News, Sentiment and Capital Flows ⋆ ,⋆⋆

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Abstract

We examine empirically the effect of two types of shocks related to expectations – "news" (increases in expected future productivity) and "sentiment" (surges in optimism unrelated to future productivity) – on gross capital flows. These two shocks together explain more than 80% of the variation in gross capital flows at all horizons, with the largest part being due to sentiment shocks. Both these shocks drive a positive correlation between gross inflows and outflows but only sentiments shocks generate procyclical gross flows. We show that sentiment shocks are not accounted for by financial, monetary or uncertainty shocks, nor are they purely global. The empirical effect of news and sentiment shocks constitute a challenge to most theories of capital flows, but are consistent with the existence of asymmetric information between domestic and foreign investors about the country's fundamentals.

Keywords: Capital flows, SVAR, Expectations, Asymmetric information

JEL: D82, E32, F32

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1. Introduction

Gross capital inflows and outflows have been shown to be procyclical, volatile and positively correlated (Broner et al., 2013; Forbes and Warnock, 2012; Davis and Van Wincoop, 2018; Avdjiev et al., 2017). The positive correlation between inflows and outflows is particularly puzzling. Studying the conditional behavior of capital flows offers information on the mechanisms driving capital flows and is a step towards understanding them. This paper moves in that direction by disentangling the reaction of domestic gross capital flows to technology and nontechnology expectation-related shocks.

A key contribution of the paper is to study the reaction of gross capital flows to shocks related to expectations: "news" shocks (increases in future productivity) and nontechnological expectation shocks (surges in optimism that are orthogonal to future productivity), which we call "sentiment" shocks, following Levchenko and Pandalai-Nayar (2020). We find that news shocks lead to a decrease in both gross capital inflows and outflows (an increase in home bias), while sentiment shocks lead to an increase in both gross inflows and outflows (a decrease in home bias). This implies that while only sentiment shocks generate procyclical flows, both shocks generate positively correlated inflows and outflows. This behavior characterizes all type of assets, except equity. Together, news and sentiment shocks explain most of the variance of gross inflows and outflows, which suggests that capital flows are tightly linked to expectations and are forward-looking.

To show this, we use a recursive structural VAR approach to identify three shocks: a total factor productivity (TFP) surprise shock, a news shock about future TFP and a "sentiment" shock. Our specification includes TFP, GDP per capita, an expectation variable and gross capital inflows or outflows in the last position. Formally, we follow Levchenko and Pandalai-Nayar (2020), who build on Barsky and Sims (2011), and define the TFP surprise shock as the TFP's own innovation. The news shock is identified as the structural shock that best explains future variations in TFP not accounted for by the TFP surprise shock. Finally, the sentiment shock is the shock that best explains short-run variations in expectations, accounted for by neither the TFP surprise shock nor the news shock. The sentiment shock captures any shock that affects expectations while unrelated to technology.

Using US data, we find that a positive news shock triggers an immediate, short-lived and negative response of capital flows, while a positive sentiment shock has positive effects on capital flows on impact with medium-lasting effects. TFP surprise shocks do not induce significant responses of capital flows. Quantitatively, news and sentiment shocks contribute up to 85% of the forecast error variance decomposition (FEVD) of capital flows. Using a panel of 17 OECD economies, we find results similar to those of the US. Overall, two main conclusions can be drawn. First, nontechnology shocks are an important driver of capital flows. They are at least as important as technology shocks. Second, contemporaneous technology shocks play a negligible role but anticipated technology (i.e., news) shocks are important. This shows that expectations play a key role in driving gross capital flows. We also show that both expectation-related shocks lead to an increase in net capital inflows, but this increase is immediate in the case of sentiment shocks while it is delayed in the case of news shocks. Finally, we examine the effect of shocks on different asset classes. While FDI, debt flows and other flows (loans, deposits, trade credit/debit,...) react like total flows, equity inflows increase following a news shock.

Before interpreting our results further, we address two issues. First, as the sentiment shock is identified as a residual, it is important to rule out potential known drivers of capital flows. We thus account for the following: financial shocks (Broner et al., 2013), uncertainty shocks, shocks to monetary policy (Rey, 2015), and shocks to international prices. In all cases, the responses of capital flows to the three shocks remain unchanged. Second, the conditional positive correlation of capital inflows and outflows can be explained by the global nature of shocks (Davis and Van Wincoop, 2018; Tille and van Wincoop, 2014). Indeed, the capital outflows of a given country are the inflows of the rest of the world. Global shocks that drive a positive response of capital inflows worldwide necessarily drive a positive response of outflows. The role of global factors in driving capital flows has also been emphasized in the literature (Forbes and Warnock, 2012; Fratzscher, 2012; Passari and Rey, 2015). We account for this issue by introducing variables for the the rest of the world (ROW) in our baseline VAR and identifying ROW shocks before the US TFP surprise, news and sentiment shocks. The US shocks identified in this way are by construction orthogonal to the ROW shocks and are therefore purely US-specific. The impact of the three US-specific shocks on capital flows remains unchanged and they still explain a large part of the FEVD of capital flows.

Given that our results are not exclusively driven by the global nature of shocks or by "usual suspects", we discuss potential explanations for the effect of news and sentiment shocks on capital flows. One key challenge for theory is to explain why gross capital flows are countercyclical in the case of news shocks and procyclical in the case of sentiment shocks. Theories of asymmetric information between domestic and foreign agents are promising in this respect.[1] Tille and van Wincoop (2014) have shown that positive news shocks generate countercyclical gross flows if domestic agents have an informational advantage over foreigners regarding domestic fundamentals. We lay down a simple two-country model in that spirit, and show that not only news shocks generate countercyclical gross flows, but sentiment (noise) shocks also generate procyclical gross flows if both information asymmetries and capital installation frictions are strong enough. The model also implies that both shocks generate positive net inflows, which is consistent with the data, and can rationalize the fact that news shocks generate positive gross inflows in markets where information asymmetries are less strong, like equity markets. We discuss other assumptions which have been mentioned by Broner et al. (2013): asymmetric risk perception and leveraged cycles. While the latter are hard to reconcile with countercyclical flows conditional on news shocks, the former constitute another interesting avenue to explain our results.

This paper is related to the literature on expectation-driven business cycles. There is increasing empirical evidence that expectations are key drivers of macroeconomic fluctuations.[2] Yet, little has been done to analyze the impact of expectations on capital flows. One exception is the paper by Milesi-Ferretti and Tille (2011) showing that countries with worse outlooks suffered larger capital retrenchments. Cordonier (2017) shows that the forward-looking component of the consumer sentiment index is significantly related to capital flows. This paper extends on

[1]See Tille and van Wincoop (2014), Albuquerque et al. (2007, 2009) and Brennan and Cao (1997).

[2]See for instance Beaudry and Portier (2006) or Barsky and Sims (2011).

this idea by using a more structural approach and distinguishing the technology-related part of expectations from their nontechnology-related part.[3]

The rest of the paper is structured as follow: Section 2 describes our methodology, Section 3 defines the data gathered for the empirical analysis, Section 4 presents the main findings of this paper and Section 5 performs robustness checks. Section 6 presents a two-country model with information asymmetry. Section 7 concludes.

2. Empirical methodology

This section describes the identification strategy for TFP surprise, news and sentiment shocks in a structural VAR model. This recursive approach is based on Levchenko and Pandalai-Nayar (2020) and Barsky and Sims (2011) and aims at identifying the following structural shocks: a TFP surprise shock, a news shock on TFP and a sentiment shock. Like Barsky and Sims (2011), we identify news shocks by maximizing the forecast error of TFP at horizons greater than 1. Following Levchenko and Pandalai-Nayar (2020), we then identify sentiment shocks as the shock, uncorrelated to TFP, that maximizes the residual forecast error variance of an expectation variable (here consumer confidence). This methodology allows us to distinguish between shocks to expectations that are related to the country's TFP ("news") from those that are unrelated ("sentiment").[4]

Formally, assume that TFP is driven both by the usual surprise TFP shock, but also by a news shock. The latter is a shock about future productivity. The process of TFP can be represented as a moving-average, with the restriction that the news shock has no contemporaneous effect on the level of TFP. With A_t denoting TFP, one example for this particular

[3]The empirical literature on capital flows, more generally, explores "push" and "pull" factors of capital flows. Calvo et al. (1993), Calvo et al. (1996), Fernandez-Arias (1996) and Chuhan et al. (1998) first referred to the "push" external forces and the "pull" domestic factors influencing the capital flows toward an economy. More recently, Fratzscher (2012), Forbes and Warnock (2012) or Adler et al. (2016) in a dynamic set-up, among others, have underlined the importance of global factors, the VIX in particular.

[4]Beaudry and Portier (2006) were the first to provide a method to identify news. A news shock is identified in a VAR with TFP and stock prices where TFP is placed first. A news shock is then the shock that explains contemporaneous stock price movements that are uncorrelated to the innovation in TFP. This methodology, however, does not allow us to distinguish between movements in stock prices that are correlated to future TFP from those that are not.

representation is given by:

$$ln(A_t) = ln(A_{t-1}) + \lambda_1 \epsilon_t^{sur} + \lambda_2 \epsilon_{t-s}^{news}$$

where ϵ_t^{sur} is the surprise TFP shock that contemporaneously affects the level of TFP, and ϵ_{t-s}^{news} is the news shock, i.e., the change in productivity that agents expect $s > 0$ periods before it materializes.

Assume then that agents' expectations about the state of the economy can also be represented as a moving average process. Both the surprise TFP shock and the news shock can affect the level of expectations, but also a sentiment shock. The latter captures variations in expectations not related to current or future changes in TFP. With the expectations denoted as F_t, a possible representation is given by:

$$F_t = F_{t-1} + \lambda_1^F \epsilon_t^{sur} + \lambda_2^F \epsilon_t^{news} + \lambda_3^F \epsilon_t^{sent} + \eta_t$$

where ϵ_t^{sent} is the sentiment shock.

As noted by Levchenko and Pandalai-Nayar (2020), identifying the three shocks based on only TFP and an expectation variable would not be possible. We thus include GDP as an additional forward-looking variable, as well as gross capital flows.[5] Let us denote by y_t the M-dimensional state vector. In our specification, we have $y_t = [TFP_t, GDP_t,\ E12m_t, KF_t]'$ where TFP is the log of TFP, GDP is the log of real GDP, $E12m$ is the consumer confidence measure (our expectation variable) and KF are capital inflows or outflows. Consider the case where y_t follows a VAR whose MA representation is:

$$y_t = B(L)u_t,$$

with $B(0)$ being an identity matrix. We assume that the linear mapping between the residuals

[5]Please note that we also have a specification including consumption and hours variables. As discussed later in the paper, the results are similar.

(or innovations) and structural shocks is given by:

$$u_t = A_0 \epsilon_t.$$

where $Var(\epsilon_t) = I$. The vector of innovations of the VAR corresponds to $A_0 \epsilon_t$. Its variance-covariance matrix of innovations is given by $A_0 A_0' = \Sigma$. The VAR estimation provides us with a consistent estimate of Σ. This is however not sufficient to get an estimate of A_0. Indeed, there is an infinity of A_0 matrices satisfying $A_0 A_0' = \Sigma$. They are all of the form $\tilde{A}_0 D$, where D is a $M \times M$ orthonormal matrix ($DD' = I$) and $\tilde{A}_0$ results from the Cholesky decomposition of Σ.

The h step ahead forecast error is given by:

$$y_{t+h} - E_{t-1} y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A}_0 D \epsilon_{t+h-\tau}$$

Define the share of the forecast error variance of variable i attributable to shock j at horizon h by $\Omega_{i,j}(h)$. The first structural shock, ϵ^{sur} is identified as the reduced-form innovation of the VAR with the TFP measure ordered first. This implies that the first row of D is of the form $[1, 0, .., 0]$.[6] Hence, the share of the forecast error variance of the first variable, the TFP measure, attributable to the surprise TFP shock is now determined. Formally, it means that $\Omega_{1,1}(h)\ \forall h$ is fixed.

Given that only the surprise TFP shock and the news shock move the level of TFP, they have to account for all the forecast error variance of TFP. Formally, it means that the sum of the shares of the forecast error variance of TFP attributable to the first and second structural shocks - the surprise TFP shock and the news shock - should be as close as possible to 1 at all horizons:

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) \approx 1\ \forall h$$

[6] This also implies that the first column is $[1, 0, ..., 0]'$ because D is orthonormal.

where $\Omega_{i,j}(h)$ is given by:

$$\Omega_{i,j}(h) = \frac{e_i'(\sum_{\tau=0}^{h} B_\tau \tilde{A}_0 D e_j e_j' D' \tilde{A}_0' B_\tau')e_i}{e_i'(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau')e_i} = \frac{\sum_{\tau=0}^{h} B_{i,\tau} \tilde{A}_0 \gamma_j \gamma_j' \tilde{A}_0' B_{i,\tau}'}{(\sum_{\tau=0}^{h} B_{i,\tau} \Sigma B_{i,\tau}')} = \frac{\gamma_j' Z \gamma_j}{(\sum_{\tau=0}^{h} B_{i,\tau} \Sigma B_{i,\tau}')}$$

with $Z = \sum_{\tau=0}^{h} \tilde{A}_0' B_{i,\tau}' B_{i,\tau} \tilde{A}_0$ and $\gamma_j = De_j$ selecting the jth column of the D matrix. e_j is the selection vector that contains zero everywhere except at the jth position and $B_{i,\tau} = e_i' B_\tau$ denotes the ith row of the matrix of moving average coefficients. As stated earlier, all the forecast error variance of TFP must be attributed to the surprise TFP and the news shocks only. As $\Omega_{1,1}(h)$ is fixed, the strategy to identify the second structural shock consists of maximizing its contribution to the forecast error variance of TFP, not attributable to the first structural shock.

Let us denote by γ^{news} the second column of D. The impact of the second structural shock on the variables is $\tilde{A}_0 \gamma^{news}$. Since D is orthonormal, we must have $\gamma^{news}(1) = 0$ an $\gamma^{news\prime} \gamma^{news} = 1$. As a result, γ^{news} is obtained by solving the following problem:[7]

$$\begin{aligned}\gamma^{news} = argmax_\gamma \sum_{h=0}^{H} (H-h)\Omega_{1,2}(h) &= \sum_{h=0}^{H} (H-h) \frac{\sum_{\tau=0}^{h} B_{1,\tau} \tilde{A}_0 \gamma \gamma \tilde{A}_0' B_{1,\tau}'}{(\sum_{\tau=0}^{h} B_{1,\tau} \Sigma B_{1,\tau}')} \\ &= \sum_{h=0}^{H} (H-h) \frac{\gamma' N \gamma}{(\sum_{\tau=0}^{h} B_{1,\tau} \Sigma B_{1,\tau}')}\end{aligned}$$

s.t

$$\gamma(1) = 0, \quad \gamma' \gamma = 1$$

with, $N = \sum_{\tau=0}^{h} \tilde{A}_0' B_{1,\tau}' B_{1,\tau} \tilde{A}_0$ The restrictions ensure that the news shock has no contemporaneous effect on TFP.[8] To summarize, we identify the news shock as the linear combination of the $M-1$ reduced form innovations - excepting the first one - that best explain TFP at long

[7]Notice that in Barsky and Sims (2011) do not explicitly include the time-weights, i.e., denoted by $(H-h)$, in their presentation of the optimisation problem, although they write about them.

[8]As pointed out by Barsky and Sims (2011) and based on the paper by Uhlig (2003), this strategy is equivalent to the identification of news shock as the first principal component of TFP orthogonalized with respect to its own innovation. Formally, γ^{news} is the eigenvector associated with the maximum eigenvalue of a weighted sum, using time-weights, of the lower $(M-1) \times (M-1)$ submatrices of $(B_{1,\tau}\tilde{A}_0)'(B_{1,\tau}\tilde{A}_0)$ over τ.

horizons.

The last structural shock to be identified is the sentiment shock. As seen earlier, this third structural shock is not related to TFP, but rather to changes in expectations not explained by any of the TFP shocks. We assume that it is a short-run shock, i.e., its impacts on the expectations' variable only last a few quarters. Hence, following Levchenko and Pandalai-Nayar (2020), the sentiment shock is identified so as to maximise its contribution to the remaining short-run forecast error variance of the expectation variables. Assume the expectations' variable, F_t, is ordered third in the VAR. The two first structural shocks have been identified, meaning that $\Omega_{3,1}(h)$ and $\Omega_{3,2}(h)$ are fixed at all horizons h. Using the same strategy as for the news shocks, identifying the third structural shock is equivalent to choosing γ^{sent} (the third column of D), such that the sentiment shock is orthogonal to the other two shocks and contributes the most to the remaining forecast error variance of F_t. Formally,

$$\begin{aligned}\gamma^{sent} = argmax_{\gamma} \sum_{h=0}^{H^{sent}} \Omega_{3,3}(h) &= \sum_{h=0}^{H^{sent}} (H^{sent} - h) \frac{\sum_{\tau=0}^{h} B_{3,\tau} \tilde{A}_0 \gamma \gamma \tilde{A}_0' B_{3,\tau}'}{(\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}')} \\ &= \sum_{h=0}^{H^{sent}} (H^{sent} - h) \frac{\gamma' S \gamma}{(\sum_{\tau=0}^{h} B_{3,\tau} \Sigma B_{3,\tau}')}\end{aligned}$$

s.t

$$\gamma(1) = 0, \quad \gamma'\gamma = 1, \quad \gamma'\gamma^{news} = 0$$

with $S = \sum_{\tau=0}^{h} \tilde{A}_0' B_{3,\tau}' B_{3,\tau} \tilde{A}_0$. Note that as the sentiment shock is assumed to be a short-run shock, the horizon H^{sent} is set to two quarters.

To sum up, the TFP surprise shock is identified as the TFP's own innovation. The news shock is identified as the structural shock that best explains future variations in TFP not accounted for by the TFP surprise shock. Finally, the sentiment shock is the shock that best explains short-run variations in expectations, accounted for by neither the TFP surprise shock, nor the news shock.

3. Data

For this analysis, we gather data on TFP, GDP, consumer confidence and capital flows for the U.S. The baseline vector y_{USt} used to estimate U.S. shocks includes four variables: the log of TFP - as a measure of technology, TFP_{USt}, the log of real GDP per capita GDP_{USt}, an expectation variable $E12M_{USt}$ and capital flows KF_{USt}:

$$y_{US,t} = [TFP_{US,t}, GDP_{US,t}, E12M_{US,t}, KF_{US,t}].$$

For TFP, we use the utilization-adjusted TFP series from Fernald (2014), where adjustments for variable utilization are based on the methodology by Basu et al. (2006). Then, as measure of output, we use the chain-weighted real GDP variable from the BEA (NIPA table 1.1.6). To obtain per capita terms, we divide by the civilian noninstitutionalized population aged 16 and over (BLS).

The main measure of expectations is from the survey of consumers produced by the University of Michigan. In particular, we use the standardized forward-looking component asking about expected changes in business conditions in a year, which is part of the main consumer sentiment index. More specifically, the survey asks the following: "Now turning to the business conditions in the country as a whole: do you think that during the next twelve months we will have good times financially, or bad times, or what?". There are 6 possible answers: good times, good with qualifications, pro-con, bad with qualifications, bad times or do not know. From these answers are computed relative scores, i.e., the percentage of favorable replies minus the percentage of unfavorable replies, plus 100. Similarly to Barsky and Sims (2012), we label this variable "E12M". Notice that there are two main reasons, why our baseline uses consumer confidence rather than the expectations obtained from the Survey of Professional Forecasters (SPF). First, it allows us to link this paper to the literature on news and sentiment shocks using the same variable. Second, Cordonier (2017) has found that this specific "E12M" variable relates significantly to capital flows (while controlling for other key factors).

The data on gross capital inflows and outflows are obtained from the Balance of Payment Statistics Database (IFS/IMF), based on the BPM6 methodology. Gross inflows are the country's net incurrence of liabilities, while gross outflows represent the net acquisitions of foreign assets by domestic agents. As in Forbes and Warnock (2012), official reserves are excluded from the gross capital outflows. Following the literature (see Broner et al. (2013) or Adler et al. (2016)), we express capital flows in terms of GDP trend (trend extracted using a Hodrick-Prescott filter).[9]

4. Baseline results

In this section, we estimate the effects of TFP surprise, news and sentiment shocks on capital flows. We show that news shocks typically generate a decrease in both gross capital inflows and outflows, while sentiment shocks generate an increase in both gross capital inflows and outflows.

We start by presenting the orthogonalized response functions obtained from the SVAR analysis for the United States. The identification of the shocks follows the methodology described earlier. We set the baseline number of lags to $p = 4$ and we use bias-corrected confidence intervals from 2000 bootstraps based on Kilian (1998). We start with a SVAR containing TFP, GDP, E12M and gross capital inflows as described in the data section. Figure 1 shows the impulse response functions (IRF) of all variables to the three shocks: TFP surprise, news and sentiment shocks. We then replace gross inflows with gross outflows and show in Figure 2 the responses of gross capital outflows only.

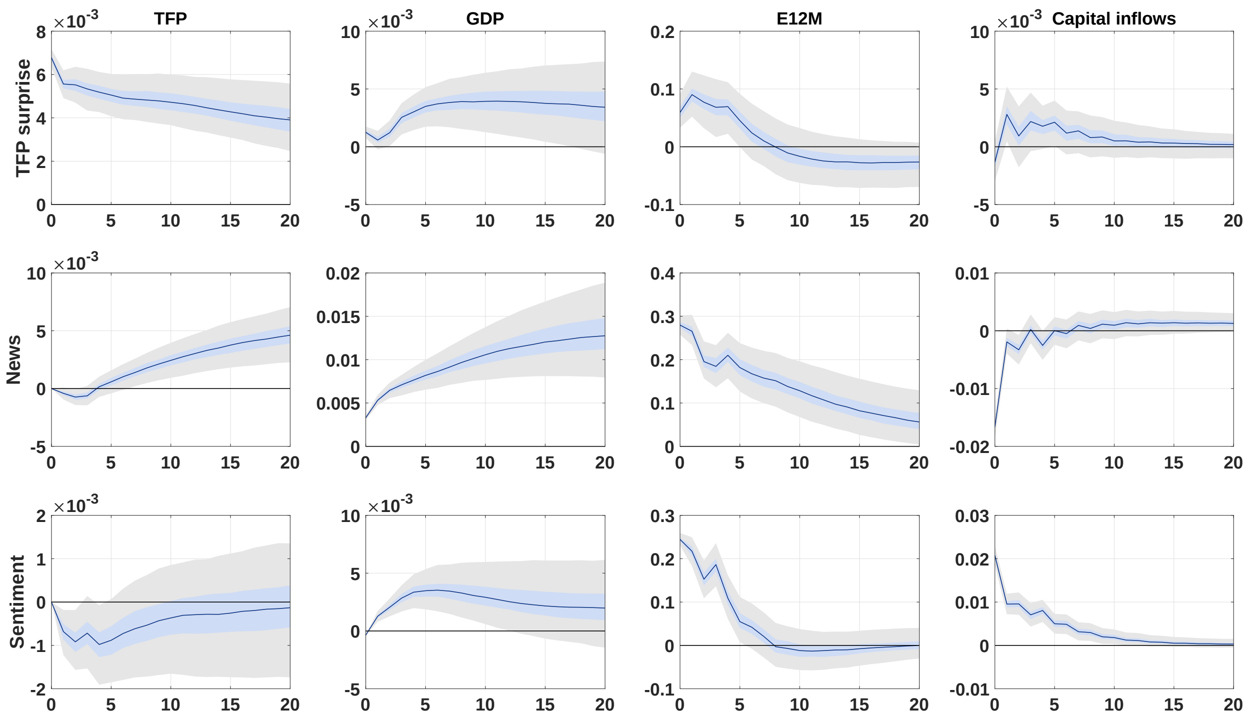
News and sentiment shocks are fairly well identified. The news shock has a slow-building persistent impact on TFP. The response of TFP to the sentiment shock is significantly negative, but low in magnitude, as in Levchenko and Pandalai-Nayar (2020).[10] The responses of GDP are as expected: TFP generates an immediate positive response and the news shock has a persistent positive impact. The consumer sentiment index reacts strongly to the sentiment shock by construction, but also to the news shocks, while it reacts less to the TFP surprise

[9] Indeed, the GDP trend reacts to shocks much less strongly than current GDP. Using current GDP would make it much harder to attribute the impact of the shock mostly on capital flows as GDP would react as well.

[10] Levchenko and Pandalai-Nayar (2020) explain this anomaly by the fact that Fernald (2014) quarterly series may not perfectly correct for capacity utilization.

shock. News and sentiment shocks are thus the main drivers of expectations. In the Appendix, Figure A.1 shows that news and sentiment shocks indeed capture more than 95% of the forecast error variance of consumer sentiment at all horizons, with the TFP surprise explaining only up to 5% of that variable. The news shock alone makes up for 55% to 65% of the variance depending on the horizon.

Figure 1: IRFs to TFP surprise, news and sentiment shocks

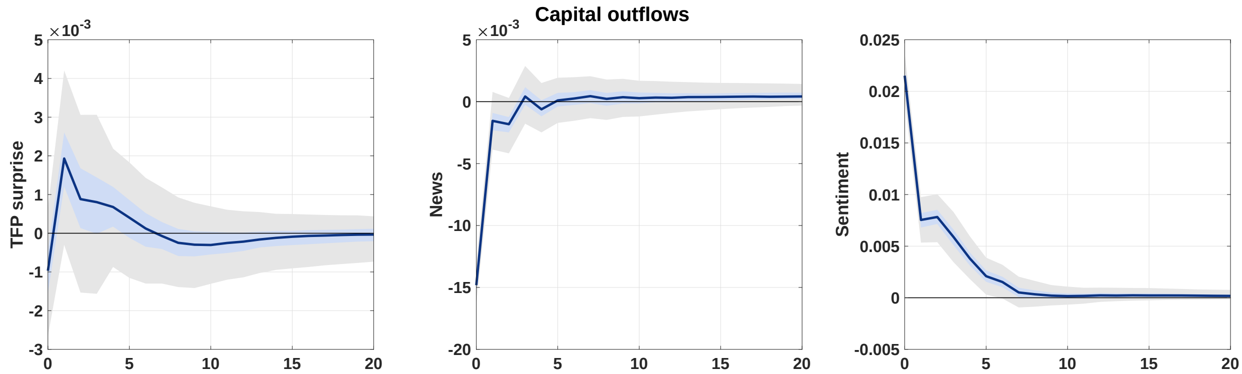


Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Regarding the impact of shocks on gross capital inflows, we see in Figure 1 that a news shock has an immediate negative impact that is short-lived (1-2 quarters), followed by a positive response after 4 quarters. Figure 2 shows that the response of gross capital outflows is similar. On the other hand, a sentiment shock triggers an immediate positive response of gross capital inflows and outflows that lasts for approximately 7 to 10 quarters.[11] Hence, optimism that

[11]Our results remain similar when we use the same variables as Levchenko and Pandalai-Nayar (2020) in our specification, i.e., including consumption and hours in third and fourth position. However, the response of capital inflows to a TFP surprise shock becomes significantly positive, and the news shocks has a more significant

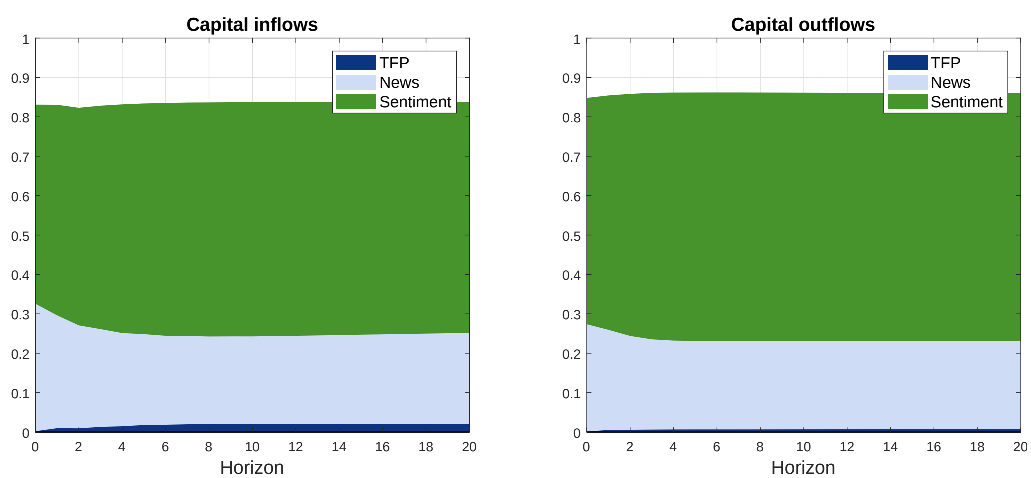
Figure 2: IRFs of capital outflows to TFP surprise, news and sentiment shocks



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

is related to fundamentals (here measured by TFP) generates an increased home bias, while optimism that is unrelated to fundamentals generates a decrease in home bias.

Figure 3: Forecast Error Variance Decomposition of gross capital flows



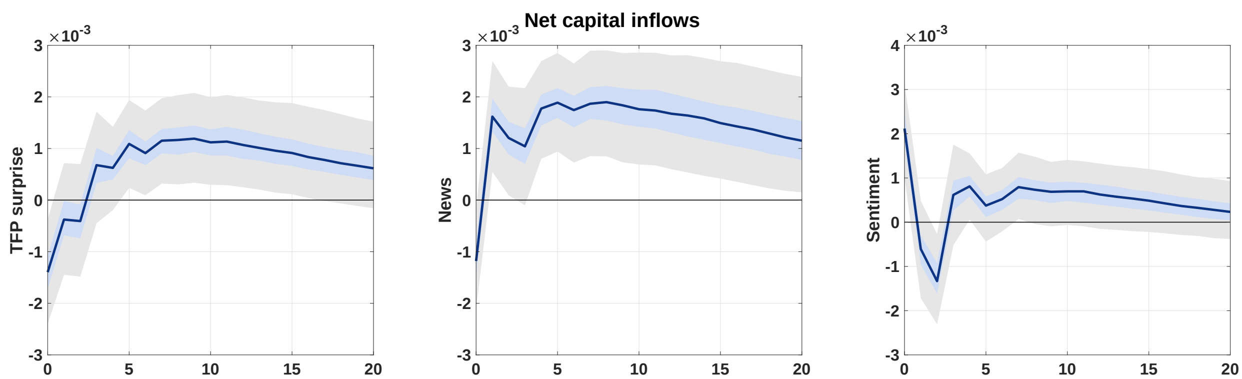
Note that the responses of gross capital flows to a surprise TFP shock are positive, but nonsignificant. Overall, capital flows are found to react not to current changes in fundamentals, but to expectations about the country's future performance. In terms of magnitude, capital flows are mainly driven by expectation-related shocks (news and sentiment). This is confirmed

and persistent effect on capital flows in the medium/long-run. The impulse responses functions are presented in Appendix A Figure A.2.

by the forecast error variance decomposition of both inflows and outflows, presented in Figure 3. The sentiment shock alone can explain up to 60% of the FEVD of gross capital flows. News shocks explain approximately 25% of capital flows, while TFP surprise shocks have a negligible contribution.

Figure 4 provides the IRFs of net inflows. The magnitude of the response to news and sentiment shocks is small in comparison to gross flows. This reflects the positive comovement in gross flows. In the case of news shocks, the initial response is insignificant, but it is followed in subsequent quarters by a significantly positive response. In the case of sentiment shocks, the impact response is positive but short-lived.

Figure 4: U.S. IRFs of net capital inflows to TFP surprise, news and sentiment shocks

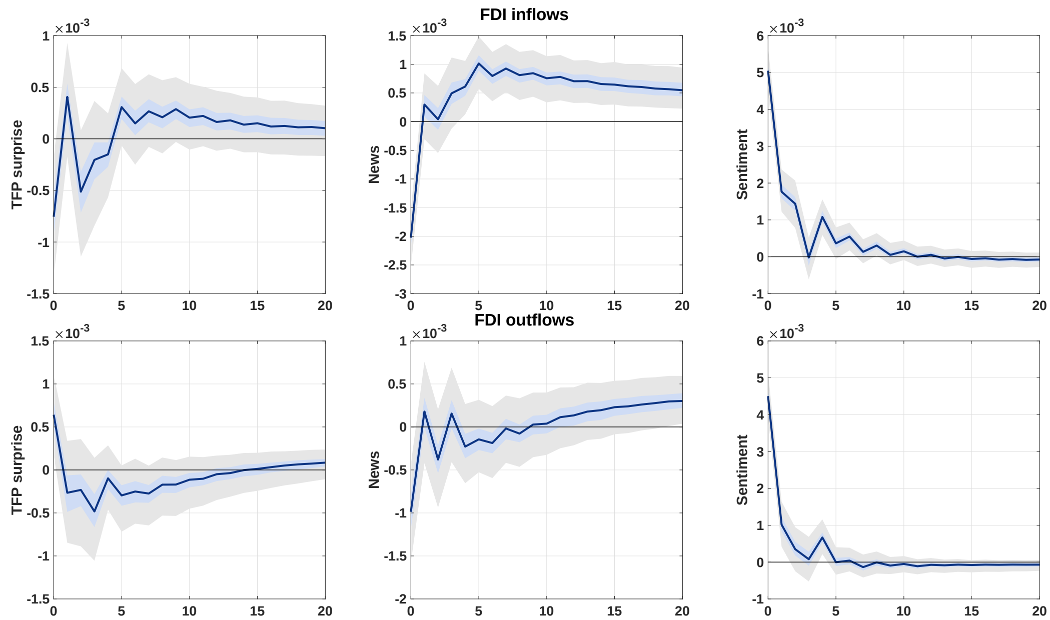


Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

The reaction of the stock prices can also be informative on the nature of shocks. We thus introduce the log of the S&P500 index as a fourth variable in the SVAR, before capital flows. The IRFs of the stock price are shown in Figure A.3 in the Appendix. The stock price increases for all shocks. This increase persists over time in the case of news shocks, which is consistent with the literature. In the case of sentiment shocks, the increase is not persistent and is quickly reversed, which suggests that sentiment shocks generate noise trading. This echoes the finding of the financial literature empirically exploring the effect of international market “sentiment” on domestic asset prices.[12]

[12]See for instance Ben-Rephael et al. (2019) and Fraiberger et al. (2018). The former identify sentiment

Figure 5: IRFs to TFP surprise, news and sentiment shocks - FDI flows

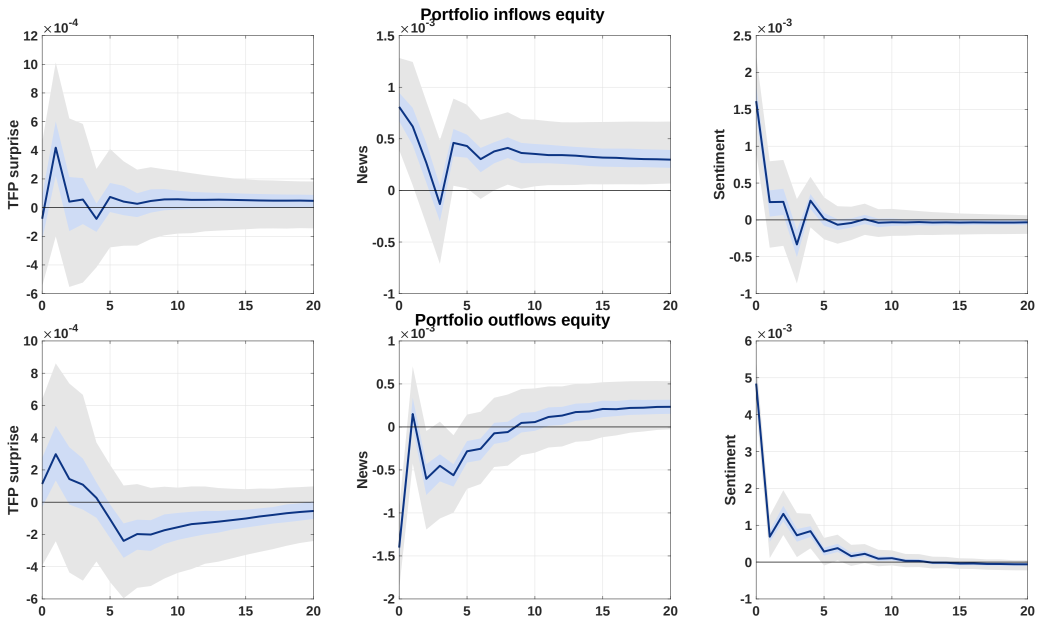


Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

One important question to explore is whether the reaction of gross capital inflows and outflows are driven by different categories of flows. Interestingly, as shown in Figures 5 to 8, the effects of shocks is essentially the same across different categories of flows. In particular, FDI flows, bond portfolio flows and other flows, which include loans, currency and deposits or trade credit and advances and compose the bulk of capital flows, react in a way similar to total flows. The only difference is that the reaction of gross FDI inflows and gross bond portfolio inflows to news shocks turns positive after 2-3 quarters, and persistently so for FDI. But all in all, on impact, following a news shock (a sentiment shock), US agents sell less (more) domestic assets in the form of FDI, bonds and other assets to foreigners at the same time as they buy less (more) of foreign assets of the same type from foreigners. One exception concerns equity flows. As shown in Figure 6, equity flows react differently to news shocks than other types of capital flows: gross equity inflows react positively from the onset. Some portfolio composition

shocks as portfolio shifts to international mutual funds. The latter identify them through international media coverage.

Figure 6: IRFs to TFP surprise, news and sentiment shocks - Portfolio equity flows



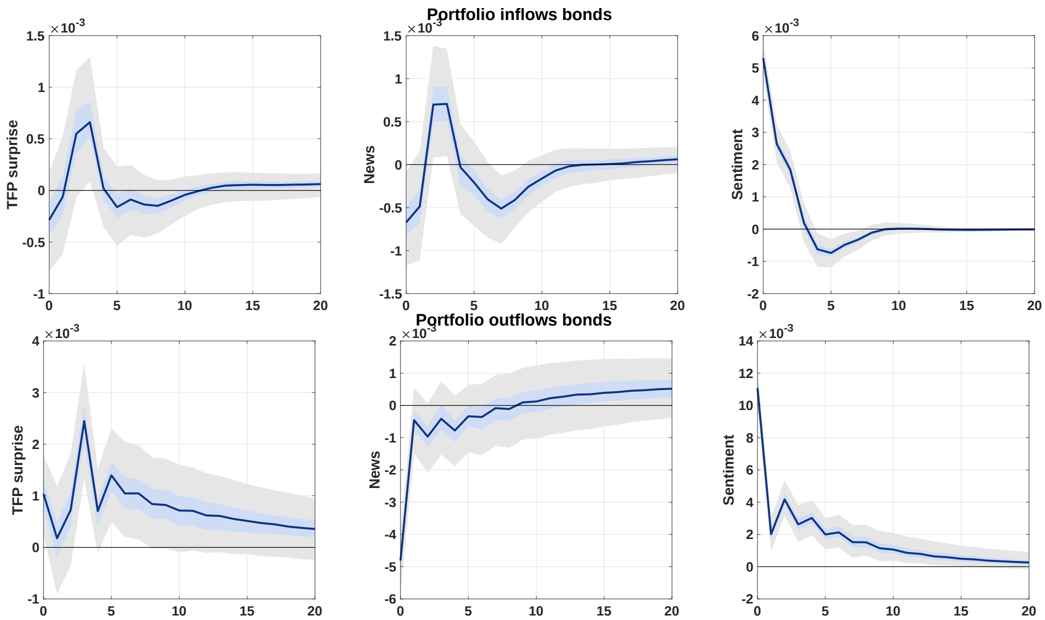
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

is therefore at play in the case of news shocks, as equity inflows increase while other types of flows decrease.

5. Robustness

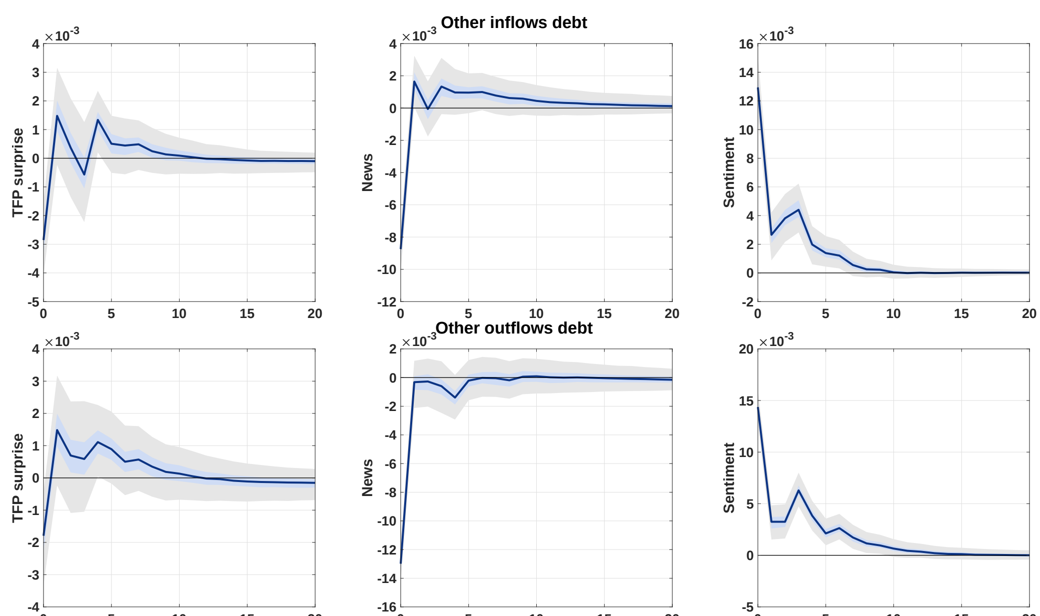
Before interpreting our results, we need to address two issues. First, the conditional positive correlation of capital inflows and outflows can be explained by the global nature of shocks. Indeed, the capital outflows of a given country are the inflows of the rest of the world. Global shocks that drive a positive response of capital inflows worldwide then necessarily drive a positive response of outflows. Second, a sentiment shock is identified as a residual, it is especially important to rule out known potential drivers of capital flows. We address these issues as follows. First, we extend our SVAR to identify US-specific shocks. We then assess whether sentiment shocks can be accounted for by other shocks, such as uncertainty, financial, monetary policy or international shocks. Finally, we run more standard robustness checks.

Figure 7: IRFs to TFP surprise, news and sentiment shocks - Portfolio bond flows



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure 8: IRFs to TFP surprise, news and sentiment shocks - Other investment flows



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

5.1. *Identifying US-specific shocks*

We identify US-specific shocks by including variables for the rest of the world and accounting for shocks to the rest of the world. To do so, we add an aggregated rest-of-the-world (ROW) GDP per capita variable, a ROW TFP and a ROW E12M variable in the first positions of our vector, before the US variables. We then obtain a 7-variable VAR with

$$y_t = [TFP_{ROW,t}, GDP_{ROW,t}, E12M_{ROW,t}, TFP_{US,t}, GDP_{US,t}, E12M_{US,t}, KF_{US,t}].$$

Using the same approach as in the baseline, we first identify three ROW shocks: ROW TFP surprise, news and sentiment shocks. Local, US-specific TFP surprise, news and sentiment shocks are then identified by imposing orthogonality with the ROW shocks. Any shock that is correlated across countries (a common shock or a shock that spills over from one country to another) will be captured by the ROW shocks, as US variables are allowed to respond to these shocks. However, the ROW variables are restricted to not respond to the US TFP surprises and to respond minimally to the US TFP news and sentiment shocks. What is important here is that, by construction, the US shocks will be orthogonal to shocks to ROW variables and can therefore "safely" be interpreted as US-specific shocks. The full set of restrictions is summarized in Table A.1 in the Appendix.

For this 7-variable VAR, we compute ROW variables as the average of 9 countries over the 1996Q1-2018Q3 time period. The selected countries are those for which a consumer sentiment index and data to build a measure of TFP are available (see Appendix B for details on the data of the 9 extra countries and Appendix D for a description of the TFP variable construction).[13] We then build the TFP, GDP per capita and E12M as the weighted-mean of the countries' variables, using real GDP as weights. Altogether, our sample averages to approximately a third of world real GDP, PPP-adjusted, over the covered time period.[14]

The IRFs of US capital flows to these shocks are presented in Figure 9. Note that to limit

[13]The included countries are Australia, Denmark, France, Germany, Italy, Portugal, Spain, Sweden and the United Kingdom.

[14]To get this ratio, we use the World Bank annual GDP constant 2011 USD, PPP-adjusted data.

the number of parameters to be estimated, we use VAR specification with 2 lags. In this set-up, the responses of US capital flows to the three US-specific shocks remain very similar to those from the baseline, i.e., without identifying ROW shocks first. Therefore, the correlation of capital flows does not arise from the cross-country correlation of shocks. Interestingly, the responses to ROW shocks are qualitatively similar to the US-specific ones. Looking at Figure A.4 in the Appendix, we see that US-specific shocks explain 30% to 40% of the FEVD of gross US capital flows, which is higher than the share explained by ROW shocks.[15]

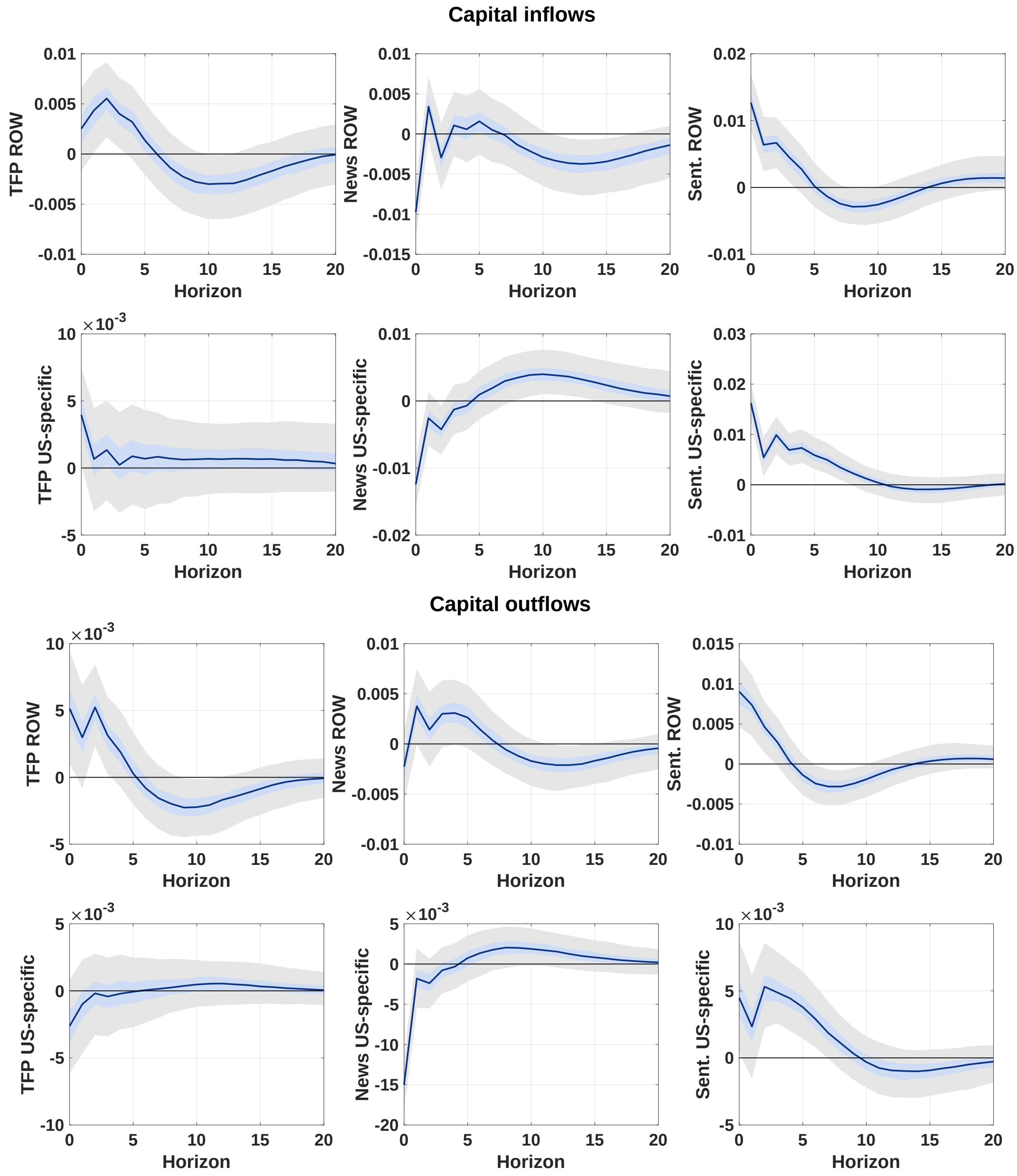
5.2. Accounting for other shocks

One could argue that our sentiment shocks merely reflect variations in uncertainty or in financial conditions. Thus, we repeat the empirical exercise but sequentially include various variables that measure economic and financial markets uncertainty, as well as financial and international conditions. First, to account for financial markets' uncertainty, we include the VIX, the equity market volatility (EMV) index built by Baker et al. (2019) and a financial stress indicator from Püttmann (2018). To give maximum weight to this additional shock, we identify it before the sentiment shock. Formally, we add this extra variable in the third position, $y_t = [TFP_t, GDP_t, Extra_t, E12M_t, KF_t]$, where $Extra_t$ stands for the financial uncertainty variable. Then, we identify the additional shock after the TFP surprise and news shocks, in a similar way as for our sentiment shock. The financial uncertainty shock is the structural shock that best explains short-run future variations (2 quarters) of the additional variable that are unexplained by the first two shocks.

Figure A.7 in the Appendix shows the responses of inflows and outflows when identifying a

[15]Figures A.5 and A.6 represent respectively the response of US variables to ROW shocks and the response of ROW variables to US shocks. Both US TFP and confidence respond positively to ROW shocks, which means that ROW shocks capture shocks that are correlated across countries. ROW TFP, on the opposite, does not respond to US shocks (at least not in a meaningful way), which implies that our identified US TFP shocks are indeed US-specific. ROW confidence increases following a US sentiment shock, but with a lag, so the US sentiment shock remains US-specific in early quarters, where we see the strongest response of capital flows. The delayed response of ROW confidence to US sentiment reflects the fact that our identification of the ROW sentiment shock focuses on a horizon of 2 quarters, leaving the response of ROW confidence to other shocks in later quarters unrestricted. Interestingly, positive US shocks lead to negative spillovers on ROW's output, as predicted by classical open economy models.

Figure 9: IRFs of US capital flows to both ROW and US shocks



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors.

financial uncertainty shocks. Consistent with the literature's findings, an increase in financial uncertainty, triggers an immediate short-lived negative responses of capital flows. This is true whatever the proxy variable we are using. The responses to the news and sentiment shocks remain qualitatively similar, although the response of capital outflows to news shock with VIX is slightly positive.

Second, we wish to identify the so-called financial shocks. One could argue that these shocks are strongly related to financial uncertainty shocks described above (for instance the VIX). Nevertheless, we deepen our analysis by including two additional indicators of a potential tightening in the financial conditions. We first include the U.S. corporate BBB option-adjusted spread (from Bank of America Merrill Lynch). This variable has an even shorter timespan than the VIX and starts only in 1997. Second, we use the U.S. security brokers and dealers leverage variable. Adrian and Shin (2010) show that global market liquidity relates to the leverage of security brokers and dealers. We define leverage as they do, i.e., the ratio of total assets over equities, which is the difference between total assets and liabilities. The IRFs of capital flows to all four shocks, including a tightening in financial conditions, are presented in Figure A.8 in the Appendix. Again, the responses of capital flows to TFP surprise, news and sentiment shocks are similar to those from the baseline. The responses to a tightening in financial conditions (mostly for corporate BBB spread) appear to be meaningful: capital flows contract as financial conditions tighten.

As a third option, we account for policy uncertainty. We use the economic policy uncertainty (EPU) index for the U.S., as well as the Monetary Policy Uncertainty (MPU) index for the U.S. from Bloom et al. (2016) and the World Uncertainty Index (WUI) from Ahir et al. (2018).[16] The IRFs of capital flows to the shocks are presented in Figure A.7 in the Appendix. Here as well, an increase in any type of policy uncertainty shock negatively and immediately impacts capital flows, but the responses to the other shocks remain similar although somewhat dampened.

To conclude, uncertainty or financial conditions shocks appear to matter for capital flows, in line with the literature. However, sentiment shocks are not mere reflections of these, as they remain significant in driving capital flows after accounting for these other shocks.

One alternative hypothesis is that sentiment shocks are reflecting monetary policy shocks.

[16]For the WUI, we use the index built as a GDP-weighted average of the local index.

Hence, we identify here a monetary policy shock, again before the sentiment shock to give it maximum weight. Then, we analyze capital flows responses to the sentiment shock. We thus include the Fed funds interest rate in third position in our SVAR, i.e., $y_t = [TFP_t, GDP_t, FFR_t, E12M_t, KF_t]$ and we identify the monetary policy shock after the TFP surprise and news shocks. As before, the monetary policy shock is defined as the structural shock that best explains short-run future variations (2-quarters) of the interest rate, unexplained by the first two shocks. The IRFs of capital flows are shown in Figure A.10 in the Appendix. Interestingly, a local monetary policy shock has a positive lagged impact on capital flows. Here as well the impact of other shocks on capital flows remain similar to the baseline. Overall, we can conclude that sentiments shocks are not a mere reflection of monetary policy shocks.

Finally, we account for shocks to international prices. We use the U.S. terms of trade from the Bureau of Economic Analysis, as well as the oil price (Global price of Brent Crude). The oil price is deflated by the CPI. IRFs of capital flows to the shocks are presented in Figure A.11 in the Appendix. A terms-of-trade amelioration and an increase in oil prices generate an increase in capital inflows and outflows (though it is subsequently reversed for the oil price shock), but the responses to the other shocks remain similar.

5.3. Further robustness checks and external validity

Can we interpret capital flows as reflecting changes in the desired cross border assets and liabilities? Gross capital flows are measures of the transactions between the US and the rest of the world. The evolution of cross-border assets and liabilities result from these transactions, but also from valuation effects. For instance, if there is an exchange rate appreciation, the foreign-currency value of US assets increases. Foreign investors might want to offset this valuation gain by selling US assets. Capital flows can then be due to "passive" portfolio rebalancing and not necessarily to a change in the desired portfolio. Figure A.12 in the Appendix shows that the news shock produces an exchange rate appreciation, whereas the sentiment shock produces a depreciation. The observed effect of these shocks on capital outflows would not be consistent with pure portfolio rebalancing, but the observed effect on inflows could be. To check this, we add the log-change in US liabilities and assets in the baseline SVAR.[17] Figure A.13 in the Appendix shows that the changes in liabilities and the change in assets, as a response to both news and sentiment shocks, go in the same direction as, respectively, capital inflows and capital outflows, with the qualification that the responses are lagged. This shows that capital flows do not simply offset valuation effects, but reflect desired changes in cross-border positions.

Our baseline specification uses four lags. Here, we repeat the analysis and plot the response functions using different lag lengths ($p = 1, 2, 3$). We present the IRFs in Appendix Figure A.14. The impulse responses computed using different lag specifications are very close to the ones of the baseline using two lags. Regarding the FEVD, adding more lags increases the contribution of our news and sentiment shocks to the variance of capital flows, and the share of unexplained FEVD diminishes.

Then, instead of including either inflows or outflows in the VAR specification, we add both inflows and outflows in our variables' vector y_t. Figure A.15 in Appendix A shows the responses of capital inflows and outflows when added together in the VAR. The responses are almost unchanged compared to a case where we identify the impact of TFP surprise, news and sentiment shocks including only inflows or outflows in the identification procedure.

We next extend our analysis to a panel of countries, thereby assessing our findings' external validity. Hence, we use the same identification strategy but include 17 additional OECD economies.[18] Again, the selected countries are those for which data are available (especially the TFP, see Appendix D). More details about the data is available in Appendix B. Our methodology for the panel is as follow: First, we run a SVAR identification including TFP, GDP, E12M and capital flows at the country level and compute the individual impulse response functions.[19] Then, the aggregate response function is obtained as the median across individual responses at all horizons.

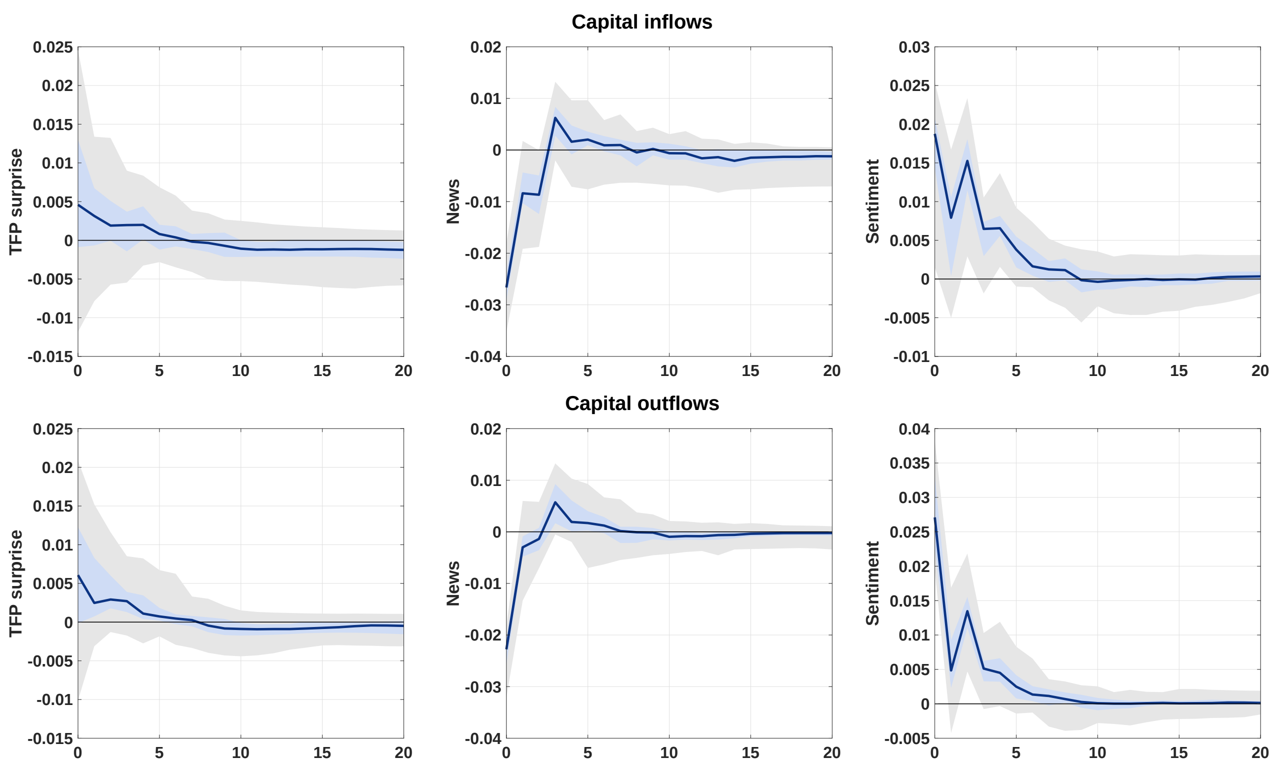
[17]The stock data come from the IMF's International Investment Position Statistics and are expressed in US dollars. In this specification, the sample reduces to 50 observations. We thus reduce the lag length from 4 to 2.

[18]We use a VAR specification with only 2 lags because of the more limited timespan of data availability for most countries. Selecting more lags or specific lags for each country does not change our conclusions, but render the IRFs less smooth.

[19]Notice that we use demeaned data to account for country-specific levels and that we use a horizon of 20 quarters for the news identification.

The median responses of both capital inflows and outflows to all three shocks are presented in Figure 10. Both inflows and outflows react immediately and negatively to news shocks and positively to sentiment shocks. In other words, the panel findings are similar to those for the United States alone, confirming the importance of sentiment shocks in driving capital flows. Computing the aggregate responses as a median rather than a mean gives less weight to extreme values. Nevertheless, the mean responses, presented in Figure A.16 in Appendix A, lead to similar responses. Regarding the panel forecast error variance decomposition, we see in Figure A.17 in the Appendix that both news and sentiment shocks can explain close to 50% of the FEVD, with roughly equal contributions of the two shocks. In constrast, TFP surprise shock plays no role in driving capital flows as pointed out by the impulse response functions and the FEVD.

Figure 10: Panel median IRFs to TFP surprise, news and sentiment shocks



Dark and light shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

6. What can explain the effect of news and sentiment shocks on capital flows?

In this section, we discuss possible explanations of our results. First, using a stylized model of cross-border investment with imperfect information, we discuss to what extent imperfect information between domestic and foreign investors can explain the effect of news and noise shocks on capital flows. We then discuss briefly other potential explanations.

6.1. Asymmetric information

We consider a simple two-period model with two equally-sized countries, home and foreign, two assets, in the form of claims to domestic and foreign capital, capital installation costs and a simple information structure. In period 1, domestic and foreign agents receive signals on a technology shock that hits the domestic economy in period 2. Domestic and foreign agents have asymmetric information about domestic shocks. While domestic agents obtain a private signal about future technology shocks, foreign agents only observe a common noisy signal. We will be able to analyze two types of shocks: fundamental shocks (shocks to future technology, which are akin to news shocks) and noise shocks (shocks to the public signal, which will influence expectations about future technology, which are akin to sentiment shocks). As we will see, these shocks will have different effects on capital flows because some agents (here the domestic agents) have private information.

Savings and portfolio choices. The home country is indexed by H and the foreign country is indexed by F. There is a unit measure of capital producers and of investors in each country. In period 1, each domestic and foreign investor is endowed with 1/2 units of foreign capital and 1/2 units of domestic capital. They can buy additional capital from capital producers, at price Q for the domestic capital and Q^* for the foreign capital. In period 2, the capital of the home country yields dividend e^{δ} per unit, and the capital of the home country yields dividend e^{δ^*} per unit, with $\delta \sim \mathcal{N}(0, \sigma_\delta)$ and $\delta^* \sim \mathcal{N}(0, \sigma_\delta)$. δ and δ^* are respectively the domestic and foreign fundamental (technology) shocks.

An investor $j \in [0, 1]$ of country H maximizes the following expected utility:

$$U_j^H = (1 - \beta) \log(C_{j1}^H) + \beta E_j^H \left\{ \log(C_{j2}^H) \right\} \tag{6.1}$$

E_j^H is the expectation conditional on home investor j's information in period 1. C_{j1}^H is j's consumption during period 1 and C_{j2}^H is her consumption during period 2.

The agent is subject to the followings budget constraints:

$$\begin{aligned} C_{j1}^H + QK_j^H + Q^* K_j^{H*} &= \tfrac{1}{2}(Q+Q^*) + \Pi \\ e^{\delta} K_j^H + e^{\delta^*} K_j^{H*} &= C_{j2}^H \end{aligned} \tag{6.2}$$

K_j^H is j's investment in the domestic asset and K_j^{H*} is her investment in the foreign asset. Π are the profits of the domestic capital producers.

Denote by $S_j^H = QK_j^H + Q^* K_j^{H*}$ the total savings of home investor j and $X_j^{H*} = Q^* K_j^{H*} / S_j^H$ the share of savings invested in the foreign asset. $1 - X_j^{H*}$ is then the share invested at home. With log-utility, savings have a simple expression:

$$S_j^H = \beta \left(\frac{1}{2}(Q+Q^*) + \Pi \right) \tag{6.3}$$

Then, assuming that returns are log-normally distributed, we obtain portfolio shares:

$$X_j^{H*} = \frac{E_j^H\{r^* - r\}}{Var_j^H\{r^* - r\}} + \frac{1}{2} \tag{6.4}$$

where $r = \log(R) = \delta - q$ is the log of the return on the home asset, $r^* = \log(R^*) = \delta^* - q^*$ is the log of the return on the foreign asset, with $q = \log(Q)$ and $q^* = \log(Q^*)$ the log of the domestic and foreign prices. $E_j^H(.)$ $(Var_j^H(.))$ is the expectation (variance) conditional on the information of investor j of country H in period 1.

Symmetric relations hold for investor $j \in [0,1]$ in the foreign country:

$$\begin{aligned} S_j^F &= \beta \left(\tfrac{1}{2}(Q+Q^*) + \Pi^* \right) \\ X_j^F &= \frac{E_j^F\{r - r^*\}}{Var_j^F\{r - r^*\}} + \frac{1}{2} \end{aligned} \tag{6.5}$$

where S_j^F are j's savings, $X_j^F = QK_j^F / S_j^F$ is the share of savings invested in the home country's asset. $E_j^F(.)$ $(Var_j^F(.))$ is the expectation (variance) conditional on the information of investor

j of country F in period 1.

Investment and asset prices. Capital producers supply additional capital $K-1$ with a quadratic cost. The profits of the domestic and foreign capital producers are, respectively:

$$\begin{aligned} \Pi &= (Q-1)(K-1) - \tfrac{\varphi}{2}(K-1)^2 \\ \Pi^* &= (Q-1)(K^*-1) - \tfrac{\varphi}{2}(K^*-1)^2 \end{aligned} \tag{6.6}$$

where 1 is the initial stock of domestic and foreign capital, $K = K^H + K^F$ is the final stock of domestic capital and $K^* = K^{H*} + K^{F*}$ is the final stock of foreign capital.

Profit maximization by the capital producers yields the following equations:

$$\begin{aligned} Q &= \varphi(K-1) + 1 \\ Q^* &= \varphi(K^*-1) + 1 \end{aligned} \tag{6.7}$$

The higher the investment friction φ, the more costly it is for capital producers to increase the supply of capital. As a result, in equilibrium, the asset price will react more to changes in the demand for assets.

Asset markets. Equilibrium on the world's asset markets implies that the asset supply should be equal to the asset demand by domestic and foreign agents:

$$\begin{aligned} QK &= (1-X^{H*})S^H + X^F S^F \\ Q^*K^* &= X^{H*}S^H + (1-X^F)S^F \end{aligned} \tag{6.8}$$

with $X^{H*} = \int_0^1 X_j^{H*} dj$ and $X^F = \int_1^1 X_k^F dk$ being the average portfolio shares. We used here the fact that savings are equal across investors in a given country ($S_j^H = S^H$ and $S_j^F = S^F$ for all j).

Information structure. As asset demand, and hence capital flows, depend on expected returns, it is crucial to specify the information structure. We assume that, in period 1, home and foreign investors receive public signals on home and foreign future productivity. We denote these signals $s = \delta + e$ and $s^* = \delta^* + e^*$, where e and e^* are i.i.d. noise shocks with mean zero and standard error σ_e. s and s^* summarizes the publicly available information.

The asymmetry in information goes as follows. In period 1, each home investor $j \in [0,1]$ additionally observes a private signal on future home productivity $x_j = \delta + \lambda_j$, with $\lambda_j \sim \mathcal{N}(0, \sigma_\lambda)$ and $\int_0^1 \lambda_j dj = 0$. Similarly, each foreign investor $j \in [0,1]$ observes a private signal on foreign productivity $x_j^* = \delta^* + \lambda_j^*$, with $\lambda_j^* \sim \mathcal{N}(0, \sigma_\lambda)$ and $\int_0^1 \lambda_j^* dj = 0$.

Finally, all investors observe assets prices q and q^*. However, we assume, for simplicity, that asset prices are not used as a source of information on the fundamental shocks. Namely, investors do not extract any information from q and q^* regarding the state of the productivity shocks δ and δ^*, i.e., they neglect the reasons why asset prices change. In other words, investors are cursed in the sense of Eyster and Rabin (2005).

With this information structure, domestic and foreign investors form the following expectations about the future fundamental δ:

$$
\begin{aligned}
E_j^F(\delta) &= \alpha_0 s \\
E_j^H(\delta) &= (1-\kappa)\alpha_0 s + \kappa x_j
\end{aligned}
$$

where $\alpha_0 = \sigma_e^{-2}/(\sigma_\delta^{-2} + \sigma_e^{-2})$ and $\kappa = \sigma_\lambda^{-2}/(\sigma_\delta^{-2} + \sigma_e^{-2} + \sigma_\lambda^{-2})$ are Bayesian weights.

We denote by $\bar{E}^H(\delta) = \int_0^1 E_j^H(\delta)dj$ and $\bar{E}^F(\delta) = \int_0^1 E_j^F(\delta)dj$ the average expectations of home and foreign investors about home fundamentals. We obtain:

$$
\begin{aligned}
\bar{E}^F(\delta) &= \alpha_0 \delta + \alpha_0 e \\
\bar{E}^H(\delta) &= \alpha_1 \delta + \alpha_2 e
\end{aligned}
\tag{6.9}
$$

where $\alpha_1 = [\alpha_0 + \kappa(1-\alpha_0)]$ and $\alpha_2 = (1-\kappa)\alpha_0$. Expectations about δ are increasing in both δ and e, but only δ materializes later in the country's technology. We therefore interpret δ as a "news" shock and e as a "sentiment" shock.

Domestic investors have more precise expectations than foreign investors. κ, which is increasing in the precision of the domestic private signal σ_λ^{-2}, is a measure of the degree of asymmetry in information between home and foreign agents. We can see that, since $\kappa > 0$, we have $\alpha_2 < \alpha_0 < \alpha_1$: domestic expectations about the domestic fundamentals react more to the fundamental (δ) and less to the aggregate noise (e) than foreign expectations.

Capital flows. Gross capital inflows in the home country are changes in the foreign holdings of domestic assets $KI^H = Q(K^F - 1/2)$, and gross capital outflows are changes in the domestic holdings of foreign assets $KO^H = Q^*(K^{H*} - 1/2)$, with $K^F = \int_0^1 K_j^F dj$, $K^{H*} = \int_0^1 K_j^{H*} dj$. Note that $KI^F = KO^H$ and $KO^F = KI^H$. Net capital inflows to the home country correspond to the difference between gross inflows and gross outflows: $NKI^H = KI^H - KO^H$. They also coincide with the difference between domestic investment and domestic saving $NKI^H = Q(K-1) - [Q(K^H - 1/2) + Q^*(K^{H*} - 1/2)]$.

Combining savings and portfolio shares (6.3)-(6.5), the supply of capital (6.7) and equilibrium in the asset markets (6.8), we can derive cross border asset holdings K^F and K^{H*}, which determine gross and net capital flows. The model is solved by log-linearization around the nonstochastic equilibrium. In Appendix C, we lay down the details of the model resolution. Here, we focus on the main results and intuition.

Domestic gross capital inflows and outflows can directly be approximated as $KI^H = k^F/2$ and $KO^H = k^{H*}/2$, where $k^F = \log(K^F) - log(1/2)$ and $k^{H*} = \log(K^{H*}) - log(1/2)$ are the log-deviations of cross-border assets from their initial level. The net capital inflows can be approximated as $NKI = (k^F - k^{H*})/2$. We can then show that the equilibrium changes in cross-border assets are:

$$\begin{aligned} k^F &= NKI + Disag \\ k^{H*} &= -NKI + Disag \end{aligned} \tag{6.10}$$

where NKI, the net capital inflows are given by

$$NKI^H = \frac{\phi}{1 + \varphi(1 + 4\phi)} \left[E^H(\delta - \delta^*) + E^F(\delta - \delta^*)\right] \tag{6.11}$$

and the term $Disag$ stands for "disagreement":

$$Disag = \phi[E^F(\delta - \delta^*) - E^H(\delta - \delta^*)] \tag{6.12}$$

We can see that gross capital flows have two components. One component simply corresponds to net inflows, and drives gross capital inflows and outflows in opposite directions. Here net inflows result from higher foreign and domestic expectations about domestic relative future productivity. As a result, both the foreign and domestic investors buy more of the domestic asset and less of the foreign asset. Foreign purchases of domestic assets constitute a capital inflow, and domestic sales of foreign assets constitute a negative outflow. Note that this component depends on the investment friction φ. Indeed, for net inflows to materialize, investment must increase. If the supply of capital is inelastic (φ goes to ∞), then there are no net inflows. In that case, the excess demand for domestic assets (and excess supply of foreign assets) is fully offset by an adjustment in asset prices.

The second component is disagreement between the domestic and foreign investors. This component drives gross capital inflows and outflows in the same direction. While net inflows depend on aggregate expectations ($E^F(.) + E^H(.)$), this term depends on relative expectations ($E^F(.) - E^H(.)$). It suggests that both capital inflows and outflows increase when foreign investors are more optimistic than domestic agents about the productivity of home relative to foreign. This comes from the adjustment in asset prices. Consider a situation where both foreign and domestic investors become more optimistic about the relative productivity of the home country, but suppose that the foreign investors are even more optimistic than the domestic investors. Out of equilibrium, both the foreign and domestic investors demand more of the home asset and less of the foreign asset, which increases the domestic asset price and decreases the foreign asset price. These price adjustments reduce the expected excess return of the domestic asset and imply that the less optimistic agents –here, the domestic investors– may actually be willing to <u>sell</u> domestic assets, which generates capital inflows, and <u>buy</u> foreign assets, which generates capital outflows. If the domestic investors are the more optimistic ones, then the foreign investors are the ones who may actually be willing to sell domestic assets, which generates negative capital inflows, and buy foreign assets, which generates negative capital outflows.

Here we assume that domestic agents are better informed than foreigners, so there is asymmetric information, measured by κ. Note that, as argued earlier, domestic expectations about the domestic fundamentals react more to the fundamental (δ) and less to the aggregate noise (e) than foreign expectations. So domestic investors become relatively more optimistic than foreign investors about the domestic fundamentals following a news shock, while they becomes relatively less optimistic following a noise shock. We may expect that news shocks will drive a negative response of gross inflows and outflows through the disagreement term, while sentiment shocks will drive a positive response. However, we must consider also the response of net inflows NKI. Intuitively, for news and noise shocks to generate such correlated responses of gross flows, we need a strong investment friction φ, which reduces the net inflows NKI, and some asymmetric information that generates disagreement between foreigners and domestic agents.

These intuitions are summarized in the following Proposition:

Proposition 1 (Capital flows). *Both a positive fundamental shock at home ($\delta > 0$) and a positive noise shock ($e > 0$) generate an increase in net capital inflows. The response of net inflows is larger when φ is lower, and it goes to zero when φ goes to infinity.*

If $\varphi = 0$, both a positive fundamental shock at home ($\delta > 0$) and a positive noise shock ($e > 0$) generate an increase in capital inflows and a decrease in capital outflows.

But if φ and κ are sufficiently large, then a positive fundamental shock at home ($\delta > 0$) generates a decrease in capital inflows and outflows, and a positive noise shock ($e > 0$) generates an increase in capital inflows and outflows.

A positive correlation between gross inflows and outflows arises only when there is asymmetric information ($\kappa > 0$) and with some friction in investment ($\varphi > 0$), with a retrenchment in capital flows following a fundamental shock ($\delta > 0$) and an expansion following a noise shock ($e > 0$). Both shocks generate a positive response of net inflows. The reaction of net inflows and gross inflows and outflows that we identify in the data can therefore be explained by the presence of information frictions and an imperfectly elastic supply of capital.

6.2. Further discussion

We have shown that the reaction of net inflows, gross inflows and gross outflows that we identify in the data are consistent with a model with imperfect information on the country's future technology, if investment and information frictions are strong enough. Here we discuss whether this explanation could be consistent with other features of the data.

Timing and magnitude of net capital flows' reaction to the shocks. The model is a two-period model and cannot help us understand the dynamics of capital flows per se. However, we may conjecture that in a multi-period model, uncertainty about the nature of the shock and thus the asymmetry between domestic and foreign agents would vanish progressively over time as agents receive more signals about the shocks. This would have implications on the dynamic response of capital flows.

In particular, we have shown empirically that the positive response of net capital inflows to the news shock takes a few periods to build up, while the positive response to the sentiment shock fades quickly. This delayed reaction of net inflows to the news shock could be linked to the fact that investors learn progressively about productivity. On the opposite, in the case of the sentiment shock, the fading reaction of net inflows could also reflect learning by firms about actual productivity.

Reaction across asset types. Can information asymmetries help explain the reaction of cross-border holdings across asset types? We have seen that capital flows react mostly in the same way across types of assets to both news and sentiment shocks, equity flows being the exception. This is compatible with information asymmetries affecting all types of investments, except for equity. Indeed, equity markets are subject to less information asymmetries than, say, FDIs. Listed companies are subject to public disclosure, and equity markets are more liquid, which implies that prices better reflect fundamentals. The empirical literature has shown that domestic investors do not necessarily outperform foreign investors in equity markets.[20]

However, for other inflows, which are almost entirely composed of bank flows (namely loans, trade credit, deposits and currency), one would actually expect less information asymmetry given that the banks' role is precisely to gather and transfer information. Indeed, many banking transactions take place within global banks, between local subsidiaries and foreign headquarters, or between local headquarters and foreign subsidiaries. Note that if the local subsidiary of a global bank extends a loan to a local firm, then this is recorded as a domestic transaction and not as a capital inflow. However, capital inflows will increase if this local subsidiary uses funds

[20]See Grinblatt and M. (2000), Hamao and J. (2001), Bailey et al. (2007), and Froot and T. (2008).

from a foreign headquarter to finance that loan. In this case, the extent to which information asymmetries affect cross-border transactions depends on how centralized the global banks' management is. Notably, Cetorelli and Goldberg (2012) have shown that the global banks' internal liquidity markets are managed in a centralized way in periods of liquidity shortage.[21] Interestingly, Avdjiev et al. (2019) show that the local lending of global banks is more related to local macroeconomic conditions than their cross-border lending. This could be consistent with information asymmetries being at play within global banks.

Note also that even though global banks play an important role in the international financial architecture, intra-group lending represents only one third of international lending positions (Cerutti et al., 2015). Two thirds of international lending positions are due to bilateral or multilateral lending and are potentially subject to information asymmetries between borrowers and lenders.

6.3. Alternative explanations

Besides asymmetric information, two types of explanations to the positive correlation of gross capital flows have been proposed (Broner et al., 2013): asymmetric risk and leveraged cycles. These explanations typically generate positively correlated flows. However, the extent to which these explanations can explain the countercyclicality of flows conditional on news shocks is still unclear.

Asymmetric risk. In theory, an increase in risk or risk aversion can lead to capital retrenchment if domestic investors perceive foreign assets as riskier. This could be due to objective reasons, because foreign and domestic investors are asymmetrically exposed to domestic risk. If, for instance, foreign investors are facing a higher expropriation risk, and if expropriation risk is countercyclical, then we should see capital retrenchment during recessions (Gourio et al., 2015; Broner et al., 2014). It could also be due to subjective reasons, because of asymmetric information. In setups similar to the model presented above, where foreign investors have less precise information than domestic agents on the return to domestic assets, and assuming

[21] See also Cerutti and Claessens (2016) and Cerutti et al. (2019).

that risk exacerbates asymmetric information, the home bias increases with the level of risk (Brennan and Cao, 1997; Tille and van Wincoop, 2010).

These mechanisms are consistent with the fact that uncertainty has been shown to be a robust factor of capital retrenchment during crises.[22] However, such mechanisms can explain the behavior of capital flows conditional on news and sentiment shocks only if uncertainty is countercyclical in the case of news shocks, and procyclical in the case of sentiment shocks.

Interestingly, Cascaldi-Garcia and Galvao (2021) have shown that news shocks are associated with an increase in realized stock market volatility and other measures of financial uncertainty.[23] However, news shocks are not associated with an increase in the disagreement among professional forecasters. These results suggest that risk or risk perception could be a potential explanation for the behavior of capital flows conditional on news and sentiment shocks, but the channels still remain unclear.

Leveraged cycles. Another explanation would be based on leveraged cycles, i.e. on expansions and contractions in the banking sector's balance sheet. Indeed, an increase in banking leverage can generate correlated gross capital flows. If a local bank borrows from its foreign headquarter, its liabilities increase due to the loan (a capital inflow), but its assets increase as well through a deposit held on its foreign counterpart (a capital outflow). Expanding balance sheets through leverage thus generate correlated inflows and outflows.[24] The role of leverage has been documented by Rey (2015) in the context of the international financial cycle and has been shown to be associated with correlated gross capital flows. This route would be especially useful to explain banking flows.

However, leveraged cycles are difficult to reconcile with the effects of news shocks, as it would imply that leverage is countercyclical. However, leveraged cycles could still be driving the countercyclical gross banking flows conditional on news shocks if the interest rate, which

[22]See Milesi-Ferretti and Tille (2011), Fratzscher (2012), Forbes and Warnock (2012), Rey (2015) and Choi and Furceri (2019).

[23]See also Forni et al. (2019).

[24]See Bruno and Shin (2014), Gabaix and Maggiori (2015), Amador et al. (2019) and Itskhoki and Mukhin (2021) for models that introduce intermediation frictions in open-economy setups.

is the commonly admitted driver of financial cycles Miranda-Agrippino and Rey (2020), was procyclical conditional on news shocks. Actually, Kurmann and Otrok (2013) show that the Fed funds rate declines following a news shock. The leveraged cycles hypothesis is therefore not supported by the behavior of the interest rate.

7. Conclusion

Overall, our findings show that domestic surges in optimism either related to future productivity - news shocks - or not - sentiment shocks - are important drivers of gross capital flows at the country level. Together they can explain up to 80% of the FEVD of capital flows for the United States and approximately 50% for a panel of 17 OECD economies. While sentiment shocks trigger positive inflows and outflows, news shocks have a negative impact on gross capital flows. These sentiment shocks are also found to be distinct from global, financial or economic uncertainty and monetary policy shocks. The fact that capital inflows rise following optimism shocks disconnected from fundamentals can raise concerns from a policy perspective.

These results are inconsistent with theories where capital flows are systematically procyclical. In contrast, they are consistent with a model where domestic agents have an informational advantage over foreigners about domestic fundamentals. Models with asymmetric risk or risk perception constitute another promising avenue to explain these findings.

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Appendix A. Additional results

Figure A.1: Forecast Error Variance Decomposition of consumer sentiment

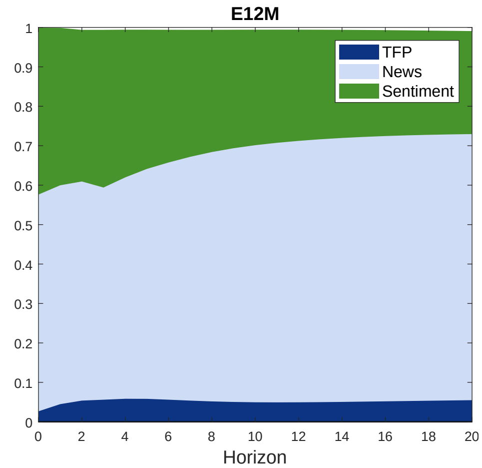
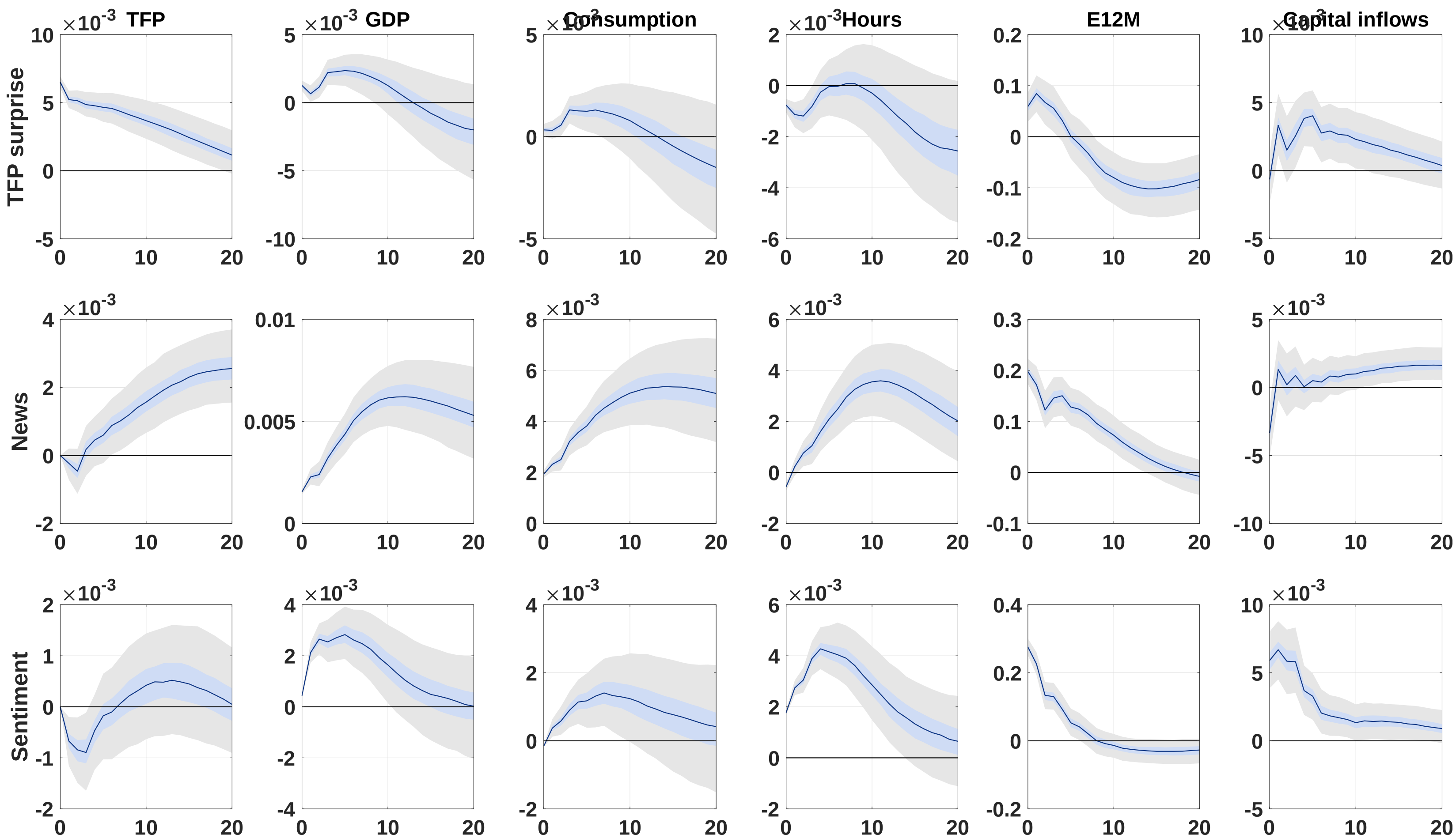
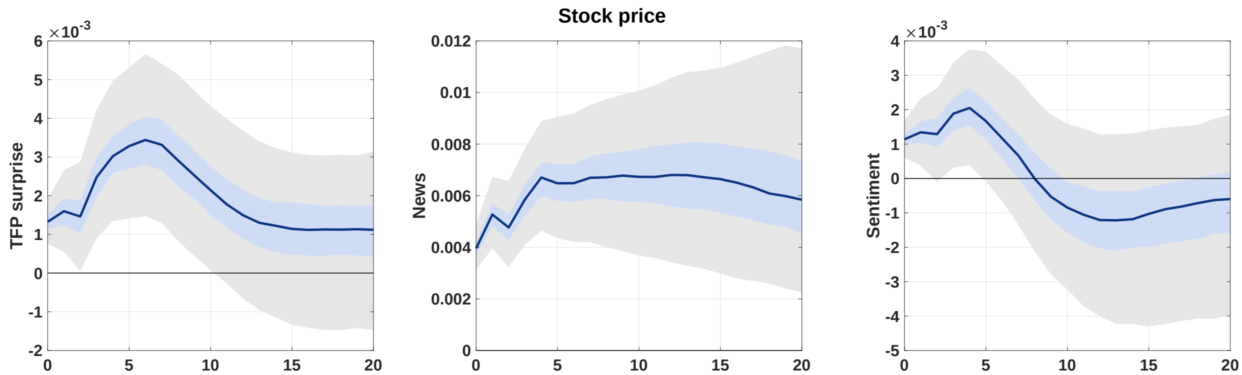


Figure A.2: U.S. IRFs to TFP surprise, news and sentiment shocks - with consumption and hours



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.3: U.S. IRFs of stock price to TFP surprise, news and sentiment shocks



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.4: Forecast Error Variance Decomposition of gross capital flows - VAR with 7 variables

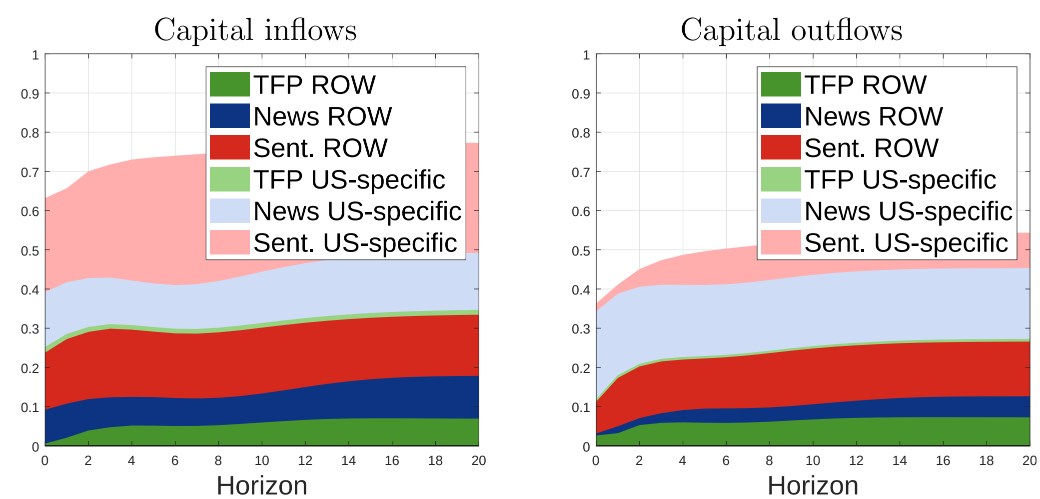
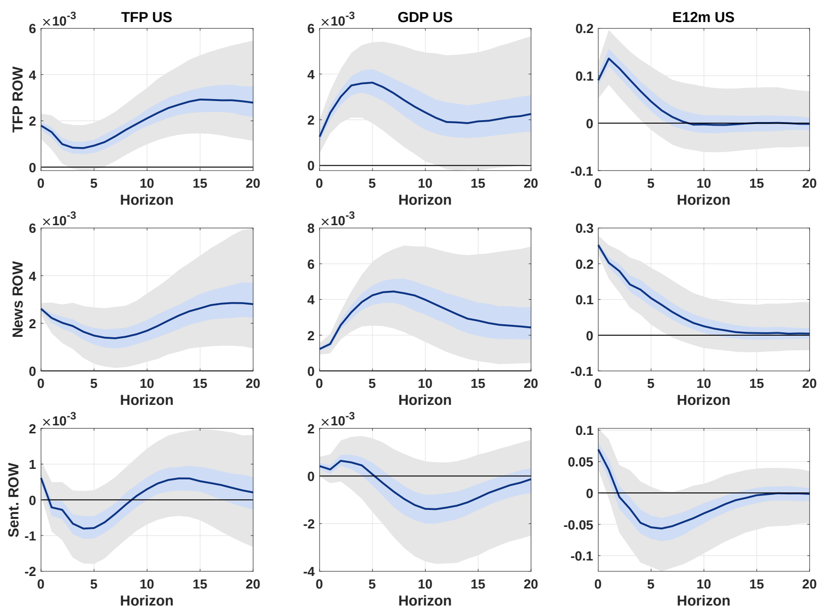


Table A.1: Restrictions for the 7-variable model

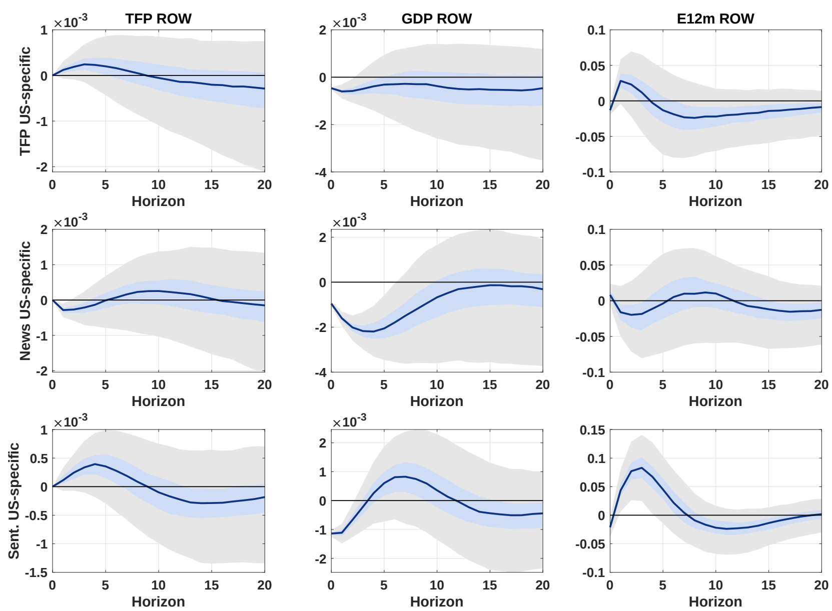
	RoW TFP surp.	RoW TFP news	RoW sentiment	US TFP surp.	US TFP news	US sentiment	Rest
RoW TFP (hor. 1)	1	0	0	0	0	0	0
RoW TFP (hor. 2-40)		Max(FEVD)					
RoW Conf. (hor 1-2)			Max(FEVD)				
US TFP (hor. 1)				1	0	0	0
US TFP (hor. 2-40)					Max(FEVD)		
US Conf. (hor. 1-2)			unrestricted			Max(FEVD)	
RoW GDP							
US GDP							
US cap. in(out)flows							

Figure A.5: IRFs of U.S. variables to ROW shocks



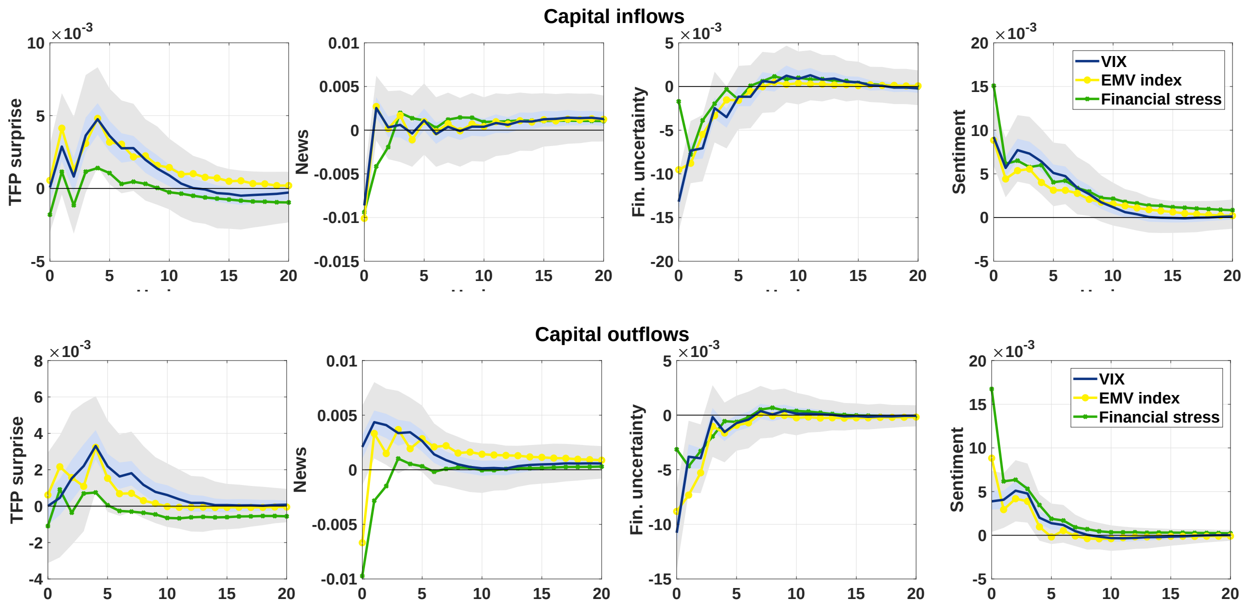
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.6: IRFs of ROW variables to U.S. shocks



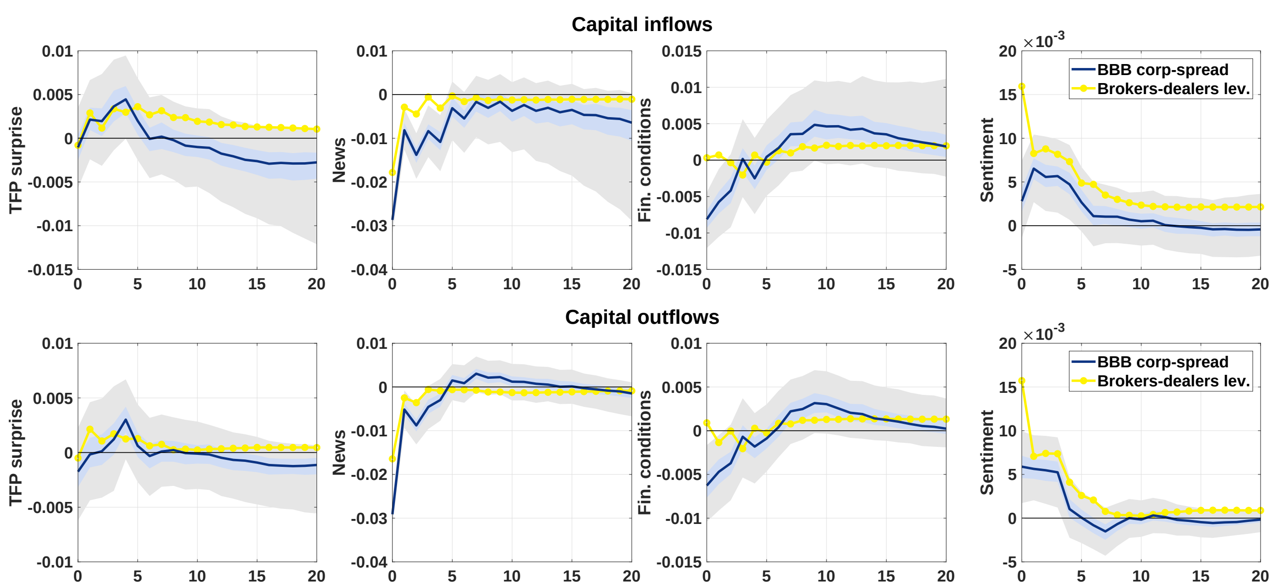
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.7: U.S. IRFs for capital flows to TFP surprise, news, financial uncertainty and sentiment shocks



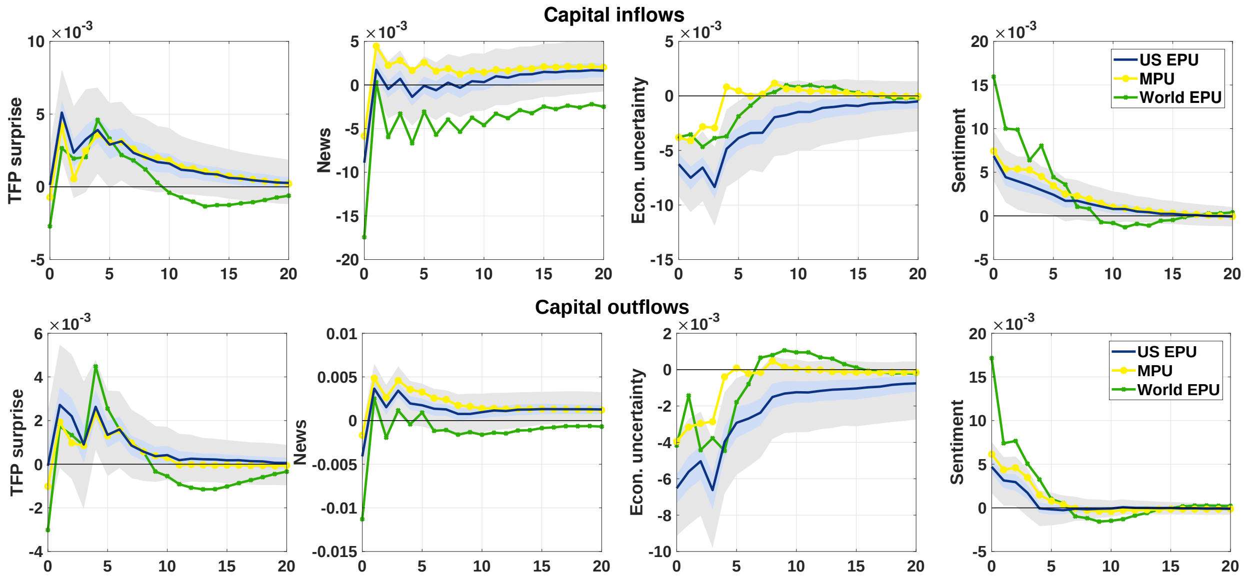
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with VIX as financial uncertainty variable.

Figure A.8: U.S. IRFs for capital flows to TFP surprise, news, financial conditions and sentiment shocks



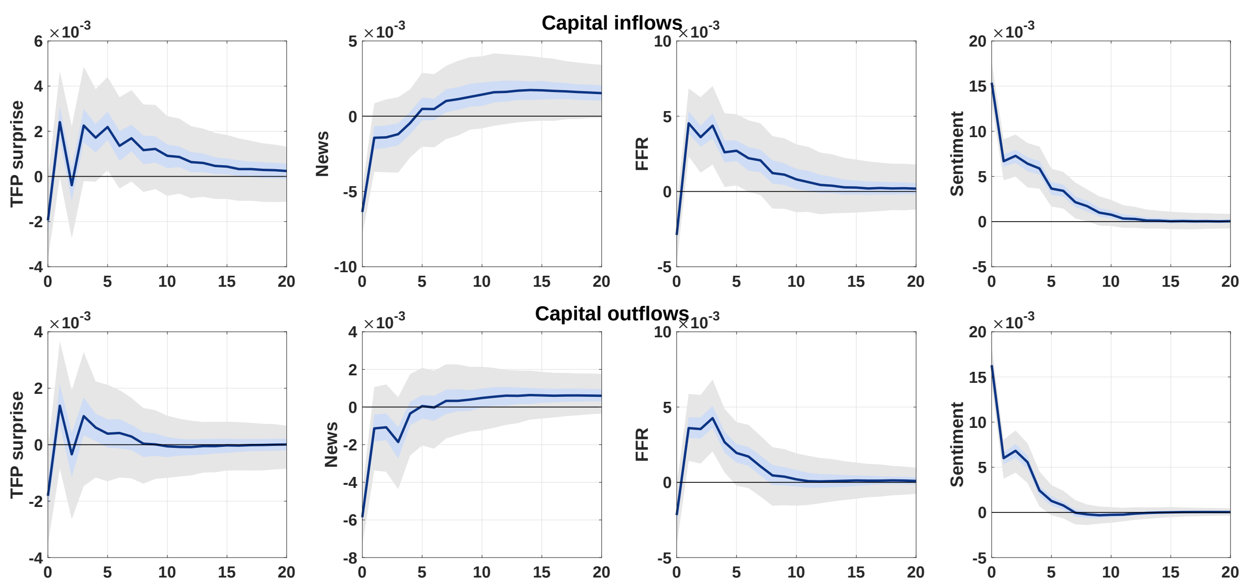
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with corporate BBB spread as financial conditions variable.

Figure A.9: U.S. IRFs for capital flows to TFP surprise, news, economic uncertainty and sentiment shocks



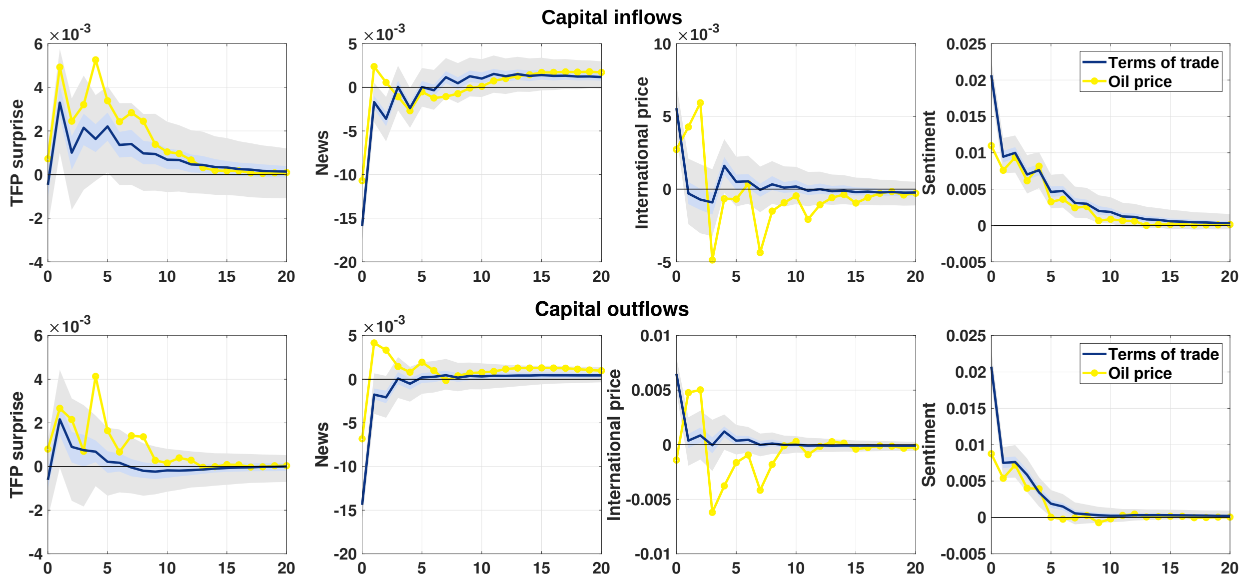
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with U.S. EPU as economic uncertainty variable.

Figure A.10: U.S. IRFs to TFP surprise, news, monetary and sentiment shocks



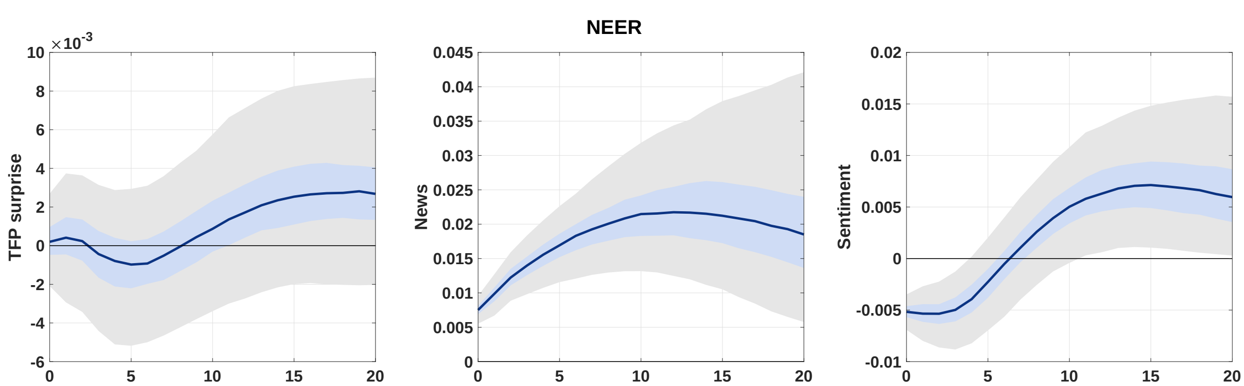
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors.

Figure A.11: U.S. IRFs to TFP surprise, news, international prices and sentiment shocks



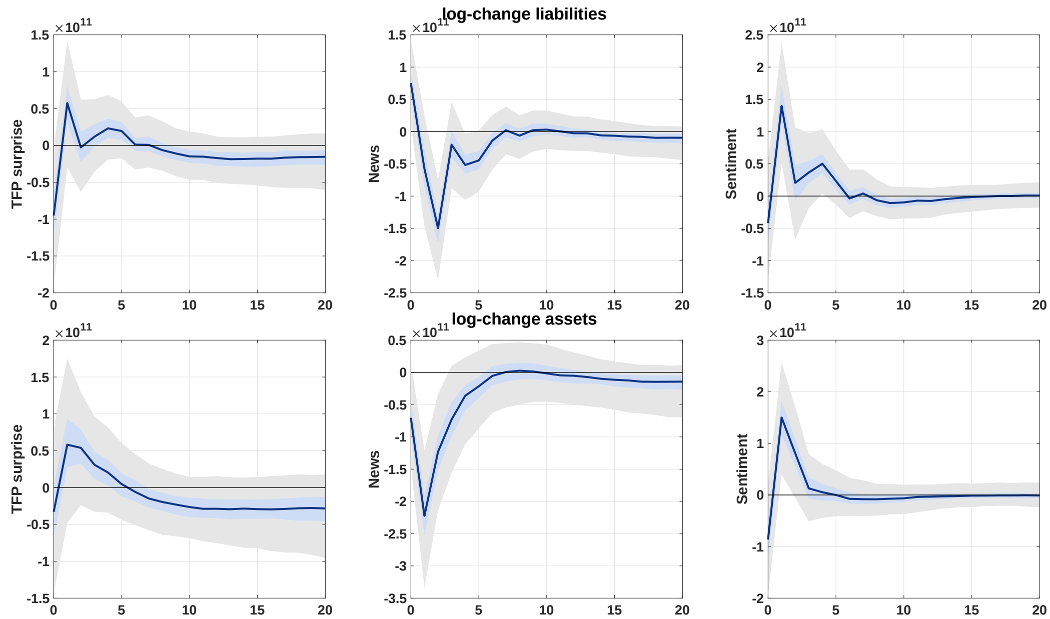
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with terms of trade.

Figure A.12: U.S. IRFs of NEER to TFP surprise, news and sentiment shocks



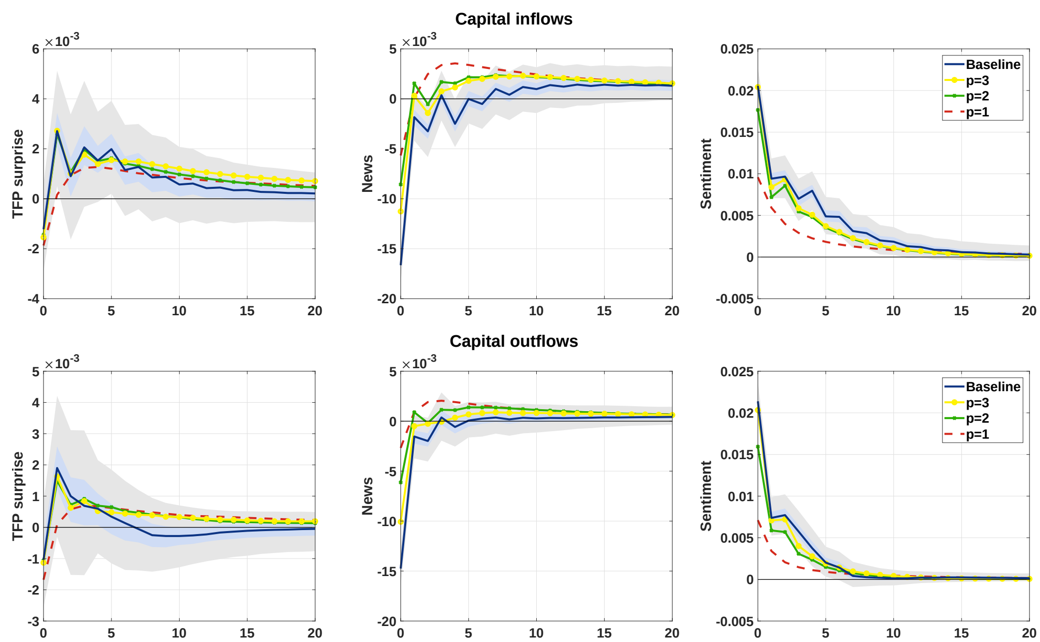
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.13: IRFs of log-change in US liabilities and assets to TFP surprise, news and sentiment shocks



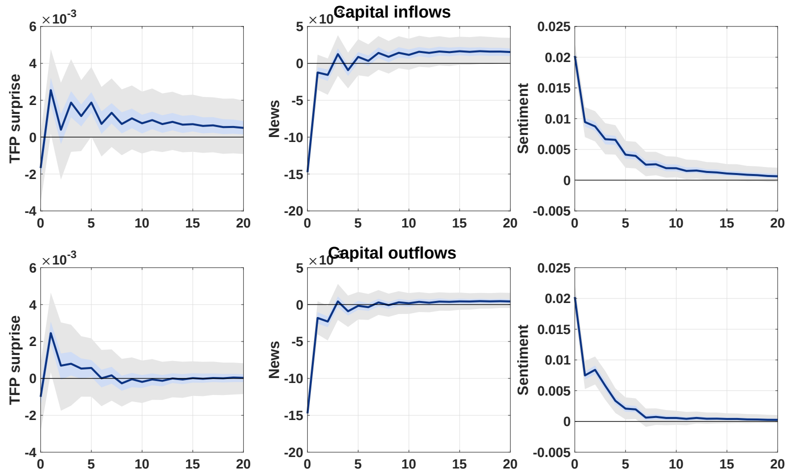
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.14: Capital flows IRFs to TFP surprise, news and sentiment shocks – Various lag specifications



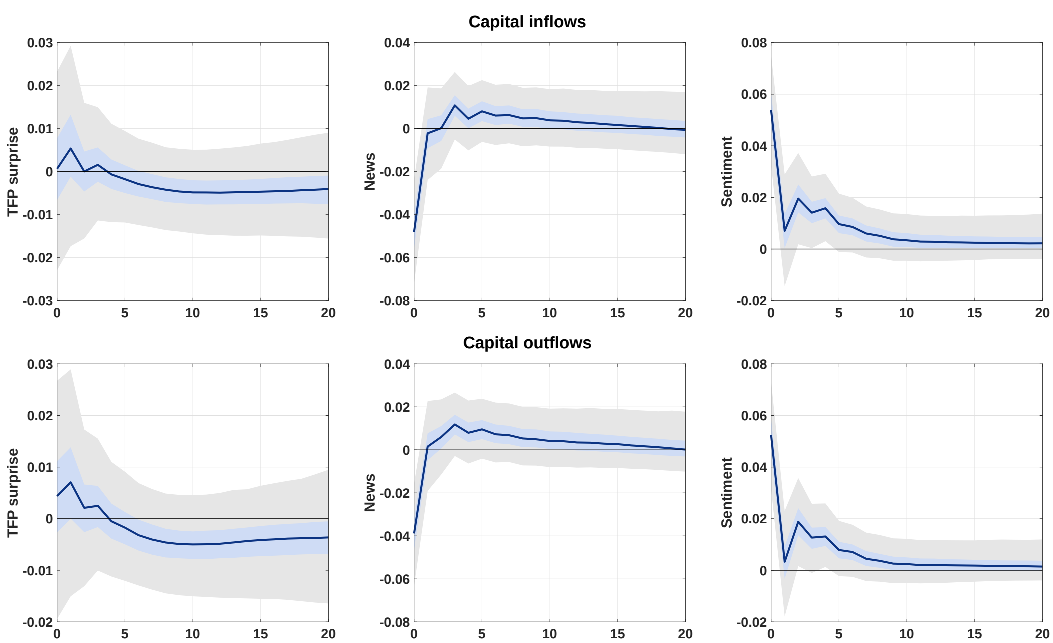
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with $p = 4$.

Figure A.15: Capital flows IRFs to TFP surprise, news and sentiment shocks – Including both inflows and outflows in estimation



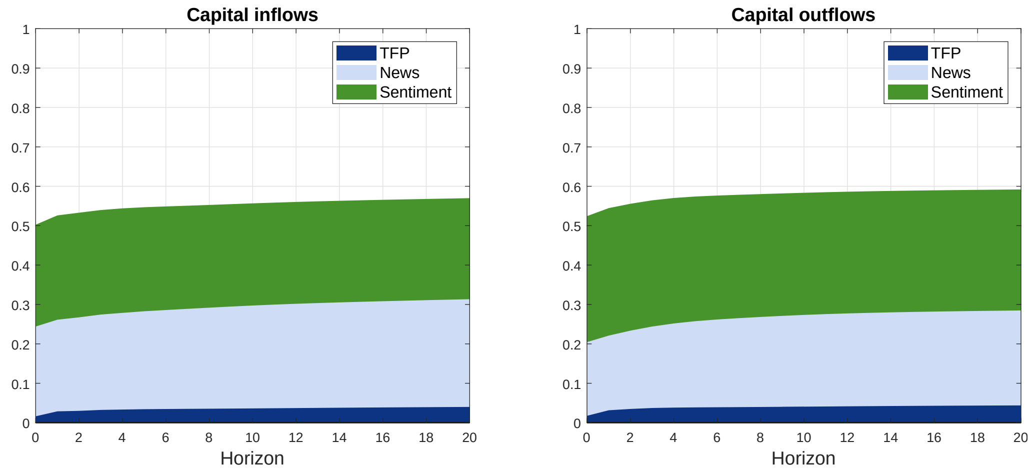
Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors.

Figure A.16: Panel mean IRFs to TFP surprise, news and sentiment shocks



Darker blue and lighter grey shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.17: Forecast Error Variance Decomposition of gross capital flows for the panel



Appendix B. Other countries

We also collect TFP, GDP and sentiment data for 17 OECD economies. Unfortunately, to our knowledge, no TFP measure similar to the U.S. series exists for any of the other countries considered in our analysis. We therefore build our own measure of TFP based on the methodology of Imbs (1999). This approach adjusts the Solow residuals for capital and labor utilization, using aggregated measures of investment, hours worked, wages and consumption. To assess the quality of our approach, we compute a TFP series for the United States and compare it with Fernald (2014)'s series. The methodology seems to do a fairly good job: a Kernel analysis of the differences between the two series does not show the presence of a systematic bias. These graphs and further details on the methodology can be found in Appendix D. Moreover, as argued by Sims (2016), the less precise the TFP measure, the smaller are the measured effects of news shocks. Therefore, if anything, bad measures of TFP imply less important effects of news shocks.

For output, we use the chain-weighted real GDP variable from the OECD database. Labor force - active population aged 15 or over, is obtained from the ILO. As expectations' variable, we use the forward-looking component of the consumer confidence index. The survey question considered is the following: "How do you expect the general economic situation in this country to develop over the next 12 months?".[25] There are six possibilities of answers: it will get a lot better (+2)/ a little better(+1)/ stay the same (0)/ a little worse (-1)/ a lot worse (-2)/ I do not know (0), from which the net balance is computed. The countries in our sample are selected based on data availability and are listed below with their respective timespans.

Table B.2: Time coverage including baseline data

Panel - OECD economies		
Australia	1995Q1	2018Q3
Austria	2005Q1	2018Q3
Belgium	2002Q1	2018Q3
Czech Republic	1995Q3	2018Q3
Denmark	1995Q3	2015Q4
Estonia	2000Q3	2017Q4
Finland	1990Q3	2017Q4
France	1985Q1	2018Q3
Germany	1992Q1	2018Q3
Ireland	2005Q1	2018Q3
Italy	1996Q3	2018Q3
Netherlands	1996Q3	2018Q3
Portugal	1995Q3	2017Q4
Spain	1995Q3	2018Q3
Sweden	1995Q4	2018Q3
Switzerland	1999Q1	2017Q4
United Kingdom	1995Q3	2018Q2
United States	1973Q1	2018Q3

[25] The question described here is the one asked in most countries that are part of the joint harmonized EU program of business and consumer surveys, but other countries' survey questions are very close. Each country's details are available on the OECD website (link).

Appendix C. Model appendix

Appendix C.1. Proof of equations (6.3)-(6.5)

Consider j investor's program in country H. Define as $\tilde{s}_j^H = S_j^H/[(Q+Q^*)/2+\Pi]$ the share of savings in the total investor's wealth and $X_j^{H*} = Q^* K_j^{H*}/S_j^H$ the share of savings invested abroad. The household's program then consists in maximizing

$$U_j^H = (1-\beta e^{-\gamma^H}) \log(1-\tilde{s}_j^H) + \beta e^{-\gamma^H} E_j^H \left\{ \log(\tilde{s}_j^H) + \log\left(e^r(1-X_j^{H*}) + e^{r^*} X_j^{H*}\right) \right\} + \log[(Q+Q^*)/2+\Pi]$$

where $r = \delta - q$ and $r^* = \delta^* - q^*$. This yields the following first-order conditions with respect to $\tilde{s}_j^H$ and X_j^{H*}:

$$\frac{(1-\beta e^{-\gamma^H})}{1-\tilde{s}_j^H} = \frac{\beta e^{-\gamma^H}}{\tilde{s}_j^H} \tag{C.1}$$

$$E_j^H \left\{ e^{r-\tilde{r}_j} \right\} = E_j^H \left\{ e^{r-\tilde{r}_j} \right\} \tag{C.2}$$

with $\tilde{r}_j = \log\left(e^r(1-X_j^{H*}) + e^{r^*} X_j^{H*}\right)$ is the average return on wealth.

After rearranging, (C.1) yields a constant saving rate across investors $\tilde{s}_j^H = \tilde{s}^H = \beta e^{-\gamma^H}$, and hence (6.3). Using the fact that $E(e^x) = e^{E(x)+\frac{1}{2}Var(x)}$ when x is normal, (C.2) yields:

$$\begin{aligned} e^{E_j^H(r-\tilde{r}_j)+\frac{1}{2}Var_j^H(r-\tilde{r}_j)} &= e^{E_j^H(r^*-\tilde{r}_j)+\frac{1}{2}Var_j^H(r^*-\tilde{r}_j)} \\ \Rightarrow \quad E_j^H(r-\tilde{r}_j) + \tfrac{1}{2}Var_j^H(r-\tilde{r}_j) &= E_j^H(r^*-\tilde{r}_j) + \tfrac{1}{2}Var_j^H(r^*-\tilde{r}_j) \end{aligned}$$

We approximate $\tilde{r}_j$ around $r = \bar{r}$ and $r^* = \bar{r}^*$, which are their steady-state values:

$$\tilde{r}_j = \bar{\tilde{r}}(X_j^{H*}) + (1-X_j^{H*})r + X_j^{H*} r^*$$

with $\bar{\tilde{r}}(X_j^{H*}) = \log[(1-X_j^{H*})e^{\bar{r}} + X_j^{H*} e^{\bar{r}^*}]$ a term that is known in period 1. Replacing in the first-order condition and rearranging, we obtain:

$$\begin{aligned} E_j^H(r^*-r) &= \tfrac{1}{2}[Var_j^H(r) - Var_j^H(r^*)] + (1-\bar{X}_j^{H*})Cov_j^H(r^*-r,r) + X_j^{H*}Cov_j^H(r^*-r,r^*) \\ \Rightarrow \quad E_j^H(r^*-r) &= -\tfrac{(1-2X_j^{H*})Var_j^H(r^*-r)}{2} \end{aligned}$$

which yields (6.4).

Equations (6.5) are derived in a similar way by solving the foreign investors' program.

Appendix C.2. Proof of Equation 6.10

Log-linearized equilibrium. We have assumed, for simplicity, that all shocks are i.i.d. As a result, log-linearizing around the nonstochastic equilibrium yields the following equilibrium home expected return, from the point of view of a home and a foreign investors:

$$\begin{aligned} &E_j^H(r) = E_j^H(\delta) - q \\ &E_j^F(r) = E_j^F(\delta) - q \end{aligned} \tag{C.3}$$

where lower-case letters denote log-deviations from the nonstochastic equilibrium.

Now consider capital inflows and outflows. They are equal to cross-border asset holdings:

$$\begin{aligned} &k^F = s^F + x^F - q \\ &k^{H*} = s^H + x^{H*} - q* \end{aligned} \tag{C.4}$$

Cross-border asset holdings depend on savings, average portfolio shares $x^F = \int_0^1 x_j^F dk$ and $x^{H*} = \int_0^1 x_j^{H*} dj$ and valuation effects.

Savings are a function of the preference shocks:

$$\begin{aligned} &s^F = -\gamma^F + \tfrac{q+q^*}{2} \\ &s^H = -\gamma^H + \tfrac{q+q^*}{2} \end{aligned} \tag{C.5}$$

and average portfolio shares are then simple functions of the average expected excess returns:

$$\begin{aligned} x^F &= 2\phi[\bar{E}^F(\delta - \delta^*) - (q - q^*)] \\ x^{H*} &= 2\phi[\bar{E}^H(\delta^* - \delta) - (q^* - q)] \end{aligned} \tag{C.6}$$

where $\phi = Var^H(r - r^*)^{-2} = Var^F(r - r^*)^{-2}$ is the inverse of the conditional variances.

The asset prices depend on the demand for capital at home and abroad:

$$\begin{aligned} q &= \varphi k \\ q^* &= \varphi k^* \end{aligned} \tag{C.7}$$

Taking asset prices as given, higher expected home productivity (higher $\bar{E}^H(\delta)$ and $\bar{E}^F(\delta)$) increases the portfolio shares, and should lead to more capital inflows (higher k^F) and less capital outflows (lower k^{H*}), as both home and foreign investors increase the share of home assets in their portfolio. However, increasing the stock of capital is costly, so an increase in the demand for the home asset leads to a price increase, which reduces the expected return of the home asset. Another effect of the asset price comes from valuation. An increase in the home asset price, by mechanically increasing the share of home assets in portfolios, reduces the need to acquire new home assets.

Asset prices are key to determine capital flows. Log-linearizing equations (6.8), we establish

$$\begin{aligned} q + k &= \tfrac{x^F - x^{H*}}{2} + \tfrac{s^H + s^F}{2} \\ q^* + k^* &= \tfrac{x^{H*} - x^F}{2} + \tfrac{s^F + s^H}{2} \end{aligned}$$

Using these equilibrium equations and the log-linearized formula for savings $s^H = (q+q^*)/2 - \gamma^H$ and $s^F = (q+q^*)/2 - \gamma^F$, we can also show that $k + k^* = -(\gamma^H + \gamma^F)$: demand shocks decrease the global demand for assets, which decreases global investment. Using $q + q^* = \varphi(k + k^*)$, we get a similar expression for asset prices: $q + q^* = -\varphi(\gamma^H + \gamma^F)$. We can then derive the equilibrium home asset price:

$$q = \frac{\varphi\phi}{1 + \varphi(1 + 4\phi)} \left[E^H(\delta - \delta^*) + E^F(\delta - \delta^*)\right] - \varphi\frac{\gamma^H + \gamma^F}{2} \tag{C.8}$$

The home asset price increases if either home or foreign investors think that the domestic asset is relatively more productive than the foreign asset, or if there is a decrease in the world demand for goods, which increases the world demand for assets. The reaction of the asset price depends on the investment friction φ. In the limit with no friction ($\varphi = 0$), the price does not react at all. Note that by using $q = \varphi k$, we can write the equilibrium domestic capital:

$$k = \frac{\phi}{1 + \varphi(1 + 4\phi)} \left[E^H(\delta - \delta^*) + E^F(\delta - \delta^*)\right] - \frac{\gamma^H + \gamma^F}{2} \tag{C.9}$$

On the opposite, the reaction of capital is maximal in the absence of friction ($\varphi = 0$), while in the limit with infinite friction ($\varphi = +\infty$), capital becomes inelastic. The foreign asset price q^* and foreign capital are then obtain simply as $q^* = -q - (\gamma^H + \gamma^F)$ and $k^* = -k - (\gamma^H + \gamma^F)/\varphi$.

Using Equations (C.4), (C.5), (C.6), (C.8) and $q^* = -q - (\gamma^H + \gamma^F)$, we obtain (6.10) and (6.11).

Appendix C.3. Proof of proposition 1

Using the expressions for cross-border holdings and net flows (6.10) and (6.11), and the expression for expectations (6.9), we can show that:

$$\begin{aligned}
k^F &= \tfrac{\phi}{1+\varphi(1+4\phi)} \left[2(\alpha_0\delta + \alpha_0 e) + \varphi(1 + 4\phi)(\alpha_0\delta + \alpha_0 e - \alpha_1\delta - \alpha_2 e)\right] ... \\
k^{H*} &= \tfrac{\phi}{1+\varphi(1+4\phi)} \left[-2(\alpha_1\delta + \alpha_2 e) + \varphi(1 + 4\phi)(\alpha_0\delta + \alpha_0 e - \alpha_1\delta - \alpha_2 e)\right] ... \\
NKI &= \tfrac{\phi}{1+\varphi(1+4\phi)} \tfrac{1}{2}\left[(\alpha_0 + \alpha_1)\delta + (\alpha_0 + \alpha_2)e\right]
\end{aligned}$$

where we consider only terms that affect the expectations of δ.

Using $\alpha_1 = \alpha_0 + \kappa(1 - \alpha_0)$ and $\alpha_2 = (1 - \kappa)\alpha_0$, we can rewrite the cross-border holdings as follows:

$$\begin{aligned}
k^F &= \tfrac{\phi}{1+\varphi(1+4\phi)} \left[\alpha_\delta^F \delta + \alpha_e^F e\right] ... \\
k^{H*} &= \tfrac{\phi}{1+\varphi(1+4\phi)} \left[\alpha_\delta^{H*} \delta + \alpha_e^{H*} e\right] ...
\end{aligned}$$

with

$$\alpha_\delta^F = 2\alpha_0 - \varphi(1+4\phi)\kappa(1-\alpha_0)$$
$$\alpha_e^F = \alpha_0\Big(2 + \varphi(1+4\phi)\kappa$$
$$\alpha_\delta^{H*} = -2\alpha_1 - \varphi(1+4\phi)\kappa(1-\alpha_0)$$
$$\alpha_e^{H*} = \alpha_0\Big(-2(1-\kappa) + \varphi(1+4\phi)\kappa\Big)$$

and the net inflows:

$$NKI = \frac{\phi}{1+\varphi(1+4\phi)}\Big[\alpha_\delta \delta + \alpha_e e\Big]$$

with

$$\alpha_\delta = (2-\kappa)\alpha_0 + \kappa$$
$$\alpha_e = (2-\kappa)\alpha_0$$

It is easy to see that α_δ and α_e are both strictly positive. As a result, NKI reacts positively to both the news δ and the noise e. However, these reactions converge to zero when φ goes to infinity.

α_e^F, the effect of noise e on capital inflows, is unambiguously positive. Similarly, α_e^{H*}, the effect of news δ on capital outflows, is unambiguously positive. In the case of the effect of news on capital inflows, the effect is ambiguous. To understand, it is useful to consider first the case with no investment friction ($\varphi = 0$). In that case, the results are unambiguous. A noise shock e and a news shock δ both generates an increase in capital inflows and a decrease in outflows. Both the domestic and foreign investors demand more of the home asset, and this demand is perfectly accommodated by the domestic capital producers. Consistently, both shocks generates positive net capital inflows.

Consider the case with no investment costs ($\varphi = 0$). In this case, α_δ^F is clearly positive and α_e^{H*} is clearly negative. Therefore, both a news shock and a noise shock generate positive gross capital inflows and negative gross capital outflows.

Now consider the case with infinite investment costs ($\varphi = +\infty$). In that case, α_δ^F is clearly negative whenever there is asymmetric information, i.e. when $\kappa > 0$. Similarly, α_e^{H*} is clearly positive. Therefore, a noise shock e generates an increase in capital inflows and outflows and a news shock δ generates a reduction in capital inflows and outflows as long as there is asymmetric information. If, additionally, there is no asymmetric information ($\kappa = 0$), δ and e generate no capital flows. Here the price adjustment equally deters the domestic and foreign agents from adjusting their portfolio.

Finally, consider the more general case. We can show that α_δ^F is negative if and only if

$$\frac{\kappa(1-\alpha_0)}{\alpha_0} > \frac{2}{\varphi(1+4\phi)}$$

This is satisfied when φ and κ are large enough. Similarly, we can show that α_e^{H*} is positive if and only if

$$\frac{\kappa}{1-\kappa} > \frac{2}{\varphi(1+4\phi)}$$

which, again, is satisfied when φ and κ are large enough.

Appendix D. TFP construction

Methodology

An ideal measure of utilisation-adjusted TFP would be similar to the US series by Fernald (2014). To our knowledge, such series cannot be constructed for the 17 countries considered in this paper. Therefore, we compute a measure of TFP using the methodology proposed by Imbs (1999) and close to the one used in Basu et al. (2006). The main idea is to adjust Solow residuals for capital and labour utilisation, using aggregated measures of investment, hours worked, wages and consumption. Hence, this approach does not use industry-level data nor control for sectors and non-constant returns to scale. The remaining of the Appendix aims at providing the equations of the iterative algorithm used to construct TFP series for each country. For more details on the derivations, the reader should refer to Imbs (1999).

Output

The output is assumed to be given by the following production function:

$$Y_t = X_t(K_t u_t)^{1-\alpha}(N_t e_t)^{\alpha}$$

where Y_t is aggregate output, K_t is the capital stock, N_t represents hours worked over the period, e_t is the labour effort and u_t the capital utilisation rate. Thus, $(K_t u_t)$ gives us the effective capital services and $(N_t e_t)$ the effective labour input.

Capital stock series

First, the capital stock series is constructed using the perpetual inventory method, with a time-varying depreciation rate:

$$K_{t+1} = (1 - \delta_t)K_t + I_t. \qquad \text{(C.1.)}$$

The initial level of capital K_0 is constructed following Berlemann and Wesselhöft (2014):

$$K_0 \approx \frac{I_1}{g_I + \delta}$$

The initial investment value I_1 is obtained by regressing the logarithm of investment series on a constant and time t. The first observation of investment is excluded and the OLS regression therefore goes from $t = 2$ to T.

$$ln(I_t) = \alpha + \beta t + \epsilon_t$$

The initial investment value is then given by the fitted value for period $t = 1$:

$$\widehat{ln(I_t)} = \widehat{\alpha} + \widehat{\beta} t$$

After taking the exponential, this fitted value of investment is used to compute the initial stock of capital. The growth rate of investment g_I is obtained using the $\hat{\beta}$ estimated in the OLS regression.

We slightly depart from their methodology by taking a fixed rather than time-varying depreciation rate to estimate the initial stock of capital. In other words, we use $\delta = 2.5\%$ and do not re-estimate K_0 after having determined a vector of time-varying depreciation rates.

Having estimated the initial stock of capital, K_0, the capital stock series can therefore be constructed using the perpetual inventory method as described in equation (C.1.).

Utilisation and depreciation rates

The second step is to determine the utilisation rate of capital, using the following equation:

$$u_t = \left(\frac{Y_t/K_t}{Y/K} \right)^{\delta/(r+\delta)} \tag{C.2.}$$

where Y/K is the average output-capital ratio. r is set to 4% and $\delta = I/K - g_I$, with I/K the average investment-capital ratio and g_I the growth rate of investments.

Then, the series for the depreciation rate is updated according to the following rule:

$$\delta_t = \delta u_t^{\phi} \tag{C.3.}$$

with $\phi = 1 + (r/\delta)$ and $\phi > 1$ such that depreciation is a convex function of utilisation.

This algorithm departs from Imbs (1999) paper regarding δ. In the original version, δ is defined as the average of the depreciation rate series. However, with this specification, the expectation of $\delta_t = \delta u_t^{\phi}$ would be equal to one.
Our definition of δ comes from the steady-state of the capital accumulation equation (C.1.);

$$\begin{aligned} & K(1 + g_K) = (1 - \delta)K + I \\ \Leftrightarrow & (1 + g_K) = (1 - \delta) + I/K \\ \Leftrightarrow & \delta = I/K - g_K \end{aligned}$$

As data on capital stock is constructed, the growth rate of capital g_K is approximated by the growth rate of investment, g_I.

Once the depreciation rate series is constructed, the process restarts at equation (C.1.), generating a new capital stock series, until (C.3.). As soon as the average depreciation rate δ converges - i.e. two consecutive identical δ, the iteration process stops and the final utilisation and capital stocks series are constructed. From these series for K_t and u_t, one can construct the series for the effective capital service, $K_t u_t$.

Labour effort series

The series for labour effort can then be constructed using the following equation:

$$e_t = \left(\alpha \frac{Y_t}{C_t}\right)^{1/(1+\psi)}$$

with C_t the data on consumption, α given by

$$\alpha = 1 - (K/Y)(r + \delta)$$

and ψ being such that

$$\psi = \frac{\alpha}{w(e_t)N_t/Y_t} - 1$$

with $w(e_t)$ the data on wages. These steps allow the computation of the effective labour input series, $N_t e_t$.

TFP series

Finally, using the utilisation adjusted series of capital and labour, the TFP series can be computed using the production function:

$$X_t = Y_t * ((u_t K_t)^{\alpha} (e_t N_t)^{(1-\alpha)})^{-1}$$

Data

The present section aims at describing the data series used in the TFP construction.

- Y_t: Real GDP - Gross domestic product using the expenditures approach, chained volume estimates at quarterly frequency, seasonally adjusted and in domestic currency. Source: OECD.
- I_t: Real investment - Gross fixed capital formation using the expenditures approach,

chained volume estimates at quarterly frequency, seasonally adjusted and in domestic currency. Source: OECD.

- C_t: Real private consumption - Private final consumption expenditures (households and non-profit organisations), using expenditures approach, chained volume estimates at quarterly frequency, seasonally adjusted and in domestic currency. Source: OECD.
- N_t: Total hours worked - Hours per worker times the total number of persons employed. Sources: OECD Economic Outlook/ILO.
- w_t: Real wages - Total wages in value, denominated in domestic currency (earning per employee times number of persons employed for Portugal), deflated by private final consumption expenditures deflator. Sources: OECD/Oxford economics.

Comparing U.S. TFP series

The two graphs presented here assess differences between the U.S. TFP series from Fernald (2014) and the one obtained using the methodology described above. The first graph on the left compares the one-year average of the Fernald's series with the constructed one: except for few spikes in the 90s it seems to do a fairly good job. This impression is confirmed by the plot of the estimated Kernel density based on differences between the two.