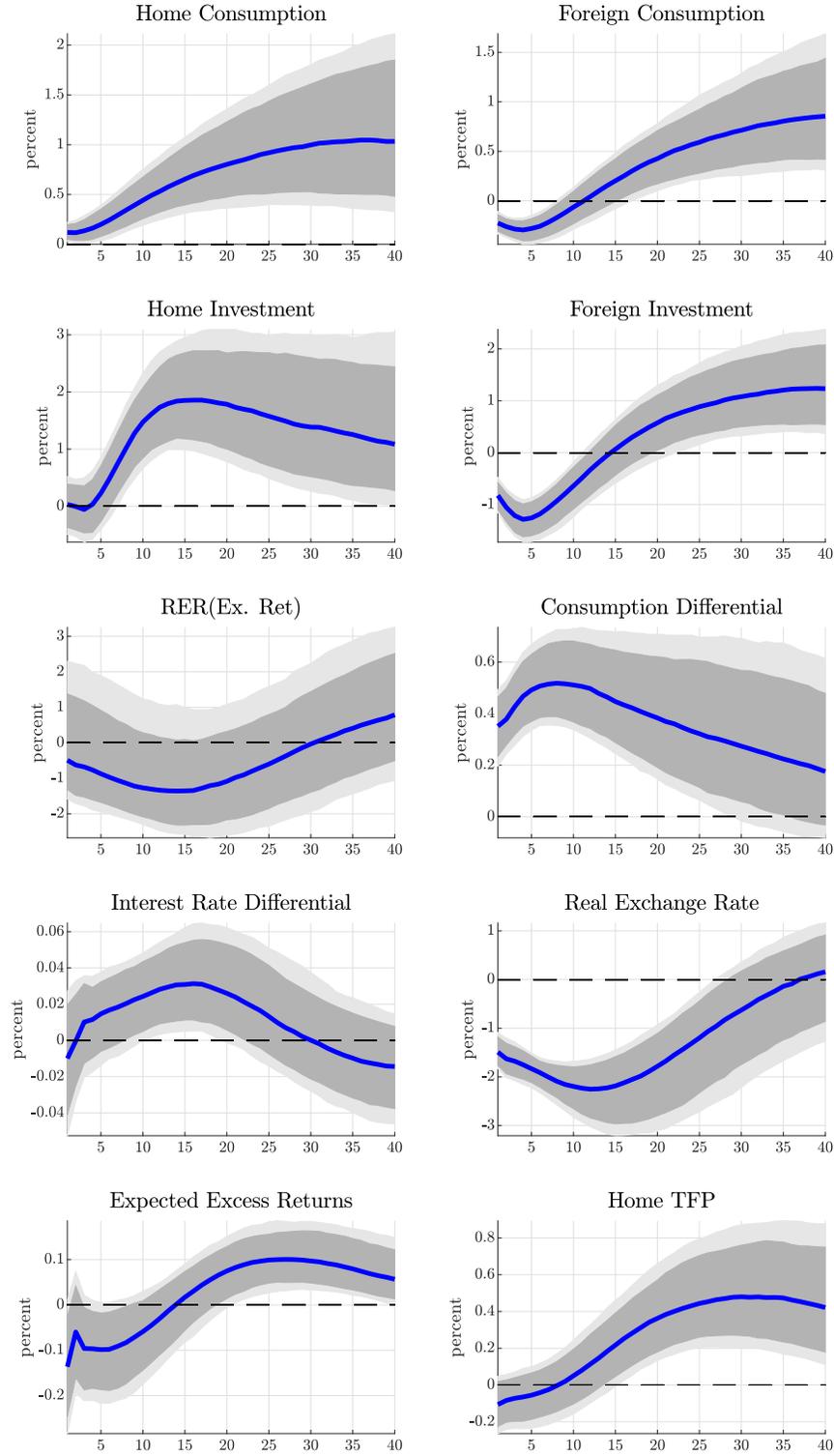
*Notes:* The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

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

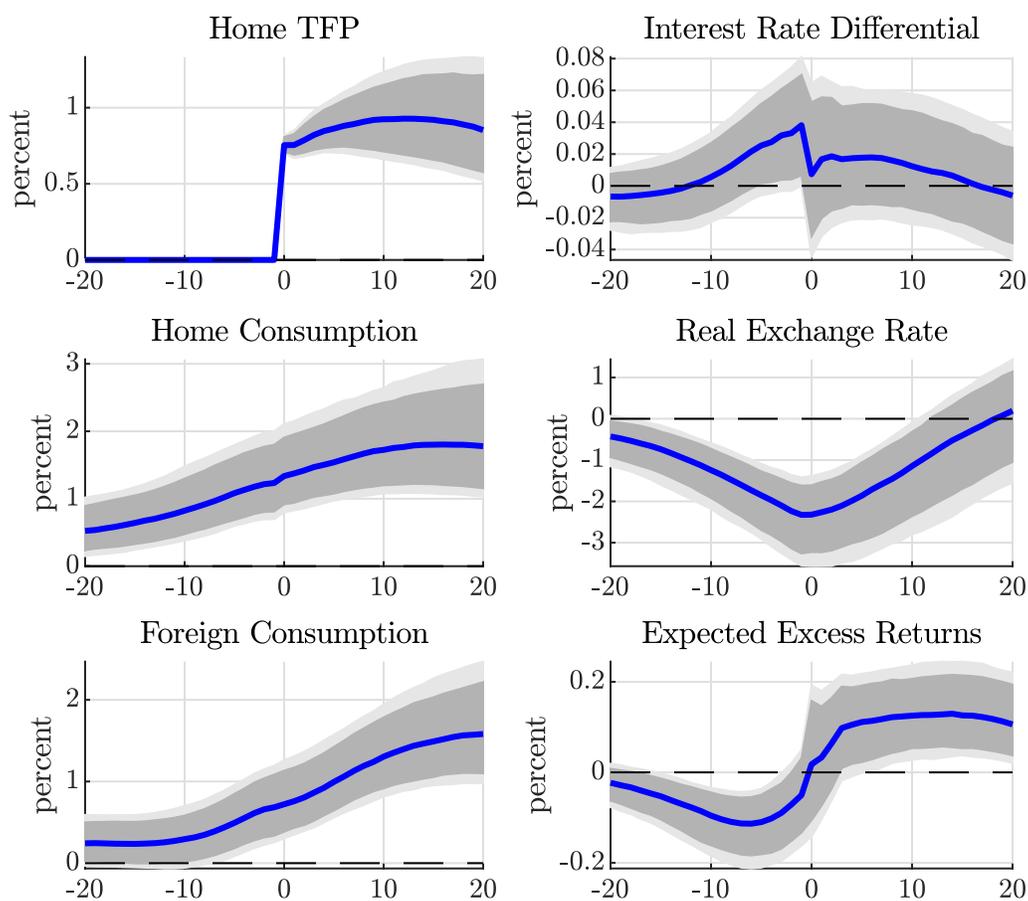
*Notes:* The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances (“Tech”), expectational disturbances (“Noise”), and the combination of both.

Figure 17: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), Canada



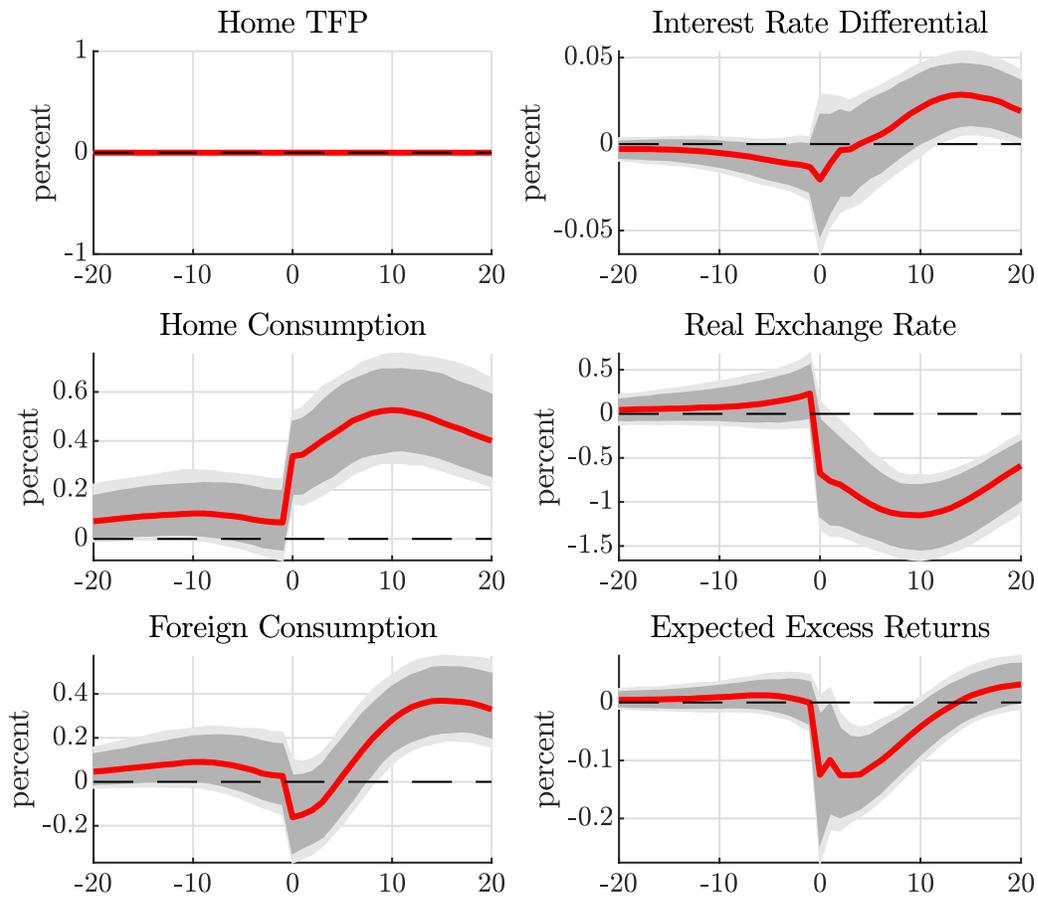
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 18: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances, Canada



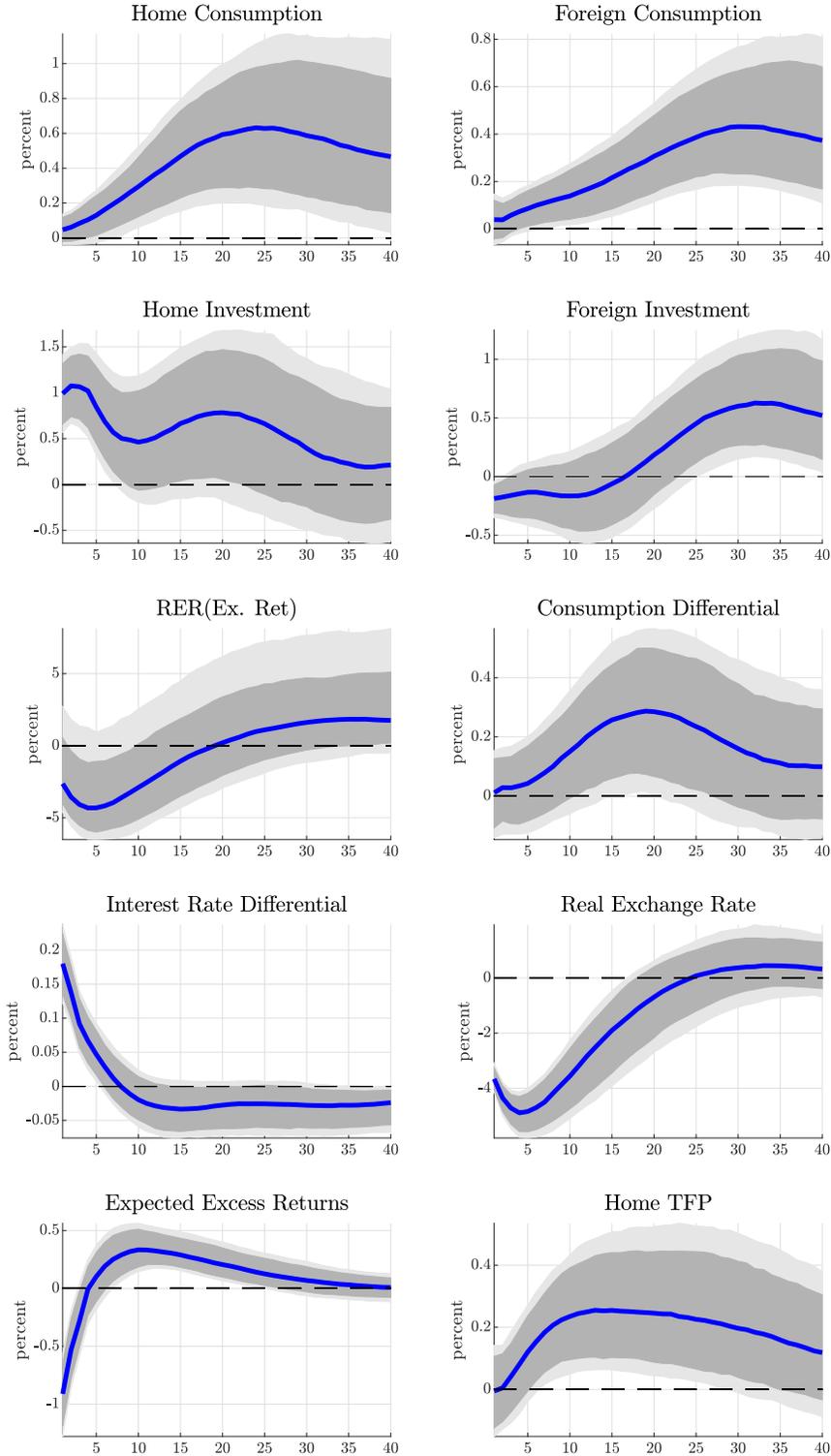
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 19: Impulse responses to Noise ( $\varepsilon^v$ ) disturbance, Canada



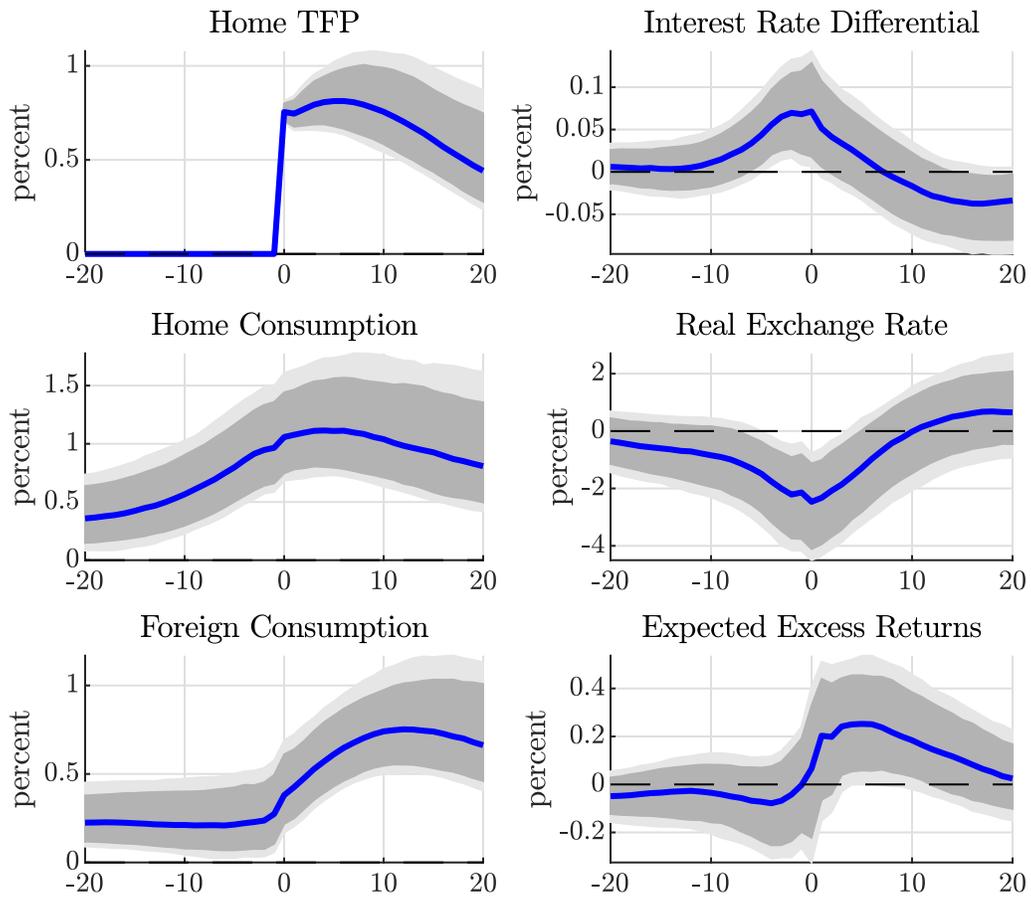
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 20: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), France



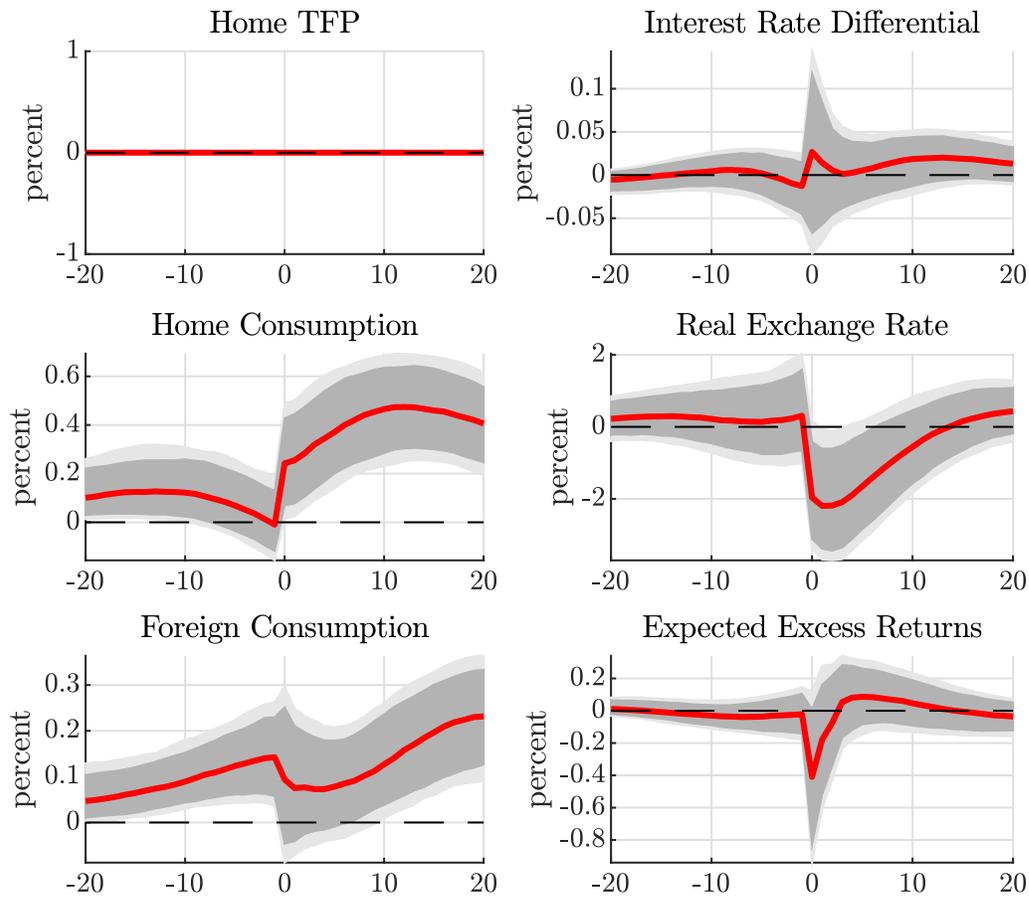
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 21: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances, France



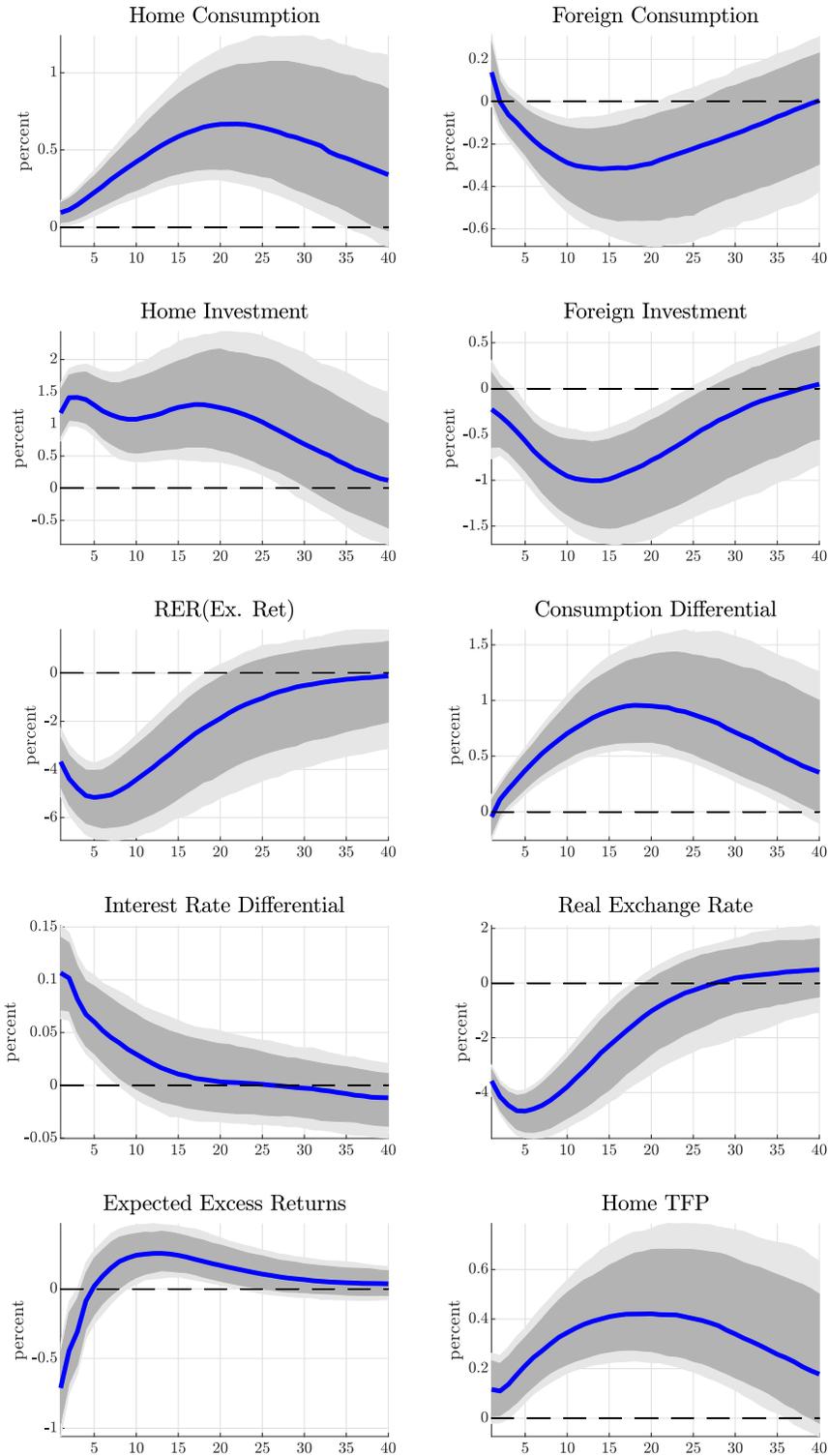
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 22: Impulse responses to Noise ( $\varepsilon^v$ ) disturbance, France



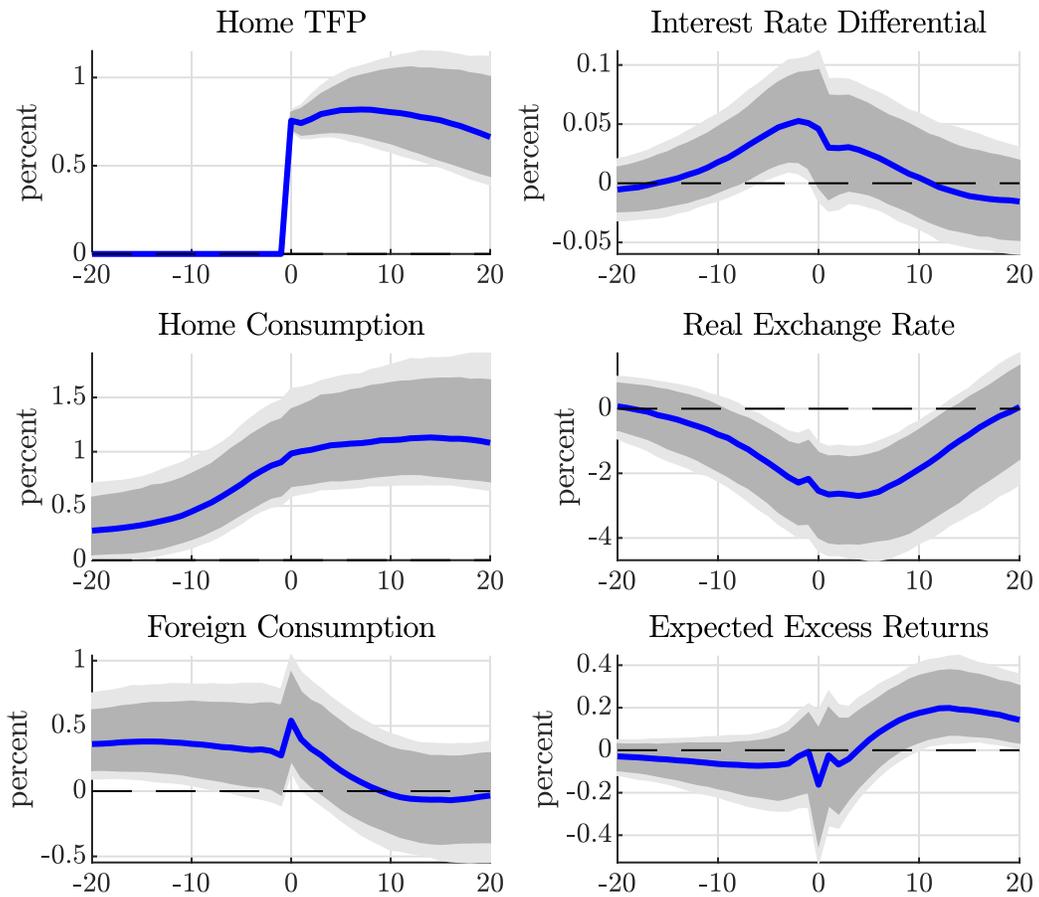
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 23: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), Germany



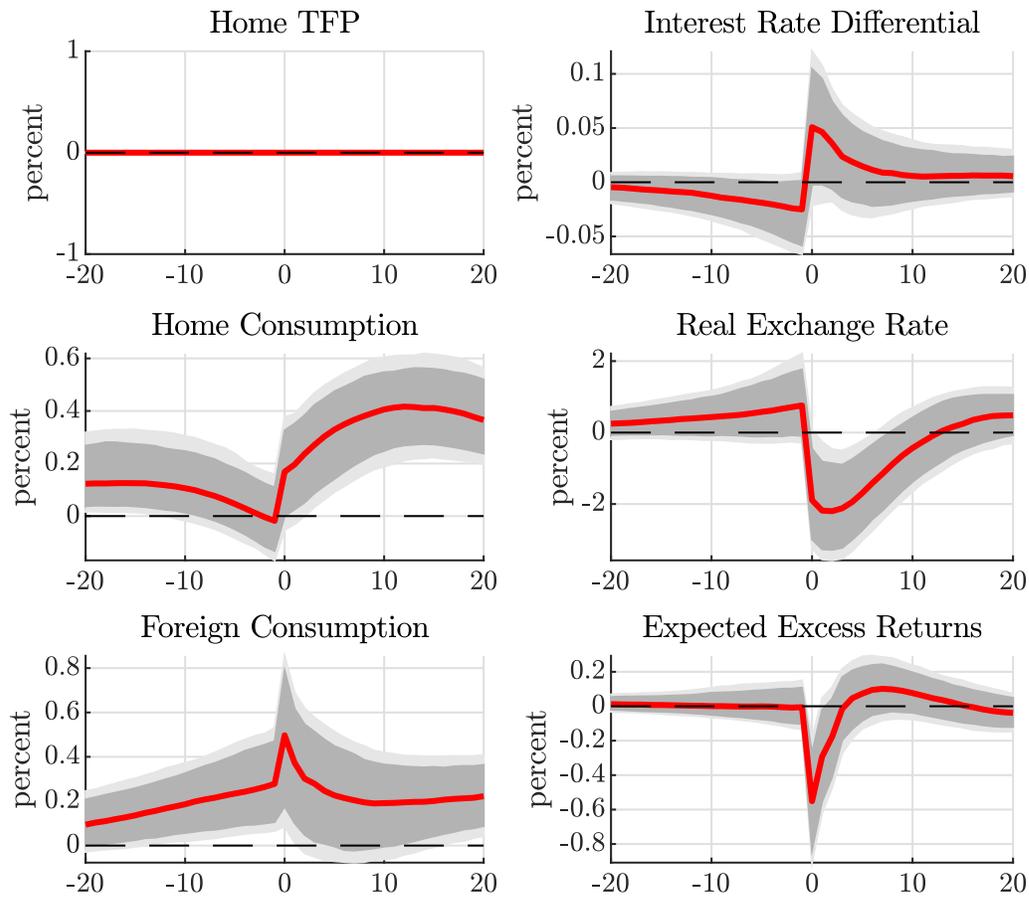
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 24: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances, Germany



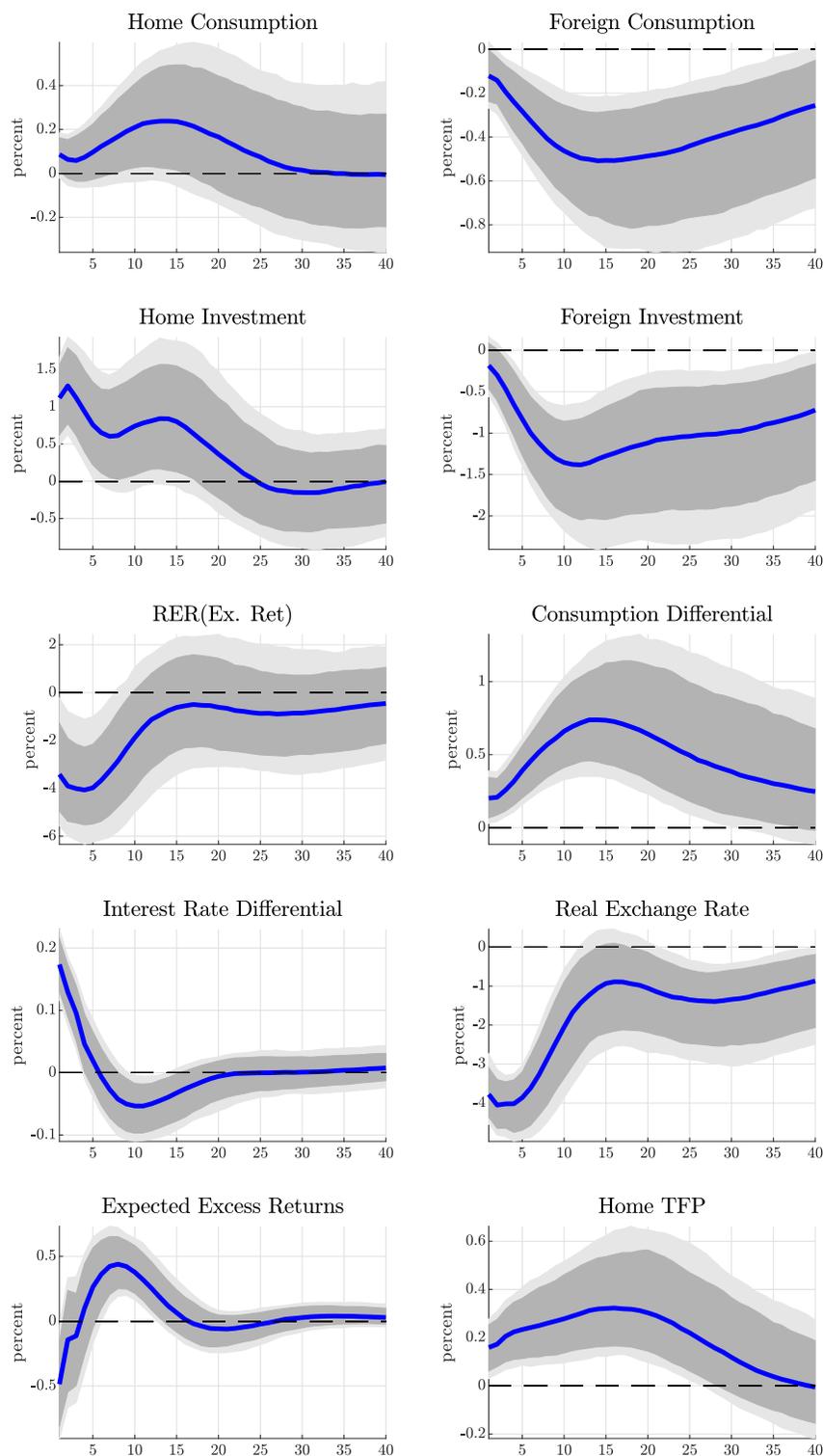
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 25: Impulse responses to Noise ( $\varepsilon^v$ ) disturbance, Germany



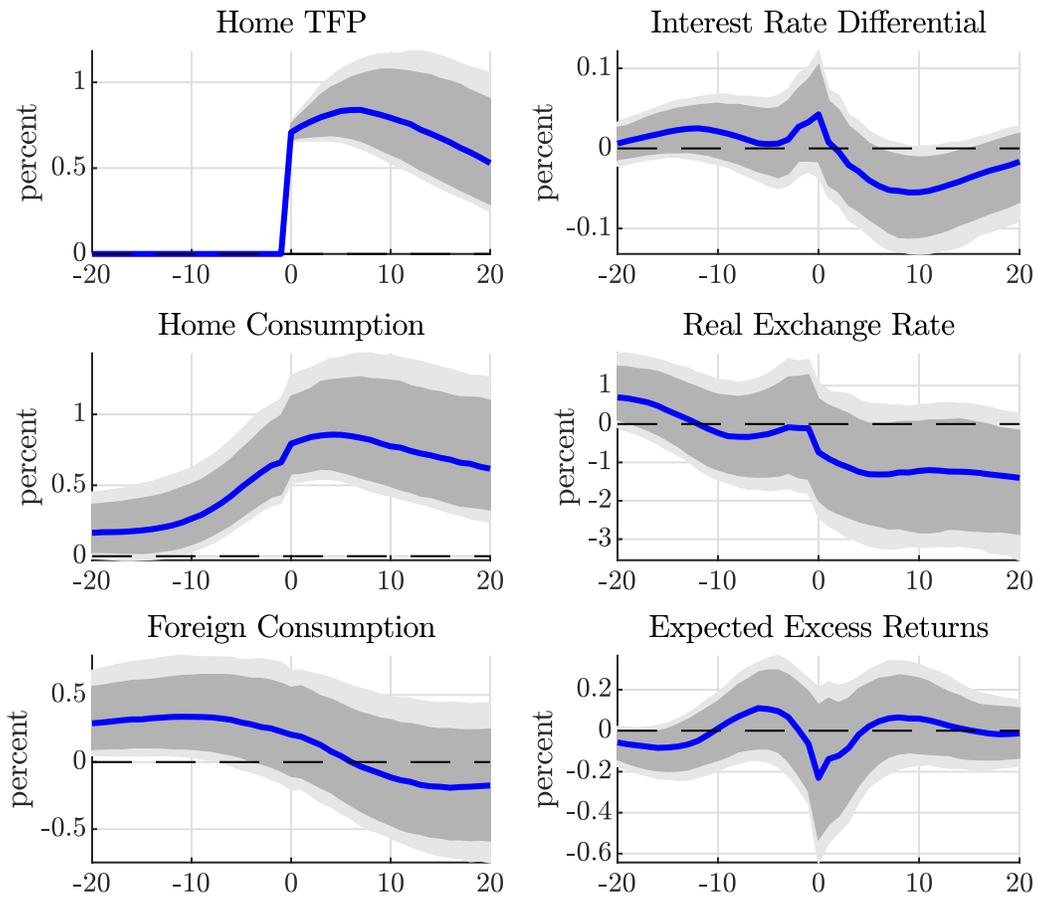
*Notes:* The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 26: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), Japan



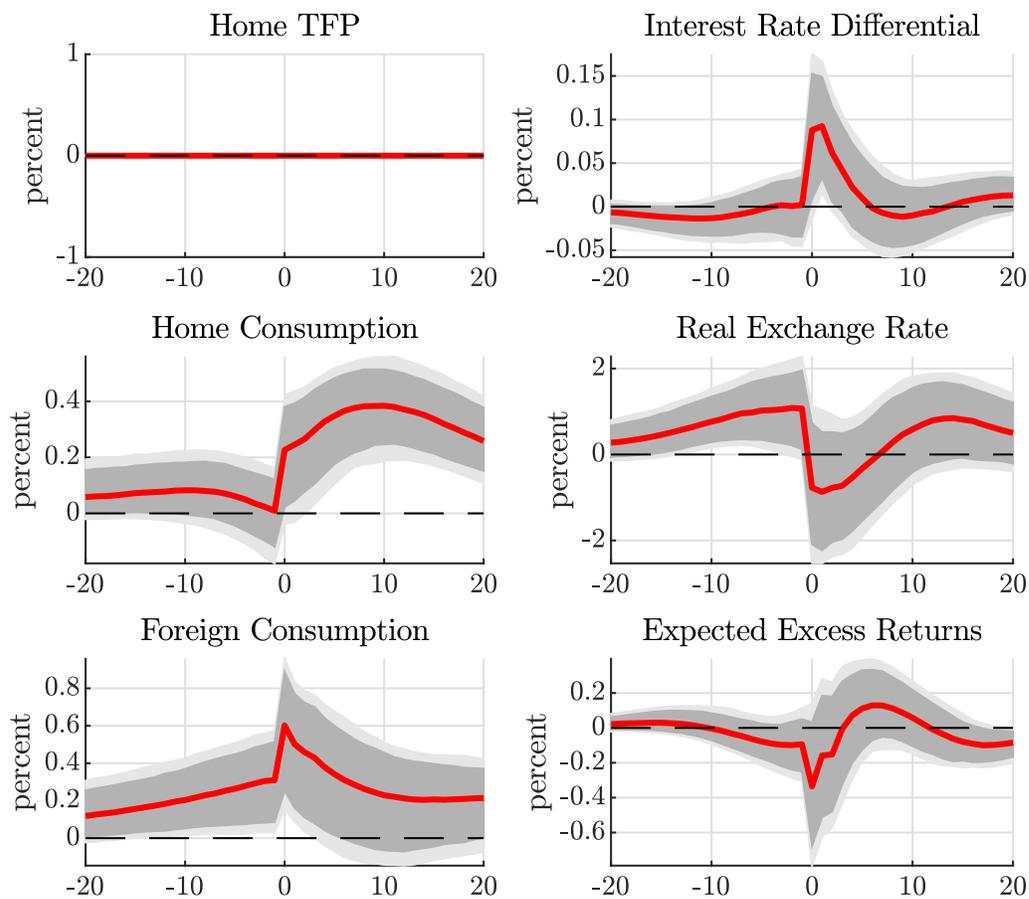
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 27: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances, Japan



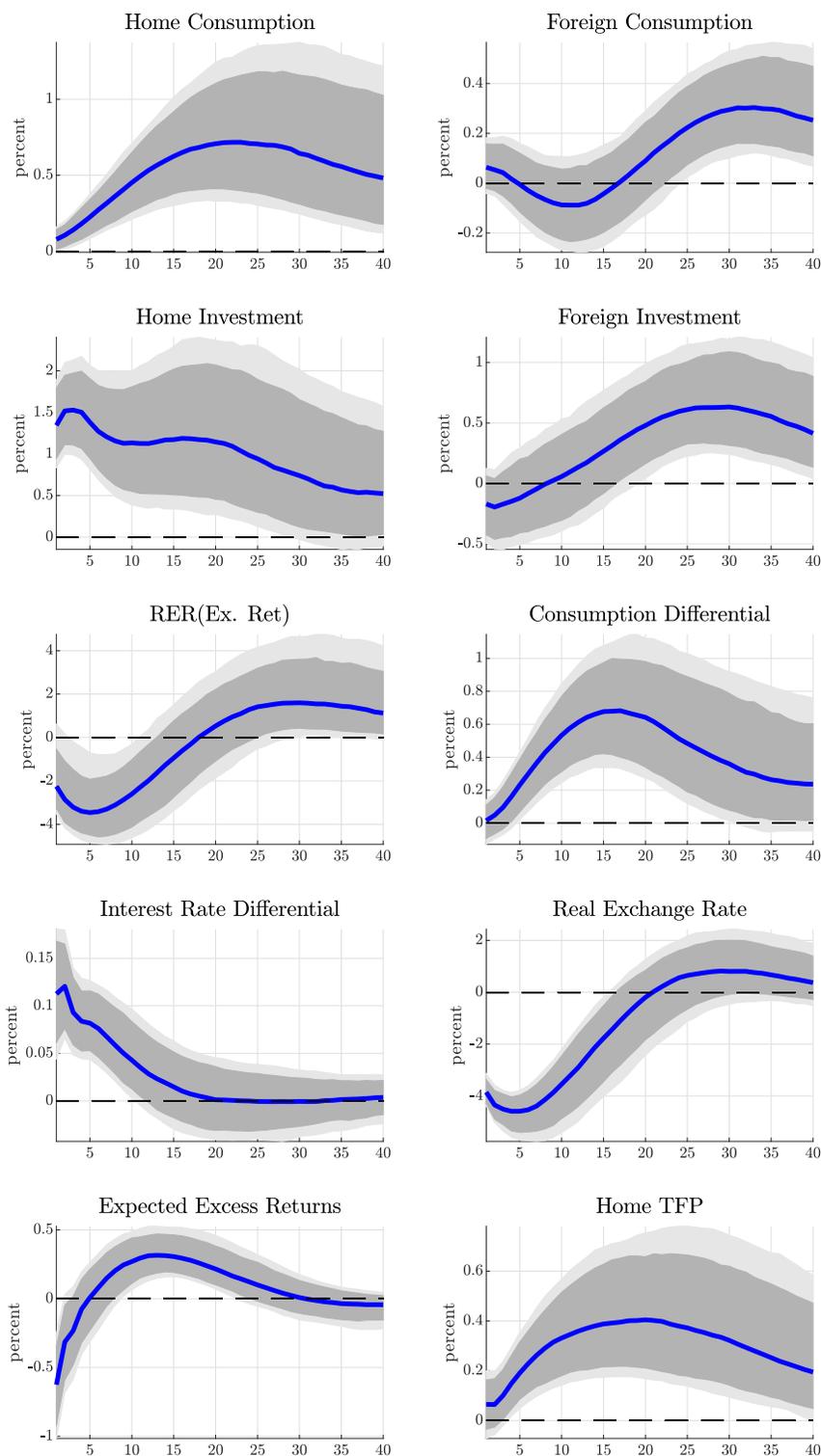
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 28: Impulse responses to Noise ( $\varepsilon^v$ ) disturbance, Japan



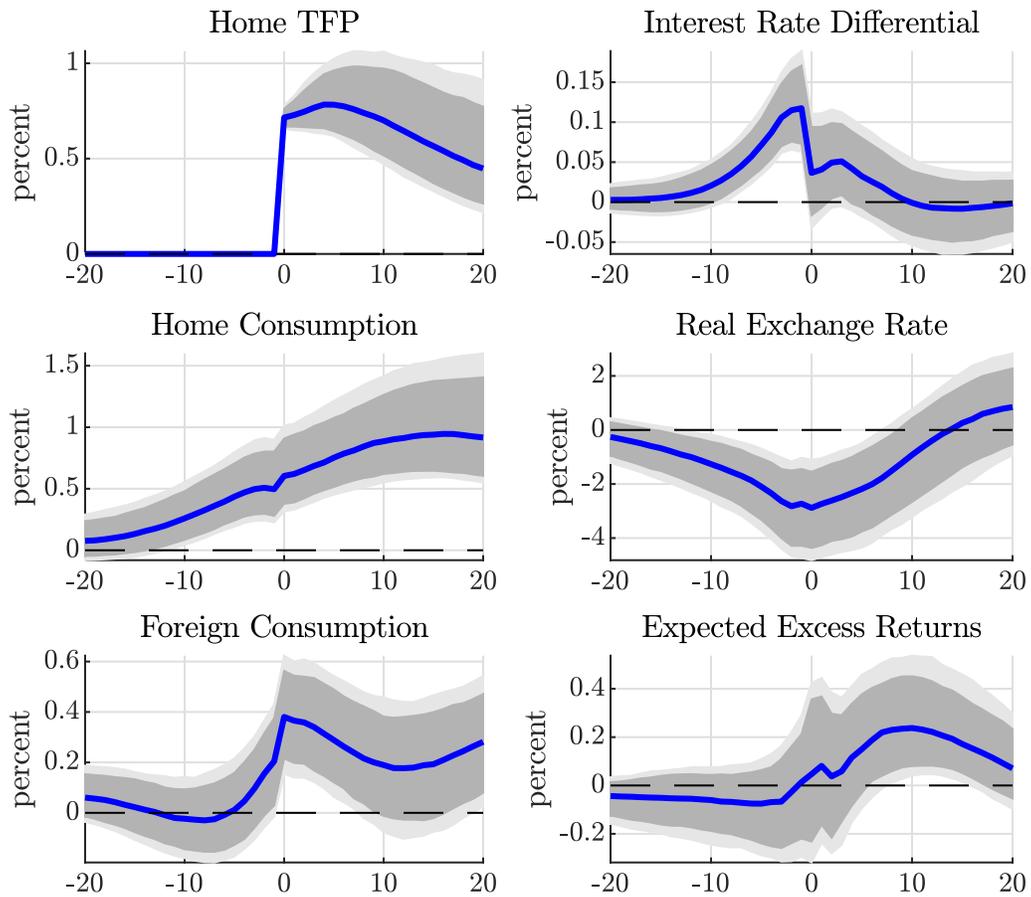
*Notes:* The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 29: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), Italy



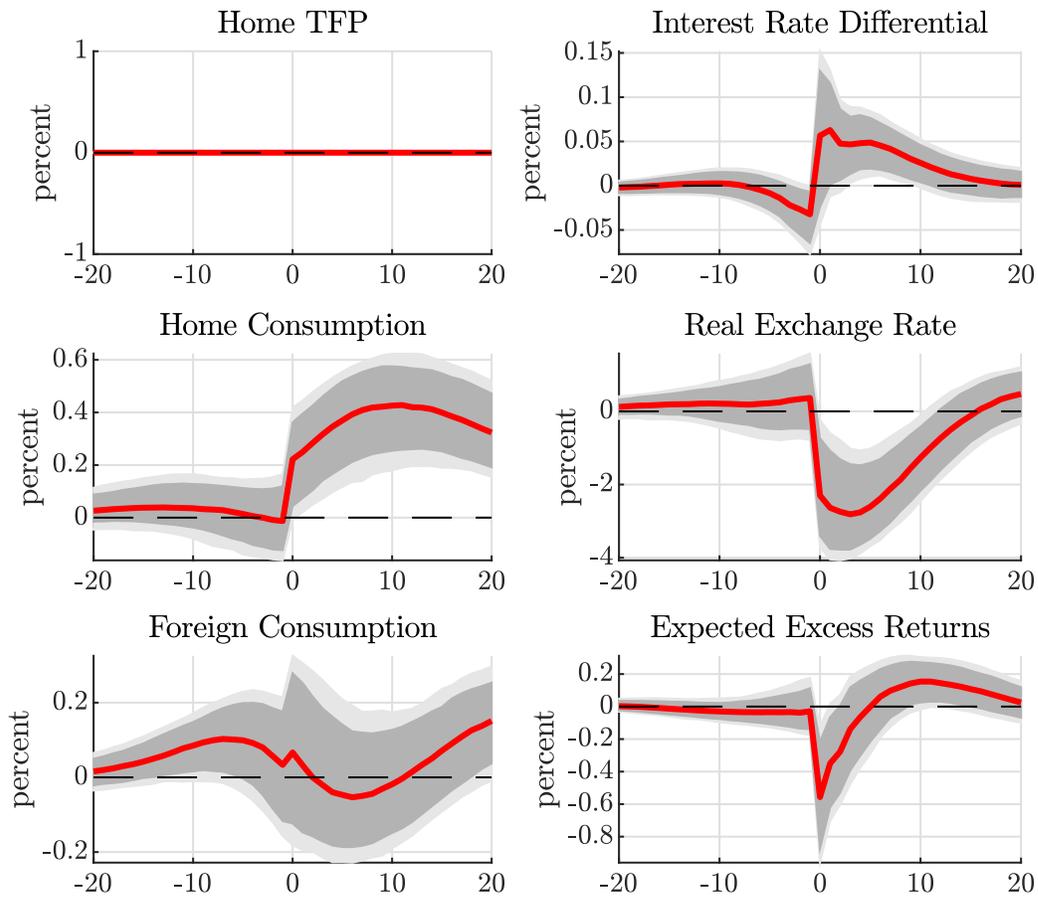
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 30: Impulse responses to Technology ( $\varepsilon^a$ ) disturbances, Italy



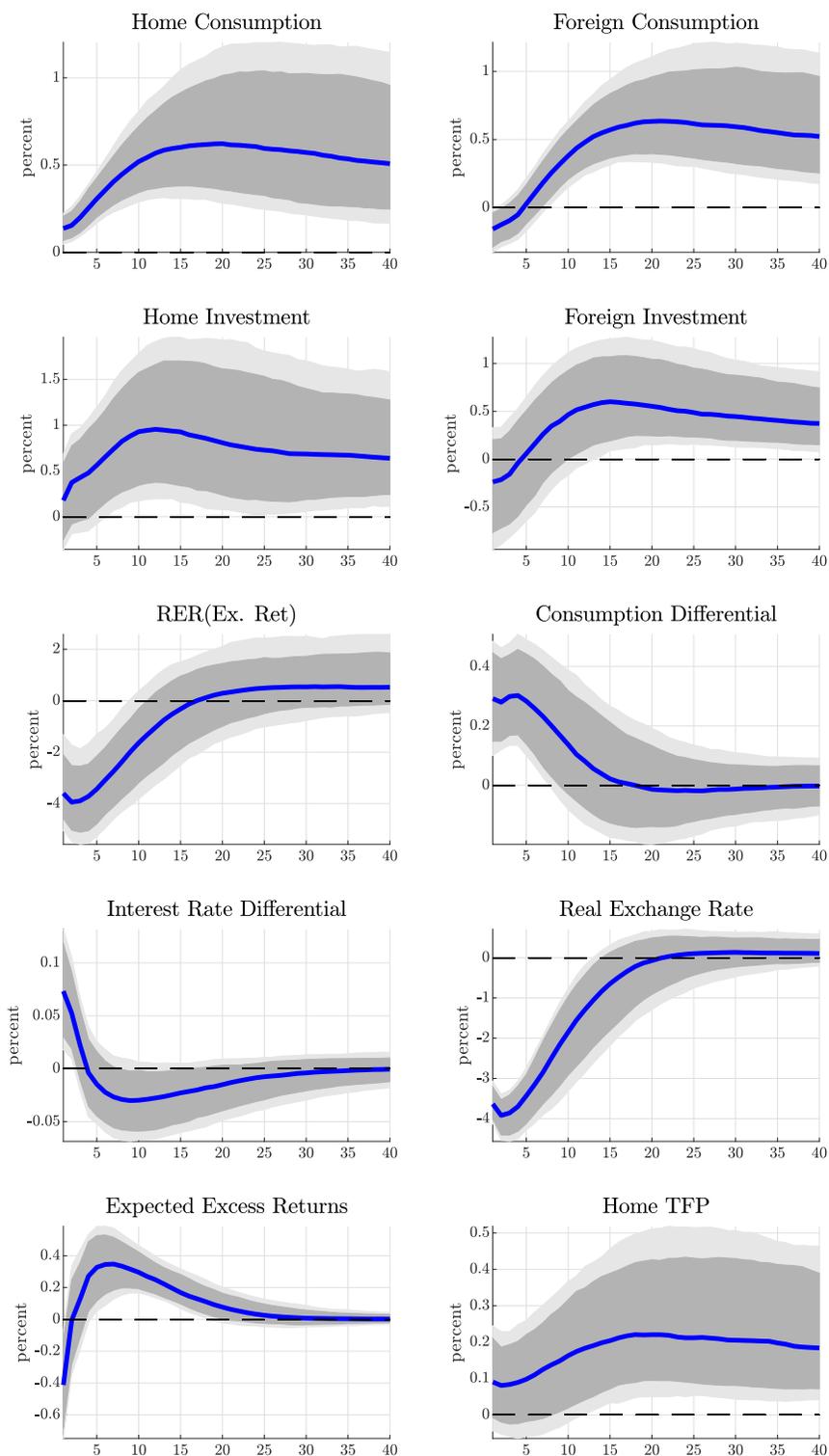
*Notes:* The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. Each period is a quarter.

Figure 31: Impulse responses to Noise ( $\varepsilon^v$ ) disturbance, Italy



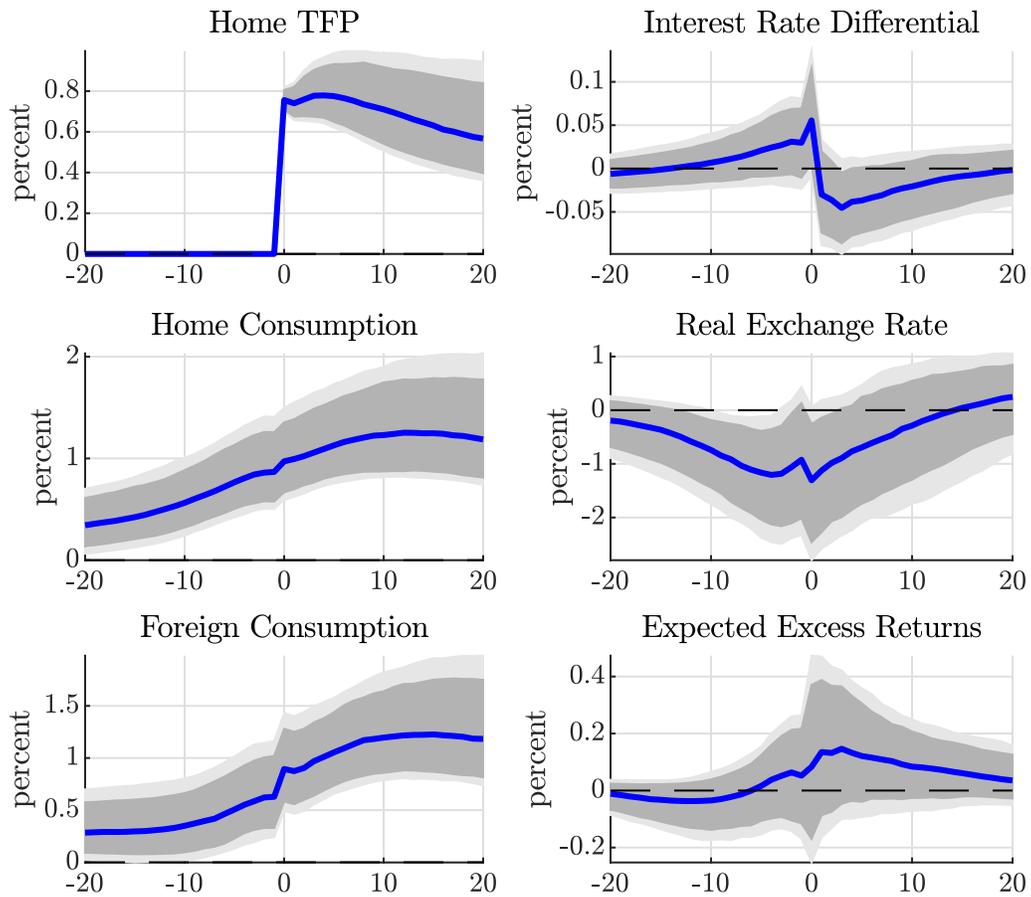
*Notes:* The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time  $t = 0$ . The shaded area are the 68% and 80% confidence intervals. All units are annualized percents. Each period is a quarter.

Figure 32: Impulse Response Functions to the Main FX shock ( $\varepsilon_1$ ), UK



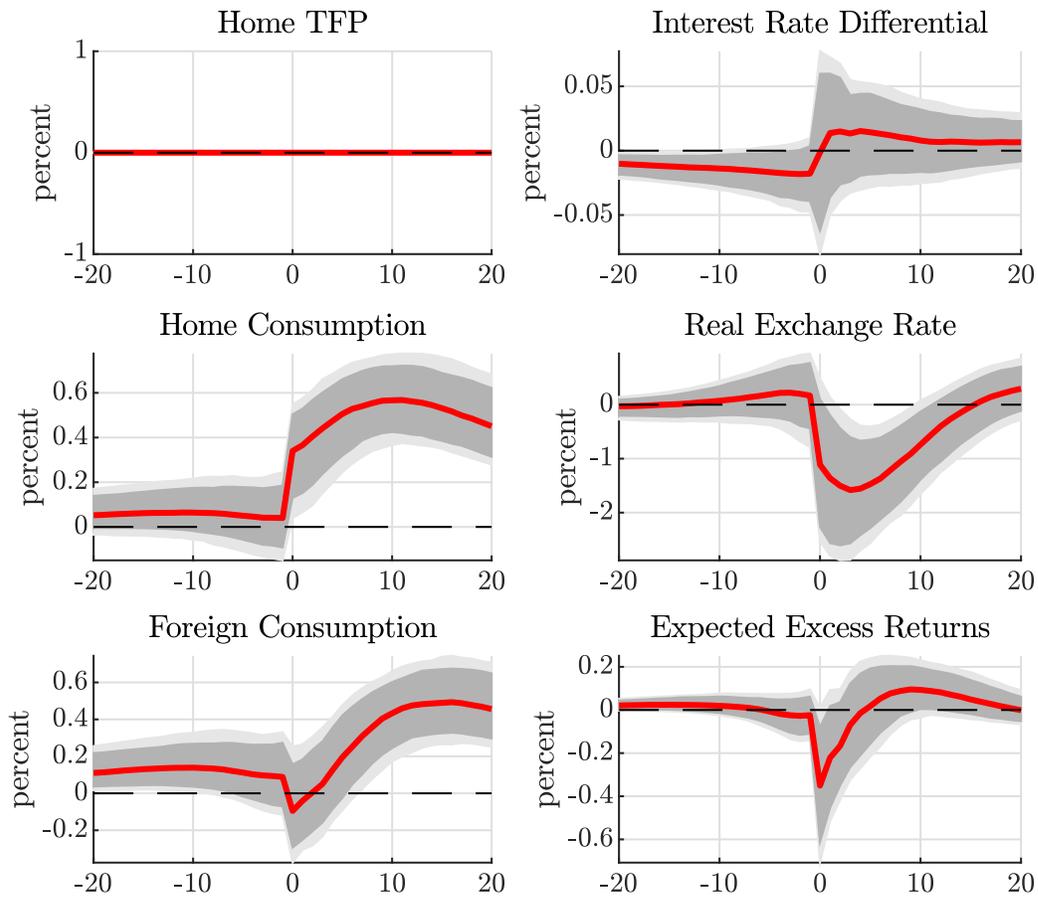
*Notes:* The figure reports the impulse responses to the main FX shock, along with the 16-84th (dark gray) and 10-90th (light gray) percentile bands. Each period is a quarter.

Figure 33: Impulse responses to Technology ( $\varepsilon^a$ ) 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 ( $\varepsilon^v$ ) 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.