Exchange Rate Disconnect Revisited*

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Abstract

We find that variation in expected U.S. productivity explains over half of U.S. dollar/G7 exchange rate fluctuations. Both correctly-anticipated changes in productivity and expectational noise, which influences the expectation of productivity but not its eventual realization, have large effects. This "noisy news" is primarily related to medium-to-long-run TFP growth, and transmits to the exchange rate by causing significant deviations from uncovered interest parity. Together, these disturbances generate many well-known exchange puzzles, including predictable excess returns, low Backus-Smith correlations, and excess volatility. Our findings suggest these puzzles have a common origin, linked to productivity expectations.

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The real exchange rate – the relative price of consumption across countries – plays a crucial role in clearing markets for both goods and financial assets in international macroeconomic models. As a result, models typically imply that exchange rates are tightly linked to cross-country differentials in macroeconomic quantities, real interest rates, and other asset prices in the economy. However, in the data, real exchange rates appear largely "disconnected" from such macro fundamentals: they exhibit virtually no correlation with current and past macro quantities (*e.g.*, Meese and Rogoff, 1983, Engel and West, 2005) or interest rates (*e.g.*, Fama, 1984), and at the same time are surprisingly volatile (*e.g.*, Rogoff, 1996). As a consequence, a tremendous amount of theoretical work seeks to understand what mechanisms could generate these puzzling patterns in models. Yet, there is relatively little direct *empirical* evidence on the origins of these puzzles in the data.

To close this gap, in this paper we aim to uncover the main empirical drivers of exchange rate fluctuations in a model-agnostic way. Our key finding is that noisy news about future TFP accounts for more than half of the overall variation in *both* real exchange rates and macroeconomic variables. Thus, our results indicate that the exchange rate is indeed intrinsically connected to macroeconomic fundamentals, and that the apparent disconnect the previous literature has documented arises because the impact of news manifests at different horizons for exchange rates and macro quantities. Specifically, we find that the response of the exchange rate leads that of the macroeconomy by two years or more, resulting in low contemporaneous correlation between the exchange rate and macro aggregates, even though ultimately both sets of variables react to the same underlying source of fluctuations. Moreover, the results indicate that the conditional responses to the noisy news we identify generate a number of famous exchange rate puzzles, suggesting that many well-known anomalies have a common, fundamental origin in noisy news about future TFP.

Our analysis proceeds in two steps. First, we seek an agnostic description of the basic comovement patterns associated with surprise changes in exchange rates in the data. To do this, we follow the VAR procedure of Uhlig (2003) to recover a set of orthogonal reduced form shocks ordered by their importance in explaining exchange rate variation. When applied to the dollar/G6 exchange rate we find that the first shock – the one most important to exchange rate fluctuations – explains two-thirds of exchange rate variation *and* around 40% of the variation in macro aggregates. However, while the shock affects the exchange rate immediately, its effects on macroeconomic quantities such as consumption, output and TFP are delayed. Thus, this shock only generates a correlation between exchange rates and *future* macro aggregates, leaving exchange rates effectively "disconnected" from contemporaneous macro aggregates. In particular, the shock has no initial effect on Fernald's (2012) utilization-adjusted U.S. TFP, but leads to a significant increase in TFP between three and five years in the future.

Intuitively, these results suggest that the exchange rate, a forward-looking asset price, reacts to the arrival of news of future macro fundamentals. These results motivate the second, and most important, step of our analysis: we directly identify and isolate disturbances to expectations about future U.S. TFP, and then estimate their effects on the real exchange rate and other cross-country macro variables. To do so, we follow the approach of Chahrour and Jurado (2021) to decompose and separately identify two orthogonal disturbances: (i) partially anticipated changes to actual future productivity and (ii) expectational "noise" disturbances that move expectations of productivity, *but never materialize in realized productivity.* Intuitively, this identification approach is designed to separately identify the signal from the noise component in noisy news. It is useful to stress that in this second step of our analysis, we first turn our focus to TFP and extract noisy news about that (arguably) exogenous macro fundamental, and then turn around and study the impact of these noisy news on the exchange rate.

We find that both correctly-anticipated future TFP changes and "noise" in TFP expectations play an important role in driving exchange rates in the data. The noise disturbances give rise to volatile but short-lived fluctuations in the exchange rate, while correctly-anticipated TFP changes impart persistent effects on the exchange rate. As a result, expectational noise appears relatively more relevant at higher frequencies, while lower-frequency movements in exchange rates predominantly reflect true technological disturbances. Taken together, the two disturbances account for more than 60% of the variation in the real exchange rate – and importantly also account for a comparable fraction of the variation in real macroeconomic quantities. However, as is to be expected, the impact on macro aggregates is delayed relative to the response of exchange rates. We also study the impulse responses of a number of other variables, such as the trade balance and equity prices, and find that the U.S. current account deteriorates and U.S. and foreign equity prices rise in anticipation of an improvement of future U.S. productivity. Thus, noisy news about future TFP prove to be the rare structural disturbances that drive a large portion of both real exchange rates, international business cycles and also other asset prices.[1]

Moreover, we find that the responses to these identified disturbances also generate a number of well-known "exchange rate puzzles", suggesting that a constellation of famous

[1]To the contrary, we find that pure surprise changes to TFP contribute little to exchange rates.

anomalies share a common, fundamental origin in noisy news about future TFP. In particular, we find that the noisy news disturbances cause significant *predictable* fluctuations in excess currency returns, which generate violations of uncovered interest parity (UIP) that are consistent with both the classic puzzle of high interest rates forecasting high domestic currency returns (Fama, 1984) and the more recently documented "reversal" in this predictability pattern at longer horizons (Engel, 2016; Valchev, 2020). Second, the conditional responses of exchange rates and consumption differentials across countries exhibit a weak negative correlation, in line with Backus and Smith's (1993) puzzle documented unconditionally. Third, the conditional responses also imply that real exchange rate dynamics are highly persistent and that the impact on exchange rates is large relative to macro quantities, two well-known features of unconditional exchange rate dynamics that the literature calls the "PPP Puzzle" and the excess volatility of the exchange rate (*e.g.*, Rogoff, 1996). Fourth, we find that the identified noisy news disturbances transmit to the exchange rate primarily by causing fluctuations in expected currency returns – the so called "UIP wedge". Our results thus indicate that in the data the UIP wedge, as well as related exchange rate puzzles, are to a large extent endogenous to and driven by noisy news about future TFP.

Lastly, we stress that two features of our analysis are particularly important for understanding why previous studies that have also examined the forward-looking nature of exchange rates have generally struggled to establish a robust correlation between exchange rates and future TFP (as well as with macro variables more broadly). First, our estimates suggest that the news that matters for the exchange rate is mainly about *medium-to-long horizon* news – specifically news about TFP changes up to 5 years in advance. On the other hand, the bulk of existing studies have concentrated on much shorter horizons, seeking lead-lag relationships at horizons of one to two years. Second, contrary to the literature we separately identify and account for expectational noise. This sharpens our results because expectational noise weakens the correlation between expectations and *realized* fundamentals, reducing the statistical power of previous empirical approaches that focus on the lead-lag relationship between exchange rates and *realized* future fundamentals.

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 using current macroeconomic fundamentals (Meese and Rogoff, 1983; Cheung et al., 2005; Rogoff and

Stavrakeva, 2008; Miyamoto et al., 2023). A related observation is that the exchange rate is "excessively" volatile and persistent, as compared to macroeconomic fundamentals (Obstfeld and Rogoff, 2000; Chari et al., 2002; Sarno, 2005; Corsetti et al., 2008a; Steinsson, 2008).

Contrary to this literature, we find that there is in fact a strong connection between exchange rates and macroeconomic fundamentals, but one that relates current exchange rates to future fundamentals. Our evidence supports the basic point of Engel and West (2005) that exchange rates are forward-looking and should therefore predict, rather than lag behind, macroeconomic variables. Our results contribute to this discussion in a number of ways. First, we show that the link between current exchange rates and future fundamentals runs specifically through *imperfect* and *noisy* anticipation of future productivity. Second, we show that the noisy TFP news priced into exchange rates primarily concern TFP at medium-to-long horizons (3 to 5 years in the future). Third, our study is unique in explicitly accounting for expectational noise – fluctuations in expectations that are not associated with actual subsequent changes in fundamentals – and we emphasize that ignoring this component of expectations leads one to understate the forward-looking nature of exchange rates.[2]

Another contribution of this paper is to show that a large number of famous exchange rate puzzles have a common fundamental origin in noisy news about future TFP. In particular, we find that the noisy news we identify do not only play an important role in the exchange rate disconnect and excess volatility puzzles referenced above, but also in generating the UIP puzzle (Fama, 1984; Engel, 2014) and the Backus-Smith puzzle (Backus and Smith, 1993). These puzzles have also received extensive theoretical attention, and interestingly the great majority of proposed models are driven by classic "pure surprise" shocks to TFP, not news about future TFP.[3] Our results showcase that the empirically relevant case, however, seems to be one where the main driving force behind exchange rate fluctuations and associated FX puzzles is the arrival of noisy, advance information about future TFP and this is important

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

[3]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, 2023) and liquidity premia (Engel, 2016; Valchev, 2020) have been proposed as explanations of the UIP Puzzle. On the other hand, Corsetti et al. (2008b), and Karabarbounis (2014) develop models that explain the Backus-Smith puzzle. The Colacito and Croce (2013) model of "long-run risk" occupies an interesting middle ground, since their shocks to TFP have persistent, non-monotonic impulse responses and hence the main impact is in the future, which is akin to news.

guidance for future theoretical work.

Moreover, our finding that the noisy news disturbances we identify transmit to the exchange rate primarily by causing large fluctuations in expected excess returns and the associated UIP wedge relates to a recent theoretical literature that emphasizes models driven by currency-markets-specific "noise trader" shocks (e.g. Gabaix and Maggiori (2015), Itskhoki and Mukhin (2021)).[4] Our empirical evidence agrees with the key insight of this literature that fluctuations in excess currency returns are at the center of several exchange rate puzzles. However, our results also indicate that a large share of the excess returns fluctuations in the data are specifically caused by the arrival of noisy news about future TFP, rather than exogenous UIP shocks orthogonal to fundamentals. Moreover, let us stress the subtle difference in the notions of "noise" used in our case relative to this literature. In the UIP-shock literature, the term "noise" typically refers to an exogenous shift in the demand for one currency relative to another, while we use the term "noise" to describe an informational disturbance to signals seen by market participants. Hence, while both notions of noise are orthogonal to realized TFP, the informational noise we consider here is conceptually an expectations error of future TFP, and not a financial markets shock. Overall, our rich empirical results provide new specific guidance and discipline for future theoretical work, perhaps shifting the focus towards models in the vein of the long-run risk literature (*e.g.*, Colacito and Croce, 2013), where the UIP wedge is due to fluctuations in long-run TFP growth.

Relatedly, there is a small but growing literature that documents the effects of "news shocks" on international business cycles and develops 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).[5,6] Perhaps most closely related to us is the work of Nam and Wang (2015), who use Barsky and Sims' (2011) approach to identifying news-

[4]Such shocks have a long tradition in the literature; see also, *e.g.*, Devereux and Engel (2002), Jeanne and Rose (2002) Kollmann (2005), Bacchetta and van Wincoop (2006), Farhi and Werning (2012), and Eichenbaum et al. (2020). Relatedly, Huo et al. (Forthcoming) 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.

[5]Corsetti et al. (2014) use sign restrictions to identify the cross-country effects of unanticipated productivity and demand disturbances in the United States, including on the real exchange rate.

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

to-TFP shocks. In contrast to us, however, they do not separately identify the effects of correctly anticipated TFP improvements and expectational noise disturbances, and also do not consider how news are propagated to the exchange rate. A key differentiating result of our analysis is that UIP deviations as caused by *noisy* news about future TFP are at the heart of many famous exchange rate puzzles, and exchange rate volatility overall.

Last, we note that a few recent papers document the presence of *contemporaneous* relationships between exchange rates and specific macro aggregates in the data. Lilley et al. (2020) find a contemporaneous correlation between U.S. purchases of foreign bonds and the U.S. dollar, but only in the post-2009 period. Over a longer time span, Engel and Wu (2024) show that monetary variables and measures of risk and liquidity account for a sizable portion of variation in U.S. dollar/G10 exchange rates. Kekre and Lenel (2024) document that higher U.S. yields relative to G10 yields (ranging from 3 months to 10 years tenors) are associated with an appreciated U.S. dollar/G10 exchange rate. Kekre and Lenel argue that this evidence, along with the Backus-Smith correlation, favors models in which exchange rates are driven by persistent demand shocks, and note that news about long-run productivity (like the ones we document) could in principle generate persistent movements in demand.[7]

1 Data and basic empirical framework

Our empirical analysis centers on a VAR

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

where the vector Y_t contains data on the U.S. and a trade-weighted aggregate for the other G7 economies. Hereinafter, we will refer to the U.S. and the other G7 economies as the "home" and "foreign" economies, respectively, and use the * notation to denote non-U.S. variables. For our baseline analyses, the vector Y_t contains eight variables: (i) the nominal exchange rate S_t expressed in units of U.S. dollar per foreign currency, (ii) Fernald's (2012) series on utilization-adjusted U.S. TFP, (iii) and (iv) are the U.S. real consumption and investment, (v) and (vi) are foreign real consumption and investment, (vii) the nominal interest rate

[7]Other papers document statistically significant relationships between exchange rates and commodity prices (Chen et al., 2010; Ayres et al., 2020), exchange rate and external imbalances (Gourinchas and Rey, 2007), as well as exchange rates and trade flows (Alessandria and Choi, 2021; Gornemann et al., 2020). In addition, Hassan et al. (2016) document a relationship between stochastic properties of exchange rates and differences in capital-output ratios across countries.

differential, (viii) and the CPI price level differential between the U.S. and a trade-weighted aggregate for the other G7 economies. The variables in our VAR can be denoted as:

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

Using a trade-weighted aggregate of the other G7 economies as the "foreign" country is standard in the literature (*e.g.*, Engel, 2016). In any case, in Appendix B, we conduct the analysis using six separate bilateral VARs between the U.S. and each other G7 country separately. The results and the emerging conclusions of the bilateral VARs are very similar, hence we have found that a VAR with a trade-weighted aggregate serves as a useful benchmark to summarize the results.[8]

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

We describe the data and their sources in detail in Appendix A. As a brief overview, the exchange rate is the average of the daily exchange rates within a quarter, obtained from *Datastream*. The interest rate differential is the average of daily Eurodollar rates within a quarter, obtained from *Datastream*.[9] The CPI indices and the consumption and investment series are from the *OECD* database. Lastly, the U.S. TFP is from John Fernald's website.

We do not have a comparable, utilization-adjusted quarterly TFP series for countries other than the US. Recently, a few papers have constructed novel utilization-adjusted TFP for foreign economies (*e.g.*, Huo et al., 2023; Comin et al., 2023), but we find that these measures are not appropriate for our purposes. Most importantly, most such measures of adjusted foreign TFP can only be constructed at annual frequencies (Huo et al., 2023) or over a very short a sample period (Comin et al., 2023), which limits the scope of the analysis. Moreover, the Huo et al. (2023) measure of utilization-adjusted TFP for the United States displays a fairly low correlation (0.42) with the widely-accepted Fernald measure for U.S.

[8] Results when we use a simple average across the foreign economies, instead of a trade-weighted average, are virtually identical.

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

TFP, suggesting it is measuring some different notion of technology (and beyond that is only available annually). As a result, our benchmark analysis does not include a measure of foreign TFP, but as a robustness exercise we report in the Appendix B, we consider alternative specifications where we use the foreign Solow residual at quarterly frequency (to maximize data coverage). All of our main results and conclusions remain unchanged.

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

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

Given the VAR estimates, our goal is to isolate structural shocks that are significant drivers of the real exchange rate. To that end, we note that the reduced-form VAR residuals, u_t can be expressed as a linear combination of leads and lags of the underlying structural disturbances ε_t

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

where we stress that $A(L) \equiv \sum_{-\infty}^{\infty} A_k L^k$ is a potentially two-sided lead-lag polynomial. This expression generalizes more traditional treatments in allowing for the innovations in the VAR to depend on past, present, and future structural disturbances.

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

We conduct our analysis in two steps, going from fewer to more structural assumptions. First, we use a "max-share" approach in the vein of Uhlig (2003) which makes the usual assumption that $A(L) = A_0$, but otherwise makes minimal structural assumptions about A_0. The results of this analysis then motivate our second step, in which we allow for a general, potentially doubled-sided form for $A(L)$, but then impose stronger economic restrictions to specifically identify anticipated TFP disturbances and noise disturbances to expectations of future TFP.

2 The main driver of real exchange rate fluctuations

We begin with an agnostic empirical approach that aims to isolate the main driver of exchange rate fluctuations in the data while imposing minimal ex-ante assumptions on the nature of the underlying structural disturbances. To do so, we follow the max-share approach of Faust (1998) and Uhlig (2003) to extract the shock that explains the biggest share of the variation in the real exchange rate. This approach was recently applied to real macro quantities by Angeletos et al. (2020) to extract a so-called "main business cycle" shock. In turn, we apply it to exchange rates, and in parallel to the Angeletos et al.'s (2020) terminology, we refer to the shock we extract here as the "main exchange rate" (MFX) shock.[10]

The real exchange rate q_t is the difference between the log nominal exchange rate and the differential in log CPIs, $q_t = s_t + p_t^\star - p_t$, and hence given the included variables in Y_t,

$$q_t = e_q' Y_t,$$

where $e_q = [1, 0, 0, 0, 0, 0, 0, -1]'$.

To apply the max-share procedure, note that given the assumption of $u_t = A_0 \varepsilon_t$ it follows that the moving average representation of the VAR in (1) can be written as

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

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

[10] Kurmann and Otrok (2013), Basu et al. (2021), Cormun and De Leo (2024), and Chahrour et al. (2023) also contain applications of the max-share approach. The concurrent paper Miyamoto et al. (2023) applies this methodology to exchange rates as well. However, among other differences, they use a VAR with variables expressed in terms of *cross-country differentials*. This transformation tends to cancel out the common component of shocks and thus filters a lot of useful variation out of the dataset. Indeed, with this restrictive treatment of the data their "main FX shock" is quite different from the one we identify, and most importantly unlike our key finding, it is not related to macro aggregates.

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

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

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

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

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

We choose the rotation matrix A_0 by maximizing (4). This requires us to specify a horizon h at which the forecast error variance in (4) is computed, and for that we choose $h = 100$ quarters, which effectively gives us the unconditional variance of q_t.[11] This procedure yields a partially identified system, in the sense that the above maximization problem will uniquely determine the first column of A_0 and thus the first element of the shock vector of ε_t (which is what we are interested in), but not the rest.

Intuitively, the resulting shock series ε_{1t} is the reduced form innovation that makes the largest contribution to the fluctuations in the log real exchange rate q_t. This is not a structural shock with a clear economic interpretation – ε_{1t} is potentially a linear combination of several underlying structural shocks. Rather, we view ε_{1t} as a reduced form way of capturing the dominant factor driving surprise changes in the exchange rate in the data, whatever its true deep origins might be (this is the topic of the second part of the paper).

Estimation results We find that this "main exchange rate shock" is indeed a dominant driver of exchange rate fluctuations – it explains roughly 70% of variance of the real exchange rate, in a variance decomposition sense (see Table 1). Given its empirical importance for the exchange rate, understanding the characteristics and the footprint this reduced form innovation leaves in the rest of the economy could be very informative about the deep origins of exchange rate variation.

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

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

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

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

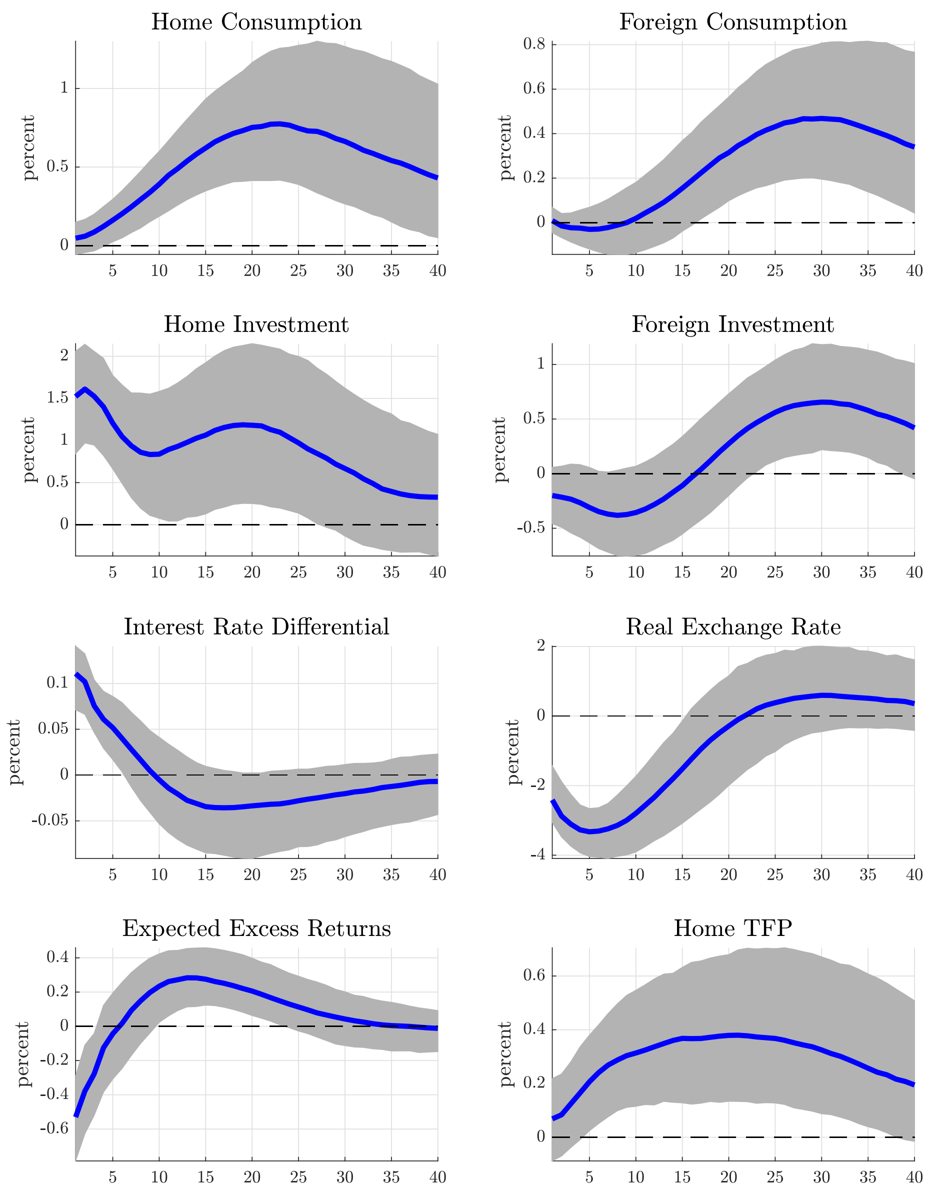
As a first step in this direction, we report the impulse response functions of the exchange rate, and also other macro variables, in Figure 1. The median impulse response to a one standard deviation shock is plotted with a solid blue line, and the shaded areas denote the 16-84th percentile bands.

The real exchange rate shows a significant response on impact, appreciating by about 2.5% after a one standard deviation increase in the MFX shock. The exchange rate response also displays persistent hump-shaped dynamics, where it continues to appreciate for another 5 quarters after the initial impact, peaking at a maximum appreciation of about 3.5%, and thereafter it steadily depreciates back to its long-run mean. These persistent non-monotonic dynamics – with a half-life of roughly three years – are similar to the estimates in Steinsson (2008) in the context of an *univariate* reduced form innovation to the exchange rate.[12]

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

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

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



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

We also observe that in response to the MFX shock, the real interest rate differential increases on impact (*i.e.* high U.S. interest rate) and gradually returns to its long-run mean. As a result, in the immediate aftermath of the shock, the exchange rate response displays the classic version of the UIP puzzle where the high interest rate currency (the USD) is earning high returns (Fama, 1984). On the other hand, in the medium run, the direction of the UIP violation reverses, with the USD earning low returns for an extended period of time – and thus the MFX shock generates exchange rate dynamics that are consistent with the reversal of UIP violations at longer horizons documented by previous studies such as Engel (2016) and Valchev (2020).

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

Broader footprint of the MFX shock The procedure for extracting ε_{1t} imposes very few ex-ante assumptions on the data. The trade-off is that we cannot uniquely label the structural origins of the MFX shock. Still, given the prevailing view that exchange rates are disconnected from the broader macroeconomy, it is interesting to consider whether the MFX shock, which is identified purely off its consequences for exchange rates, is potentially associated with significant dynamic effects on any *other* macro aggregate.

And surprisingly, given the vast prior literature on the disconnect between exchange rates and macro fundamentals (*e.g.*, Meese and Rogoff, 1983 and Engel and West, 2005), we find that the MFX shock does explain a significant portion of the overall variation of several important macro aggregates. Most importantly, it accounts for around 40% of the forecast error variance of consumption (both home and foreign) and TFP at long horizons (see Table 1, rows 1 through 5). The reason this surprisingly strong connection with fundamentals has been largely overlooked so far is that the effects of our main exchange rate shock materialize at different horizons in exchange rates and macro aggregates – the exchange rate reacts strongly immediately, while most macro aggregates react with a significant lag. This difference in *timing* implies there is actually only a mild correlation between exchange rates and current and past macro aggregates (conditional on this shock), in line with previous findings.

We can see this most clearly from the impulse responses reported in Figure 1. Home consumption only responds in statistically significant terms to the MFX shock after a year, and foreign consumption does not exhibit a significant response until four 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 (by this time the effect on exchange rates has completely died out). Moreover, the relatively stronger and quicker impact on home consumption implies that the MFX shock generates the celebrated empirical violation of the Backus and Smith (1993) condition, where high domestic consumption is associated with an appreciated exchange rate, rather than a weak exchange rate.

Similarly, the MFX shock causes no significant impact on U.S. TFP up to four quarters in the future, but productivity displays a significant and prolonged increase at longer horizons. The effect peaks at an increase of 0.4% around 20 quarters after the initial impulse. Thus, overall both consumption and TFP display a significant response in the medium-to-long run, but no response in the immediate aftermath of the shock.

The differences in the timing of the effects of the MFX shock among different variables can also be observed in performing forecast error variance decompositions at different horizons h. In Table 1, 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 shapes of the IRFs in Figure 1, while this shock is equally important for both short-run and long-run exchange rate fluctuations, it only explains 2% and 3% of the one-quarter-ahead forecast error variance of U.S. consumption and TFP, respectively. At the same time, the MFX shock explains roughly 20% of the forecast error of consumption and TFP at the 3 year horizon, and 40% of their forecast error variance at longer horizons.

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

Indeed, our results confirm that the bulk of the variation in the real exchange rate is essentially unrelated *contemporaneously* to aggregate consumption or TFP, two key macro aggregates the prior literature has often studied in the context of exchange rates. Rather, we find that the exchange rate *leads* these macro aggregates. Thus, our results suggest that the canonical finding of a "disconnect" does not emerge because of an actual separation between exchange rates and fundamentals, but rather because of a difference in the timing of the responses in these variables.

The empirical approach so far offers an enlightening statistical summary of the data that relies on minimal assumptions, but it cannot sharply label the deep structural origins of the reduced form exchange rate innovation ε_{1t} we have uncovered. Still, the key finding that macroeconomic quantities such as consumption and TFP only respond with a significant delay, while forward looking variables such as asset prices (the exchange rate itself, but also interest rates) jump on impact, suggests the further hypothesis that the MFX is capturing (or at least heavily loading on) the classic notion of a news shock about TFP.

This is an interesting hypothesis, and challenges the emerging consensus in the literature that exchange rate fluctuations are primarily due to currency market-specific financial or risk shocks that are unrelated to macroeconomic fundamentals. In order to investigate this news about TFP hypothesis in detail, in the next section we introduce some simple structural assumptions that are sufficient to identify disturbances to expectations about TFP, and evaluate whether they are indeed an important driver of exchange rates.

3 Expectations of TFP and exchange rates

In this section, we seek to identify two types of disturbances to expected TFP using the identification approach of Chahrour and Jurado (2021). The first type of disturbance captures all realized changes to TFP, and may be imperfectly anticipated at an arbitrary horizon. The second disturbance captures the noise in expectations that leads agents forecasts about future TFP to fluctuate even when realized TFP does not change.

Under our working hypothesis, agents see the current realization of TFP and its full history, and in addition the agents potentially have advance information about future TFP as summarized by a noisy signal, η_t. We allow for the structure of this signal to be general, and only assume that it can be represented as an unrestricted linear combination of future values of TFP plus an orthogonal noise component v_t:

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

where we impose no restrictions on the coefficients ζ_k, and the noise component of the signal, v_t, is also general and allowed to have an arbitrary lag structure with iid disturbances ε_t^v:

$$v_t = \sum_{k=0}^{\infty} \nu_k \varepsilon_{t-k}^v, \tag{6}$$

Lastly, we also impose no ex-ante assumptions on the time-series dynamics of the TFP process a_t, and simply assume it can be represented as a MA(∞) process with unrestricted lag coefficients δ_k:

$$a_t = \sum_{k=0}^{\infty} \delta_k \varepsilon^a_{t-k}, \tag{7}$$

where ε^a_t are the true structural innovations to TFP.

We seek to separately identify the true technological disturbances ε^a_t and the expectational noise shocks ε^v_t, and in doing so we follow the method of Chahrour and Jurado (2021). The assumptions of their procedure are that (i) the productivity disturbances ε^a_t are orthogonal to other structural shocks (as is standard) and (ii) the signal-noise innovations ε^v_t are orthogonal to ε^a_t (hence unrelated to actual TFP at all leads and lags).

To get some intuition of how it works in practice, consider first the illustrative case where η_t is observed by the econometrician. In that case, the dynamic structure of equations (5)-(6) can be represented as a two-variable VAR in $[a_t, \eta_t]$. In turn, the assumption of orthogonal ε^a_t and ε^v_t, can be restated in terms of placing zeros in the MA representation of that bivariate VAR in the following way:

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

The identification assumption that the noise disturbances ε^v_t are not related to TFP at any lead or lag implies that the upper right corner of *all* matrices, leads and lags, is zero. In addition, since ε^a_t is the Wold-innovation to TFP the upper left corner of all *lead* matrices is zero – i.e. these are true innovations that move TFP only after they realize. As Chahrour and Jurado (2021) show, this gives us enough zero restrictions to point-identify the system – intuitively, the number of remaining unrestricted coefficients is equal to the number of moments we can estimate from data on the realizations of the vector $[a_t, \eta_t]$. In turn, with the coefficient estimates we can separately recover the series of disturbances ε^a_t and ε^v_t.

Of course, the above illustrative example implausibly assumes that the econometrician directly observes the relevant signal η_t. However, the same identification can be achieved by replacing η_t in the observation vector $[a_t, \eta_t]$ with forecasts of future TFP, $\mathbb{E}_t(a_{t+k})$, since the main role of the signal η_t is to affect expectations. So in practice, when we take this to the data we will use the forecast of future TFP implied by our estimated VAR (equation (1)). Formally, the key assumption needed for replacing η_t with the VAR-implied $\mathbb{E}_t(a_{t+k})$ is that the forward-looking variables in the VAR, *e.g.* exchange rates and interest rates, indeed reflect the forward information about TFP that agents receive through the unobserved signals η_t. In any case, if the data in our VAR fail to capture some of agents' forward information, this will only bias us *against* finding any anticipation effects in our estimation. So if anything, it will be harder to reject our null hypothesis that future TFP innovations are at least partly forecastable, that is $\mathbb{E}_t(\varepsilon^a_{t+k}) \neq 0$.

For practical implementation with more than two variables, we need to specify a target "horizon" k for the VAR-expectation $\mathbb{E}_t(a_{t+k})$ that we will use to proxy for η_t. We choose $k = 20$ to match the peak in the impulse response of TFP in Figure 1. According to that preliminary estimation, it seems that TFP is most forecastable at medium-to-long horizons and we pick k accordingly. However, it is interesting to observe that in principle if agents truly only observe one independent signal η_t about future TFP, then the choice of horizon k is irrelevant, as any choice of k will yield identical estimation results (see Chahrour and Jurado (2021)). And in practice, we find that our estimation yields very similar results for a wide range of k choices.

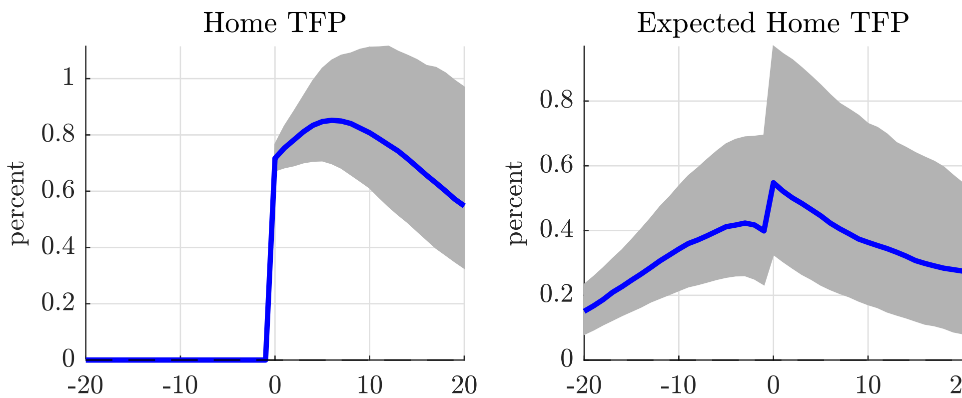
Lastly, it is interesting to note that when there are more than two variables in the VAR, as in our baseline application, the procedure imposes only a subset of the restrictions implied by the signal structure (5)-(6). In particular we do not impose the restriction that other variables besides the target expectation ($\mathbb{E}_t(a_{t+k})$) have a zero response prior to the realization of the noise disturbance ε^v_t. Because we do not impose these additional over-identifying restrictions *ex ante*, one can use these additional restrictions as an *ex post* test of the information assumptions that motivates our identification approach. In our main application, we find very small responses of other variables in this anticipation period, suggesting that equations (5)-(6) provide a good description of the expectations process driving the economy.

3.1 The dynamic effects of TFP and noise disturbances

After we separately identify the TFP and informational noise disturbances, ε^a_t and ε^v_t, we compute the resulting impulse responses of a number of variables of interest.

In order to understand first what our estimates suggest about how much forward information about future TFP there really is in the economy, we start by examining the impulse responses of TFP itself, a_t and also the IRF of the 20-quarter ahead expectation of TFP, $\mathbb{E}_t(a_{t+20})$ in Figures 2 and 3 respectively. Since our approach allows for productivity disturbances to potentially be anticipated, we plot each impulse response starting from 20 quarters

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



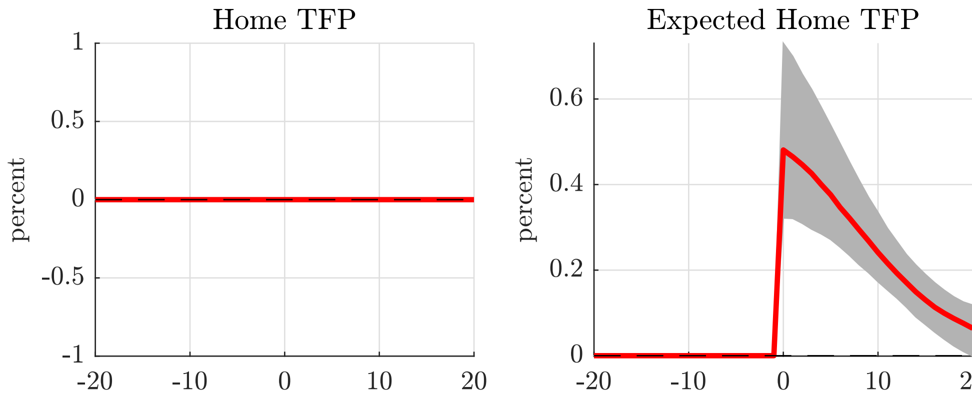
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded areas are 16-84th percentile bands. Each period is a quarter.

before the actual change in productivity, which we normalize to be $t = 0$, and then also plot the evolution of the IRFs until 20 periods after the realization of the disturbance. Hence, x-axis ranges from -20 to +20. The extent to which TFP anticipation plays a role in the data can be evaluated by examining whether the estimated TFP forecast $\mathbb{E}_t(a_{t+20})$ responds significantly to ε_t^a prior to the shocks actual realization in period 0.

Consider first the response of TFP to an increase in ε_t^a, depicted in the left panel of Figure 2. This IRF is exactly zero in periods -20 to -1, reflecting the identification assumptions described above – *i.e.* the estimated ε_t^a is the true innovation to TFP, hence there is no impact on TFP before the actual realization. Consistent with typical empirical results on U.S. TFP dynamics, we estimate that technological disturbances have very persistent effects. A one standard deviation disturbance increases the level of TFP by around 0.75% on impact (at $t = 0$), and the level of TFP is still a full 0.50% above trend 20 quarters after that.

In the right panel of Figure 2 we plot the impulse response of the expectation of TFP 20-quarters ahead, $\mathbb{E}_t(a_{t+20})$. For this and other endogenous variables, our estimation imposes no *ex-ante restrictions* on whether anticipation effects are present (*i.e.* an effect before $t = 0$). The key result is that indeed expected TFP is significantly higher than its long-run mean even 20 quarters before the innovation actually realizes, manifesting a significant amount of anticipation. Specifically, we estimate that 20-quarters before the actual increase of 0.75% in TFP at time 0, agents expect that this future quarter's TFP will be 0.2% higher than average. Thus, roughly about one quarter of the actual improvement is anticipated a full five years ahead. Moreover, as we get closer to the actual realization of ε_t^a at $t = 0$, the TFP

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



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded areas are 16-84th percentile bands. Each period is a quarter.

forecast steadily rises, as could be expected if forecasting near-term TFP is easier. Still, even one quarter ahead anticipation is not perfect, as can be deduced from the jump in the IRF at time 0, which jump indicates that the actual realization of ε_t^a still surprises agents and leads to an adjustment of expectations upwards.

Another way to see that expectations are imperfect is by considering the impulse response to the pure expectational noise disturbance, ε_t^v, which we plot in Figure 3. The left panel reflects our identification assumption that the expectational noise disturbances have no effect on TFP at any lead or lag. Nevertheless, the right panel shows that these disturbances move *expected TFP* significantly, as we estimate that a one standard deviation increase in expectational noise (so an "optimistic" revision of future TFP), leads to a 0.5% increase in $\mathbb{E}_t(a_{t+20})$. The expectational effect is mean-reverting, which is consistent with the idea that over time agents learn that their initial optimism was misplaced and expectations gradually return back to their long-run mean in the absence of actual TFP changes.

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

Broader effects We now turn to the effects of these two disturbances on the rest of the endogenous variables in the VAR, with a special attention paid to the response of the exchange rate. In Figure 4 we plot the responses of the interest rate differential, home consumption, the real exchange rate, foreign consumption and the expected currency returns,

$\mathbb{E}_t(\lambda_{t+1})$, to a TFP improvement (an increase in ε_t^a). In the top left panel we report again the response of the level of TFP for reference.

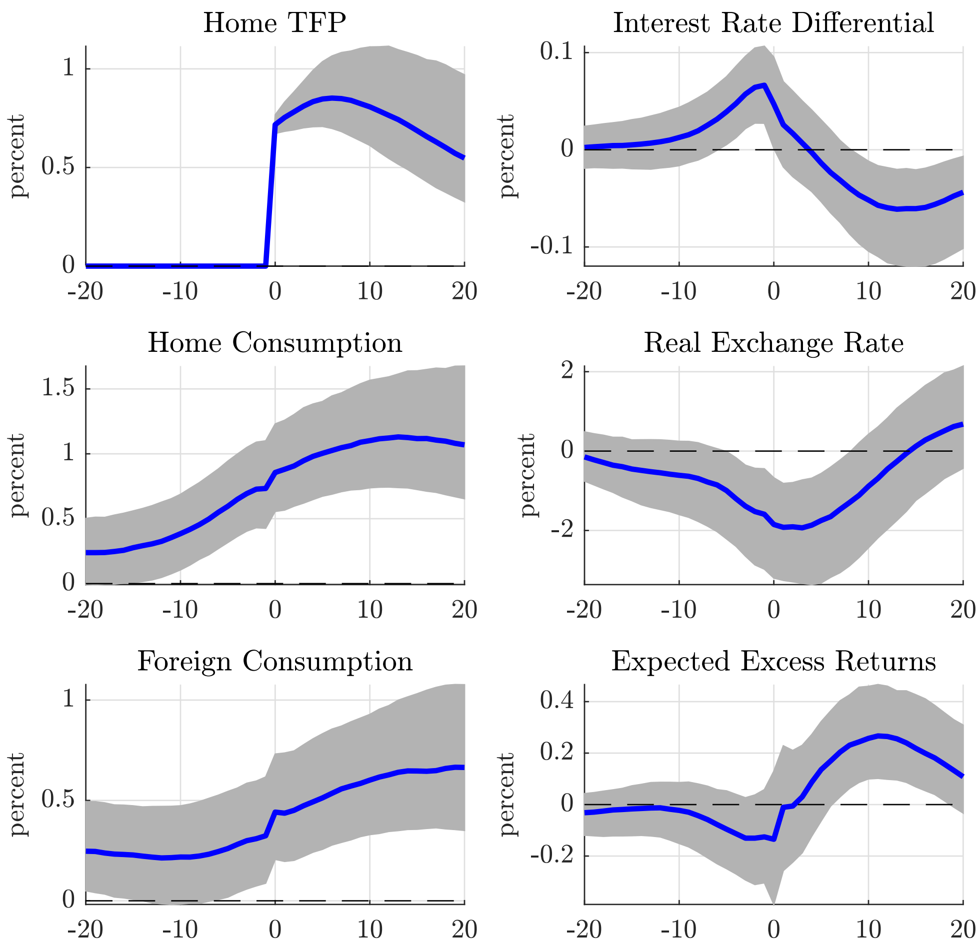
We focus on the real exchange rate first. The response shows a pronounced V-shape, reflecting significant anticipation effects where the real exchange rate steadily appreciates *before* the actual TFP improvement. Moreover, there is only a small jump in the real exchange rate right at time 0, which suggests that the *surprise* component in the TFP change at time 0 does not matter much for the exchange rate. After the actual TFP improvement the real exchange rate steadily depreciates back to its long-run mean. Thus, we estimate that news about future TFP are indeed strongly reflected in the real exchange rate.

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

This difference in the timing of effects is in fact more straightforward to see in the impulse responses to the expectational shock ε_t^v, which we plot in Figure 5 and discuss next. First, upon the improvement in expectations (recall that is period 0 on the x-axis), the real exchange rate immediately appreciated strongly. This is another, and perhaps more direct, estimate of the anticipation effects on the exchange rate, as the expectational noise disturbance has no impact on TFP at any horizon. The exchange rate response to the fluctuations in expectations is also fairly persistent, with the exchange rate returning to its long-run mean only after around 12 quarters. The interest rate differential (another asset price), also jumps immediately upon impact of the upward revision in expectations.

On the other hand, the response in consumption is much more gradual and delayed, with no significant jump upon the shift in expectations at time 0, but rather a delayed increase in consumption peaking around 3 years after the shift in expectations. This is a direct evidence of the delayed effects on consumption which contrast with the immediate impact of news on the exchange rate. These differential responses suggest that the underlying information

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

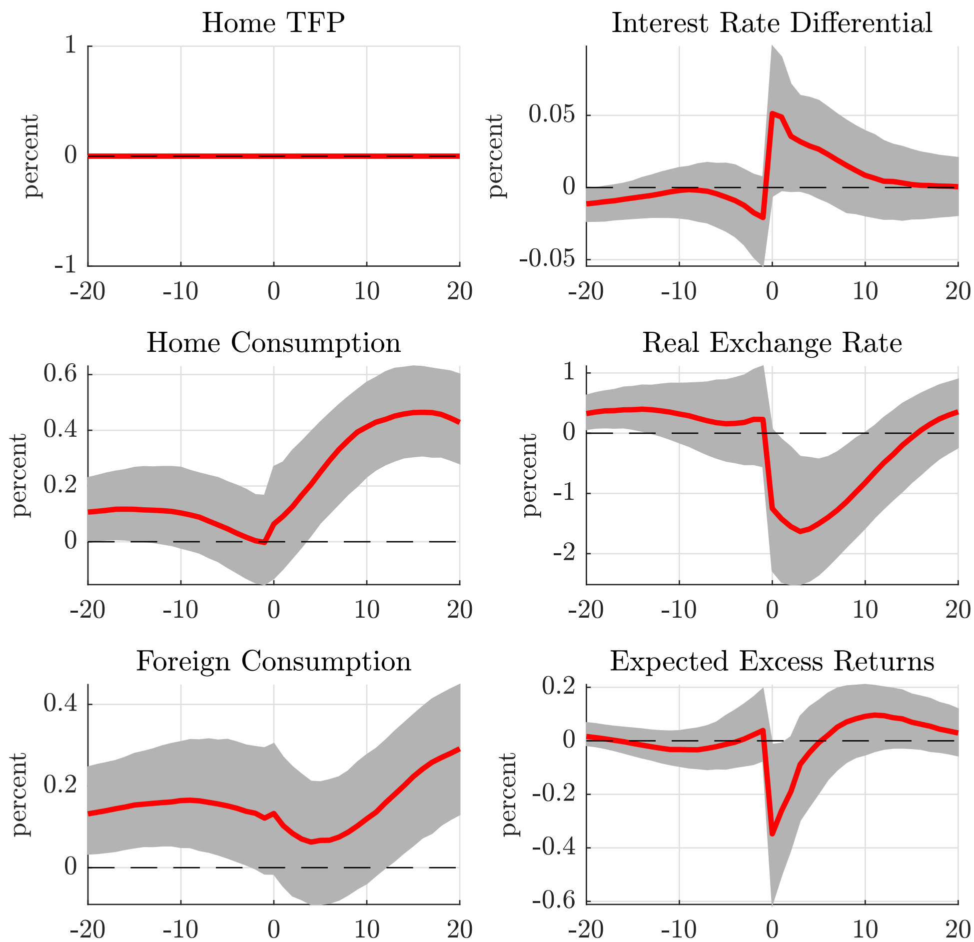


Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$. The shaded areas are 16-84th percentile bands. Each period is a quarter.

structure is one where the news agents receive is primarily about TFP at medium-to-long horizons. And while the exchange rate, as a forward-looking asset price, jumps on impact, consumption does not respond strongly until the expected TFP improvement becomes closer in time. Lastly, foreign consumption also increases, but weakly so, and thus the consumption differential is positive and significant throughout.[13]

[13] As described above, the responses of real variables prior to a noise disturbance are zero under the information assumptions summarized by (5)-(6), but our procedure does not impose these restrictions *ex ante*. The small responses before $t = 0$ in Figure 5 suggest that our baseline description of information captures the data

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



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$. The shaded areas are 16-84th percentile bands. Each period is a quarter.

In Appendix Figure B.1, we report the dynamics of the U.S. trade balance (as a % of U.S. GDP) in response to technological and noise disturbances. We find that the real exchange rate and the trade balance appear highly positively correlated in their conditional responses, suggesting that technological and noise disturbances are responsible, at least in part, for the positive comovement between the real exchange rate and the trade balance documented in the literature (Alessandria and Choi, 2021; Gornemann et al., 2020). We also

well.

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

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.

find that the U.S. trade balance deteriorates in anticipation of expected TFP improvements, albeit mildly, consistent with the so-called intertemporal approach to the current account, as well as 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 U.S. current account (see also Nam and Wang, 2015).

Variance Decomposition To further quantify the effects of technology and noise disturbances, we compute the shares of the variance of the endogenous variables that these disturbances explain. Table 2 reports the decomposition of variation over both a wide band of frequencies (2-100 quarters) and the higher, business cycle frequency (6-32 quarters) many models target. As per our identification restrictions, technological disturbances account for 100% of the variation in TFP, while expectational noise disturbances are orthogonal to TFP.

Perhaps most importantly, our estimates indicate that the two disturbances together explain 60-70% of the lower-frequency variation in the levels of both the real exchange rate and also U.S. and foreign real consumption and physical investment. Thus, noisy news about future TFP appears to be a very important, common source of fluctuations for both exchange rates and real quantities in the data, reinforcing the notion that there is indeed a fundamental connection between exchange rates and the broader macroeconomy. Similar to these lower-frequency results, the two noisy-news disturbances we identify are also important at business cycle frequencies, as they explain between 30-45% of business cycles variation in the real macro aggregates and 36% of the business cycles variation in the exchange rate.

The relative importance of the true technological disturbance ε_t^a and the expectational disturbance ε_t^v differ across frequency bands in an interesting way. The true technological disturbances are more important in the lower frequencies, where they generates two-thirds of the exchange rate variation that is explained by the two disturbances combined (45% of 64% in total). On the other hand, at the business cycle frequencies the expectational noise is the dominant force and explains two-thirds of the variation that the two disturbances generate (22% vs 36% in total). This is a reflection of the characteristics of the IRFs we discussed above, where we saw that noise disturbances give rise to volatile and short-lived fluctuations in the exchange rate, while correctly-anticipated future TFP changes impart persistent effects on the exchange rate. A similar pattern in the relative importance of disturbances across frequencies can also be observed in the variance decompositions of all real quantities.

We stress that the variance contribution of technological disturbances are due to both movements in anticipation of the realized change in TFP, and also fluctuations that come *after* the actual change in TFP (that is, impacts both before and after time 0 in Figure 4). With this in mind, it is interesting to quantify the pure anticipation effect. To do so, we compute the variance contributed by just the leading terms in the impulse responses, *i.e.* the response of the variables in anticipation of the subsequent TFP change. We find that this anticipation effect is the main driver of the exchange rate fluctuations we estimate. Specifically, the exchange movements *before* the actual realization of TFP account for 34% of the lower-frequency variation of the exchange rate, while the impact after the actual realization of TFP is only responsible for 11% of exchange rate variation. Thus, the component after the realized change in TFP has little importance in explaining the real exchange rate, while the anticipation component and the expectational noise combined contribute up to 53% of the lower-frequency variation in the real exchange rate.

4 Expectations of TFP and exchange rate puzzles

We next further characterize our empirical findings. Section 4.1 highlights the importance of predictable UIP deviations in contributing to the exchange rate fluctuations in response to news and noise. Section 4.2 documents that news and noise disturbances give rise to exchange rate fluctuations that display many well known exchange rate puzzles, thereby revealing that these puzzles share a common, fundamental origin. We then document the effects of news and noise on other asset prices in Section 4.3. Section 4.4 discusses potential explanations for the challenges encountered by previous studies in establishing a robust correlation between exchange rates and fundamentals (including TFP as well as macro variables more broadly). Section 4.5 documents that identified technological and noise disturbances are orthogonal to other economic disturbances such U.S. monetary policy shocks.

4.1 The role of fluctuations in the UIP wedge

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

To evaluate this hypothesis, note that the real exchange rate can be decomposed into two terms, (i) the sum of expected future interest rate differentials; and (ii) the sum of future currency excess returns, as follows:[14]

$$q_t = \underbrace{-\sum_{k=0}^{\infty} \mathbb{E}_t(r_{t+k} - r^*_{t+k})}_{q_t^{UIP}} + \underbrace{\left(-\sum_{k=0}^{\infty} \mathbb{E}_t \lambda_{t+k+1}\right)}_{q_t^{\lambda}}. \tag{8}$$

Thus, one can write the real exchange rate as the sum of the counter-factual exchange rate that would obtain if there are no deviations from interest parity, q_t^{UIP}, and the contribution of any predictable fluctuations in deviations from interest parity, q_t^{λ}.

We ask whether the second component of equation (8), q_t^{λ}, plays an important role in transmitting noisy news to the exchange rate or not. That is, we want to know whether the deviations from interest parity caused by the arrival of noisy news contributes meaningfully to the resulting exchange rate effects, or if the noisy news disturbances primarily transmit to the exchange rate through fluctuations in real interest rates.

The decomposition in (8) results in two components that are not necessarily orthogonal.

[14] As is common in the literature, we assume that the real exchange rate is stationary. Nevertheless, our analysis can be extended to the case of non-stationary q_t as well, in which case the decomposition in (8) reflects only the stationary component of q_t.

Nevertheless, (8) implies that the variance of q_t can be expressed as

$$\text{var}(q_t) = \text{cov}(q_t, q_t^{UIP}) + \text{cov}(q_t, q_t^{\lambda}).$$

We then use our VAR to estimate the dynamic responses of q_t^{UIP} and q_t^{λ} (both are directly constructed from variables included in the VAR) to technological and noise disturbances, and thus can then estimate the above covariances conditional on our shocks. And it turns out that while the decomposition in (8) is not necessarily orthogonal, in practice (conditional on our disturbances) the two components in (8) are close to orthogonal, yielding the informative decomposition we report in Table 3 below.

Table 3: Decomposition of the variance of the exchange rate

	Technology		Noise		Both	
	q_t^{UIP}	q_t^{λ}	q_t^{UIP}	q_t^{λ}	q_t^{UIP}	q_t^{λ}
$\frac{\text{cov}(q_t,q^i)}{\text{var}(q_t)}$	-0.11	1.11	0.12	0.88	-0.04	1.04
	$[-0.70, 0.30]$	$[0.70, 1.71]$	$[-1.410.71]$	$[0.29, 2.41]$	$[-0.93, 0.34]$	$[0.66, 1.93]$
$\frac{\text{cov}(\Delta q_t,\Delta q^i)}{\text{var}(\Delta q_t)}$	-0.15	1.15	0.43	0.57	0.15	0.84
	$[-0.78, 0.49]$	$[0.51, 1.79]$	$[-2.39, 1.61]$	$[-0.61, 3.39]$	$[-1.54, 0.87]$	$[0.13, 2.53]$

Notes: The table reports decompositions of the fluctuations in the real exchange rate q_t, following equation (8), caused by technological disturbances ("Technology", ε_t^a) and expectational disturbances ("Noise", ε_t^v), as well as the combination of both. Moments are computed over periodicities between 2 and 100 quarters. The 90% credible bands are reported in parentheses.

The main takeaway is that the noisy-news we find primarily transmit to the exchange rate via fluctuations in the q_t^{λ} component, reflecting the importance of a volatile "UIP wedge." The first row of Table 3 reveals that the component due to the UIP wedge explains close to 100% of all fluctuations caused by the technological and noise disturbances. If anything, the q_t^{UIP} term tends to move *against* the real exchange rate. We draw similar conclusions when we look at quarterly changes Δq_t as well (second row of Table 3).

Thus, overall we find that fluctuations in the expected currency returns, or the so-called UIP wedge, play an important role in the transmission to the exchange rate of the noisy news we estimate. This implies that in order to understand our empirical results through the lens of equilibrium models, one needs to step beyond international macro models where UIP typically holds, and explore models in which the deviations from UIP are significant and also specifically driven by noisy news of future TFP.

4.2 Common origin in exchange rate puzzles

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

The UIP Puzzle Clearly, the results in Section 4.1 indicate that our noisy news disturbances cause significant deviations from interest parity – however, is the nature of these deviations the same as the classic UIP puzzle of Fama (1984), where high interest rate currencies are predicted to make high returns?

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

These patters indeed suggest a negative correlation between currency returns and the interest rate differential, which is qualitatively consistent with the "classic" UIP puzzle of Fama (1984) that high interest rates predict high currency returns. To directly test whether the disturbances we identify indeed generate the Fama puzzle or not, we consider the so-called UIP regression, which has been used to document this pattern in the past:

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

Estimating this regression in our raw dataset, we find a significantly negative β_{UIP} of -2.46, an estimate which is in line with previous findings (*e.g.*, Engel, 2014). Next, we compute the resulting β_{UIP} in a counter-factual dataset where only the two noisy-news disturbances we identify, ε_t^a and ε_t^v, are active. To obtain these series, we simulate from our estimated VAR by setting the variance of all other disturbances to zero.

In this counter-factual simulation we estimate a $\beta_{UIP} = -2.20$, revealing that the combination of disturbances to TFP and to expectations of future TFP qualitatively and quantitatively reproduces the classic UIP Puzzle relationship. Drilling down further, we construct similar counter-factual β_{UIP} based on either only-TFP disturbances (including anticipation effects) and only expectational noise disturbances. The results imply that the TFP disturbances by themselves generate a β_{UIP} of -2.08, while the β_{UIP} based on only expectational disturbances is -2.96, as we also report in Table 4 below.

The regression coefficients β_{UIP} are interesting because they are comparable to many previous findings, but it is also informative to consider how much of the raw covariance $\text{cov}(\lambda_{t+1}, r_t - r_t^\star)$ – the numerator in the β_{UIP} – our disturbances can account for. This is reported in the second row of Table 4, where we can see that our two disturbances account for roughly two-thirds of $\text{cov}(\lambda_{t+1}, r_t - r_t^\star)$ – the raw covariance is -1.30, and in the counter-factual data based on our two disturbances we find a covariance of -0.86. Thus, indeed the bulk of the negative correlation between interest rates and excess returns that underlies the famous Fama puzzle is due to the noisy-news disturbances we identify.

In addition to this "classic" UIP Puzzle, the conditional responses of the exchange rate to our identified disturbances also exhibit the Engel (2016) observation that the UIP puzzle essentially "reverses" direction at longer horizons. 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 again qualitatively see this pattern in the impulse responses documented by Figure 4: high excess currency returns in the periods following the actual 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 response to technological disturbances).

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

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

In the raw data, we find $\beta_\Lambda = 2.53$, indicating that the whole sum $\sum_{k=0}^{\infty} \text{cov}(\lambda_{t+k+1}, r_t - r_t^\star)$ is positive, even though the very first term of the sum (*i.e.* the Fama regression coefficient) is negative. In our counter-factual simulation where only the two disturbances we identify are active, we find $\beta_\Lambda = 2.62$. Moreover, the two disturbances together generate around 60% of the overall $\text{cov}\left(\sum_{k=0}^{\infty} \mathbb{E}_t \lambda_{t+k+1}, r_t - r_t^\star\right)$ in the data, though it is interesting to note that the expectational noise shocks are responsible for only one tenth of this effect. Thus, the reversal in the UIP puzzle also largely emerges as a result of the dynamic responses to the

Table 4: Exchange Rate Related Puzzles and TFP Expectations

Panel A: UIP Puzzle Moments

	Technology	Noise	Both	Unconditional
Fama β_{UIP}	-2.07	-2.96	-2.20	-2.43
$\text{cov}(\lambda_{t+1}, r_t - r_t^*)$	-0.68	-0.14	-0.86	-1.30
Engel β_Λ	2.17	1.72	2.50	2.56
$\text{cov}(\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}), r_t - r_t^*)$	0.52	0.06	0.60	1.08
$\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$	0.37	0.13	0.25	0.17
$\text{autocorr}(r_t - r_t^\star)$	0.99	0.93	0.98	0.95

Panel B: Backus-Smith Moments

	Technology	Noise	Both	Unconditional
$\text{corr}(\Delta q_t, \Delta(c_t - c_t^\star))$	-0.31	-0.38	-0.35	-0.27
$\text{cov}(\Delta q_t, \Delta(c_t - c_t^\star))$	-0.08	-0.12	-0.26	-0.70
$\text{cov}(\Delta q_t^\lambda, \Delta(c_t - c_t^\star))$	-0.05	-0.08	-0.17	-0.49

Panel C: Excess Volatility and Persistence

	Technology	Noise	Both	Unconditional
$\text{autocorr}(\Delta q_t)$	0.90	0.33	0.58	0.29
$\text{autocorr}(\Delta q_t^\lambda)$	0.80	0.42	0.60	0.73
$\sigma(\Delta q_t)/\sigma(\Delta c_t)$	3.99	8.14	5.65	6.04
$\sigma(\Delta q_t^\lambda)/\sigma(\Delta c_t)$	5.82	7.74	6.58	7.30

Notes: The table reports the estimated moments conditional on technological disturbances (Technology), expectational disturbances (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.

noisy news disturbances we have identified.

In closing, we also note that our two disturbances not only generate empirically relevant regression β's, but the underlying dynamics of the interest rate differentials are also largely in line with their unconditional counterpart, as can be seen by the $\sigma(r_t - r_t^\star)/\sigma(\Delta q_t)$ and $\text{autocorr}(r_t - r_t^\star)$ moments reported in Table 4.

Deviations from the Backus-Smith condition We now turn to the so called Backus-Smith puzzle. The classic international risk-sharing condition of Backus and Smith (1993) predicts that relative consumption across countries should be strongly positively correlated with the real exchange rates. However, this condition is largely violated in the data (Kollmann, 1995; Corsetti et al., 2008b), where, in fact, this correlation is mildly negative.

And indeed, we can see this negative relationships qualitatively in our IRFs. From Figure 4 we can see that in anticipation of the U.S. TFP improvement (*i.e.* $t < 0$) the U.S. dollar *appreciates* even though U.S. consumption is relatively high. The IRFs in response to the expectational noise disturbances in Figure 5 also showcase a similar relationship.

To quantify the effects, we consider the following moment much of the literature has focused on,

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

and calculate the moment in both the raw data, and in a counter-factual simulation where only the noisy-news disturbances are active. The results are presented in Table 4 (Panel B). As in previous research the correlation in the raw data is mildly negative, equal to -0.27 in our sample. In the counter-factual sample generated by only the two disturbances we identify, this correlation is very similar and equals -0.35. Moreover, computing the covariance $\text{cov}(\Delta q_t, \Delta c_t - \Delta c_t^{\star})$ which underlies the negative correlation of the Backus-Smith puzzle, we find that our two disturbances combined explain around 40% of this moment in the data. Thus, the noisy-news disturbances we find indeed play an important role in generating the celebrated Backus-Smith puzzle as well.

Furthermore, in light of the results in Section 4.1, we also ask whether the negative covariance generated by the noisy-news disturbances is due to the component of exchange rates driven by deviations from interest parity, q_t^{λ}, and we find that indeed two-thirds of it is – that is, $\frac{\text{cov}(\Delta q_t^{\lambda}, \Delta c_t - \Delta c_t^{\star})}{\text{cov}(\Delta q_t, \Delta c_t - \Delta c_t^{\star})} = 0.65$) in the counter-factual simulation with only the noisy news disturbances active.

Thus, we find that noisy news to TFP not only generate a meaningful portion of the puzzling negative correlation between exchange rates and consumption differential behind the famous Backus-Smith puzzle, but also that this puzzle is intricately linked to the UIP puzzle. The noisy news are only causing a negative correlation between the exchange rate and consumption because of the fluctuations they impart on the UIP wedge.

Excess volatility and persistence Two other well-known exchange rate "puzzles" are the excess persistence and volatility of the real exchange rate, and next we ask to what extent these phenomena are also accounted for by the noisy-news disturbances we identify.

In Table 4, we consider a few related moments. We find that the exchange rate dynamics conditional on the two disturbances we extract are indeed highly persistent. This is exemplified by the autocorrelation of the quarterly change in the real exchange rate: conditional on both identified disturbances the autocorrelation is 0.58 versus 0.29 in the unconditional data. Thus, our two disturbances generate an even higher degree of persistence than the exchange rate exhibits on average (which unconditional persistent is already "puzzling"). It suggests that all other disturbances driving the exchange rate (*e.g.* monetary shocks) have relatively transitory effects (as is true in standard models). Thus, the puzzling persistence of the exchange rate is indeed mainly due to its responses to noisy-news about TFP.

Second, we find that the volatility of the exchange rate generated by the noisy-news disturbances is also very high, relative to macro aggregates. For example, the ratio of the standard deviation of the quarterly growth in the exchange rate and consumption conditional on both identified disturbances is 5.65, while the same ratio is 6.05 in the raw data. Notably, noise disturbances generate twice the amount of excess volatility in exchange rates compared to technological disturbances. This outcome is not surprising, as noise disturbances affect expectations, and thus asset prices, without being linked to subsequent changes in productivity. Consequently, they give rise to volatile fluctuations in exchange rates while causing only minor shifts in macroeconomic aggregates, such as consumption and output.

Lastly, we again observe that both the high persistence and volatility in the response of the real exchange rate are to a large extent due to persistent and volatile fluctuations in deviations from interest parity, q_t^{λ}, and not the q_t^{UIP} component of the exchange rate. This again highlights the role of the fluctuations in expected excess returns (the UIP wedge) in the transmission of technological and noise disturbances, and showcases that two more exchange rate puzzles are intricately tied to the UIP puzzle itself.

Common and fundamental origin to many exchange rate puzzles Overall, these results lead us to two overarching conclusions. First, a collection of famous exchange rate puzzles have a *common* and *fundamental* origin in noisy news about future TFP. Second, since the noisy-news primarily impact the exchange rate by causing fluctuations in expected currency returns, this puts the UIP wedge, as driven by noisy-new to TFP, at the center of the different exchange rate puzzles.

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

In a sense, our results shift the focus back to a long tradition in the literature of developing models of currency premia that are primarily driven by TFP innovations (*e.g.*, Verdelhan, 2010, Bansal and Shaliastovich, 2012, and Colacito and Croce, 2013). At the same time, contrary to our empirical results, the vast majority of such models has strictly focused on standard information structures where TFP shocks are pure surprises, and thus there are no anticipation effects. Instead, we find that anticipation effects and noisy news are crucial.

An important exception are the long-run risk models of the exchange rate in the vein of Colacito and Croce (2013). Intuitively, these models share many of the key features of the noisy news disturbances we identify. For example, our empirical estimates suggest that the news that are priced in the exchange rate are about productivity at *medium-to-long* horizons (*e.g.* we find TFP expectations are significantly elevated even 5 years before the actual innovation). While not identical, such long-run news are similar in spirit to the very persistent low frequency "long-run" component of TFP that Colacito and Croce (2013) emphasizes. In this context, we note that our results offer a sharp estimate of the nature of long-run news of TFP actually present in the data, and it would be interesting for future research to evaluate existing long-run risk models against our direct evidence.

That said, beyond the intuitive connection in the focus on long-run TFP news, we caution that the existing long-run risk models appear to be inconsistent with at least one important facet of our empirical results. We find that home consumption is elevated and persistently increasing in expectation of the future TFP improvement, while in the log-run risk class of models following Colacito and Croce (2013), home consumption is in fact *depressed* upon an improvement in the long-run growth rate of TFP. This opposite movement in consumption is a characteristic feature of the full risk-sharing setup typical of this class of models where home agents effectively "share" the good news about high future home output with foreign agents by transferring resources abroad today. We thus conclude that there is more work to be done on the modeling front, and our empirical results can be used to guide and discipline future development in theoretical models.

4.3 Technology, noise, and other asset prices

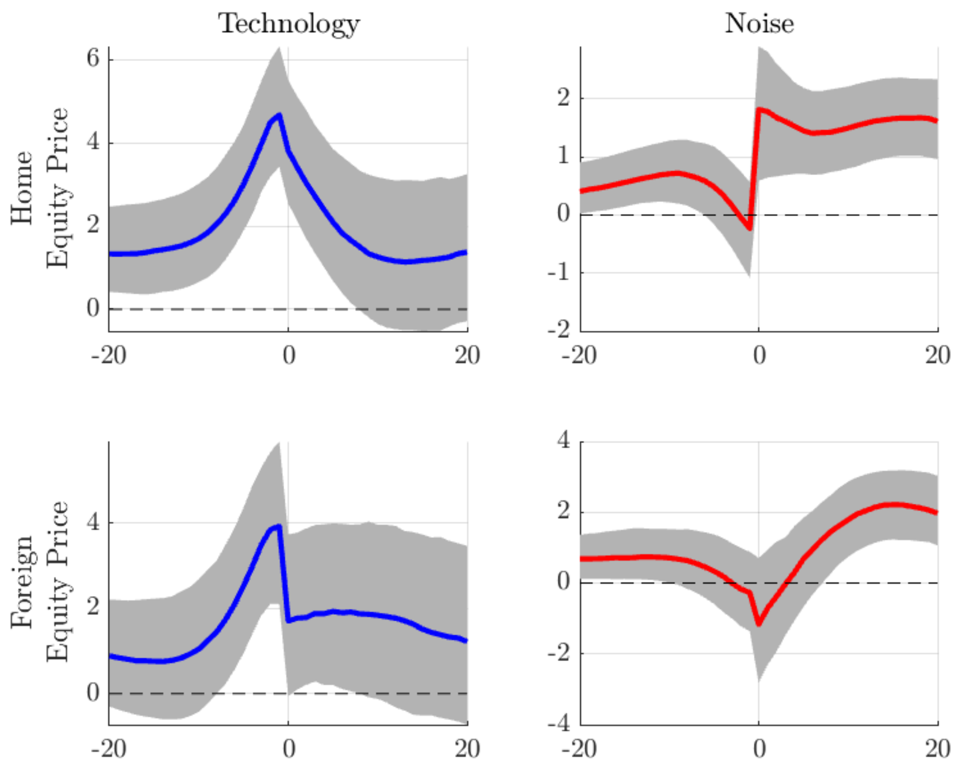
Do other asset prices react to the noisy news we identify? In Figure 6, we present the response of domestic and foreign equity prices to technological and noise disturbances. Indeed, we find a significant increase in equity prices, both domestically and internationally, in anticipation of future improvements in home productivity.[15] This finding is consistent with Beaudry and Portier (2006), who also find that equity prices incorporate, at least in part, news about future economic fundamentals. From the right column of the Figure (the IRF in response to ε_t^v) we can also directly see the intuitive result that the US equity prices react first to the arrival of news about future US TFP.

In turn, Figure 7 reports the response of *risk premia* across home and foreign assets, calculated as the VAR-implied expected quarterly excess return differentials for both equity and long-term bonds. Analogously to the excess currency returns we analyzed earlier, excess return differentials in stocks and bonds are calculated by subtracting the *expected* foreign return on equity or long-term bonds (expressed in foreign currency) from the corresponding home return (expressed in home currency), in excess of the foreign interest rate differential. We estimate significant fluctuations in cross-country returns across both equity and long-term bonds in response to our shocks, indicating that the news we estimate indeed impact risk premia of other assets as well.

Nevertheless, the fact that risk premia across many different assets respond to the noisy news about TFP does not mean that the implied contemporaneous correlation between these risk premia is necessarily high. In fact, the variation generated by technology and noise disturbances implies a correlation between equity and currency expected excess returns of only around -0.10. This is consistent with the fact that unconditionally (in the raw data), some studies find that equity and currency returns are only mildly negatively correlated (*e.g.*, Verdelhan, 2010, and Hau and Rey, 2005) while other studies find no significant correlation (Chernov et al., 2023a). The low correlation is due to the fact that equity and currency returns are negatively correlated due to pure fluctuations in TFP expectations (*e.g.* see IRF to ε_t^v), but are *positively* correlated following an actual improvement in TFP (see IRF to ε_t^a for $t \geq 0$). This showcases that while the link between noisy news and assert prices is highly significant, it is also subtle. Our results provide sharp guidance and discipline for

[15] We estimate the impulse response of equities and long-term bonds (which are not directly included in the VAR), by projecting those returns on the VAR and its lags, and then using the VAR impulse responses. In any case, the results reported in this section are unchanged if instead we alternatively add equity or bond prices in our VAR and repeat the whole identification procedure.

Figure 6: Technology, noise, and equity prices



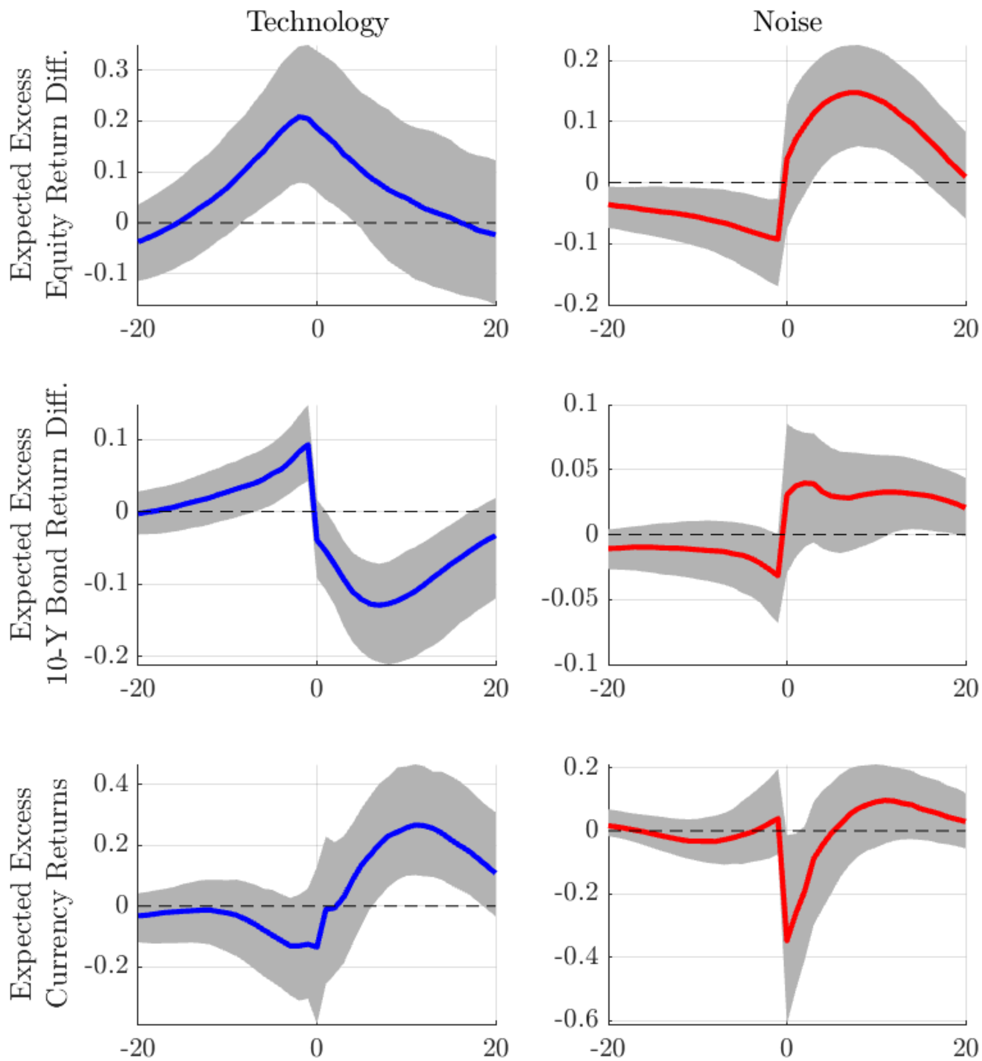
Notes: The figure displays the IRF a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The shaded area is the the 16-84th. Each period is a quarter.

the development of future models, as they require a model where equity and currency risk premia comove differently in anticipation of future TFP improvements and following actual changes in TFP.

Contrary to the low-implied correlation between the generated fluctuations in equity and currency risk premia, the implied correlation between bond and currency returns, on the other hand, is a robust -0.50. This implies that noisy-news disturbances could also underlie the strong negative correlations observed in studies examining the joint relationship between long-term bonds and exchange rates (*e.g.*, Lustig et al., 2019, Greenwood et al., 2023, Gourinchas et al., 2022, and Lloyd and Marin, 2020).

Thus, overall, noisy news disturbances are reflected across a variety of asset classes, as is to be expected. And the significant effects on all these different asset prices is indeed

Figure 7: Technology, noise, and other asset prices



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 is the the 16-84th. Each period is a quarter.

consistent with prior results on both the low unconditional correlation between currency and equity risk premia, and the strong correlation between currency and bond risk premia. At the same time, it's important to note that these disturbances account for only a portion of the variation in risk premia: the two identified disturbances explain around 50% of the business cycle fluctuations in equity and bond returns. Their residual variation could be attributed to idiosyncratic factors, potentially explaining the overall weak relationship between exchange rate returns and returns in other asset classes (Burnside, 2011; Chernov and Creal, 2023; Chernov et al., 2023b).

4.4 Exchange rates and future fundamentals

Overall, our headline result is that exchange rate fluctuations are significantly related to predictable changes in future TFP (*i.e.* "news"). As TFP is the quintessential macroeconomic "fundamental" in most models and empirical studies, it is perhaps surprising that the strong connection we uncover has gone unnoticed until now. We discuss possible explanations, which also help shed some more intuition on what are the key features of the data that underlie our identification.

First, many of the previous studies that have tried to find a link between exchange rates and macro fundamentals, and TFP in particular, take as a working hypothesis the standard model formulation where all TFP disturbances are pure surprises. From that point of view, one would only look for a relationship between the exchange rate and current and past TFP (and macro aggregates more generally). Studies looking for a relationship between the exchange rate and past fundamentals show a very low empirical connection between the two.

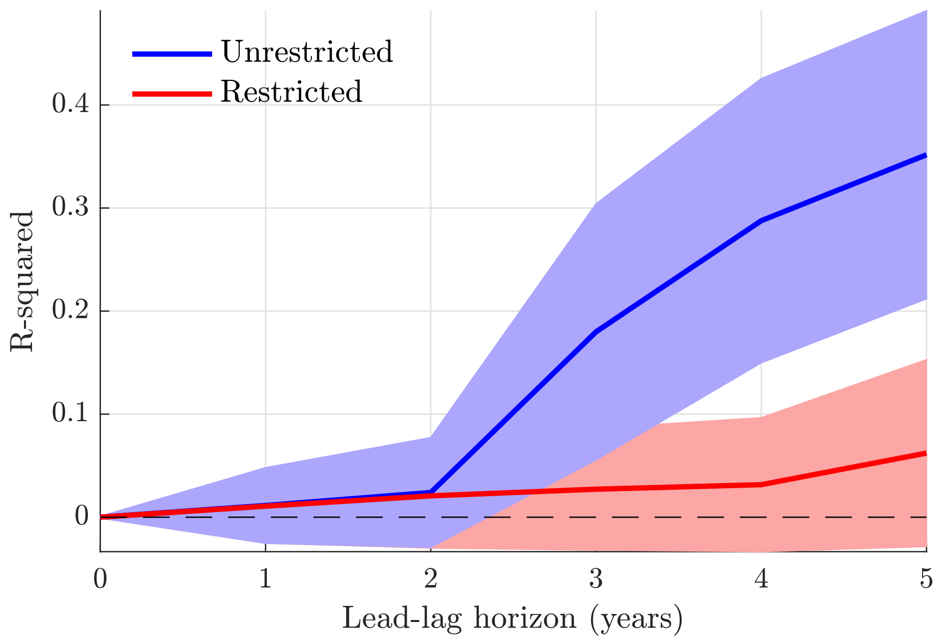
The lead-lag relationships between exchange rates and TFP is the key feature of the data that underlies our VAR identification. To show this clearly, consider the following simple exercise, where we regress the annual change in the real exchange rate at time t on leads and lags of the annual change in TFP:

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

If we included just the constant and the first term on the right-hand side, 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 also the first summation term on the right-hand side, 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 also the second summation term, we also consider a potential correlation with *future* TFP changes, of up to h-years ahead.

Figure 8 reports the R^2 of two versions of the regression equation (9): a "Restricted" backward-looking version that includes only current and lagged TFP growth terms (red line),

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 (9).

and an "Unrestricted" version that includes all terms on the right-hand side of (9) (blue line).

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

More specifically, the above results also highlight again that the exchange rates contain in particular a substantial amount of information about future TFP growth in the *medium-run to long-run* – a message that also emerged from our more detailed analysis earlier. This long-horizon nature of the noisy news we estimate is important in the context of the existing literature. A number of existing papers have also made the observation that the exchange rate, a forward looking asset price, ought to lead macroeconomic fundamentals.

Yet, this literature has generally struggled to find robust correlation between exchange rates and future macroeconomic fundamentals.

One key difference is that the existing empirical approaches focus on testing relatively short-horizon lead-lag relationships. For example, Engel and West (2005) run a number of Granger-causality type of tests, but only include 1-year lags, while papers like Sarno and Schmeling (2014) adopt a more non-parametric approach, but still limit their null hypothesis to testing predictive relationships to a maximum of two years ahead. Instead, our results indicate that the news driving the exchange rate are of a low frequency nature that only truly takes form over 3-to-5-year horizons.

Lastly, it is important to stress that our analysis is also unique in that it directly accounts for the noise in expectations of future TFP and this increases the statistical power of our approach. The reason is that the expectational noise causes changes in TFP expectations that do not subsequently result in actual TFP. Since exchange rates react to expectations regardless of whether those expectations are correct ex post, the raw correlations between realized fundamentals and exchange rates is likely to systematically understate the importance of fluctuations in expected TFP (since a significant portion of the expectations is noise). By accounting for the expectational noise directly, rather than relying on a simple correlation between exchange rates and ex-post realizations of future TFP, we obtain much greater statistical power in estimating the potential impact of noisy news. This same reasoning could help explain why studies employing direct measurement of expectations through survey data tend to reveal a much higher degree of connection between exchange rates and fundamentals (*e.g.*, Engel et al., 2008; Stavrakeva and Tang, 2020).

4.5 Other economic shocks

In order to interpret our empirical results as picking up disturbances that are solely about TFP and its expectations, and not potentially also mixing up other economic shocks that could be endogenously related to TFP growth, in Sections 3 and 4 we make the (common) assumption that the Fernald utilization-adjusted TFP is orthogonal to any other economic shock. One may be concerned that other economic disturbances such as shocks to R&D productivity, monetary policy, or may be even FX noise trader/sentiment shocks in the vein of Itskhoki and Mukhin (2021) may lead to a future change in TFP through endogenous investment in research and development (R&D). In that case, our identified technological and noise disturbances might be contaminated by other economic shocks.

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

On the other hand, if current *contractionary* monetary shocks spur R&D investment and thus future TFP growth, then indeed our identified noisy news disturbances might be related to such monetary shocks. We stress, however, that for this to be a viable alternative explanation it must be the case that contractionary monetary shocks spur R&D investment and improve future TFP, since our empirical results in Figures 4 and 5 show that the exchange rate *appreciates* in anticipation of TFP improvements, and if that appreciations is to be driven by monetary shocks it must be due to monetary tightening.

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

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

Lastly, we should not lose sight of the fact that while our estimated noisy news about TFP account for a significant portion of RER variation (up to 66% overall, and roughly a third of the variation of q_t at business cycle frequencies), our identified disturbances still leave a non-trivial fraction of the exchange rate variation unexplained. Certainly a number of other shocks also play an important role in the exchange rate fluctuations in the data, with monetary shocks a prime example of such disturbances.

Estimation of VAR without exchange rate We have also performed the baseline analysis after removing the exchange rate from the set of observables we use to estimate the

Table 5: Correlation between Technology, Noise and U.S. Monetary Policy disturbances

	Technology	Noise
U.S. Monetary Policy disturbances	0.09 (p-value = 0.46)	0.06 (p-value = 0.62)

Notes: The table reports the correlation between technological disturbances (Technology) and expectational disturbances (Noise) with U.S. monetary policy disturbances from Gertler and Karadi (2015) and recently updated by Jarocinski and Karadi (2020).

VAR. We do so to guard from the possibility that some FX noise trader/sentiment shock is leaking into our estimated noisy news disturbances. The key result here is that with this restricted VAR, we still recover essentially the same set of technology and noise disturbances (Figure B.6), and, in turn, these disturbances have a similar effect on the exchange rate (Figure B.7).[16] This highlights again that the key empirical variation our analysis exploits is that a substantial portion of TFP growth is predictable, and the relevant (noisy) TFP expectations are priced into the exchange rate.

5 Conclusions

We document novel empirical evidence that exchange rates are not disconnected from macro aggregates, but that they are indeed tightly linked to fluctuations in noisy expectations of future TFP improvements. Our empirical approach is particularly notable for directly accounting for the possibility that TFP expectations are noisy. Separately identifying the noise in expectations helps sharpen our results, because expectational noise reduces the raw correlation between expectations and *realized* fundamentals in the data.

In addition, we show that the noisy news disturbances we identify appear to generate a number of famous exchange rate puzzles at the same time. Thus, a myriad of FX puzzles share a common and fundamental origin in noisy news about future TFP. Also, the noisy news specifically transmits to exchange rates by causing large fluctuations in expected excess currency returns. Our evidence thus implies that the common thread that ties many FX puzzles together are news-driven UIP wedge fluctuations, providing important guidance for the development of future theoretical models.

[16] We estimate the impulse response of the exchange rate in the restricted VAR by first projecting the exchange rate on the VAR variables and their lags, and then constructing the impulse response from this approximation of the exchange rate. The procedure is akin to using Jorda-projections to estimate the response of q_t to the shocks we identify from the restricted VAR that does not include the exchange rate.

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A Data Appendix

A.1 Data sources

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

- Nominal exchange rate
  - Daily bilateral exchange rates, Foreign Currency/USD;
  - Source: *Datastream*;
  - Quarterly aggregation: period-average.
- Nominal interest rates
  - Daily Eurodollar deposit rates;
  - Source: *Datastream*;
  - Quarterly aggregation: period-average.
- Consumer Price Indexes
  - CPI Index (Chained 2010)
  - Source: *OECD*, https://stats.oecd.org/index.aspx?DataSetCode=PRICES_CPI.
- Consumption
  - Real consumption;
  - Source: *OECD*, Private final consumption expenditure
- Investment
  - Real Investment;
  - Source: *OECD*, Gross Fixed Capital Formation (`GFCF`), Quarterly growth rates, https://data.oecd.org/gdp/investment-gfcf.htm.
- U.S. TFP:
  - U.S. utilization-adjusted TFP as constructed in Fernald (2012);
  - Source: John Fernald's website, https://www.johnfernald.net/TFP (latest available vintage, downloaded on January 2, 2022);
- U.S. R&D:

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

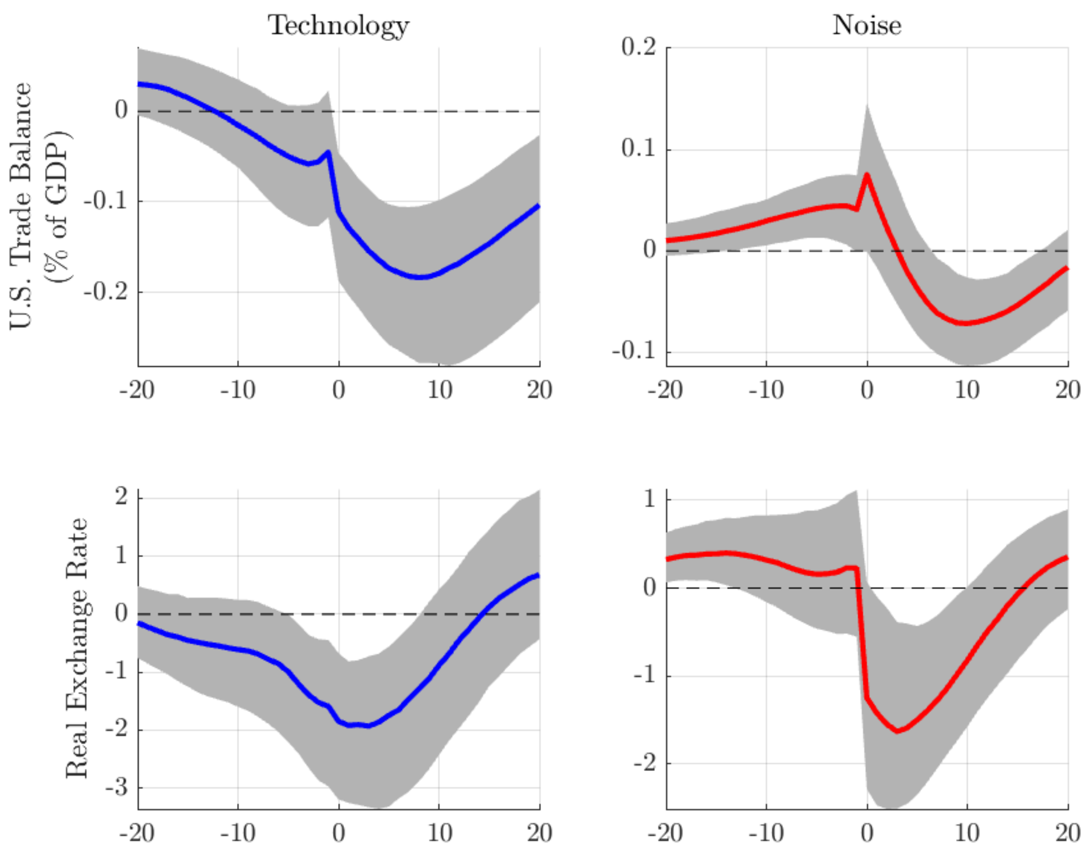
- U.S. trade balance (% of GDP)
  - Shares of gross domestic product: Net exports of goods and services
  - Source: *U.S. Bureau of Economic Analysis*, retrieved from *FRED*, https://fred.stlouisfed.org/ser

- Equity prices and equity returns
  - MSCI price indexes and total returns indexes
  - Source: retrieved from *Datastream*

- Long-term bond yields
  - Interest Rates: Long-Term Government Bond Yields: 10-Year
  - Source: *Global Financial Data*

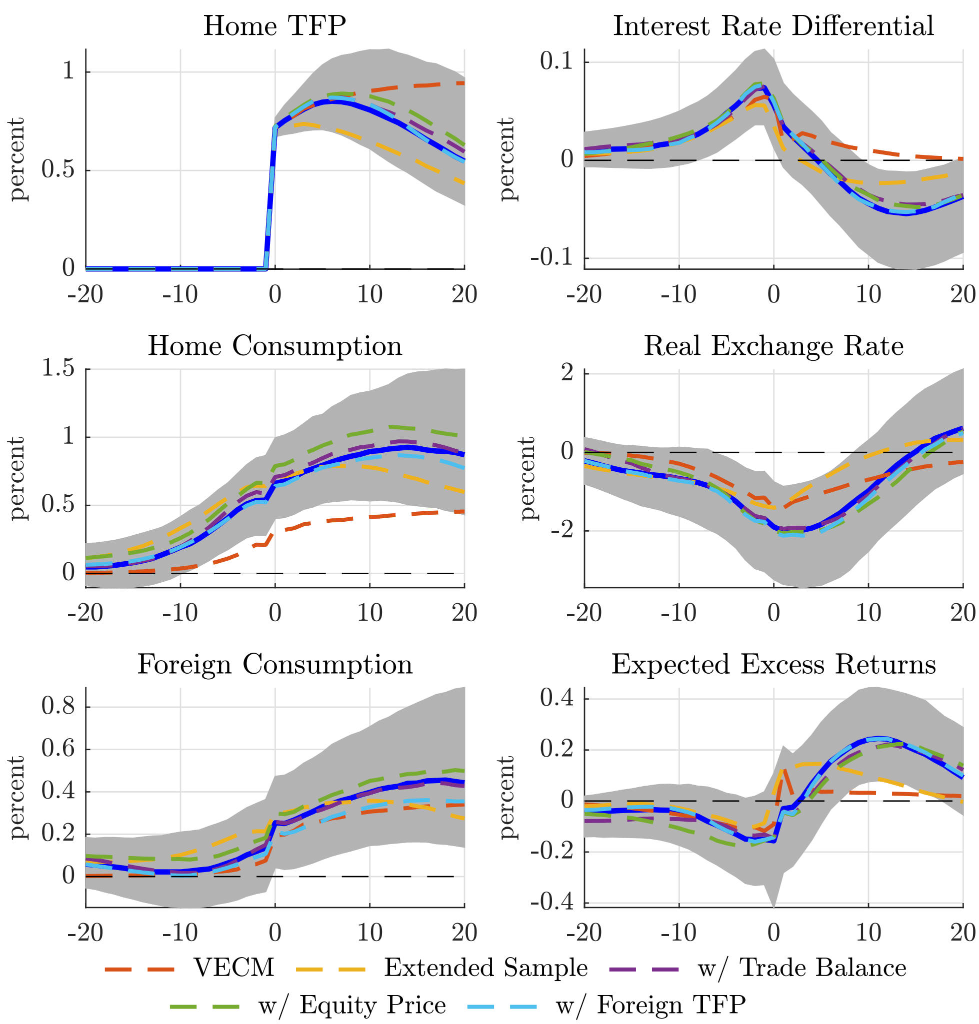
B Additional evidence and alternative empirical specifications

Figure B.1: Technology, Noise and the Trade Balance



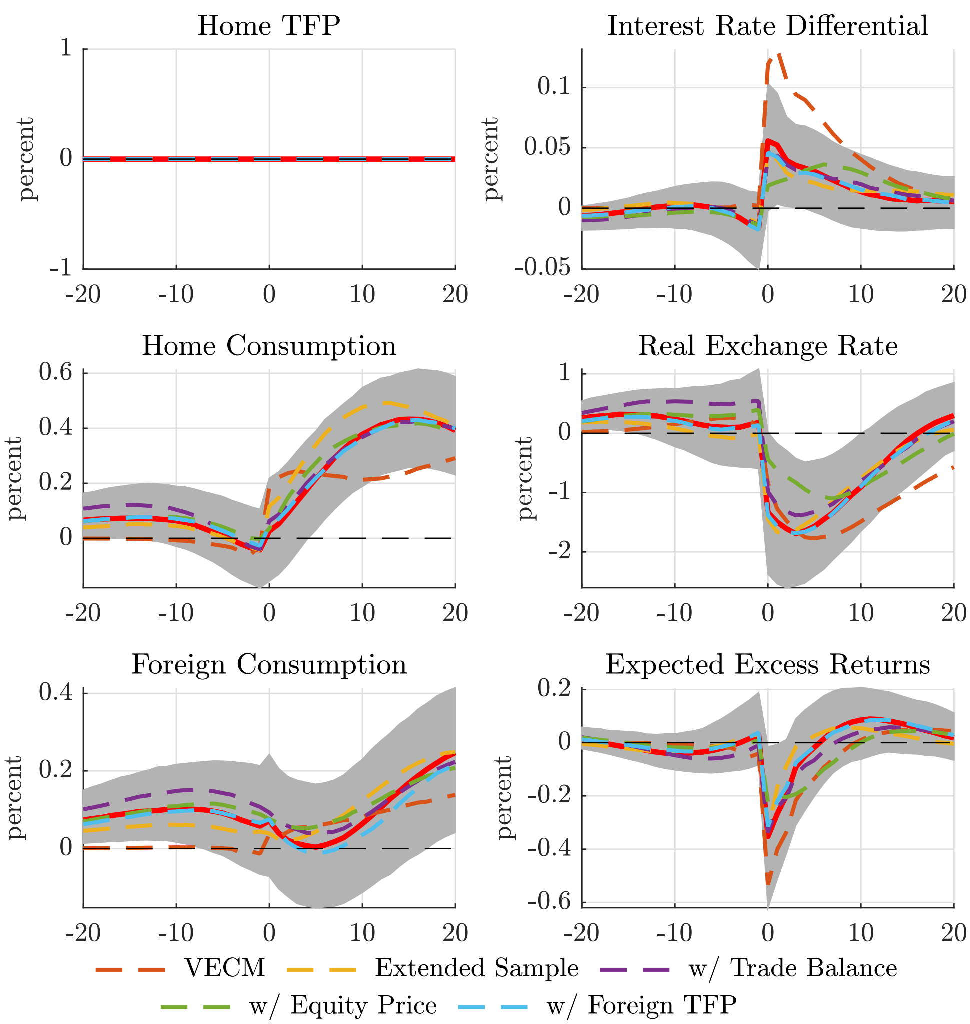
Notes: The figure displays the responses a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The shaded areas are 16-84th percentile bands. Each period is a quarter.

Figure B.2: Impulse responses to Technology disturbances (Alternative specifications)



Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$ for the baseline sample (blue lines), where the shaded areas are 16-84th percentile bands. In addition the figure displays the point estimate of the responses obtained from the VAR applied to the extended sample (1978:Q3-2018:Q4) and from a VECM where the real exchange rate and interest rate differential are assumed stationary. The figure also displays the point estimate of the responses obtained from the baseline VAR with one additional variable. Each period is a quarter.

Figure B.3: Impulse responses to Noise disturbance (Alternative specifications)



Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$ for the baseline sample (blue lines), where the shaded areas are 16-84th percentile bands. In addition the figure displays the point estimate of the responses obtained from the VAR applied to the extended sample (1978:Q3-2018:Q4) and from a VECM where the real exchange rate and interest rate differential are assumed stationary. The figure also displays the point estimate of the responses obtained from the baseline VAR with one additional variable. Each period is a quarter.

Table B.1: Share of variance explained by the Main FX shock (Alternative specifications)

Panel A: Extended sample (1978:Q3-2018:Q4)

	Forecast Horizon (Quarter)					
	$Q1$	$Q4$	$Q12$	$Q24$	$Q40$	$Q100$
Home TFP	0.03	0.03	0.07	0.18	0.28	0.33
Home Consumption	0.04	0.07	0.26	0.45	0.48	0.43
Foreign Consumption	0.01	0.02	0.04	0.18	0.30	0.31
Home Investment	0.20	0.25	0.32	0.38	0.39	0.38
Foreign Investment	0.03	0.03	0.05	0.12	0.22	0.24
Interest Rate Differential	0.41	0.39	0.31	0.30	0.30	0.31
Real Exchange Rate	0.59	0.74	0.83	0.74	0.70	0.67
Expected Excess Returns	0.56	0.29	0.30	0.36	0.36	0.37

Panel B: Vector Error Correction Model

	Forecast Horizon (Quarter)					
	$Q1$	$Q4$	$Q12$	$Q24$	$Q40$	$Q100$
Home TFP	0.01	0.01	0.05	0.10	0.13	0.15
Home Consumption	0.09	0.13	0.25	0.41	0.50	0.58
Foreign Consumption	0.02	0.02	0.04	0.10	0.16	0.20
Home Investment	0.09	0.15	0.14	0.14	0.15	0.18
Foreign Investment	0.02	0.02	0.03	0.06	0.07	0.09
Interest Rate Differential	0.49	0.52	0.45	0.44	0.44	0.45
Real Exchange Rate	0.72	0.87	0.92	0.90	0.90	0.90
Expected Excess Returns	0.55	0.40	0.39	0.43	0.44	0.44

Panel C: Individual countries (Median)

	Forecast Horizon (Quarter)					
	$Q1$	$Q4$	$Q12$	$Q24$	$Q40$	$Q100$
Home TFP	0.03	0.06	0.11	0.26	0.44	0.45
Home Consumption	0.03	0.05	0.16	0.34	0.36	0.40
Foreign Consumption	0.04	0.04	0.15	0.20	0.38	0.38
Home Investment	0.02	0.04	0.20	0.34	0.34	0.36
Foreign Investment	0.05	0.05	0.10	0.19	0.32	0.37
Interest Rate Differential	0.08	0.07	0.11	0.22	0.26	0.32
Real Exchange Rate	0.27	0.42	0.68	0.80	0.76	0.72
Expected Excess Returns	0.21	0.18	0.29	0.32	0.39	0.43

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

Table B.2: Variance decomposition (Alternative specifications)

Panel A: 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

Panel B: Vector Error Correction Model

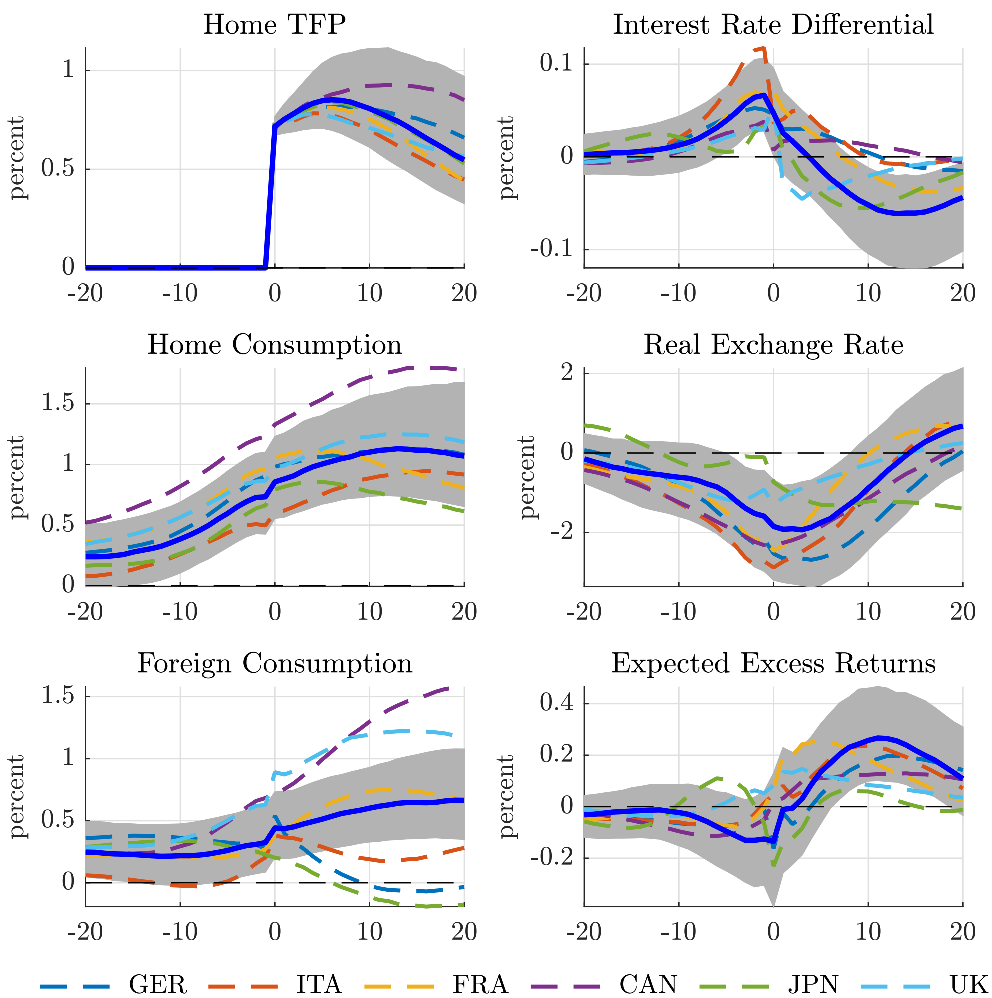
	Periodicities of 2-100 Quarters			Periodicities of 6-32 Quarters		
	Both	Tech.	Noise	Both	Tech.	Noise
Home TFP	1.00	1.00	0.00	1.00	1.00	0.00
Home Consumption	0.28	0.12	0.16	0.25	0.05	0.20
Foreign Consumption	0.24	0.16	0.09	0.15	0.08	0.07
Home Investment	0.29	0.08	0.22	0.40	0.06	0.34
Foreign Investment	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

Panel C: Individual countries (Median)

	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	0.69	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

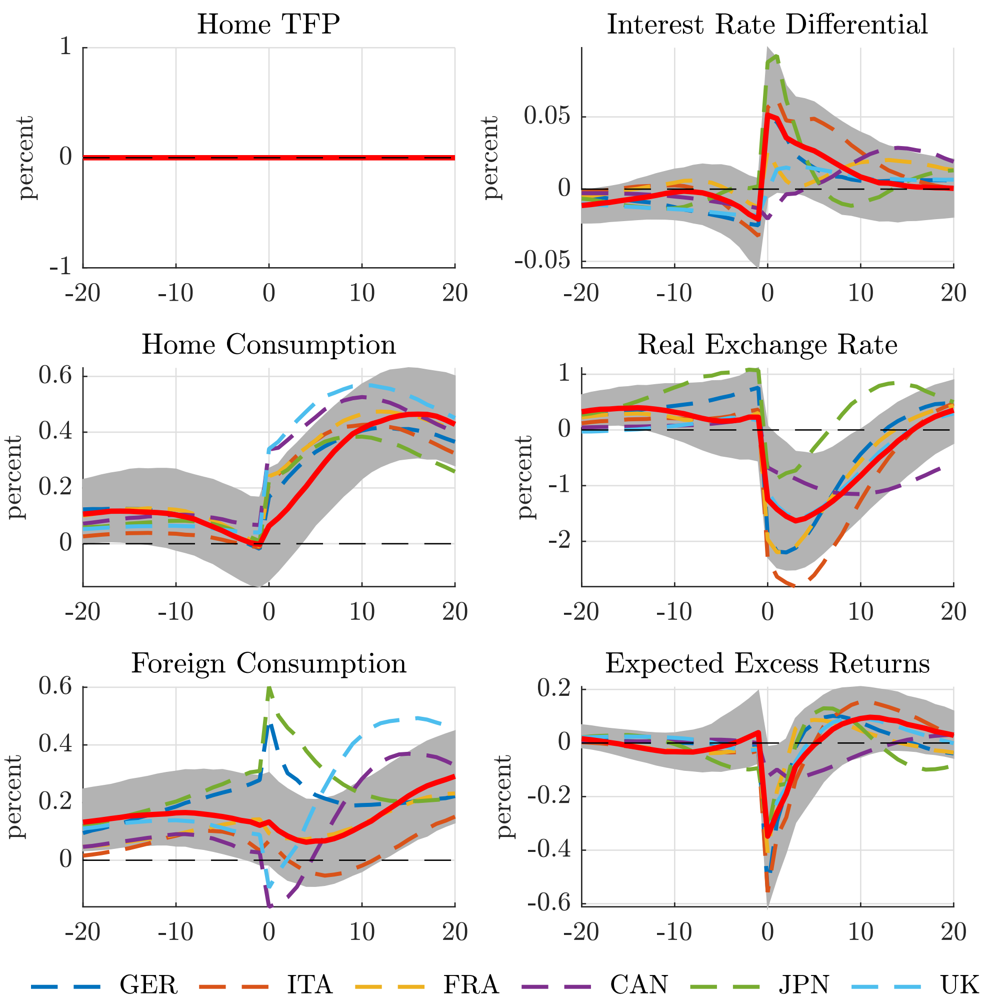
Notes: The table reports the estimated variance shares (at periodicities between 2 and 100 quarters and between 6 and 32 quarters) explained by technological disturbances ("Tech."), expectational disturbances ("Noise"), and the combination of both.

Figure B.4: Impulse responses to Technology disturbances (Individual countries)



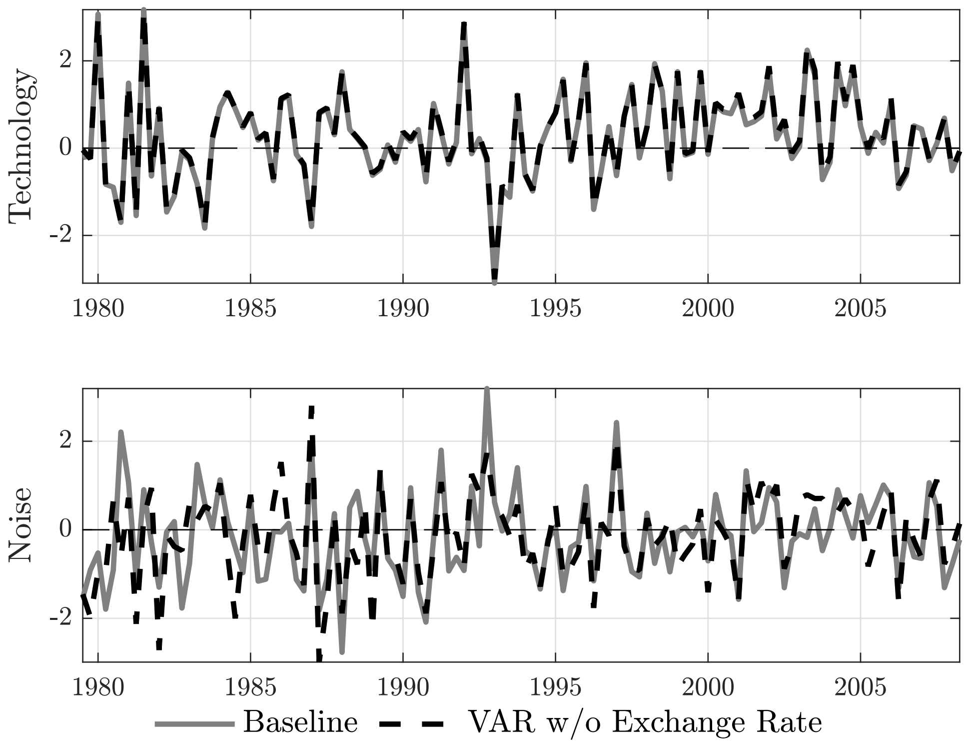
Notes: The figure displays IRFs to a one standard deviation impulse in the technological disturbance at time $t = 0$ for the baseline sample (blue lines), where the shaded areas are 16-84th percentile bands. In addition the figure displays the point estimate of the responses obtained from six different bilateral VARs. Each period is a quarter.

Figure B.5: Impulse responses to Noise disturbance (Individual countries)



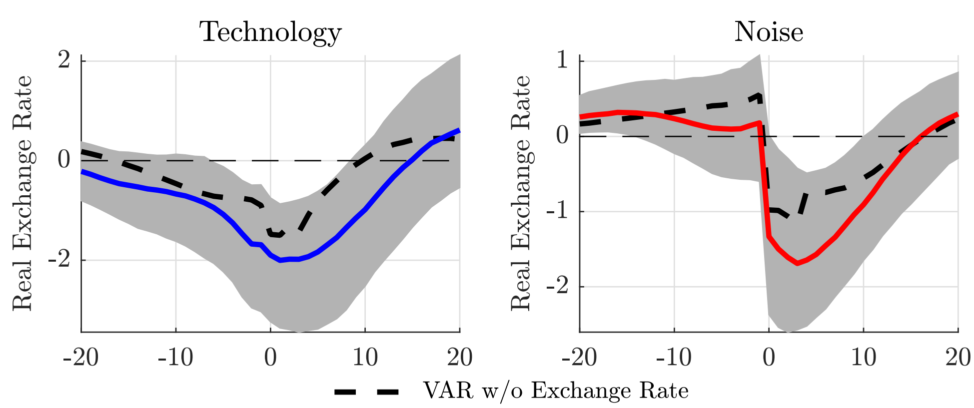
Notes: The figure displays IRFs to a one standard deviation impulse in the expectational disturbance at time $t = 0$ for the baseline sample (blue lines), where the shaded areas are 16-84th percentile bands. In addition the figure displays the point estimate of the responses obtained from six different bilateral VARs. Each period is a quarter.

Figure B.6: Series of estimated technology and noise disturbances



Notes: The figure displays the series of technology and noise disturbances estimated by the baseline VAR as well as the VAR without the exchange rate.

Figure B.7: The exchange rate response to technology and noise disturbances



Notes: The figure displays the IRF of the real exchange rate a one standard deviation impulse in the technological disturbance (left column) and the expectational disturbance (right column) at time $t = 0$. The dashed black line is the exchange rate response when the disturbances are estimated using a VAR without the exchange rate. The shaded area is the the 16-84th. Each period is a quarter.