

News, Sentiment and Capital Flows ^{*†}

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August 26, 2019

Abstract

We examine empirically the effect on gross capital flows of two types of expectation-related shocks: “news” (increases in expected future productivity) and “sentiment” (surges in optimism unrelated to future productivity). We find that news shocks lead to a decrease in both gross capital inflows and outflows, while sentiment shocks lead to an increase in both gross inflows and outflows. Both these shocks drive a positive correlation between gross inflows and outflows but only sentiments shocks generate procyclical gross flows. These effects are not driven by global shocks or financial shocks. They are consistent with the existence of asymmetric information between domestic and foreign investors about the country’s fundamentals.

JEL-Classification: D82, E32, F32.

Keywords: Capital flows, SVAR, Asymmetric information.

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[†]We thank Philippe Bacchetta, Frédéric Dufourt, Jean Imbs, Alessandro Rebucci, Jean-Paul Renne, Cédric Tille and seminar and conference participants at the Macro Workshop from the University of Lausanne, Aix-Marseille University, The Graduate Institute (Geneva), the AMSE and MaGHiC Macroeconomic Workshop 2017, ESSIM 2018. We acknowledge financial support from the SNF grant number 100018_150068.

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1 Introduction

Gross capital inflows and gross capital 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 informs on the mechanisms driving capital flows and is a step towards understanding them. This paper goes into that direction by disentangling the reaction of domestic gross capital flows to technology and non-technology expectation-related shocks.

In the case of capital flows, the forward-looking dimension is central, as capital flows should respond to expected excess returns. However, expected excess returns are related to expected future productivity, but they can also be driven by excessive optimism. A key contribution of the paper is to disentangle the effect of “news” shocks (increases in expected future productivity) from non-technological expectation shocks (surges in optimism that are unrelated to future productivity), which we call “sentiment” shocks, following Levchenko and Pandalai-Nayar (2018). We find that news shocks lead to a decrease in both gross capital inflows and gross capital outflows, while sentiment shocks lead to an increase in both gross inflows and outflows. These results show that while only sentiment shocks generate procyclical flows, both shocks generate positively correlated inflows and outflows. Also, expansions in cross-border flows are typically not associated with improving technology.

We use a recursive structural VAR approach that allows us 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. The “sentiment” shock captures any shock that affects expectations while unrelated to technology. Formally, and following Levchenko and Pandalai-Nayar (2018), who builds on Barsky and Sims (2011), we 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. And finally, the sentiment shock is the shock that best explains short-run variations in expectations, not accounted for by the TFP surprise shock nor by the news shock.

Focusing first on the United States, we use data at quarterly frequency between 1973Q1 and 2018Q3. Our findings show that news and sentiment shocks affect significantly the U.S. capital inflows and outflows. A positive news shock triggers an immediate, short-lived and negative response of capital flows. Sentiment shocks have significantly positive effects on capital flows on impact with medium-lasting effects. Interestingly, TFP surprise shocks do not induce significant responses of capital flows. This shows that expectations play a key role in driving capital flows at the country level. Quantitatively, we show that news and sentiment shocks are key drivers of capital flows: these shocks contribute for up to 85% of their forecast error variance decomposition (FEVD). Sentiments shocks alone can explain around 60% of the FEVD and about 25% can be attributed to news shocks. We then extend the analysis for the U.S. to a panel of 18 OECD economies. The results are similar to those of the United States, confirming the validity of our results for other countries. Overall, two main conclusions can be drawn from these results. First, non-technology shocks are important driver of capital flows. They are at least as important as technology shocks, often even more important. Second, contemporaneous technology shocks play a negligible role but anticipated technology (i.e. news) shocks are important.

Before interpreting our results, we conduct a further empirical analysis. We address two issues. First, the sentiment shock being identified as a residual, it is important to rule out potential known drivers of capital flows. Financial shocks and crises are important candidates, since they have been shown to drive a procyclical and correlated response of inflows and outflows (Broner et al., 2013). In particular, in the last few years, a new strand of the capital flows literature has focused on “global financial cycles” (Rey, 2015) with a central role for the VIX and the FED funds rate. Second (and related), 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 then 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 address these issues as follows. We start by introducing global variables in our baseline US VAR and identify global shocks before the local TFP surprise, news and sentiment

shocks. The impact of the three local shocks on capital flows remains unchanged and they still explain a large part of the FEVD of capital flows. Consistently with the literature, global shocks seem to also play a significant role in driving capital flows. Then, we assess whether sentiment shocks could be merely reflecting financial shocks (VIX, financial stress indicator), economic uncertainty or monetary policy shocks, by identifying these shocks before the sentiment shocks. In all cases, responses of capital flows to the three shocks remain unchanged.

Given that our results are not exclusively driven by the global nature of shocks or by financial shocks, we examine whether information frictions can explain them. We lay down a two-country model with asymmetric information between domestic and foreign investors about the country's fundamentals. All agents share a noisy public signal that can be driven by "news" (i.e. by actual improvements in the fundamentals) or by "noise" (i.e. by excessive optimism), but home agents have additional private information. A news shock about future productivity generates a drop in both gross inflows and gross outflows. Following a news shock, domestic investors, who are better informed about their domestic productivity, increase their demand for domestic assets relatively more than foreign investors do. In equilibrium, this leads domestic investors to increase their share of domestic assets while foreign investors reduce theirs. As a result, domestic investors sell foreign assets - decreasing capital outflows - and buy domestic assets from foreign investors - decreasing capital inflows.¹ On the contrary, a noise shock generates an increase in both gross inflows and outflows. Following a noise shock, domestic investors, who are better informed about their domestic productivity, increase their demand for domestic assets relatively less than foreign investors do. In equilibrium, this leads domestic investors to decrease their share of domestic assets while foreign investors increase theirs. As a result, domestic investors sell domestic assets - increasing capital inflows - and buy more foreign assets - increasing capital outflows.

In our empirical analysis, we have not ruled out demand shocks as a potential explanation of sentiment shocks. Disentangling the noise from demand shocks is actually a challenge, as one theoretical prediction is that noise and demand shocks are observationally equivalent. We indeed find that the estimated effect of sentiment shocks on GDP, consumption and hours

¹These results are consistent with Tille and van Wincoop (2014), who examine the effect of foreseen productivity growth and capital flows.

do look like the reaction to demand shocks. However, we show, using the model, that demand and noise shocks have different implications for capital flows. In fact, domestic demand shocks (dissaving shocks) typically generate an increase in inflows, but also a decrease in outflows, which is not consistent with the effect of our identified sentiment shock.

This paper is related to the literature on expectation-driven business cycles. It is a widely shared view that expectations are key drivers of macroeconomic fluctuations. Indeed, there is increasing empirical evidence that expectations do induce movements in key domestic macroeconomic aggregates.² Their international financial dimension has however been neglected, despite the idea that expected returns play a key role in capital flows.³ We inform on this issue by studying the effects of news and sentiment shocks on international capital flows.

Then, little has been done to analyze the impact of expectations on capital flows. One example is the paper by Milesi-Ferretti and Tille (2011) showing that countries with worse outlooks suffered larger capital retrenchments, using measures of growth and public finances' prospects. Their focus is, however, on the great recession between 2006 and 2009. In a previous paper, Cordonier (2017) shows that the forward-looking component of the consumer sentiment index is significantly related to capital flows. This paper extends on this idea by using a more structural approach and distinguishing the technology-related part of expectations (news) from their non-technology-related part (sentiment). Moreover, to our knowledge, most specifications in the literature have little explaining power. An additional contribution of our paper is that the identified shocks explain a significant portion of domestic capital flows' variations, suggesting a key role for expectations.⁴

Our model is related to Albuquerque et al. (2007, 2009) and Brennan (1997), who study the role of information asymmetries on capital flows. But our model is especially close to Tille and van Wincoop (2014), as it is a general equilibrium model. Unlike Tille and van Wincoop (2014), we do not consider endogenous responses of saving and investment.

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

³The role of news and sentiment on international comovement is the object of Levchenko and Pandalai-Nayar (2018) and Siena (2017), but both studies do not consider capital flows.

⁴The 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.

Indeed, our focus is on portfolio shifts due to changes in expected returns, so we abstract from portfolio growth effects and time-varying risk. While they also consider what we call news (a partly foreseen increase in future productivity) and noise shocks (an aggregate error in public signal), they study the effect of noise without private information, and in that context noise shocks have no effect on capital flows. We show that when there are also private signals, and especially with asymmetric information between the home and foreign country, noise shocks have non-trivial effect on capital flows. Last but not least, we introduce two types of information asymmetries, micro and macro: This enables us to show that micro information asymmetries should prevail to explain the data.

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. Section 5 presents a two-country model with information asymmetry. Section 6 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 (2018) 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 (2018), we then identify sentiment shocks as the shock, uncorrelated to TFP, that maximizes the forecast error of a forward-looking 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”), which we believe is important in terms of their impact on capital flows.⁵

Formally, assume that TFP is driven both by the usual surprise TFP shock, but also by

⁵Beaudry 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 movements in stock prices that are uncorrelated to the innovation in TFP. This methodology however does not allow to distinguish between movements in stock prices that are correlated to future TFP from those that are not.

a news shock. The latter has the particularity to be observable some periods in advance by the agents. 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. Using A_t to denote TFP, one example for this particular 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 affects contemporaneously the level of TFP, and ϵ_{t-s}^{news} is the news shock, observed some period $s > 0$ in advance by the agents.

Assume then that agents' expectations about the state of the economic 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 anticipated changes in TFP. Denoting the expectations with 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.

Let's 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 sentiment measure 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 $B(0)$ an identity matrix. We assume that the linear mapping between the residuals (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 $[1, 0, \dots, 0]$.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 are moving 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:

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

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 $\gamma_j = D e_j$ selecting the j th column of the D matrix. e_j is the selection vector that contains zero everywhere except at the j th position and $B_{i,\tau} = e_i' B_{\tau}$ denotes the i th 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

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

only. As $\Omega_{1,1}(h)$ is fixed, the strategy to identify the second structural shock consists in maximizing its contribution to the forecast error variance of TFP, not attributable to the first structural shock.

Let's 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 $\gamma^{news}(1) = 0$ and $\gamma^{news}'\gamma^{news} = 1$. As a result, γ^{news} is obtained by solving the following problem:⁷

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

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 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 for few quarters. Hence, following Levchenko and Pandalai-Nayar (2018), the sentiment shock is identified such 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

⁷Notice that in Barsky and Sims (2011) they 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.

⁸As 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 the 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 $(M-1) \times (M-1)$ sub-matrices of $(B_{1,\tau}\tilde{A}_0)'(B_{1,\tau}\tilde{A}_0)$ over τ .

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,

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

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. And finally, the sentiment shock is the shock that best explains short-run variations in expectations, not accounted for by neither the TFP surprise shock, nor the news shock.

3 Data

For this analysis, we gather data on TFP, GDP, an expectation variable and capital flows for the U.S. The baseline vector y_{USt} used to estimate U.S. shocks includes four variables: TFP - as a measure of technology, the log of real GDP per capita, an expectation variable and capital flows. 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). This measure has been frequently used in the empirical literature identifying news shocks in the United States.⁹ 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 non-institutionalized population aged 16 and over (BLS).

The main measure of expectations is from the survey of consumers produced by the

⁹See for instance, Barsky and Sims (2011) or Levchenko and Pandalai-Nayar (2018)

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, they ask “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?”. They have 6 possibilities of answers: Good times, good with qualifications, pro-con, bad with qualifications, bad times or do not know. From these answers, they compute 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 three main reasons, why our baseline uses consumer sentiment rather than the expectations obtained from the Survey of Professional Forecasters (SPF). First, such a survey does not exist for the panel of countries considered later in this paper. Second, it allows us to link this paper to the literature on news and sentiment shocks using the same variable. Last, Cordonier (2017) has found that this specific “E12M” variable relates significantly to capital flows (while controlling for other key factors).

The data on capital flows are obtained from the Balance of Payment Statistics Database (IFS/IMF), based on the BPM6 methodology. This study considers both gross capital inflows and outflows.¹⁰ 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).¹¹

4 Empirical 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

¹⁰Our theoretical model shows that domestic and foreign investors should react differently to shocks if asymmetry of information exists. Thus, our focus is on gross capital flows.

¹¹Indeed, GDP trend reacts much less to shocks 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.

outflows.

4.1 Baseline results

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).¹² We start with a SVAR containing TFP, GDP, E12M and gross capital inflows as described in the data section. First, Figure 1 shows the responses 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.

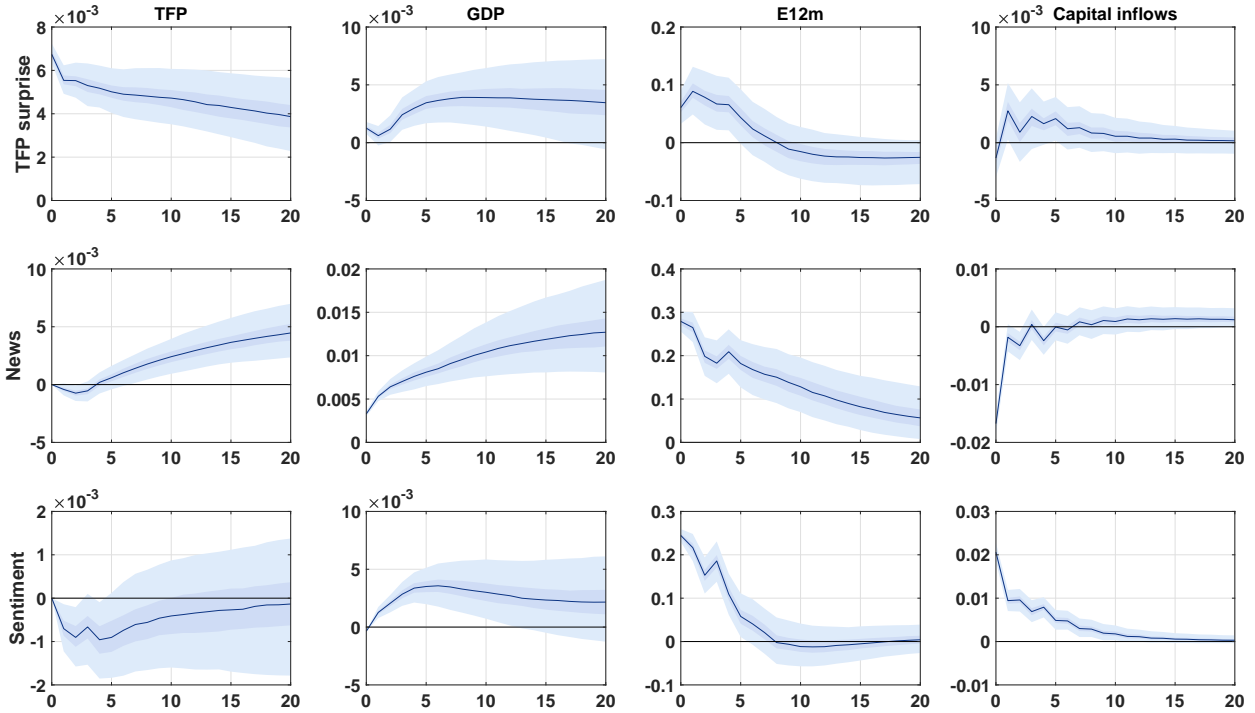
The first point to stress is that news and sentiment shocks are fairly well identified. The news shock has a slow-building persistent impact on TFP, while, overall, TFP does not react significantly to a sentiment shock. Thus, the sentiment shock does not relate to technology. Moreover, responses of GDP 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 shock. News and sentiment shocks are thus the main drivers of expectations.

Regarding the impact of shocks on gross capital inflows, the focus of this paper, we see in Figure 1 that the news shock has an immediate negative impact that is short-lived (2-4 quarters). Figure 2 shows that the response of gross capital outflows is similar. On the opposite, the sentiment shock triggers an immediate positive response of gross capital inflows and outflows, which lasts for about 7 to 10 quarters.¹³ Hence, optimism that is unrelated to fundamentals (here measured by TFP) generates an expansion in cross-border holdings.

¹²In the robustness part, specification with different number of lags, e.g. $p = 2$ will be presented. Results are robust to the lag specification.

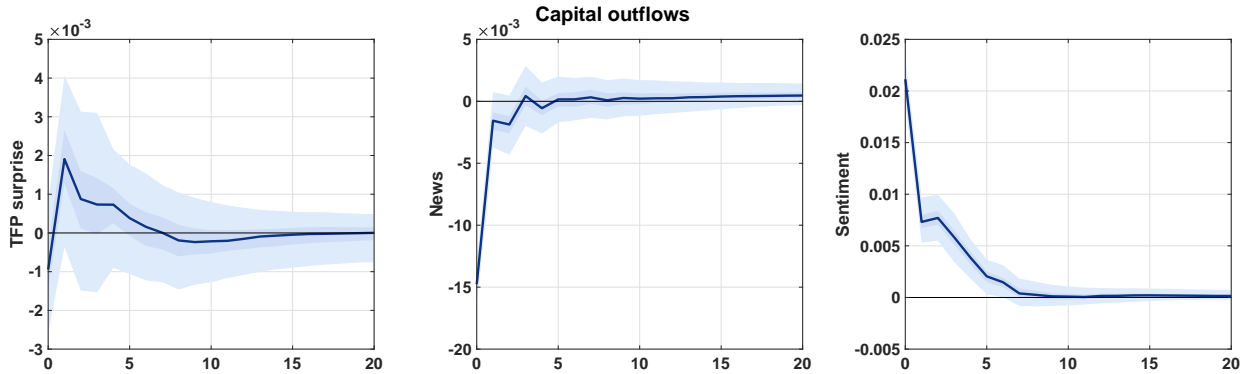
¹³Our results remain similar when we use the same variable as Levchenko and Pandalai-Nayar (2018) in our specification, i.e. including consumption and hours in third and fourth position. Responses of capital inflows to TFP surprise shock becomes however positive and the news shocks have more significant and persistent effects on capital flows in the medium/long-run. The impulse responses functions are presented in Appendix A Figure A.1.

Figure 1: 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

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

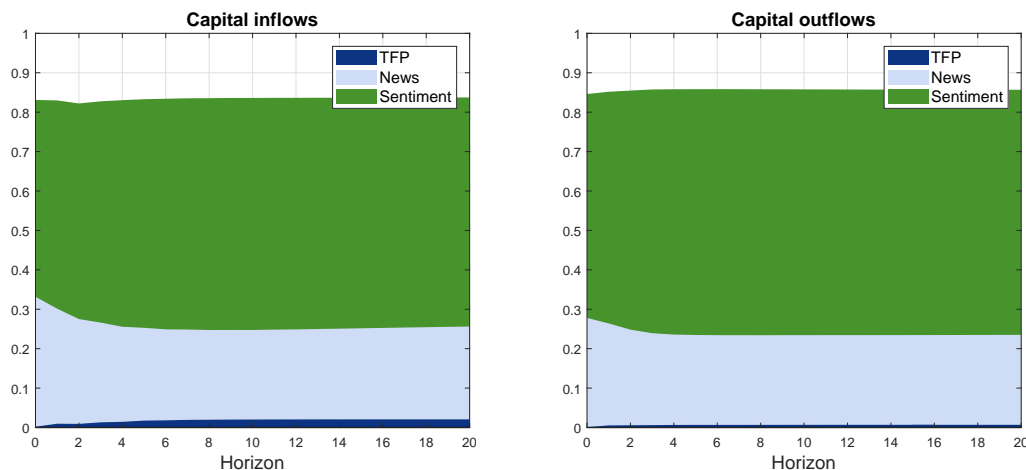


Dark and light shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Finally, the responses of capital flows to a surprise TFP shock are positive, although non-significant. 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), and especially

by sentiment shocks.¹⁴ This is confirmed 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 about 25% of capital flows, while TFP surprise shocks have a negligible contribution.

Figure 3: Forecast Error Variance Decomposition of gross capital flows



Before interpreting our results, we conduct further empirical analysis. Mainly, we 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, the sentiment shock being identified as a residual, it is especially important to rule out known potential drivers of capital flows, global or local. We address these issues as follows. First, we extend our SVAR in order to control for global shocks. We then assess how sentiment shocks relate to markets or economic uncertainty (VIX, economic policy uncertainty index,...) and monetary policy shocks.

4.2 Accounting for global shocks

We assess the global dimension of our shocks by including global variables and applying alternative specifications that accounts for global shocks.

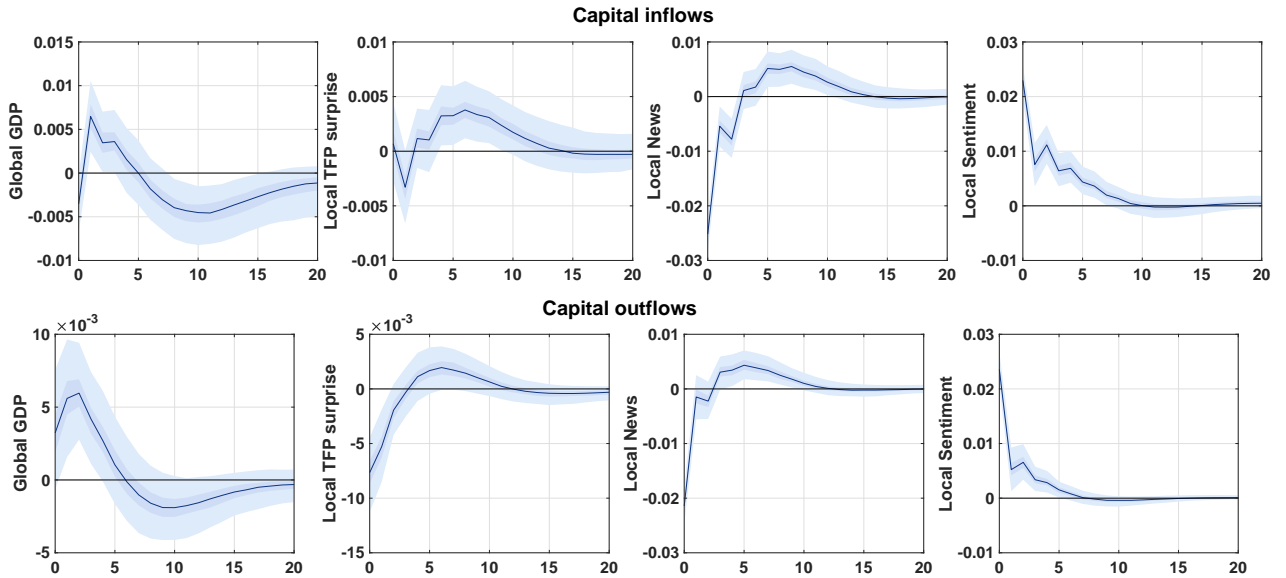
¹⁴This suggests that the expansionary effect of a country's optimism on capital flows, as documented by Cordonier (2017), is not related to the country's technology, but to sentiment.

The first strategy consists in identifying a global GDP shock, and then apply the same strategy as above to get the three “local” U.S. shocks. In other words, we add a measure of real GDP per capita aggregated over a number of countries in the first position of our vector, $y_t = [GDP_{Global,t}, TFP_t, GDP_t, E12M_t, KF_t]$. The global GDP shock is identified first, as the structural shock that best explains future variations in the global real GDP per capita variable. The three local shocks (TFP surprise, news, sentiment) are then identified in the same way as in the baseline, except that we impose orthogonality with the global GDP shock. As measure of global GDP per capita, we use the weighted average of the real GDP per capita of 14 OECD economies.¹⁵ The number of countries is determined based on data availability to obtain a balanced panel between 1995Q2 to 2017Q4. Altogether, these countries average to around 24% of world real GDP, PPP-adjusted (or around 30% when using world GDP without the U.S.) over the covered time-period.¹⁶ The IRFs of capital flows to the identified shocks are shown in Figure 4 and the FEVD in Figure 5. As we can see, the responses to local shocks are qualitatively similar. Interestingly, the global GDP shock triggers a short-lived positive response of both gross inflows and outflows, consistently with the literature. Nevertheless, the lion’s share of the FEVD remains explained by local rather than global GDP shocks.

¹⁵These are Australia, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Portugal, Spain, Sweden, Switzerland and United Kingdom.

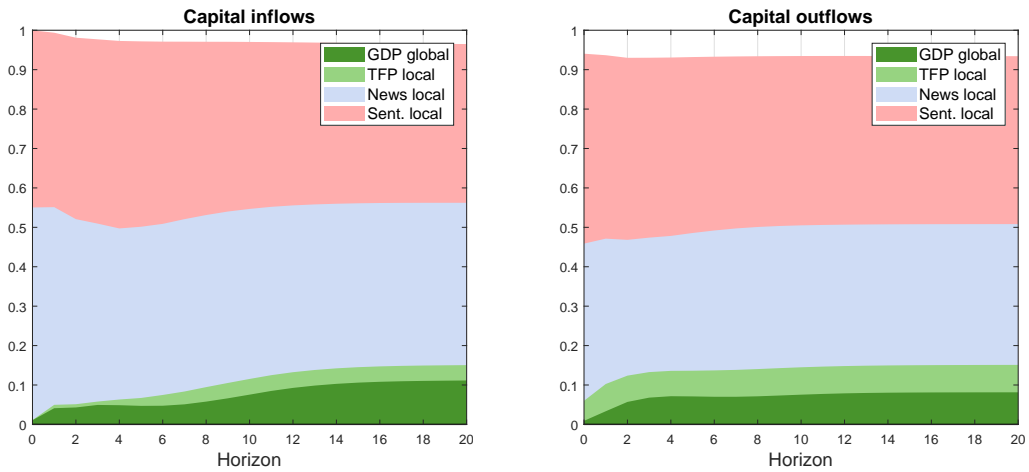
¹⁶To get this ratio, we use the World Bank annual GDP constant 2010 USD, PPP-adjusted data.

Figure 4: IRFs of capital flows to global GDP, local TFP surprise, local news and local sentiment shocks



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

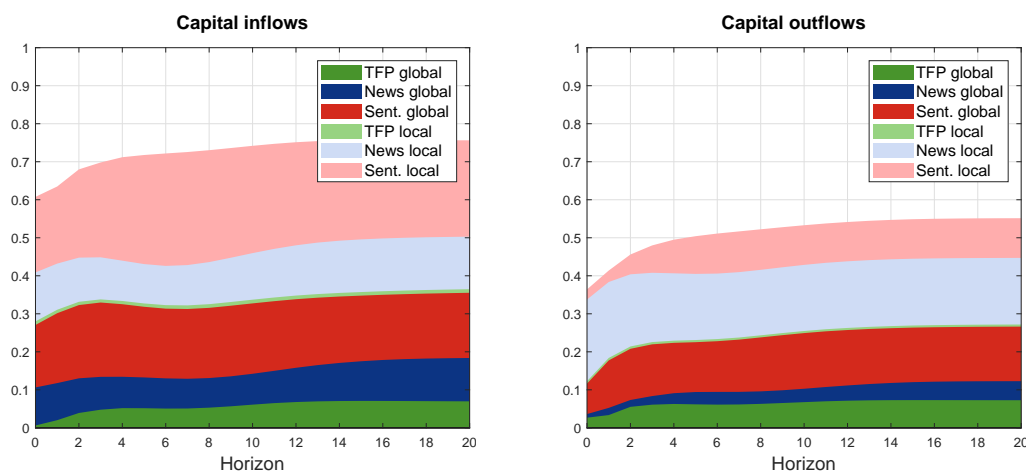
Figure 5: Forecast Error Variance Decomposition of gross capital flows with global real GDP per capita shock



Our second approach is to not only add a global GDP per capita variable but also a global TFP and a global E12M variable. We then obtain a 7-variable VAR with $y_t = [TFP_{Global,t}, GDP_{Global,t}, E12M_{Global,t}, TFP_t, GDP_t, E12M_t, KF_t]$. Using again the same approach as in the baseline, we first identify three global shocks: global TFP surprise, news and sentiment shocks. Local TFP surprise, news and sentiment shocks are then identified by imposing orthogonality with the global shocks. For the 7-variable VAR, we use a balanced

panel 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 C for a description of the TFP variable construction).¹⁷ We then build the TFP, GDP per capita and E12M as the weighted-mean of the countries' variables, using real GDP as weights. IRFs of these shocks on capital flows are presented in Figure 6. Note that to limit the number of parameters to be estimated, we use VAR specification with 2 lags.¹⁸ In this set-up, responses of capital flows to the three local shocks remain very similar to those from the baseline, i.e. without identifying global shocks first. Interestingly, responses to global shocks are qualitatively alike to the local ones. Looking at FEVD in Figure 7, we see that an important part remain explained by local shocks. Overall, global shocks seem to have similar effects on capital flows as local ones. Nevertheless, local shocks are still significantly affecting capital flows.

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



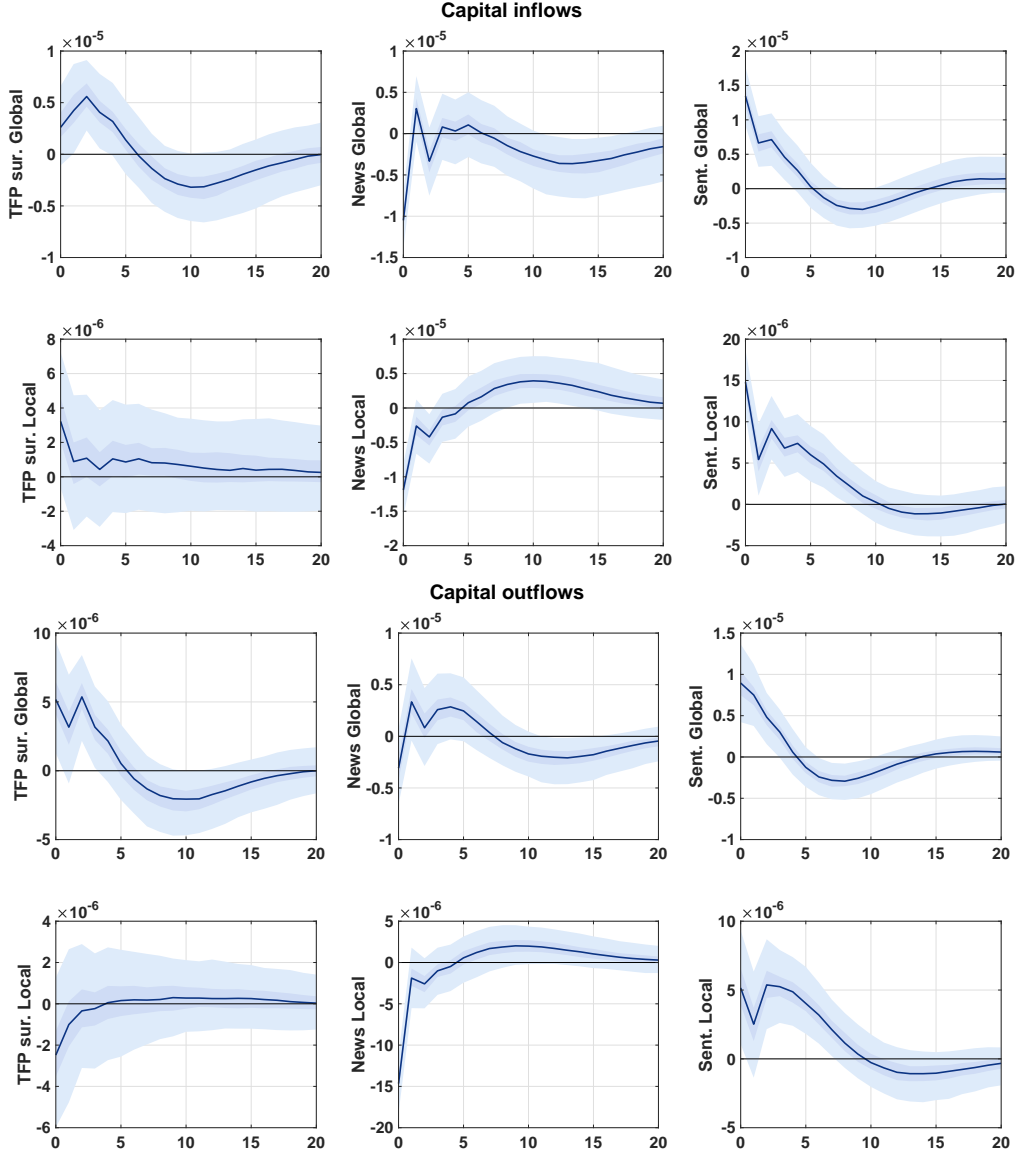
4.3 Accounting for other shocks

One could argue that our sentiment shocks merely reflect variations in uncertainty or in financial conditions. Thus, we repeat the empirical exercise but sequentially including various variables that measures economic and financial markets uncertainty, as well as financial

¹⁷Included countries are Australia, Denmark, France, Germany, Italy, Portugal, Spain, Sweden and United Kingdom.

¹⁸Using 4 lags, has little qualitative impact except that responses are less smooth and we observe a smaller negative response of capital inflows to the local news shock. FEVD explained by the shocks would on the other hand be larger.

Figure 6: IRFs of capital flows to both global and local shocks

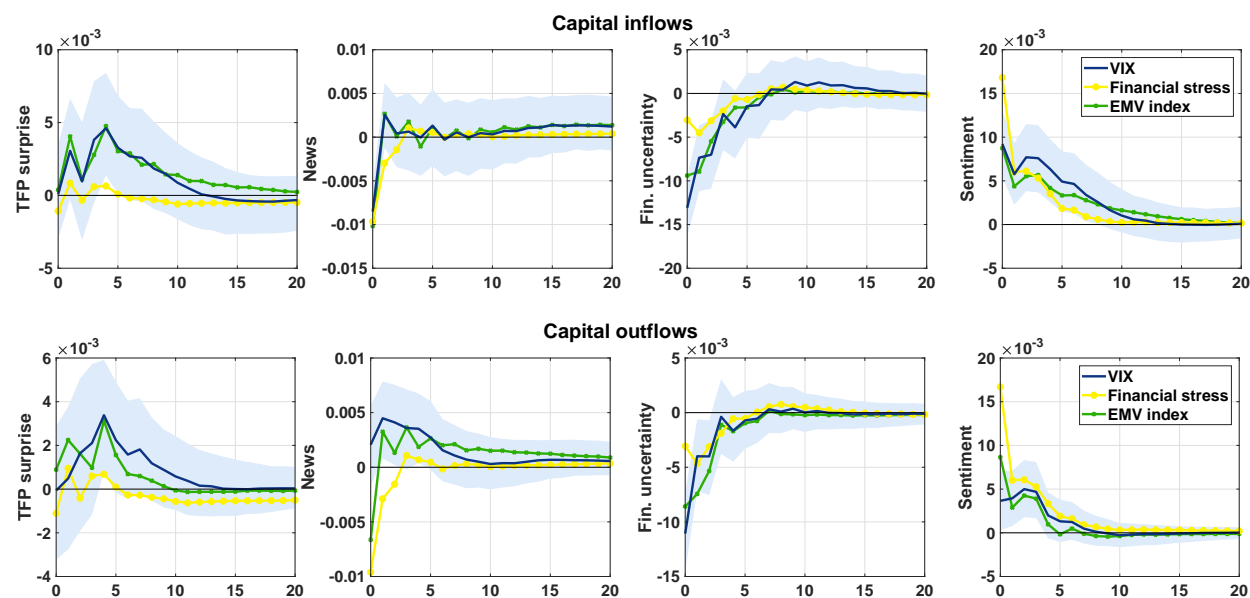


Dark and light shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors.

conditions. First, to account for financial markets' uncertainty, we include the VIX, the equity market volatility (EMV) index built by Baker et al. (2019), as well as a financial stress indicator from Püttmann (2018). To give a maximum weight to this additional shock, we identify it before the sentiment shock. Formally, we add this extra variable in 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, unexplained by the first two shocks.

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



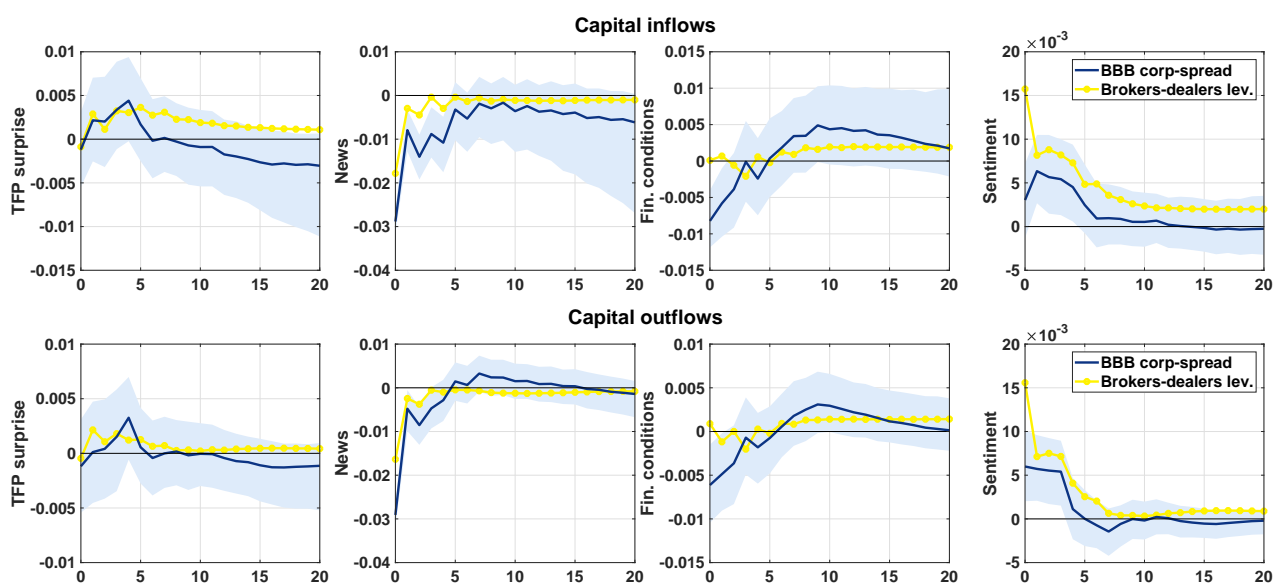
Shaded areas represent the 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with VIX as financial uncertainty variable.

Figure 8 shows responses of inflows and outflows when identifying a financial uncertainty shocks. Consistently with the literature’s findings, an increase in the financial uncertainty, triggers an immediate short-lived negative responses of capital flows. This is true whatever proxy variable we are using. The responses to the news and sentiment shocks remain qualitatively similar. Their sizes are however reduced, although we should keep in mind that the weight given to the financial uncertainty shock was maximized. In other words, the impact of the sentiment shocks could be interpreted as a lower band.

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 the 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 dealers leverage variable. Adrian and Shin (2010) show that global market

liquidity relates to the leverage of security brokers 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. IRFs of capital flows to all four shocks, including a tightening in financial conditions, are presented in Figure 9. Again, responses of capital flows to TFP surprise, news and sentiment shocks are similar to those from the baseline. Responses to a tightening in financial conditions (mostly for corporate BBB spread) appear to be meaningful: capital flows contract as financial conditions tighten.

Figure 9: U.S. IRFs for capital flows to TFP surprise, news, financial conditions and sentiment shocks

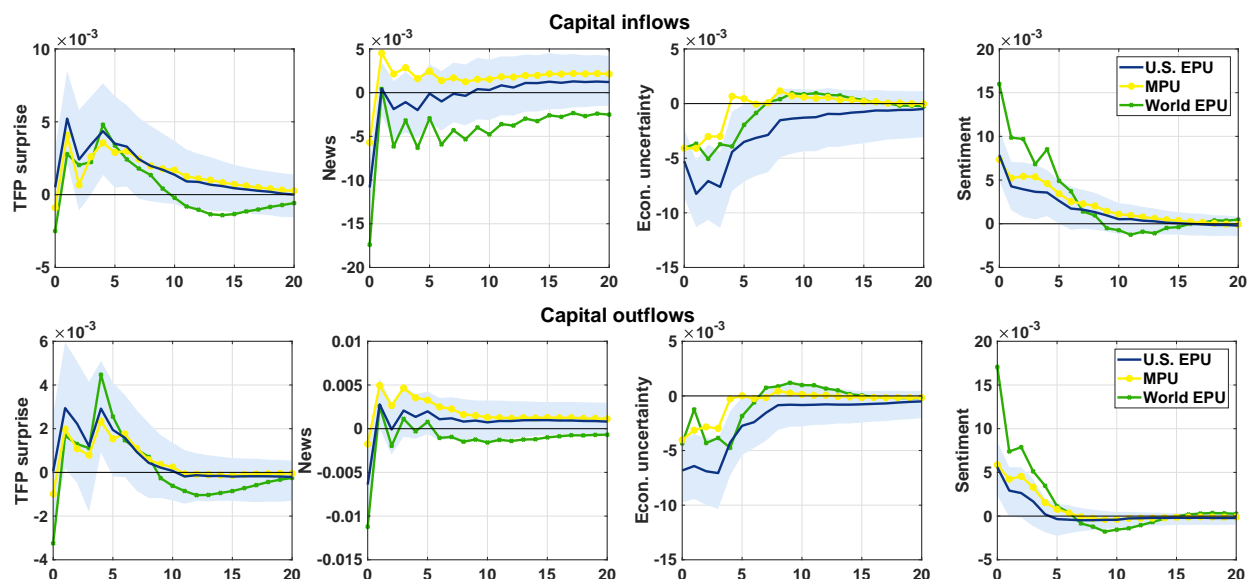


Shaded areas represent the 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with corporate BBB spread as financial conditions variable.

As 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).¹⁹ IRFs of capital flows to the shocks are presented in Figure 8. Here as well, an increase in any type of policy uncertainty shocks impacts immediately and negatively capital flows, but the responses to the other shocks remain similar although somewhat dampened.

¹⁹For the WUI, we use the index built as a GDP-weighted average of local index.

Figure 10: U.S. IRFs for capital flows to TFP surprise, news, economic uncertainty and sentiment shocks

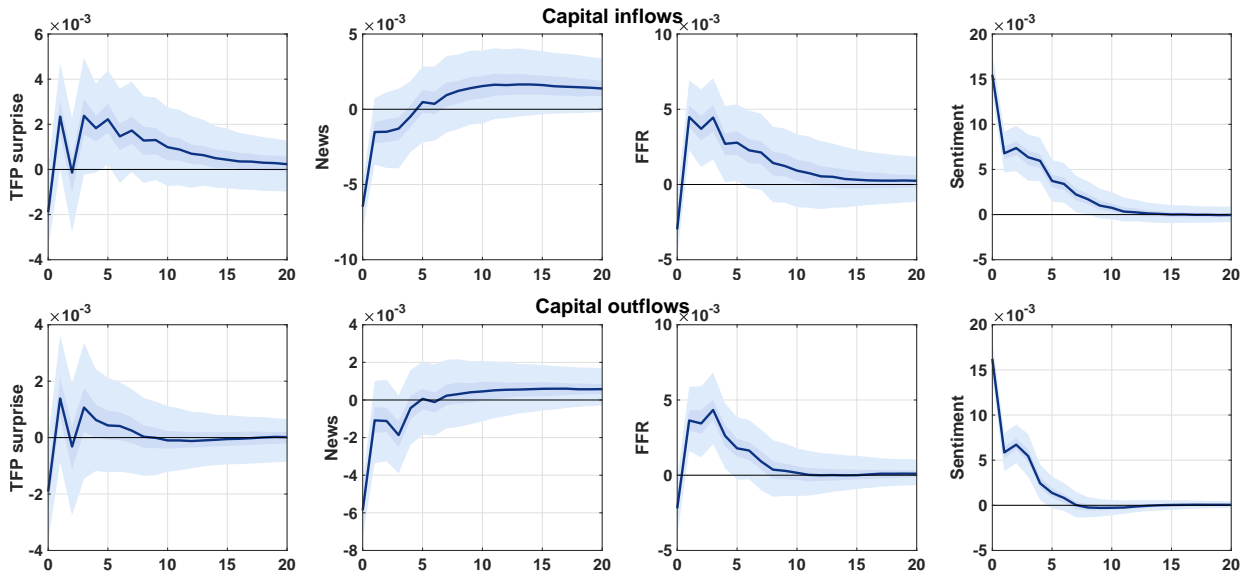


Shaded areas represent the 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with U.S. EPU as economic uncertainty variable.

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 remained significant in driving capital flows after accounting for these other shocks.

Finally, one alternative hypothesis is that sentiment shocks are reflecting monetary policy shocks. Hence, we identify here a monetary policy shock, again before the sentiment shock to give it the 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 11. 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.

Figure 11: U.S. IRFs to TFP surprise, news, monetary and sentiment shocks



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

4.4 Further robustness checks and external validity

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.2. 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.3 in Appendix A shows the panel 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, therefore assessing our findings' external validity. Hence, we use the same identification strategy but include 17 additional OECD economies.²⁰ Again, the selected countries are those for which data are available

²⁰We use a VAR specification with only 2 lags because of the more limited timespan of data availability

(especially to compute TFP variables, see Appendix C). More details about the data is available in Appendix A. 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.²¹ Then, the aggregate response function is obtained as the median across individual responses at all horizons.

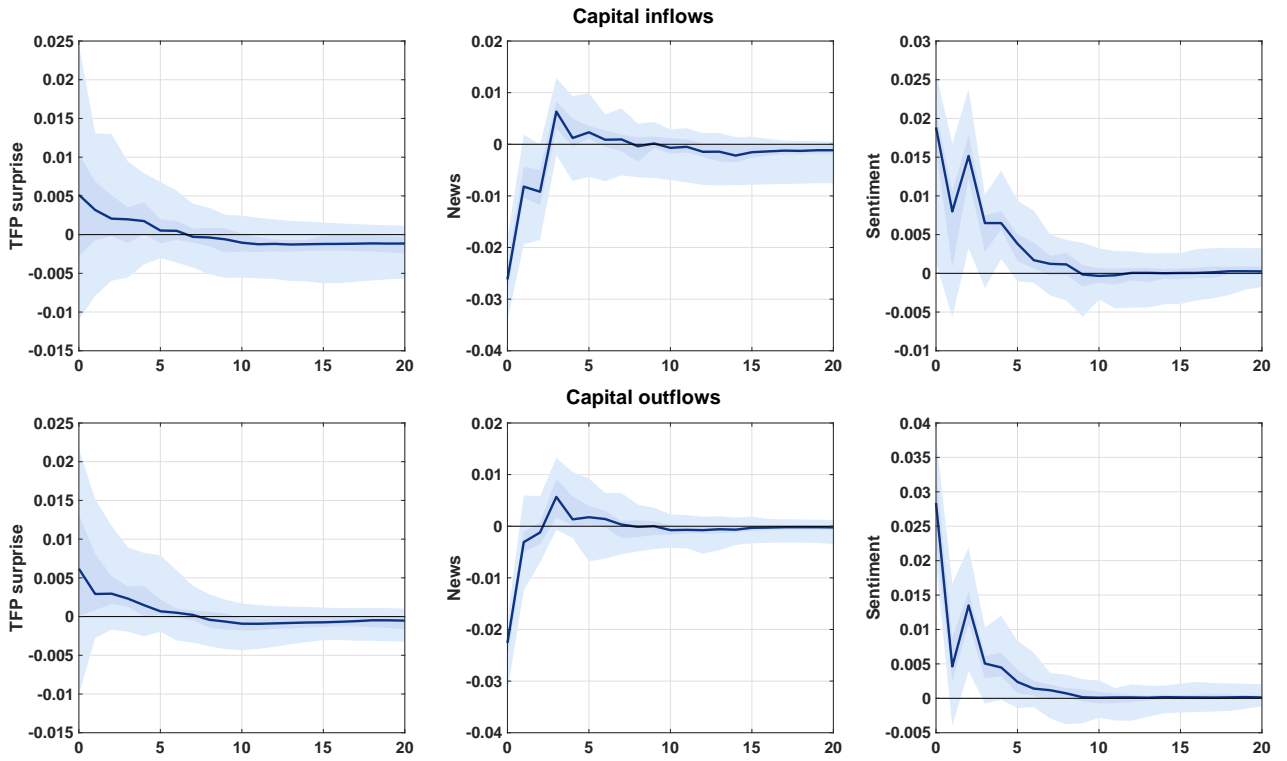
The median responses of both capital inflows and outflows to all three shocks are presented in Figure 12. Both inflows and outflows react immediately and negatively to news shocks and positively to sentiment shocks. In other words, the panel findings are similar to those for the United States alone, 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, mean responses, presented in Figure A.4 in Appendix A, lead to similar, although smoother responses. Regarding the panel forecast error variance decomposition, we see in Figure 13 that both news and sentiment shocks can explain close to 50% of the FEVD, with roughly equal contributions of the two shocks. On the contrary, TFP surprise shock plays no role in driving capital flows as pointed out by the impulse response functions and the FEVD. This suggests that if technology plays a role in explaining international capital movements, then only “anticipated” technology shocks matter.²²

for most countries. Selecting more lags or specific lags for each country does not change our conclusions, but render the IRFs less smooth.

²¹Notice that we use demeaned data to account for country-specific effects and that we use a horizon of 20 quarters for the news identification.

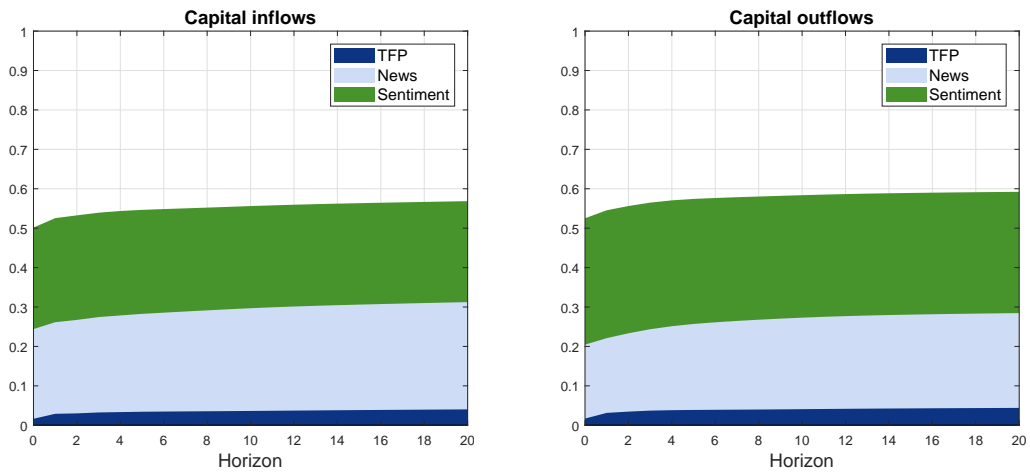
²²Note that, since TFP is less precisely measured for the panel of countries than for the U.S., we cannot exclude that part of the sentiment shock is wrongly attributed to news.

Figure 12: 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

Figure 13: Forecast Error Variance Decomposition of gross capital flows for the panel



5 A stylized model of gross capital flows with asymmetric information

We develop a two-country model of gross capital flows to understand the effects of our empirically identified shocks. We consider a simple two-period model with two assets (home and foreign), equally-sized countries and a simple information structure. Technology shocks increase the return of domestic assets, while demand shocks are shocks that reduce savings in the domestic economy. Domestic and foreign agents have asymmetric information about domestic shocks. While domestic agents get a private signal about domestic shocks, foreign agents only observe a common noisy signal about future domestic technology. We will be able to analyze three types of shocks: “news” shocks (shocks to future technology), “noise” shocks (shocks to the noisy component of the public signal) and demand shocks. We find that the effect of “news” and “sentiment” shocks documented in the data are consistent with the effects of “news” and “noise” in the model, when domestic investors have an informational advantage, while we rule out demand shocks as an explanation for “sentiment” shocks.

The home country is indexed by H and the foreign country is indexed by F . There is a unit measure of asset suppliers and of investors in each country. In period 1, each domestic investor is endowed with $1/\beta$ units of good. They can either consume it or invest it in period 1, in order to consume their dividends in period 2. In period 1, the asset suppliers of the home country are endowed with a domestic tree, which yields dividend e^δ in period 2, and the asset suppliers of the foreign country are endowed with a foreign tree, which yields dividend e^{δ^*} in period 2, with $\delta \sim \mathcal{N}(0, \sigma_\delta)$ and $\delta^* \sim \mathcal{N}(0, \sigma_\delta)$. Asset suppliers sell their tree in period 1 to investors of both countries, at price Q for the home tree and Q^* for the foreign tree, in order to consume.

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

$$U_j^H = (1 - \beta e^{-\gamma^H}) \log(C_{j1}^H) + \beta e^{-\gamma^H} E_j^H \{ \log(C_{j2}^H) \} \quad (5.1)$$

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. γ^H is a preference shock that increases the investors' demand for goods, with $\gamma^H \sim \mathcal{N}(0, \sigma_\gamma)$.

The agent is subject to the followings budget constraints:

$$\begin{aligned} C_{j1}^H + QK_j^H + Q^*K_j^{H*} &= \frac{1}{\beta} \\ e^\delta K_j^H + e^{\delta^*} K_j^{H*} &= C_{j2}^H \end{aligned} \quad (5.2)$$

K_j^H is j 's investment in the domestic asset and K_j^{H*} is her investment in the foreign asset.

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:

$$S_j^H = e^{-\gamma^H} \quad (5.3)$$

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

$$X_j^{H*} = \frac{E_j^H\{r^*-r\}}{Var_j^H\{r^*-r\}} + \frac{1}{2} \quad (5.4)$$

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. $E_j^H(\cdot)$ ($Var_j^H(\cdot)$) 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:

$$\begin{aligned} S_j^F &= e^{-\gamma^F} \\ X_j^F &= \frac{E_j^F\{r-r^*\}}{Var_j^F\{r-r^*\}} + \frac{1}{2} \end{aligned} \quad (5.5)$$

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. γ^F is the foreign demand shock, with $\gamma^F \sim \mathcal{N}(0, \sigma_\gamma)$. $E_j^F(\cdot)$ ($Var_j^F(\cdot)$) is the expectation (variance) conditional on the information of investor j of country F in period 1.

We assume that asset suppliers get utility from consuming in period 1, so that the home

asset suppliers sell the home asset in period 1 and consume Q , while the foreign asset suppliers sell the foreign asset and consume Q^* .

Gross capital inflows in the home country are changes in the foreign holdings of domestic assets $KI^H = K^F$, and gross capital outflows are changes in the domestic holdings of foreign assets $KO^H = K^{H*}$, 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 $KO^F = KI^H$. Combining savings and portfolio shares as described in (5.3)-(5.5), we can determine cross border asset holdings K^F and K^{H*} , which correspond to gross capital flows.

Equilibrium on the world's asset markets implies that the asset supply should be equal to the asset demand:

$$\begin{aligned} Q &= (1 - X^{H*})S^H + X^F S^F \\ Q^* &= X^{H*}S^H + (1 - X^F)S^F \end{aligned} \tag{5.6}$$

with $X^{H*} = \int_0^1 X_j^{H*} dj$ and $X^F = \int_1^1 X_k^F dk$ are 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).

Asymmetric information As assets demand, and hence capital flows, depends on expected returns, it is crucial to specify the information structure. We assume that there are public signals on home and foreign future productivity that are observed both by home and foreign investors. 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^* summarize the publicly available information.

The asymmetry in information goes as follows. Each home investor $j \in [0, 1]$ additionally observes a private signal on 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 $\int_0^1 \lambda_j^* dj = 0$. Besides, home investors observe their own demand shock γ^H , while foreign investors observe their own demand shock γ^F .

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). This assumption is without loss of generality. Indeed, in our setup, prices are imperfect signals of the fundamentals, because they are also driven by demand shocks.²³ As a consequence, allowing investors to extract information on fundamentals from prices would not dramatically change our results.

With this information structure, domestic and foreign investors form the following expectations about fundamentals:

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

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:

$$\begin{aligned} \bar{E}^F(\delta) &= \alpha_0 \delta + \alpha_0 e \\ \bar{E}^H(\delta) &= \alpha_1 \delta + \alpha_2 e \end{aligned} \tag{5.7}$$

where $\alpha_1 = [\alpha_0 + \kappa(1 - \alpha_0)]$ and $\alpha_2 = (1 - \kappa)\alpha_0$. We can see that, when $\kappa > 0$, 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. Domestic investors thus 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.

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

$$\begin{aligned} E_j^H(r) &= E_j^H(\delta) - q \\ E_j^F(r) &= E_j^F(\delta) - q \end{aligned} \tag{5.8}$$

²³This is similar to the finance literature, where “noise traders” make asset prices noisy signals of the fundamentals.

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

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

$$\begin{aligned} k^F &= s^F + x^F - q \\ k^{H*} &= s^H + x^{H*} - q^* \end{aligned} \tag{5.9}$$

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:

$$\begin{aligned} s^F &= -\gamma^F \\ s^H &= -\gamma^H \end{aligned} \tag{5.10}$$

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

$$\begin{aligned} x^F &= 2\phi[\bar{E}^F(\delta - \delta^*) - (q - q^*)] \\ x^{H*} &= 2\phi[\bar{E}^H(\delta^* - \delta) - (q^* - q)] \end{aligned} \tag{5.11}$$

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

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, the home asset is in limited supply, 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.

Taking into account Equations (5.10), (5.11), and the equilibrium asset prices, we show

(see details in Appendix B) that equilibrium cross-border asset holdings are:

$$\begin{aligned} k^F &= \phi [E^F(\delta - \delta^*) - E^H(\delta - \delta^*)] + \frac{\gamma^H - \gamma^F}{2} \\ k^{H*} &= \phi [E^H(\delta^* - \delta) - E^F(\delta^* - \delta)] + \frac{\gamma^F - \gamma^H}{2} \end{aligned} \quad (5.12)$$

Consider k^F , the foreign holdings of the home asset. Foreign expectations about the relative productivity of the home country have a positive effect on these foreign holdings. On the opposite, home investors' expectations about the relative productivity of the home asset have a negative effect on the foreign holdings of the home asset. This comes from the fact that a higher domestic demand for the home asset increases its price. This price increase limits the excess return of the home asset and lowers the demand of foreign investors, and it mechanically increases the share of home assets in the foreign investors' portfolios, which pushes foreign investors to sell the home asset to rebalance their portfolio.

As a result, capital flows are not affected by absolute optimism about fundamentals but by relative optimism ($\bar{E}^F(\cdot) - \bar{E}^H(\cdot)$). To understand, consider a shock (either news or noise) that generates a positive public signal on home fundamentals δ while holding everything else constant. As both home and foreign investors receive the public signal, they become both more optimistic about those fundamentals. Holding the home asset price constant, this leads both home and foreign investors to demand more of the home asset. However, in equilibrium, home (foreign) investors can hold more home assets only if foreign (home) investors hold less home assets. Therefore, optimism about home productivity changes asset holdings only to the extent that the beliefs of home and foreign are affected in an asymmetric way ($\bar{E}^F(\delta) - \bar{E}^H(\delta) \neq 0$). The adjustment then takes place through the increase in the home asset price. In equilibrium, this adjustment is large enough to keep away the agents with a relatively lower demand from the home asset.

The effect of shocks on capital flows We are now able to derive the aggregate effect of news shocks (δ), noise shocks (e) and demand shocks (γ^H) on capital flows.

The results are summarized in the following Proposition:

Proposition 1 (Capital inflows and outflows) *If $\kappa > 0$, a positive news shock on the home asset ($\delta > 0$) generates a decrease in capital inflows and outflows, and a positive noise*

shock on the home asset ($e > 0$) generates an increase in capital inflows and outflows. If $\kappa = 0$, news and sentiment shocks do not generate any capital flows.

A positive demand shock at home (γ^H) generates a decrease in capital outflows and an increase in capital inflows.

A positive demand shock at home decreases capital outflows and increases capital inflows. Indeed, an increase in the demand for goods reduces savings. This means that domestic agents invest less in both home and foreign assets. This implies that demand shocks not only generate a decrease in capital outflows, but they also cannot drive a positive correlation between inflows and outflows. A positive correlation between inflows and outflows arises only in the presence of expectation-related shocks, when there is asymmetric information ($\kappa > 0$), with a retrenchment in capital flows following a news shock and an expansion following a noise shock. Indeed, expectation-related shocks do not change total savings, so larger holdings of home assets (in the case of a news shock for instance) have to come with a reduction in foreign asset holdings.²⁴ This mechanically generates a positive correlation of flows.

Consider now more specifically the effect of news and noise shocks on capital flows. Remember that, as illustrated by (5.12), capital flows change only to asymmetric demand shifts. One parameter is especially crucial to generate asymmetric demand shifts: the relative precision of home investors' information about the home asset, which is reflected in $\kappa > 0$. In the case of a positive news shock, domestic agents are more confident about the fundamental nature of the shock. Hence, they are relatively more optimistic than foreign agents about domestic excess returns, and relatively more pessimistic about foreign excess returns. This generates a decrease in both capital inflows and outflows, as domestic agents prefer to sell foreign assets and buy back domestic assets from foreigners. In the case of a positive noise shock, foreign agents are more easily confused by the optimistic public signal. As a result, they are relatively more optimistic than home agents about domestic excess returns, and relatively more pessimistic about foreign excess returns. This generates an increase in both capital inflows and outflows, as home agents sell foreign assets and buy domestic assets from domestic agents. The effects of news and sentiment shocks identified

²⁴The independence of the saving rate from expected returns comes from log-utility, which is characterized by a unitary elasticity of intertemporal substitution, and might not hold with a more general utility function. However, the elasticity of intertemporal substitution is consistently estimated to be close to one in the data.

in the data are therefore consistent with the effects of news and noise shocks in our model with information asymmetries.

6 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 around 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. This suggests that the increase in cross-border capital positions is not related to better fundamentals, but rather driven by surges in optimism unrelated to future productivity. 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, even though forces driving these flows are not necessarily global.

These results are largely consistent with a model where domestic agents have an informational advantage over foreigners about domestic fundamentals. A relatively higher optimism among domestic agents explains the typical increase in home bias triggered by a news shock, while a relatively higher optimism among foreign agents explains the typical capital flows expansions observed in the case of a sentiment shock.

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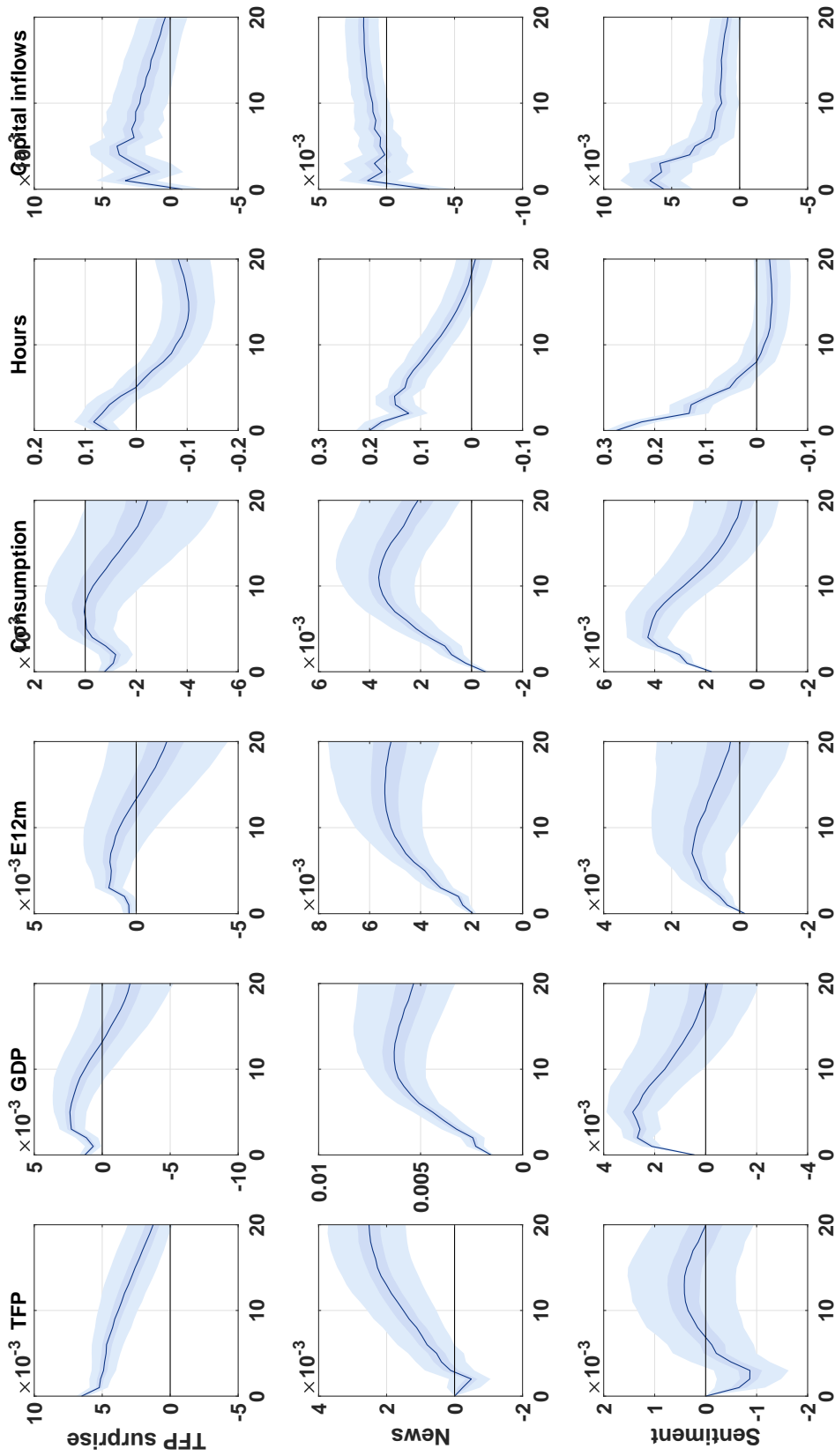
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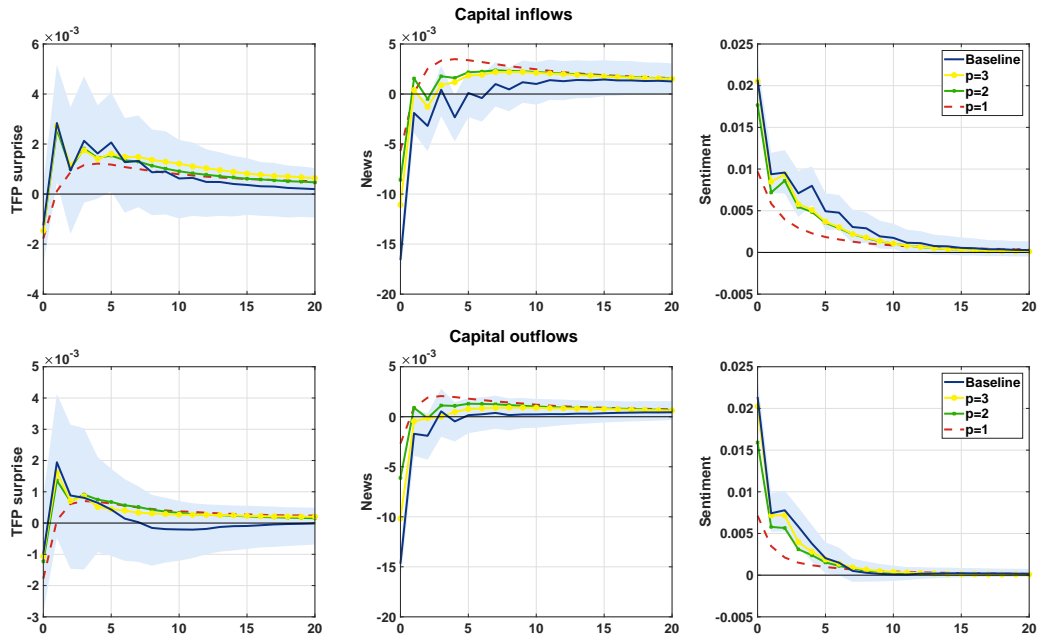
A Additional results

Figure A.1: U.S. IRFs to TFP surprise, news and sentiment shocks - with consumption and hours



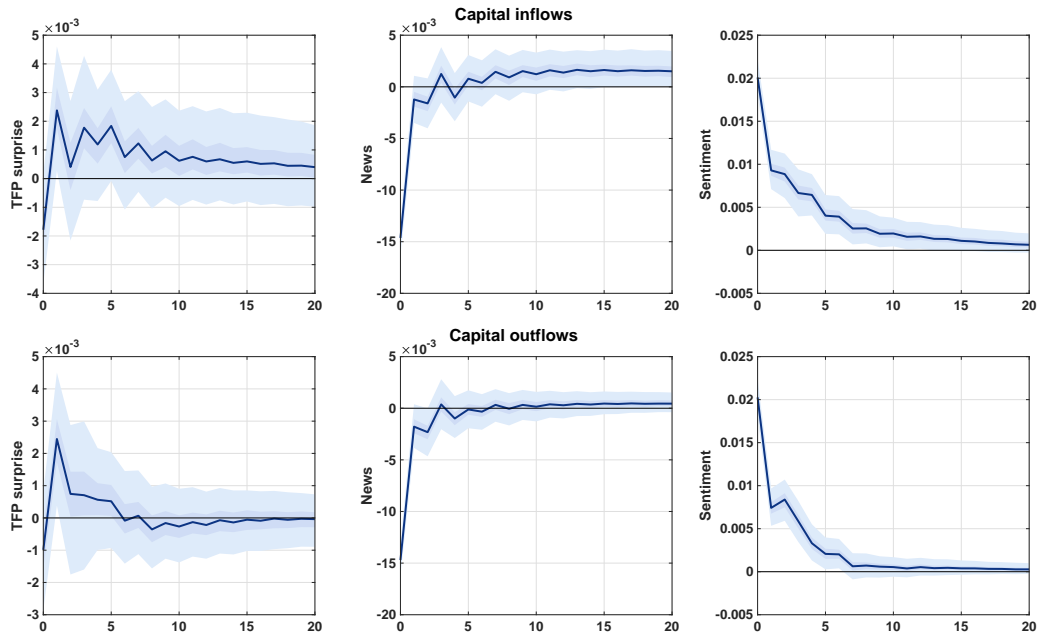
Dark and light shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.2: Capital flows IRFs to TFP surprise, news and sentiment shocks – Various lag specifications



Shaded areas represent the 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors. Confidence intervals are built for the model with $p = 4$.

Figure A.3: Capital flows IRFs to TFP surprise, news and sentiment shocks – Including both inflows and outflows in estimation



Shaded areas represent the 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors.

A.1 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. In order to assess the quality of our approach, we compute a TFP series for the United States and compare it with the 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. So if anything, bad measures of TFP imply less important effects of news shocks.

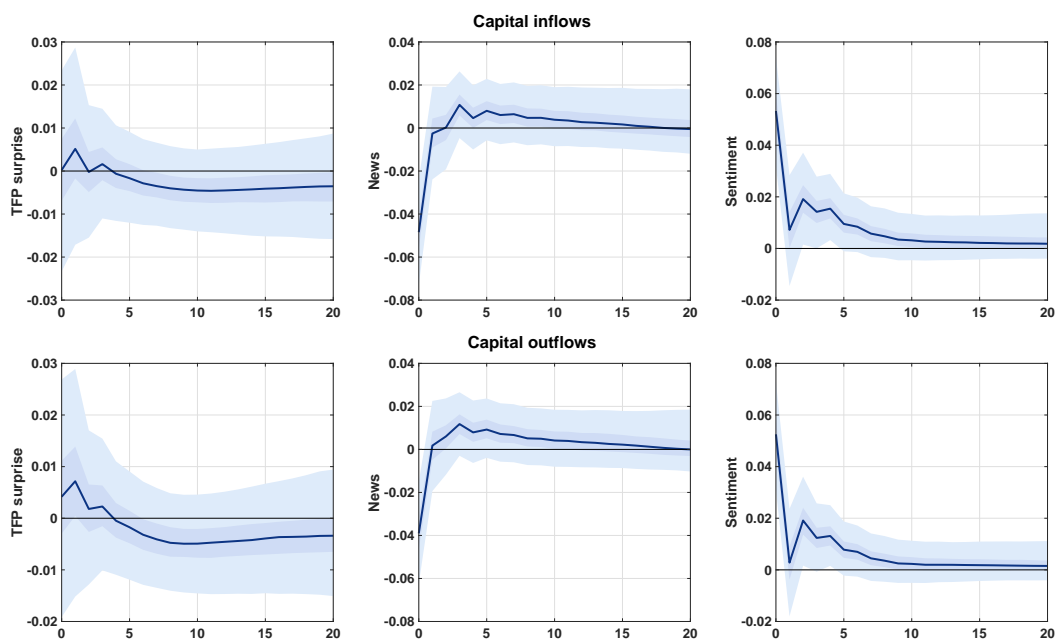
For output, we use the chain-weighted real GDP variable from the OECD database. Labor force - active population aged 15 or over, is obtained from the ILO. As expectations' variable, we use the forward-looking component of the consumer confidence index. The survey question considered is the following: "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 they compute the net balance. The countries in our sample are selected based on data availability and are listed below with their respective timespan.

²⁵The question described here is the one asked to 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](#)).

Table A.1: Time coverage including baseline data

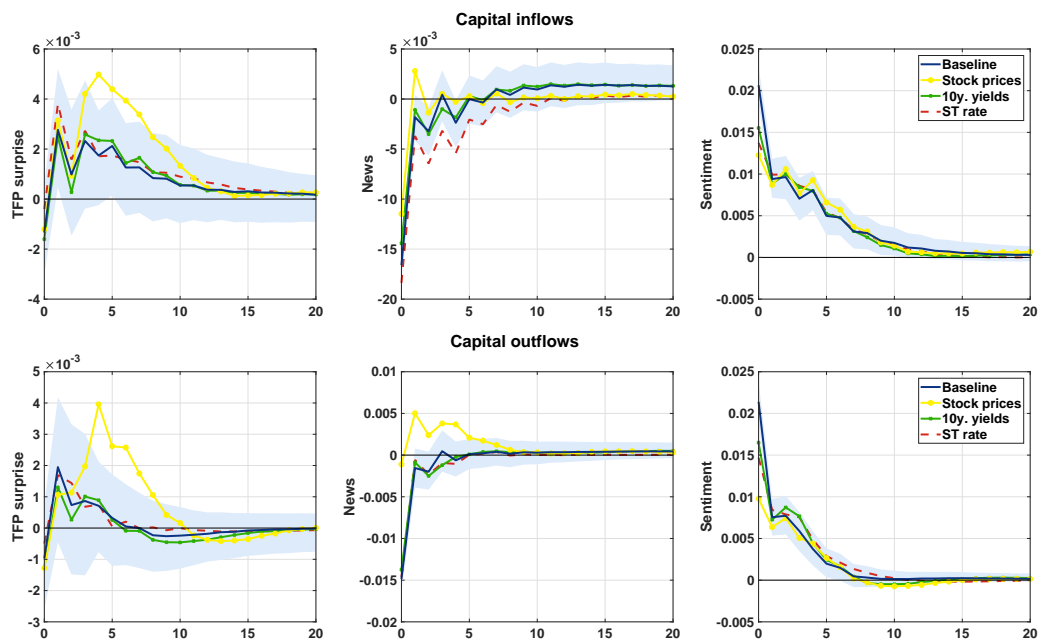
Panel - OECD economies		
Australia	1995Q1	2018Q3
Austria	2005Q1	2018Q3
Belgium	2002Q1	2018Q3
Czech Republic	1995Q3	2018Q3
Denmark	1995Q3	2015Q4
Estonia	2000Q3	2017Q4
Finland	1990Q3	2017Q4
France	1985Q1	2018Q3
Germany	1992Q1	2018Q3
Ireland	2005Q1	2018Q3
Italy	1996Q3	2018Q3
Netherlands	1996Q3	2018Q3
Portugal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

Figure A.4: Panel mean IRFs to TFP surprise, news and sentiment shocks



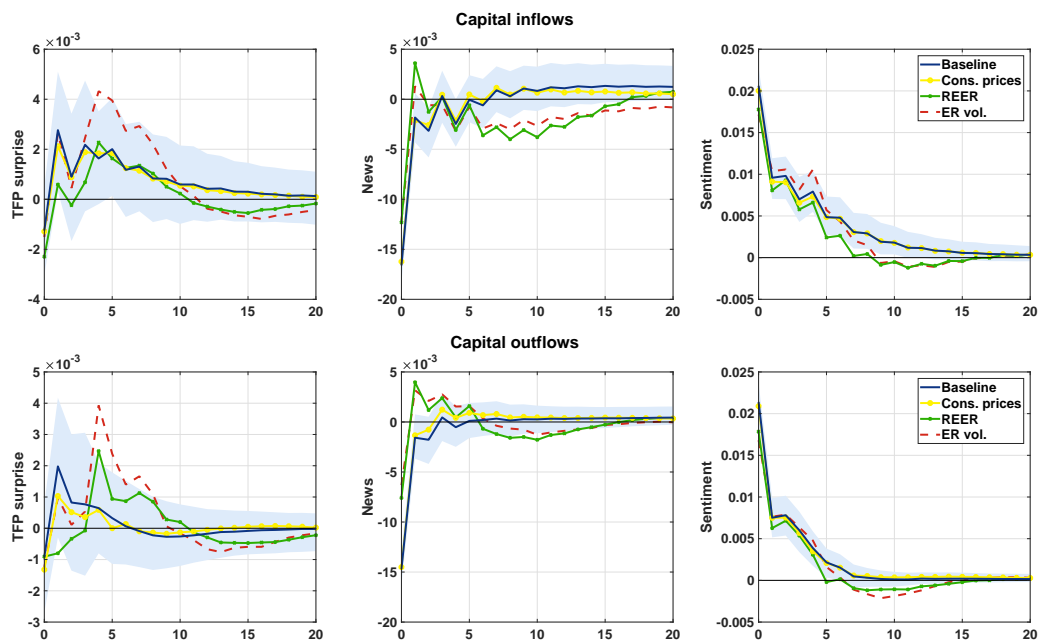
Dark and light shaded areas represent the 67.5% and 90% confidence intervals from 2000 bias-corrected bootstrapped standard errors

Figure A.5: IRFs of capital flows to TFP surprise, news and sentiment shocks with additional variables in the specification



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

Figure A.6: IRFs of capital flows to TFP surprise, news and sentiment shocks with additional variables in the specification



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

B Model appendix

B.1 Proof of equations (5.3)-(5.5)

Consider j investor's program in country H . Define as $s_j^H = S_j^H/\beta$ the share of savings in the total investor's endowment 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

$$U_j^H = (1 - \beta e^{-\gamma^H}) \log(1 - s_j^H) + \beta e^{-\gamma^H} E_j^H \{ \log(s_j^H) + \log(e^r(1 - X_j^{H*}) + e^{r^*} X_j^{H*}) \} - \log(\beta)$$

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

$$\frac{(1 - \beta e^{-\gamma^H})}{1 - s_j^H} = \frac{\beta e^{-\gamma^H}}{s_j^H} \tag{B.1}$$

$$E_j^H \{ e^{r - \tilde{r}_j} \} = E_j^H \{ e^{r^* - \tilde{r}_j} \} \tag{B.2}$$

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

After rearranging, (B.1) yields a constant saving rate across investors $s_j^H = s^H = \beta e^{-\gamma^H}$, and hence (5.3). Using the fact that $E(e^x) = e^{E(x) + \frac{1}{2}Var(x)}$ when x is normal, (B.2) yields:

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

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

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

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:

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

which yields (5.4).

Equations (5.5) are derived in a similar way by solving the foreign investors' program.

B.2 Proof of Equation 5.12

Asset prices are thus key to determine capital flows. Log-linearizing equations (5.6), we establish

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

Using the equilibrium equations (5.6), we can also show that $q + q^* = -\gamma^H - \gamma^F$: demand shocks decrease the global demand for assets, which decrease the global asset price. We can derive the equilibrium home asset price:

$$q = \frac{\phi}{1 + 4\phi} [E^H(\delta - \delta^*) + E^F(\delta - \delta^*)] - \frac{\gamma^H + \gamma^F}{2} \quad (\text{B.3})$$

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 foreign asset price q^* is then obtain simply as $q^* = -q - \gamma^H - \gamma^F$.

Using Equations (5.10), (5.11), (B.3) and $q^* = -q - \gamma^H - \gamma^F$, we obtain (5.12).

B.3 Proof of proposition 1

Using the expression for cross-border holdings (5.12) and the expression for expectations (5.7), we can show that

$$\begin{aligned}k^F &= -\phi(\alpha_1 - \alpha_0)\delta + \phi(\alpha_0 - \alpha_2)e + \dots \\k^{H^*} &= -\phi(\alpha_1 - \alpha_0)\delta + \phi(\alpha_0 - \alpha_2)e + \dots\end{aligned}$$

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

Since $\kappa > 0$ in the presence of asymmetric information, we have $\alpha_1 = [\alpha_0 + \kappa(1 - \alpha_0)] > \alpha_0 > \alpha_2 = (1 - \kappa)\alpha_0$. 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.

In the absence of asymmetric information ($\kappa = 0$), δ and e generate no capital flows.

C 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:

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

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 $\widehat{\beta}$ 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.

