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Growth Prospects and the Trade Balance in Advanced Economies

Abstract

Does an improvement in growth prospects lead to a fall in the trade balance? The relevance of this question stems from the tendency for countercyclical fluctuations in the trade balance stressed by both the academic literature and policymakers. However, we do not find that improved growth prospects (news shocks) necessarily lead to negative trade balance effects in the G7 countries. We develop a novel news shocks identification scheme, apply it to country-level vector autoregressions (VARs), and obtain the following results. While in the U.S., news shocks induce a persistent deterioration of the trade balance, the negative trade balance effect in Germany is only temporary. By contrast, in other G7 countries, news shocks induce positive and transitory trade balance effects. Consumption smoothing and substantial fluctuations in investment and labor input are important drivers of these results for the U.S., and less so in other G7 countries. Therefore, policy recommendations to reduce the trade imbalances through productivity-enhancing reforms in advanced economies are likely to yield only temporary effects.

JEL-Code: F41, E32, F32, D83, O40

Keywords: Terms of trade; trade balance; news shocks; productivity; learning

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1 Ansgar Belke, UDE, Centre for European Policy Studies, Brussels, Institute of Labor Economics, Bonn and King's College, London; Steffen Elstner, RWI; Svetlana Rujin, RWI and RUB. *– We thank Daniel Gros, Danilo Cascaldi-Garcia, Volker Clausen, Gregor von Schweinitz, Roland Döhrn, and the participants of the 29th Annual Meeting of the Midwest Econometrics Group in Columbus (Ohio) for helpful comments and suggestions.-* *All correspondence to: Svetlana Rujin, RWI, Hohenzollernstr. 1/3, 45128 Essen, Germany, e-mail: svetlana.rujin@rwi-essen.de*

1 Introduction

The trade balance positions across the G7 countries diverged substantially in recent decades. While the U.S. and the U.K. experienced a persistent trade balance deficit, other advanced economies exhibited a sustained buildup of the trade balance surpluses.[1]

The persistence of these trade imbalances has prompted a lot of research and has been involved in major policy debates. Krugman and Baldwin (1987) relate the failure of the U.S. trade deficit to improve to a sluggish growth of foreign demand as opposed to a robust performance of the U.S. economy, which recent studies find to be an optimal outcome.[2] To fix these imbalances, economic officials call for productivity-enhancing reforms leading to an improvement in output growth prospects in advanced economies whose economic performance is lagging behind the U.S.[3]

Our study challenges this proposition and asks whether a persistent improvement in growth prospects generates countercyclical trade balance fluctuations. Literature finds that the existence of the imbalances might reflect a convergence process between countries with different income levels per capita, which may in turn be determined by the differences in their productivity levels (Blanchard and Giavazzi, 2002; Glick and Rogoff, 1995; Iscan, 2000; Marquez, 2002).[4] A balanced position may not be optimal in the short run, and policy interventions directed to restore the balance can be harmful in this case. In line with the intertemporal approach to the current account, countries with lower per capita income may attract foreign capital due to higher growth perspectives. Consistent with the consumption smoothing assumption, they should consume more and save less in anticipation of higher permanent income. Thus, domestic absorption is higher than output, implying external deficits over the catching up period. Similarly, richer countries tend to run current account surpluses (Gourinchas and Rey, 2007).

While an improvement in a country's growth prospects cannot be directly observed, it can be inferred, i.a., from the expected domestic productivity level. To obtain these measures for the G7 countries, we develop a novel identification scheme of exogenous productivity-enhancing changes in technology that are expected in advance, the news shocks, and apply it to country-level VARs. The literature on news shocks builds around the idea that forward-looking agents observe productivity-enhancing changes in technology well in advance of their effect on the economy's productive capacity. These shocks result in predictable and persistent changes in the productivity level.

[1] Furthermore, Belke and Dreger (2013) show that while the current account of the euro area countries has been close to being balanced over the past decades at the aggregate level, the disparities across the member states are striking. Persistent current account deficits of Greece, Portugal, and Spain were accompanied by large surpluses in Germany and the Netherlands.

[2] See Hoffmann, Krause, and Laubach (2017), Engel and Rogers (2006), Aguiar and Gopinath (2007). The development of the current account has been traced back to such factors as catching up, competitiveness, and moderate wage growth (Belke and Dreger, 2013; German Council of Economic Experts, 2014).

[3] See European Commission (2019) and International Monetary Fund (2019).

[4] Assessing the impact of productivity increases on the trade balance was of interest, however, already in the early 1970s (see, for example, Kretzmann, 1974).

Related studies extract changing perceptions about long-run economic developments using proxy measures, such as stock prices (Beaudry and Portier, 2006), consumer confidence (Barsky and Sims, 2012), forecast data (Miyamoto and Nguyen, 2014), survey expectations of long-run (6 to 10 years ahead) output growth (Hoffmann et al., 2017), changes in the expected share of U.S. income (Engel and Rogers, 2006), and consumption and income data (Aguiar and Gopinath, 2007). Furthermore, Kurmann and Otrok (2013) use the spread between the yield on a long-term treasury bond and a short-term bill rate, and Cascaldi-Garcia and Vukotić (2019) use firm-level data on patent grants and subsequent reactions of their stocks to extract the news shocks. In contrast, Arezki, Ramey, and Sheng (2017) use the worldwide giant oil and gas discoveries as a directly observable measure of news shocks about future output.

The focus on the trade balance effects of news shocks is motivated by the findings in Aguiar and Gopinath (2007) and Hoffmann et al. (2017), who show that a positive shock to productivity is an important source of countercyclical fluctuations in the trade balance. Moreover, the persistence of this shock determines the strength of its negative effect on the trade balance. Therefore, a particularly important feature of a news shock is that it diffuses slowly over time and therefore generates a persistent increase in productivity level.

From the perspective of the intertemporal approach to the trade balance (Obstfeld and Rogoff, 1996), the anticipated and unanticipated changes in future economic developments imply different incentives for savings and investment decisions (Barsky, Basu, and Lee, 2015). The unanticipated technology shock increases current and expected future income. However, consumption does not increase by the same amount as output in the current period. As a result, the trade balance improves. By contrast, the anticipated changes in future economic developments, which we capture by extracting the news shocks, induce a higher consumption in the current period even though the current output is still produced with the old technology. It follows that the savings behavior plays an important role for the countercyclical fluctuations in the trade balance following an anticipated shock.

The effects of the anticipated improvements in future output growth on investment and labor input are ambiguous. The responses of these variables to anticipated shocks crucially depend on the preferences that govern the wealth elasticity of labor supply and the assumed real rigidities (Jaimovich and Rebelo, 2009; Schmitt-Grohé and Uribe, 2012).

Taken together, the news shocks are expected to generate a trade deficit, which is, for example, the basis for several policy statements proposed by the European Commission to the German government regarding its current account surplus.

Our identified news shocks lead to a permanent increase in the productivity level, which is accompanied by an increase in productivity growth in the transition period to its higher level. The results for the U.S. show that an improvement in growth prospects leads to a gradual and persistent deterioration of the trade balance, which is in line with previous studies. The sources behind countercyclical fluctuations in the trade balance are sustained increases in consumption, investment, and labor input, which make the domestic absorption more variable than output and thus induce a negative trade balance effect.

For Germany, however, we find a transitory deterioration of the trade balance in response to improved growth prospects. While consumption in Germany settles at a permanently higher level in expectation of a higher future output growth, this increase is less pronounced compared to the U.S. At the same time, investment and labor input do not show substantial fluctuations following an improvement in domestic growth prospects. For the remaining G7 countries, we find mixed results concerning the transmission of an improvement in domestic growth prospects to the real economy. Surprisingly, we find that the news shocks generate positive and short-lived trade balance effects in these countries.

The remainder of this paper proceeds as follows. In Section 2, we discuss the transmission of news shocks to the trade balance based on the intertemporal approach. In Section 3, we review the recent literature on news shocks and propose an alternative identification approach. In Section 4, we discuss our key results. In Section 5, we check the robustness of our baseline results. Section 6 concludes the analysis.

2 The effects of expectations on the trade balance

Hoffmann et al. (2017) and Engel and Rogers (2006) show that the U.S. current account deficit is consistent with the intertemporal optimizing behavior of forward-looking agents to expected changes in future economic developments. Aguiar and Gopinath (2007) reach similar conclusions studying the current account fluctuations in emerging markets. Following Beaudry and Portier (2014), changes in agents' expectations about future economic developments occur due to the arrival of news that is useful for predicting future economic fluctuations. The authors stress that while there are many sources of changes in expectations concerning different macroeconomic variables, the literature focuses on the role of technological news, that is expected future changes in productivity level.[5]

When analyzing the forces behind trade balance fluctuations, it is crucial to distinguish between two structural shocks that affect the aggregate productivity level (see, for example, Barsky and Sims, 2011). First, the *unanticipated* technology shock that induces an immediate increase in the productivity level. Second, the *anticipated* technology shock—the news shock—that diffuses slowly over time and therefore generates a gradual and persistent increase in the productivity level. Following the expositions in Barsky and Sims (2011), the stochastic process characterizing the aggregate level of productivity, denoted by $\ln A_t$, can be represented by the following moving average process:

[5] Schmitt-Grohé and Uribe (2012) provide insights into how news about future changes in different macroeconomic variables affects the behavior of forward-looking agents. Following Beaudry and Portier (2014), agents who accurately form expectations of future economic developments adjust their behavior before the anticipated changes materialize. Hoffmann et al. (2017) study the effects of shocks to productivity under different assumptions about the agents' expectations formation process. They show that imperfect information in conjunction with a news shock is able to explain the gradual and persistent decline of the U.S. current account.

$$lnA_t = \begin{bmatrix} B_{11}(L) & B_{12}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \quad (1)$$

where ε_{1t} is the unanticipated technology shock and ε_{2t} is the news shock. The timing assumptions related to the effects of ε_{1t} and ε_{2t} on $\ln A_t$ are crucial to isolate the two shocks. While ε_{1t} is allowed to affect $\ln A_t$ contemporaneously, the literature identifies the news shock ε_{2t} using the assumption that it is the shock that best explains future movements in $\ln A_t$.[6] Thus, forward-looking agents incorporate the *news* about future productivity level into their behavior before the expected changes materialize.

The unanticipated technology shock and the news shock imply different incentives for agents' savings and investment decisions (Barsky et al., 2015; Arezki et al., 2017). Consequently, Aguiar and Gopinath (2007) and Hoffmann et al. (2017) show that the two types of shocks to productivity have markedly different implications for the trade balance.[7] While the unanticipated technology shock generates a positive relationship between output and the trade balance, the news shock induces countercyclical fluctuations in the trade balance, that is the trade balance deteriorates. The difference in these effects is mainly driven by the agents' savings behavior. Given that news shocks diffuse gradually over time, agents are willing to increase their current spending in the expectation of a persistently higher future income. As a result, this shock is associated with a positive wealth effect, causing a stronger reaction of consumption compared to output. Overall, savings decline and the trade balance deteriorates. By contrast, in case of an unanticipated technology shock, consumption responds less than output, leading to an increase in savings and an improvement in the trade balance.

The effects of news shocks on investment and labor supply are ambiguous. Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), and Arezki et al. (2017), for example, show that the reactions of these variables to news shocks crucially depend on the specification of the preferences that govern the wealth elasticity of labor supply and the assumed real rigidities, like the internal habit formation in consumption, investment adjustment costs, variable capacity utilization, and imperfect competition in labor markets. A similar statement can be made for the unanticipated technology shocks. Overall, it is often the case that in the same theoretical model, the news shock and the unanticipated technology shock lead to different reactions of investment and labor. It is, therefore, important to distinguish between both shocks in our analysis.

Our research focuses on the consequences of technological news as we are primarily interested in the effects of improved growth prospects on the trade balance. To the best of our knowledge, the literature concerning the link between news shocks and the trade balance is

[6] Barsky and Sims (2011) assume that news shocks have no contemporaneous effect on $\ln A_t$, which translates into imposing the impact zero restriction $B_{12}(0) = 0$ in (1).

[7] In the presence of the terms of trade adjustments to these shocks, the explanation of the trade balance effects of the two types of shocks to productivity is even more challenging. Enders and Müller (2009) provide a detailed analysis of the transmission of the unanticipated technology shocks to the U.S. trade balance in the presence of the terms of trade adjustments to these shocks.

scarce.[8] Specifically, we aim at identifying structural shocks that induce a delayed and permanent improvement in the productivity level, but do not affect it immediately. In the transition period to the permanently higher productivity level, this shock is expected to induce higher growth rates of productivity, which we associate with an improvement in growth prospects. The increase in the productivity growth rates is, however, only transitory. Our empirical analysis and, in particular, our identification approach, face several challenges:

1) We need to isolate unanticipated and anticipated technology shocks from other structural shocks (e.g. demand shocks). The other structural shocks are not allowed to affect the true productivity level of the economy.

2) Our identification approach needs to separate unanticipated and anticipated (news) technology shocks.

3) We need to insure that the news shocks affect the future productivity level permanently. Put differently, our news shock must have only a transitory effect on productivity trend growth.

3 Identification of news shocks

3.1 Revisiting the basic identification approaches

Our identification news shocks draws on two approaches proposed in the literature.[9] The first approach, introduced by Barsky and Sims (2011) (BS), extracts news shocks using a medium-run identification procedure developed by Uhlig (2004a,b). BS identify the *news* as the shock that is orthogonal to the contemporaneous innovation in the cyclically adjusted technology measure that best explains variations in future technology. In contrast to Uhlig (2004a,b), who uses labor productivity, BS use utilization-adjusted total factor productivity (PTFP) by Fernald (2014). However, this PTFP measure is only available for the U.S., which is a challenge for our analysis.

The second approach relies on Kurmann and Sims (2019) (KS), who show that the results in BS are sensitive to revisions in PTFP. They therefore develop a robust identification of news shocks that differs from the BS model in two aspects. First, instead of cumulatively maximizing the FEV shares over all horizons from impact onward, KS extract the news shock that accounts for the maximum forecast error variance (FEV) share of PTFP at one long horizon using the Max Share approach by Francis, Owyang, Roush, and DiCecio (2014).[10] Notably, this approach should substantially reduce the contribution of the non-technological component that may remain in PTFP to the extracted news shock. Second, KS drop the zero restriction because it may lead to biased estimates of the impact responses to the news shock. KS argue that if PTFP is an inaccurate measure of *true* technology, then its non-technological

[8] A notable exception is Berg (2013), who examines the role of stock price shocks, which he interprets as shifts in expectations, in explaining current account fluctuations in 17 OECD countries.

[9] A comprehensive summary of the literature on news shocks can be found in Beaudry and Portier (2014).

[10] In contrast, Francis et al. (2014) use a VAR with labor productivity to identify technology shocks.

component reacts immediately to a news shock and thus violates the orthogonality assumption. Moreover, forward-looking agents may update their expectations about future productivity based on currently realized changes in technology (Barsky et al., 2015).

3.1.1 The medium-run identification technique

Consider the reduced-form moving average (MA) representation of Y_t, a $k \times 1$ vector of variables at time t, with productivity ordered first:

$$Y_t = C(L)u_t, \tag{2}$$

where u_t is a vector of prediction errors with covariance matrix Σ_u.[11] The vector of structural shocks ε_t can be represented as a linear combination of prediction errors $u_t = A\varepsilon_t$. To obtain ε_t, the impact matrix A must satisfy $\Sigma_u = AA'$, which given the symmetry of Σ_u is not unique. The Cholesky decomposition of Σ_u gives such a matrix $\tilde{A}$, which allows to summarize the entire space of acceptable impact matrices as $A = \tilde{A}Q$, where Q is a $k \times k$ orthonormal matrix ($QQ' = I$). Thus, the structural MA representation of Y_t takes the form:

$$Y_t = C(L)\tilde{A}Q\varepsilon_t. \tag{3}$$

The idea of the medium-run identification approach by Uhlig (2004b) is to find the structural shock that accounts for the largest FEV share of some variable $y_{i,t}$ in Y_t over the forecast horizons $h = \underline{h} \leq \overline{h}$.[12] The h-step ahead forecast error of $y_{i,t}$ can be written as:

$$y_{i,t+h} - E_t y_{i,t+h} = e_i' \left[\sum_{l=0}^{h-1} C_l \tilde{A} Q \varepsilon_{t+h-l} \right], \tag{4}$$

where e_i is a column vector with one in the i-th position and zeros elsewhere. The shock explaining most of the FEV of the i-th variable in Y_t results from the maximization problem:

$$q_1^* = arg \ \underset{q_1}{max} \ e_i' \left[\sum_{h=\underline{h}}^{\overline{h}} \sum_{l=0}^{h-1} C_l \tilde{A} q_1 q_1' \tilde{A}' C_l' \right] e_i, \quad \text{s.t.} \quad q_1' q_1 = 1, \tag{5}$$

where q_1 is a vector of unit length that represents a column of Q. Uhlig (2004b) shows that the maximization problem in (5) can be expressed as $Sq_1 = \lambda q_1$, where $S = \sum_{h=\underline{h}}^{\overline{h}} \sum_{l=0}^{h-1} (C_l\tilde{A})'(e_i e_i')(C_l\tilde{A})$. To find the structural shock associated with the largest FEV of $y_{i,t}$ over $h = \underline{h} \leq \overline{h}$, we need to find the eigenvector q_1 with the maximal eigenvalue λ of the matrix S.

The Max Share approach by Francis et al. (2014) is a special case of the maximization problem (5), as it extracts the shock explaining the maximum FEV share of a variable in Y_t at one horizon instead of cumulatively maximizing the FEV shares over all horizons from $\underline{h}$ to $\overline{h}$.

[11] The constant is omitted to save on notation. The estimation of an unrestricted VAR gives $C(L)$ and Σ_u.

[12] $\underline{h}$ and $\overline{h}$ are, respectively, the starting and ending points of the maximization horizon.

3.2 An alternative identification of news shocks

To conduct our empirical analysis, we propose a novel identification approach that combines the key elements of the BS and KS methods. We need to deviate from the pure BS and KS methods, as PTFP is only available for the U.S. We use labor productivity as our technology measure to extract the news shocks. In contrast to PTFP, labor productivity is not adjusted for cyclical variations in factor utilization, which has implications for the identification of news shocks. While short-run shocks appear to more easily account for fluctuations in factor utilization over shorter horizons (Uhlig, 2004b), predictable fluctuations in utilization become negligible at longer horizons (Barsky et al., 2015).

Following the discussion in Section 2, technology is driven by two exogenous processes: (i) the unanticipated technology shocks that explain the largest shares of changes in the productivity level over shorter horizons and (ii) the news shocks that diffuse slowly over time and induce persistent changes in the future productivity level.[13] The key feature of the Max Share identification is that while it extracts the shock that is the *dominant* source of fluctuations in the productivity level at long horizons, it also allows other shocks to play a role.[14] Therefore, applying the Max Share routine to a VAR with labor productivity is likely to extract a shock containing both short- and long-run components of the technology process. However, we need to disentangle both types of structural shocks as they have presumably different implications for the dynamics of the trade balance.

Our news shock identification approach consists of three steps. In the first step, we apply the Max Share routine to a VAR with labor productivity (in levels) to extract the shock containing both short- and long-run components of the technology process. We identify the candidate shock as the one that explains the largest FEV share of fluctuations in the level of labor productivity at one long horizon of 80 quarters ($h(1) = 80$).

In the second step, we exploit the idea that the short-run fluctuations in the technology process are mainly caused by the unanticipated technology shocks. Using the same VAR specification as in the first step, we extract the shocks that cumulatively maximize the FEV shares of fluctuations in the level of labor productivity over all horizons from impact and up to eight quarters ($h(2) = 0-8$). Following Uhlig (2004b), we set the length of the maximization horizon $h(2)$ to eight quarters to isolate the short-run shocks. Choosing a maximization horizon between zero and eight quarters seems to be arbitrary at first glance. However, in our robustness checks we show that the baseline results do not change for horizons of up to four or twelve quarters.

Importantly, in this setting, news shocks are allowed to affect labor productivity on impact and over the maximization horizon $h(2)$. Note that extracting the shock that maximizes the

[13] See, for example, Beaudry and Portier (2006), Barsky and Sims (2012), Kurmann and Otrok (2013), Barsky et al. (2015), Kurmann and Sims (2019).

[14] In contrast, Galí (1999) assumes that technology is the *only* source of fluctuations in the productivity level in the long run.

FEV share of labor productivity only on impact ($h(2) = 0$) is equivalent to the zero impact restriction of the BS model.

In the third step, we regress the Max Share shock covering short- and long-run fluctuations in the level of labor productivity from the first step on the short-run shocks from the second step. The residuals from this regression represent our series of news shocks, which we use to compute the impulse response functions (IRFs) in a standard VAR setting.

Alternatively, the BER identification approach can be implemented as follows. Instead of deriving the news shocks using the auxiliary regression in the third step, one can apply the QR-decomposition to the two eigenvectors that originally define the shocks in the first and second steps. This approach is proposed by Cascaldi-Garcia and Galvao (2018) and leads to identical results as the third regression step. Employing the QR-decomposition to both eigenvectors yields two new vectors that define the two structural shock series that are orthogonal to each other. Importantly, the original eigenvector determining the short-run shock ($h(2) = 0 - 8$) must be ordered before the eigenvector explaining the largest FEV share of labor productivity at the 80-quarter horizon ($h(1) = 80$). The new identification restrictions are thus obtained from the orthonormal "Q part" of the QR-decomposition. The second column of the "Q part" defines the main restrictions for the news shock.

In sum, our news shocks identification offers a more flexible setting for isolating the unanticipated and anticipated (news) technology shocks by specifying the length of the horizon over which the FEV share of the shock of interest is maximized. Another important advantage of our identification over the BS approach is that we relax the controversial restriction of impact orthogonality between news and the measure of technology by assuming that the FEV of technology over short-run horizon is *dominated* by the unanticipated technology shock.

3.3 Comparison of the results for the U.S.

To compare the results from the BER identification with the outcomes of the BS and KS models, we estimate the following 7-variable VARs, which include quarterly U.S. data. We use, one at a time, the 2015 vintage of PTFP (PTFP-15) and hourly labor productivity (LP), defined as the ratio of real GDP to total hours worked, as our measures of technology.[15] The VARs also include real consumption of non-durables and services, real investment, total hours worked in the non-farm business sector, inflation measured as the growth rate of the GDP price deflator, the real stock price (nominal S&P 500 index deflated by the GDP price deflator), and consumer confidence (a qualitative index of five-year ahead business condition expectations). Consumption, investment, and hours are expressed in per capita terms by dividing the series by the civilian non-institutionalized population aged sixteen and over. The macroeconomic aggregates are from the NIPA tables and all variables are available for download on the homepage of Eric Sims (see also Sims, 2016). All variables are specified in log levels,

[15] Our VAR specification closely follows Barsky and Sims (2011) and Sims (2016). Because, in contrast to these studies, we use labor productivity instead of PTFP as our measure of technology to extract the news shocks, we deviate from their original specifications by not including real GDP in the VARs.

except for the inflation rate.[16] The VARs are estimated with four lags and a constant over the period 1960:1–2007:3, excluding the period since the Great Recession.

Table 1: **Correlations of U.S. news shocks**

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Identification scheme	BS	BS	KS	KS	BER	BER	BER	BER
Target variable	PTFP-15	PTFP-15	PTFP-15	LP	PTFP-15	PTFP-15	LP	LP
Maximization horizon	h=0–40	h=80	h=80	h=80	h(1)=0–40 h(2)=0	h(1)=80 h(2)=0–8	h(1)=0–40 h(2)=0–8	h(1)=80 h(2)=0–8
(I)	1.00							
(II)	0.53	1.00						
(III)	0.76	0.83	1.00					
(IV)	0.38	0.86	0.83	1.00				
(V)	0.98	0.40	0.67	0.27	1.00			
(VI)	0.76	0.94	0.88	0.76	0.64	1.00		
(VII)	0.30	0.70	0.50	0.62	0.23	0.62	1.00	
(VIII)	0.06	0.77	0.42	0.70	-0.05	0.61	0.87	1.00

Notes: This table reports the pairwise correlations of the U.S. news shocks. We obtain the news shocks from 7-variable VARs by applying the Barsky and Sims (BS), Kurmann and Sims (KS), and our alternative (BES) identification schemes. The target productivity variables are Fernald's purified TFP published in 2015 (PTFP-15) and hourly labor productivity (LP). Besides the target productivity variables, the models in this table differ with respect to the specification of the horizons used in the medium-run identification steps. Details are discussed in the text.

We first compare the news shocks determined using different identification schemes by computing the pairwise correlations between these structural news shocks (see Table 1). In the BS model (I), we use PTFP-15 and define the maximization horizon as $h = 0 - 40$. In the BS model (II), the maximization horizon is set to $h = 80$. In the KS and BER models, we use interchangeably PTFP-15 and LP to extract the news shocks. The maximization horizon in the KS models (III) and (IV) is set to $h = 80$ quarters. In the BER model (V), similar to the BS identification (I), we use PTFP-15 and define the maximization horizon as $h = 0-40$ in the first step and $h(2) = 0$ in the second step. In the BER model (VI), the maximization horizon is set to $h(1) = 80$ in the first step and $h(2) = 0 - 8$ in the second step. The BER model (VII) extracts the news shock using LP and employs the maximization horizon $h = 0-40$ in the first step and $h(2) = 0 - 8$ in the second step. Finally, the BER model (VIII), our baseline identification, uses LP to extract the news shock and sets the maximization horizons as $h(1) = 80$ and $h(2) = 0 - 8$. The results in Table 1 highlight the following three aspects that are crucial for the identification of news shocks in the context of the models under consideration.

The first aspect concerns the long-run maximization horizon. For example, focusing on one long horizon of 80 quarter in the BS model (II) instead of truncating the maximization horizon at 40 quarters as in the original BS model (I) results in a correlation between the two shock series of only 0.53. Further, increasing the maximization horizon in the BS model leads to a higher correlation of the resulting shocks with the news shocks from the KS model (III). Thereby, the controversial zero restriction in the BS model becomes less important. Finally, increasing the maximization horizon in the first step of our BER model (V) from $h(1) = 0-40$

[16] Following Barsky and Sims (2011), estimating the system in levels results in consistent estimates of impulse responses and is robust to cointegration of unknown form.

to $h(1) = 80$ in model (VI) results in a lower correlation with the shocks from the BS model (I) and higher correlation with the shocks from the BS model (II). The correlation with the news shocks from the KS model (III) increases considerably. As noted by Kurmann and Sims (2019), new productivity-enhancing technologies diffuse slowly over time and therefore an identification that extracts the shock accounting for most of productivity fluctuations in the long run should therefore capture news. Moreover, the authors stress that by focusing on one long forecast horizon reduces the consequences of technology mismeasurement for news identification. We therefore favor the longer horizon specification of $h(1) = 80$.

The second aspect concerns the timing assumptions related to the effects of news shocks on the technology measure that are necessary to isolate the unanticipated and anticipated technology shocks. As stressed by Kurmann and Sims (2019), while, on the one hand, the non-technological component remaining in the technology measure reacts immediately to news shocks and thus violates the zero impact restriction. On the other hand, agents may update their expectations about future productivity based on the currently observed technological innovations (and also the unanticipated technology shocks), which poses a conceptual challenge to the zero restriction. Therefore, in contrast to the BS model, KS model avoids taking a stand on whether (true) technology reacts to the news shock only with a lag or not.

Comparing the correlations between the BS model (II) with the zero restriction and the KS model (III) shows that indeed extending the long-run horizon diminishes the importance of the zero restriction. Thus, the two shocks are highly correlated (0.83). Our BER identification scheme in (VI), however, relaxes the zero restriction and assumes instead that the short-run fluctuations in PTFP are dominated by unexpected technology and other short-run shocks. This approach results in a news shock series that is highly correlated with the shock series from the BS model (II) 0.94 and with the shock series from the KS model (III) 0.88. The latter correlation is higher than that obtained for the link between the models (II) and (III), which shows that our short-run assumption produces reasonable news shock series while taking into account the concerns related to the short-run fluctuations in the technology measure.

In addition, the correlations between the unanticipated technology shocks from the BS model (I) (not reported in Table 1) and the news shocks from the BER models (V)–(VIII) are near-zero, which indicates that our news shocks identification is successful in accounting for short-run fluctuations in the measure of technology driven by unanticipated technology and other short-run shocks.

The final aspect concerns the consequences related to the technology measure used to extract the news shocks. For example, employing identical identification schemes to, respectively, PTFP and LP in the KS models (III) and (IV), and our BER models (VI) and (VIII), yields shock series that are not perfectly correlated. Moreover, while the shock series from model (VI) is highly correlated with shocks from the original BS model (I), evidenced by a correlation of 0.76, the correlation between the shocks from our baseline BER model (VIII) and model (I) is near zero. Also the correlation with the shock series from the KS model (III) drops from 0.88 to 0.42. Nevertheless, our baseline identification using LP still shows significant positive correlation coefficients with our preferred specifications using PTFP-15 (BS model (II) and KS model (III)).

Table 2: **Forecast error variance decomposition**

	(I)		(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Identification scheme	BS		BS	KS	KS	BER	BER	BER	BER
Target variable	PTFP-15		PTFP-15	PTFP-15	LP	PTFP-15	PTFP-15	LP	LP
Maximization horizon	h=0–40		h=80	h=80	h=80	h(1)=0–40	h(1)=80	h(1)=0–40	h(1)=80
(quarters)	*UTS*	*NS*				h(2)=0	h(2)=0–8	h(2)=0–8	h(2)=0–8
Horizon (quarters)	*Percentage of the FEV of target variable explained by the news shock*								
(0)	100.0	0.0	0.0	16.7	15.3	0.0	0.2	19.7	8.7
(4)	89.3	2.3	0.5	20.2	36.6	2.3	0.5	9.5	5.6
(8)	77.2	9.1	0.3	21.5	53.6	10.0	0.8	17.7	12.9
(12)	70.1	17.1	0.6	26.1	59.6	19.1	2.3	26.2	19.9
(20)	60.1	30.0	4.7	37.8	69.9	28.9	8.9	33.4	26.3
(40)	38.6	42.1	31.4	58.0	86.0	33.9	39.2	38.6	41.3

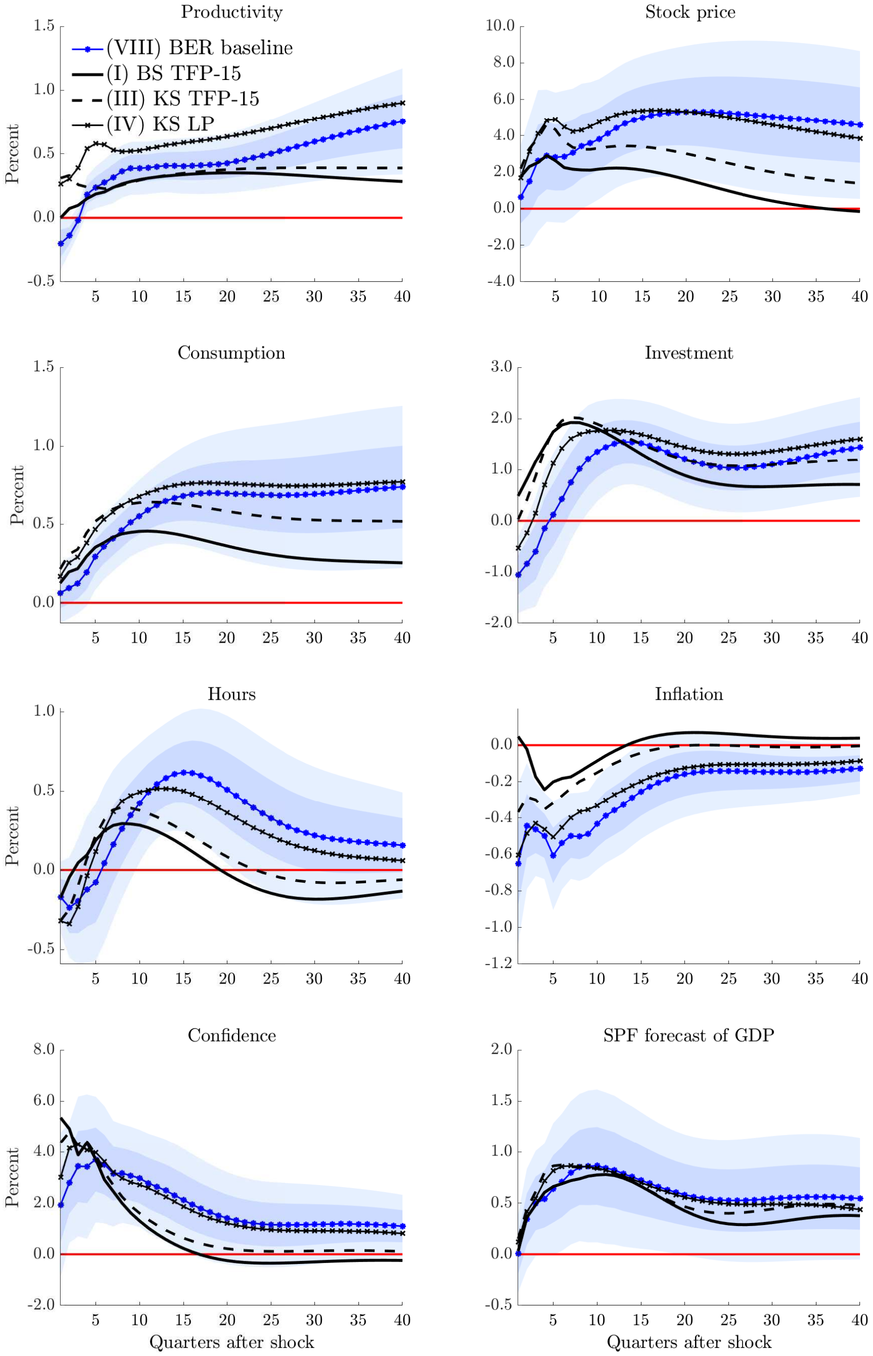
Notes: This table reports the percentages of the FEV of a target productivity variable—PTFP-15 or LP—accounted for by the news shock at various forecast horizons. We obtain the news shocks from 7-variable VARs by applying the Barsky and Sims (BS), Kurmann and Sims (KS), and our alternative (BES) identification schemes. The target productivity variables are Fernald's purified TFP published in 2015 (PTFP-15) and hourly labor productivity (LP). Besides the target productivity variables, the models in this table differ with respect to the specification of the horizons used in the medium-run identification steps. Details are discussed in the text. Considering the BS model (I), we report the FEVD results for both the unanticipated technology shocks (**UTS**) and the news shocks (**NS**).

Table 2 reports the FEV shares of PTFP-15 and LP explained by the news shocks. For the BS model (I), we report the results for the unanticipated technology (UTS) and news (NS) shocks. The FEVD results indicate that news shocks explain a negligible FEV share of productivity in the short run, but become increasingly important at longer horizons. The contributions of the news shocks to fluctuations in PTFP-15 on impact in the BS models (I) and (II), and in the BER model (V) are zero by assumption. Moreover, the FEV shares reported for our baseline BER model (VIII) are broadly in line with the results for the news shocks (NS) in model (I) and are consistent with previous studies. Importantly, news shocks in our baseline model (VIII) are allowed to affect LP on impact, though only negligibly, as evidenced by the small FEV shares explained by this shock at short horizons. An important result for our BER short-run identification assumption in the second step is that, while the unanticipated technology shock (UTS) in the BS model (I) is the dominant source of immediate fluctuations in PTFP-15, its importance declines considerably in the first two years after the shock occurs.[17]

Finally, Figure 1 illustrates the IRFs of the variables in the VAR system to news shocks obtained from the models (I), (III), (IV), and our baseline model (VIII). Furthermore, to examine how our news shocks affect the expectations of future growth prospects, we estimated 8-variable VARs that additionally include the data on the forecasts of U.S. GDP from the Survey of Professional Forecasters (SPF), provided by the Federal Reserve Bank of Philadelphia (see, for example, Levchenko and Pandalai-Nayar, 2018). The results in Figure 1 corroborate the robust key features of a positive news shock that is associated with a persistent and therefore predictable increase in future productivity level, accompanied by a gradual rise in output and

[17]This outcome is consistent with Barsky et al. (2015), who show that following an unanticipated technology shock, PTFP growth starts reverting to its pre-shock level roughly ten quarters after the shock.

Figure 1: **Impulse responses to U.S. news shocks from different models**



Notes: This figure shows the IRFs to U.S. news shocks identified in 7-variable and 8-variable VARs using the BS, KS, and our BER baseline identification schemes. The shaded areas are the 68% and 95% confidence intervals corresponding to BER baseline model (VIII), which are based on the recursive-design wild bootstrap procedure by Gonçalves and Kilian (2004).

an immediate jump in consumption and its consequent increase towards a permanently higher level.[18] After an initial decline, the response of hours worked to a news shock follows a hump-shaped pattern before returning to its pre-shock level. The impact decrease in hours is consistent with a wealth effect of news shocks emphasized in the literature (see, for example, Barsky and

[18]See, for example, Beaudry and Portier (2006), Barsky and Sims (2011), Kurmann and Otrok (2013, 2017), Barsky et al. (2015), Sims (2016), Kurmann and Sims (2019).

Sims, 2011; Kurmann and Sims, 2019; Levchenko and Pandalai-Nayar, 2018). In contrast, inflation declines immediately and persistently following a news shock.[19] Stock prices increase strongly on impact and display a mild but persistent hump-shaped response in the following periods after the shock. The confidence indicator displays a sharp but short-lived increase in response to a news shock. Reassuringly, the forecasts of GDP show an immediate and persistent improvement following a news shock, which supports our association of this shock with an improvement in the expected future growth prospects.

In sum, our BER identification is successful in accounting for the short-run movements in the non-technological component contained in labor productivity and in isolating news shocks from other shocks that are likely to affect productivity in the short run. Furthermore, our news shock affect the future productivity level in a gradual and persistent manner.

4 Empirical evidence

4.1 Data and VAR specification

Our baseline VARs include ten country-specific variables and a world production index.[20] We use the dataset of Ohanian and Raffo (2012) to compute internationally harmonized, quarterly labor productivity measures, which are the ratios between real GDP and hours worked.[21] We consider the following 13 countries in our analysis: Australia, Austria, Canada, Finland, France, Germany, Italy, Japan, Norway, South Korea, Sweden, the U.K., and the U.S. We discuss the key results for the G7 countries in the main text. Full results are available upon request.

The key variable of interest in our analysis is the trade balance, defined as the ratio of nominal net exports (exports minus imports of goods and services) to nominal GDP. We also consider the terms of trade, which we define as the relative price of imports to exports (a fall implying an improvement, in line with Backus, Kehoe, and Kydland, 1994; Enders and Müller, 2009). In addition, we control for global shocks by considering the world industrial production index by Baumeister and Hamilton (2019), which comprises data for the OECD countries and six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation, and South Africa), that together account for 75% of global GDP.[22]

To provide a comprehensive picture on the transmission of news shocks to the real economy, the VARs include output, consumption, investment, and hours worked. We convert the latter

[19] The impact response of inflation for model (I) in Figure 1 is similar to the evidence in Sims (2016).

[20] While large VAR systems suffer from a low statistical precision of the results, it is important to cover the information set of agents in the economy. To improve the accuracy of news identification, Sims (2016) argues in favor of a richer VAR specification that includes forward-looking variables.

[21] The dataset is available on Andrea Raffo's website. Hours worked are constructed to be internationally consistent and may, therefore, slightly deviate from the official series. For example, the correlation between the constructed and the official growth rates of total hours worked for the U.S. is 0.89 (see Rujin, 2019). All data sources and definitions are provided in the Data Appendix A.1.

[22] The index is available on Christiane Baumeister's website. See Baumeister and Hamilton (2019).

three variables in per capita terms using population aged 15 to 64, which avoids introducing additional trends and thus helps sharpen the results of the impulse response analysis.[23] To learn how monetary policy affects our results, we use the short-term interest rate and inflation (the growth rate of the GDP deflator). Finally, to improve the accuracy of the news shocks identification, we include the spread between the long-term interest rate on government bonds and the short-term interest rate as a forward-looking variable. Besides the interest spread, consumption and inflation serve as forward-looking variables in our analysis (Barsky et al., 2015).

All variables are quarterly and specified in log levels, except for the variables that are expressed in rates, which are taken in levels. The country-level VARs are estimated with four lags and an intercept for the period 1970:1 to 2016:4. We employ the BER baseline approach (as described in Section 3.2) to identify country-specific news shocks.

Following Hoffmann (2003), trade balance positions are mainly driven by idiosyncratic (country-specific) shocks (see also Marquez, 2002; Bussière, Fratzscher, and Müller, 2010). To examine whether we identify idiosyncratic news shocks, we check their correlations across countries. Low pairwise correlations suggest that the news shocks indeed capture a country-specific component and vice versa (Hoffmann, 2003). We also compute the correlations of news shocks with the world industrial production index and U.S. GDP, since both measures reflect global economic fluctuations. We report the results in Table B.1 in the Appendix. The pairwise correlations are close to zero in all cases. Thus, there is no evidence that our news shocks are affected by global factors in any sizable way.

4.2 Impulse response analysis

This section presents our baseline results. Since news shocks diffuse slowly over time and thus improve the long-run growth prospects, we normalize the magnitude of these shocks to induce a one percent increase in output after ten years. Figures 2 and 3 show the IRFs of key variables of interest to our news shocks and the IRFs obtained by applying the KS identification to VARs for the G7 countries.[24] The 95%-confidence intervals are based on the recursive-design wild bootstrap procedure by Gonçalves and Kilian (2004).

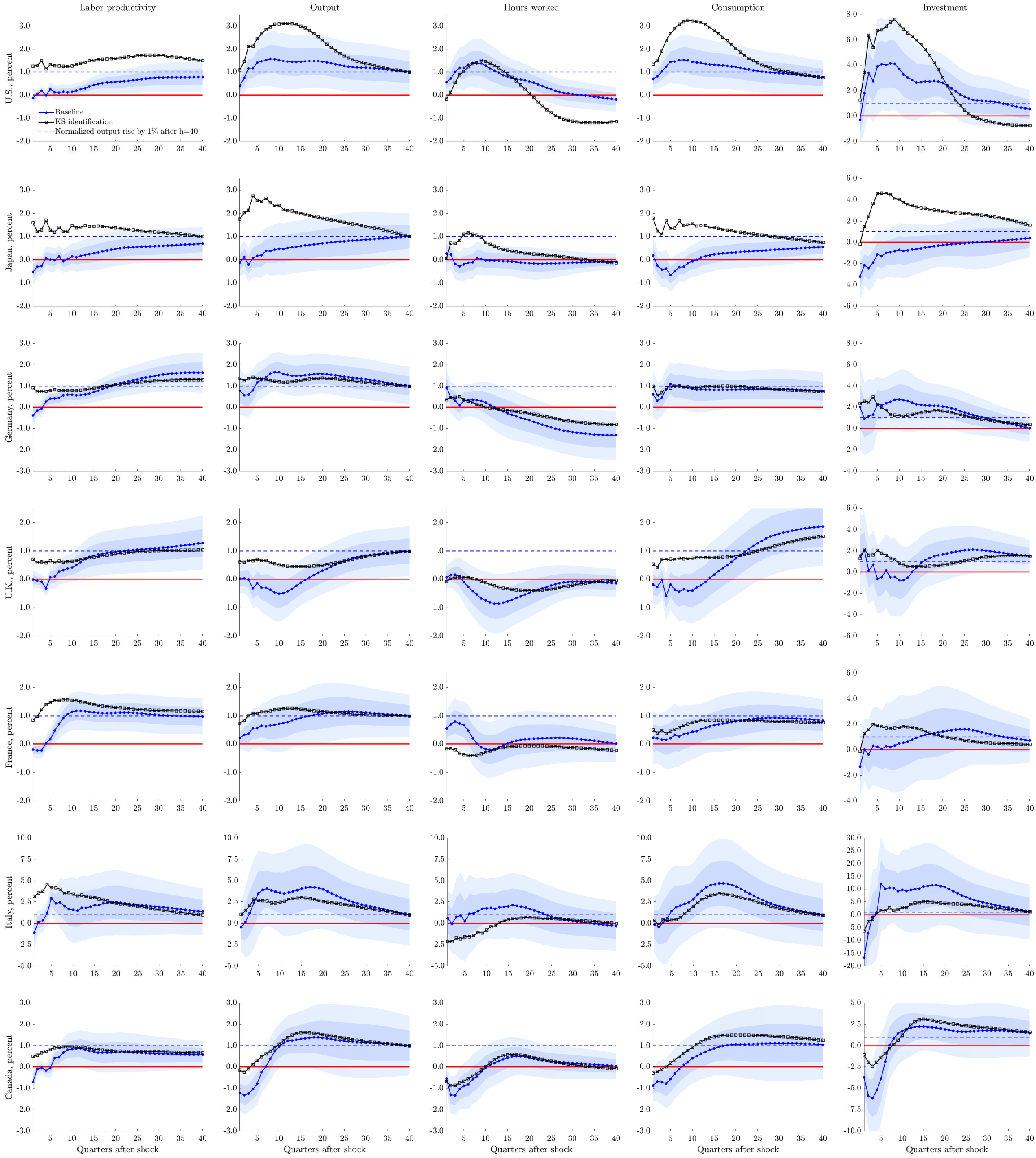
The responses of labor productivity to news shocks in Figure 2 are close to zero on impact and display a gradual and persistent increase in subsequent periods, which stresses the news shock interpretation of our BER identification. Specifically, a delayed and persistent rise in productivity is the key identifying restriction of news shocks generally accepted in the literature.[25] In contrast, the IRFs from the KS identification rise on impact across all countries.

[23]The macroeconomic variables and population series are from the dataset assembled by Ohanian and Raffo (2012). Kurmann and Otrok (2017) show that the coverage intervals for the IRFs are wider when consumption is not population adjusted, which worsens the accuracy of the results for the long-run shocks.

[24]To save space, we show the results for the remaining variables in our VARs in Figure B.1 in the Appendix.

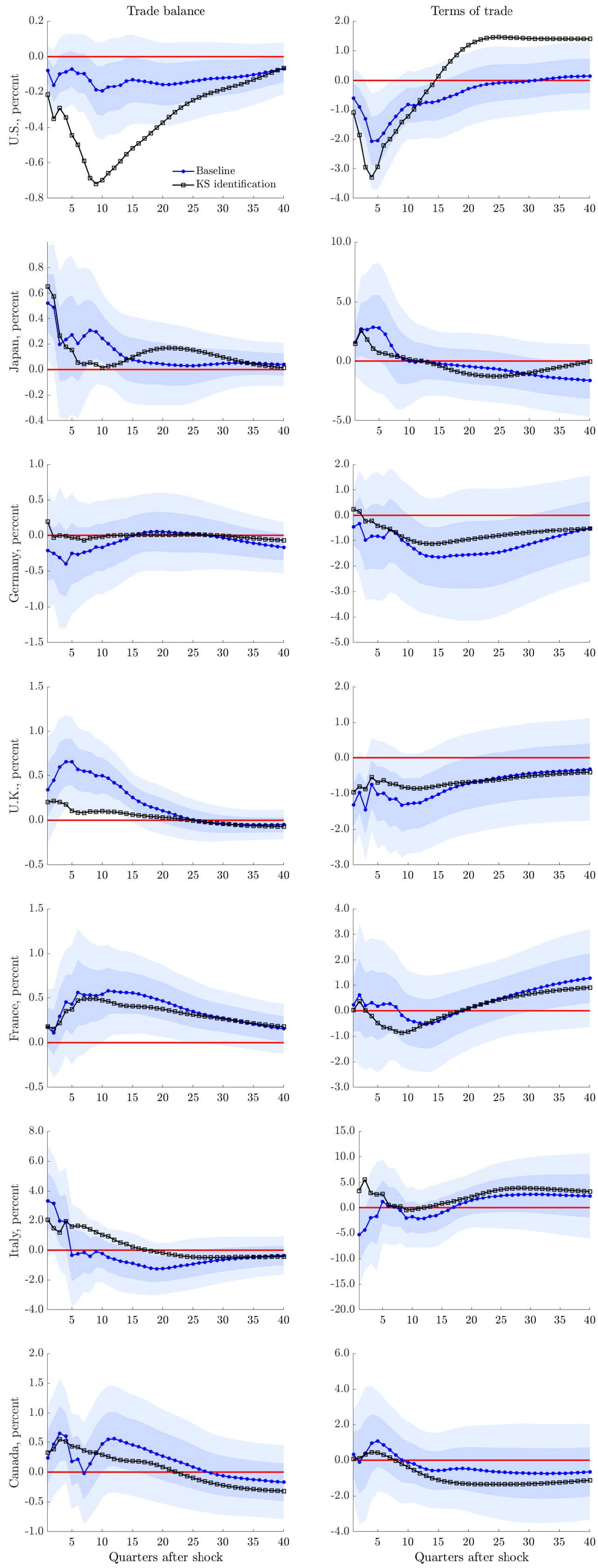
[25]By contrast, an unanticipated technology shock has an immediate effect on the productivity level.

Figure 2: **Impulse responses of macroeconomic aggregates to a news shock**



Notes: This figure shows the IRFs to country-specific news shocks for the G7 countries. We obtain the IRFs by applying, respectively, the baseline BER and the KS identifications. We estimate VARs including 11 variables for each country at a time. of news shocks to 11-variable VARs. The magnitude of the news shocks is normalized to produce a 1% increase in output at a horizon of 40 quarters after the shock. Shaded areas are 68% and 95% confidence intervals based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).

Figure 3: **Impulse responses of trade-related variables to a news shock**



Notes: This figure shows the IRFs to country-specific news shocks for the G7 countries. We obtain the IRFs by applying, respectively, the baseline BER and the KS identifications. We estimate VARs including 11 variables for each country at a time. For the terms of trade (specified in growth rates) we report the cumulative IRFs. The magnitude of the news shocks is normalized to produce a 1% increase in output at a horizon of 40 quarters after the shock. Shaded areas are 68% and 95% confidence intervals based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).

The responses of output to news shocks show a smooth and sustained increase across countries (though in the U.K. and Canada after a short-run decline), which is consistent with the property of anticipated growth shocks. However, the responses of output resulting from the KS identification display substantial increases in the short-run and lie in each case above our baseline results. In line with a robust finding in the literature, our news shocks induce a substantial short-run fall in inflation and in the (nominal) short-term interest rate (see Figure B.1 in the Appendix). Since the drop in inflation exceeds that in the short-term interest rate in most countries, the real interest rate rises. Thus, there is a contractionary monetary policy response to a news shock. While Rujin (2019) finds that unanticipated technology shocks generate a sustained drop in labor input across the G7 countries, the responses of hours worked to our news shocks are different.

Our first main result is that in the U.S., a news shock generates an immediate and persistent deterioration of the trade balance (see Figure 3), which is in line with the gradual learning effect stressed by Hoffmann et al. (2017). At the same time, the terms of trade appreciate substantially, though only temporary, following a news shock. In contrast, the shock from the KS identification generates more pronounced and mean reverting responses of the trade balance and the terms of trade. Another important outcome for the U.S., which stands out compared to other countries, concerns the dynamics of labor input and investment. With a short delay, investment and hours worked display a strong and lasting hump-shaped increase (Figure 2). Similarly, Arezki et al. (2017) examine a special case of news about oil discoveries and stress the importance of the saving and investment channels for fluctuations in the current account.

Our second key result concerns the news-driven fluctuations in the trade balance in Germany. Following a news shock, the German trade balance displays a short-lived deterioration and the terms of trade appreciate in a persistent hump-shaped manner. At the same time, in response to this shock, there is an immediate increase in consumption, which settles rapidly on a permanently higher level. However, in contrast to the U.S., this increase is less than proportional with respect to output. While investment rises on impact in response to a news shock and continues to increase in the hump-shaped manner, hours worked show a muted response in the short-run and start declining in the medium to the long run. Raffo (2008) shows that the negative trade balance effects emerge if domestic absorption is more volatile than output, which, however, turns out to be only transitory in Germany. In the medium to the long run, the news shock has no effect on the trade balance in Germany.

For the remaining G7 countries, we obtain heterogeneous results. While we find that news shocks induce immediate and transitory improvements in the trade balance in these countries, the sources behind these fluctuations are different. In Japan, Italy, and Canada, a sharp impact decline in investment following a news shock drives contemporaneous trade balance improvements. At the same time, hours worked and consumption in Japan and Italy show only a delayed response to a news shock. In Japan, these variables slowly improve over time and only consumption is slightly above its pre-shock level. However, in Italy, consumption, investment, and hours bounce back and settle at a permanently higher level in the long run and thus induce a slight deterioration of the trade balance. In Canada, hours worked respond with a transitory decline, which is consistent with a strong drop in investment. At the same time, after a pronounced initial decline, consumption, investment, and hours worked rise to a permanently higher level, which generates a slowdown in the buildup of the trade balance surplus. The terms of trade display only moderate deviations from their pre-shock levels in these countries.

In the U.K. and France, news shocks generate strong positive trade balance effects, which are associated with a depreciation of the terms of trade in the medium to the long run. However, the transmission of news shocks to the real economy in these countries is different. In the U.K., the initial positive response of the trade balance arises from a short-run drop in consumption and investment. With a delay, the pattern of hours worked mimics the behavior of rising investment, remains, however, below the pre-shock level throughout the entire horizon. In contrast, consumption shows a very strong recovery in the medium run and settles at the highest level observed across the G7 countries. Therefore, we observe a fast decay in the positive trade balance response to a news shock and a muted response after roughly six years.

In France, the positive trade balance effect of a news shock arises primarily due to a strong increase in hours worked, whereas consumption and investment increase only gradually in response to this shock. The fact that labor input increases more strongly than consumption suggests that in France, agents prefer to increase their savings.

Table 3: Cross-country correlations of the trade balance IRFs

Horizon (quarters)	Output	Hours worked	Consumption	Investment	Terms of trade
(4)	0.03	-0.25	-0.31	-0.17	-0.55*
(20)	-0.81***	-0.73***	-0.79***	-0.83***	-0.05
(40)	0.45*	0.31	-0.45	-0.24	-0.16

Notes: This table reports the cross-country correlations of the normalized baseline IRFs (see notes to Figure 2) of the trade balance with the IRFs of other key variables of interest at various horizons. To compute the correlations, we use the IRF estimates for 13 advanced economies obtained by applying the baseline BER identification to 11-variable VARs. We denote the statistical significance of correlation coefficients by asterisks *, **, *** at 10, 5, and 1 percent level, respectively.

Finally, since the sources of the news-driven trade balance fluctuations across countries are heterogeneous, we summarize the results by computing the correlations between the IRFs of the trade balance with, respectively, the IRFs of the key macroeconomic aggregates at various horizons (see Table 3). To this end, we use the IRFs for 13 countries. We find that the trade balance fluctuations are negatively related to movements in the key macroeconomic aggregates. In the long run, this relationship becomes positive with respect to output and labor input, and weakly negative for other variables. The terms of trade seem to be negatively linked to the IRFs of the trade balance at a horizon of four quarters. We stress that the strong negative relationships that we find in Table 3 are not conditional on the direction of the fluctuations in respective variables in response to news shocks and only confirm the generally accepted negative relationship between these variables.

5 Robustness checks

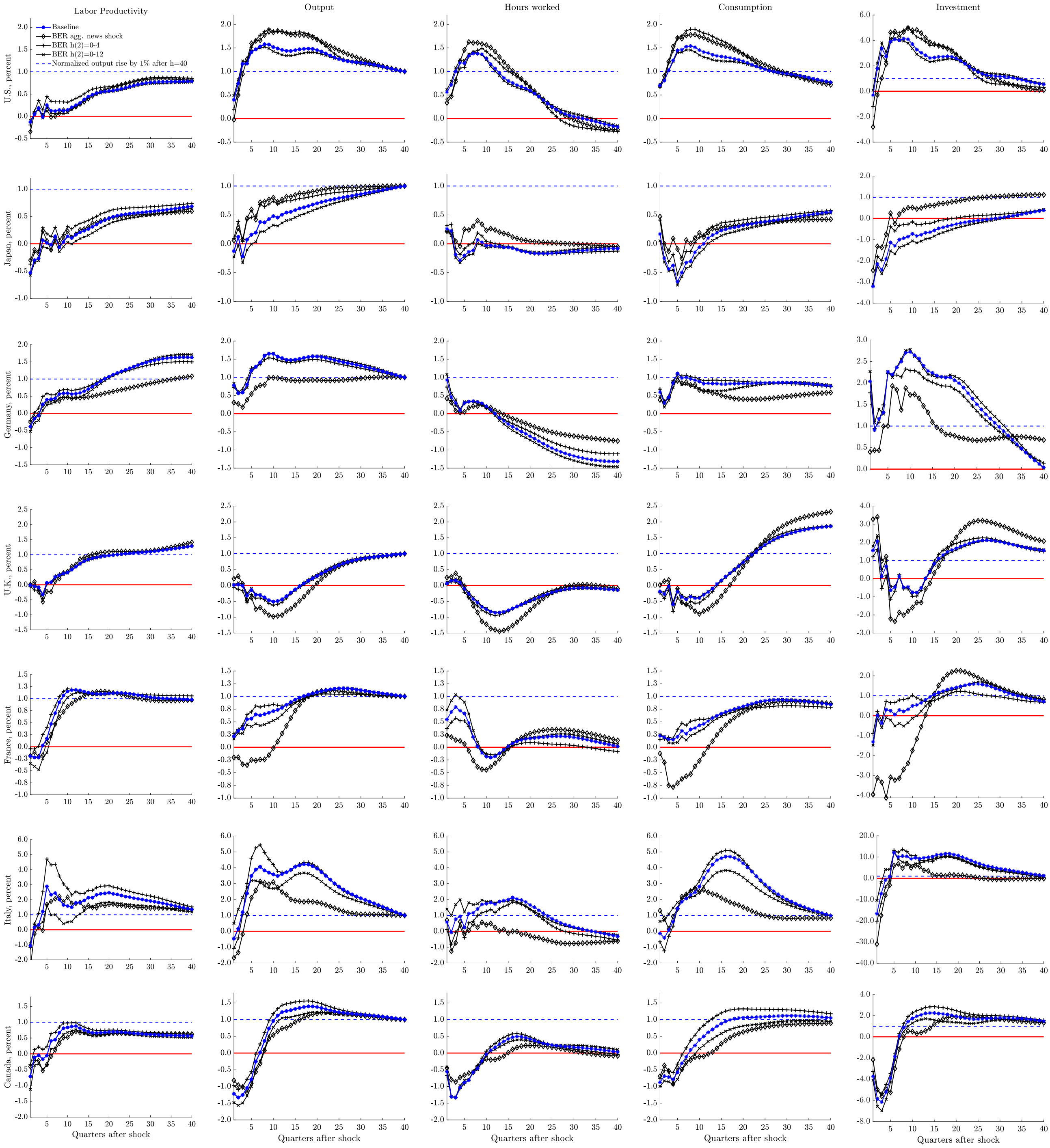
We check the robustness of our baseline results with respect to an alternative VAR specification and modifications of our BER identification. Following Hoffmann et al. (2017), the U.S. current account deficit can be explained by improved expectations of long-run output growth for the U.S. relative to the rest of the world (ROW). To account for improved growth prospects in the ROW for each country separately, we construct aggregate measures of news shocks.[26] For example, for the U.S., we compute a proxy representing growth prospects in the ROW by aggregating our baseline news shocks for the remaining 12 countries in our sample. The news shocks are aggregated by weighting each country's shock series by its GDP share in the respective group's total GDP. In each country-level VAR, we replace the world industrial production index by the respective aggregate news shocks series. All other variables correspond to our baseline VAR specification. To extract the news shocks from this alternative VAR specification, we apply our BER identification, as described in Section 3.2.

Second, as discussed in Section 2, isolating the unanticipated technology and news shocks is crucial for the analysis of the trade balance fluctuations. Our BER news shocks identification implements this idea in the second step of the approach, as described in Section 3.2. Therefore, we check whether our main results still hold if we extract the news shocks using alternative maximization horizons $h(2)$ in the second step of our BER identification, which we apply to our baseline VARs. In particular, to isolate the unanticipated technology and the short-run shocks, we cumulatively maximize the FEV shares of labor productivity over all horizons from impact and up to four quarters ($h(2) = 0 - 4$) and over all horizons from impact and up to twelve quarters ($h(2) = 0 - 12$), respectively.

Figure 6 shows the impulse responses of macroeconomic aggregates and trade-related variables to news shocks obtained from the alternative VAR specification and modifications to our BER identification approach. Overall, we find that our baseline results are robust to these modifications. In particular, labor productivity displays a delayed and persistent rise in response to a news shock and the patterns of the dynamic effects of news shocks on output remain unchanged across all countries and models. The latter implies that the basic qualitative and quantitative nature of the transmission of news shocks to the real economy remains unaffected by our various modifications. Moreover, the alternative assumptions concerning the maximization horizon in the second step of our identification approach result in highly correlated shock series with our baseline news shocks (the correlation in both cases exceeds 0.9). The results in Figure 6 support our main conclusions related to the persistent trade balance deterioration in the U.S. and a temporary drop in Germany in response to a news shock, on the one hand, and transitory improvements in the trade balance in other G7 countries, on the other hand.

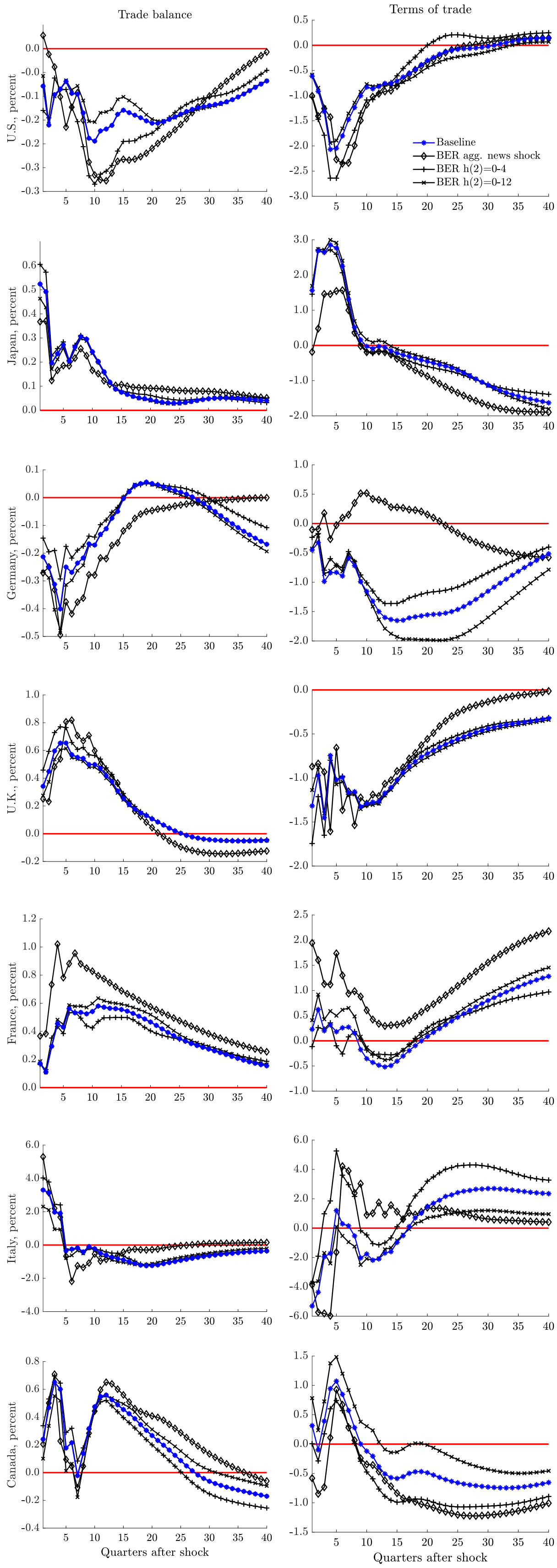
[26] Hoffmann et al. (2017) compute a proxy for the ROW relying on survey expectations of long-run GDP growth in nine of the main trading partners of the U.S.: Japan, Germany, France, the U.K., Italy, Canada, China, South Korea, and Taiwan.

Figure 6: **Impulse responses to a news shock from different models**



Notes: Figure continued on the next page.

Figure 6: **(Continued from previous page)**



Notes: IRFs to country-specific news shocks from different BER model specifications. The magnitude of the news shocks is normalized to produce a 1% increase in output at a horizon of 40 quarters after the shock (**blue dashed lines**). **Baseline**: Baseline IRFs. **BER agg. news shock**: IRFs from VARs with an aggregate of news shocks instead of world industrial production. **BER h(2)=0–4** and **BER h(2)=0–12** show the IRFs from alternative specifications of the maximization horizon $h(2)$.

Nevertheless, there are some notable differences in the magnitudes of the dynamic responses of macroeconomic aggregates to news shocks obtained from the alternative specification of the empirical model. Specifically, the effects of these shocks on investment in Germany and France become strongly negative in the short run, whereas the pattern of these responses remains broadly unchanged. Another difference concerns the short-run response of consumption in France, which turns negative in the case of the alternative VAR specification. However, these differences in the responses of key macroeconomic aggregates to news shocks from the alternative VAR specification relative to our baseline IRFs do not change the qualitative conclusions about the effects of news shocks on the trade balance in these countries.

In sum, our key conclusions hold for the alternative VAR specification and modifications to the empirical model.

6 Conclusions

This study adds to the empirical literature on the implications of improved growth prospects for fluctuations in the trade balance. Specifically, we provide new evidence on the trade balance effects of news shocks for the G7 countries. To this end, we develop a novel news shocks identification and analyze their dynamic effects on the trade balance and a set of key macroeconomic aggregates on a country-by-country basis.

We provide evidence of a persistent deterioration of the U.S. trade balance and a transitory decrease in the trade balance in Germany in response to a news shock.[27] In contrast, the evidence for the remaining G7 countries does not imply that improved growth prospects necessarily lead to countercyclical fluctuations in the trade balance. In particular, a few results stand out.

First, our results highlight the role of consumption smoothing in generating countercyclical trade balance effects of news shocks observed for the U.S. Following Hoffmann et al. (2017), a predictable improvement in future output growth is associated with a positive wealth shock. As a result, forward-looking agents move some of the higher expected income to the present before the anticipated changes materialize. Due to a strong relation between consumption and imports, a news shock may well result in a trade balance deficit if consumption increases more than proportionally with respect to output. For example, Backus, Henriksen, Lambert, and Telmer (2009) document that the trade balance deficit in the U.S. is a reflection of a particularly high consumption-to-GDP ratio, on the one hand, a low saving rate, on the other hand, compared to other advanced economies. In sum, Hoffmann et al. (2017) stress that a current account deficit emerges as the optimal response to improved expectations of future output growth perceived by the forward-looking agents.

[27]This is generally consistent with earlier findings that productivity acceleration accounts for a large fraction of the increase in the U.S. current account deficit through its impact on saving and investment (Valderrama, 2007).

A second important outcome of our analysis concerns the role of news shocks in explaining the dynamics of investment and their implications for the trade balance effects. The results for the U.S. stand out compared to other G7 countries. Following Backus et al. (1994), investment dynamics play an important role in explaining the countercyclical fluctuations in net exports in response to exogenous technological improvements. Similarly, Arezki et al. (2017) examine a special case of news about oil discoveries and find that while these shocks induce an immediate and permanent rise in consumption, they affect the behavior of the current account primarily through the saving and investment channels.

In sum, news shocks induce negative trade balance effects if the resulting domestic absorption is more volatile than output (Raffo, 2008). Correspondingly, our results show that the increases in both the U.S. consumption and investment following a news shock exceed the respective increase in output. As a result, the overall positive effect of a news shock is associated with a deepening of the trade balance deficit. However, in other advanced economies, positive trade balance dynamics following a news shock are the consequence of a delayed and very gradual increase in consumption accompanied by a moderate increase in investment and labor input.

Our results are particularly relevant in light of economic policy recommendations raised by international organizations that emphasize the negative link between the fluctuations in the trade balance and growth prospects that, at least partly, seem at odds with our empirical results. For example, the EU Commission repeatedly claims in its in-depth reviews on the prevention and correction of macroeconomic imbalances that further reform progress to unleash Germany's growth potential will help to strengthen investment and contribute to a lower trade surplus in the country over time.[28] The German Council of Economic Experts does share the Commission's view that measures should be taken to increase the potential output growth. However, the Council is more careful regarding the impact on the German trade balance. It emphasized this judgment "irrespective of whether the measures are capable of reducing the current account surplus". It does rightly so in view of our empirical results for Germany.[29]

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[28]See, for example, European Commission (2016, 2019), International Monetary Fund (2019), and Kreditanstalt für Wiederaufbau (2017).

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Appendix

A Data definitions and sources

Table A.1: **Data sources and definitions**

Variable	Sample	Definitions and sources
Fernald (2014), http://www.johnfernald.net/TFP		
Utilization-adjusted quarterly-TFP series for the U.S. Business Sector	1970:1–2016:4	The 2017 vintage of utilization-adjusted quarterly-TFP series by John Fernald and Andrew Tai. The data on inputs, including capital, are used to produce a quarterly series on total factor productivity. In addition, the dataset implements an adjustment for variations in factor utilization—labor effort and the workweek of capital. The utilization adjustment follows Basu, Fernald, and Kimball (2006).
Ohanian and Raffo (2012) dataset, http://andrearaffo.com/araffo/Research.html		
Total hours worked	1970:1–2016:4 1971:1–2016:4 (U.K.) 1974:1–2016:4 (SE)	Total hours worked series are obtained as the product of hours worked per worker and employment.
Population aged 15 to 64	1970:1–2016:4	Time series are from national statistical offices and the OECD-Economic Outlook (EO) database.
Real GDP	1970:1–2016:4	Time series are from the OECD EO database.
Real private consumption	1970:1–2016:4	Time series are from the OECD EO database.
Real gross fixed capital formation	1970:1–2016:4	Time series are from the OECD EO database.
Sims (2016) dataset, https://www3.nd.edu/~esims1/tfp_vintage.html		
U.S. time series	1960:1–2007:3	Replication data for the previous draft by Eric Sims (2016) "Differences in Quarterly Utilization-Adjusted TFP by Vintage, with an Application to News Shocks" and the current paper by Kurmann and Sims (2019).
World industrial production index by Baumeister and Hamilton (2019)		
World industrial production index	1970:1–2016:4	Baumeister and Hamilton (2019) propose an extended version of the OECD's index of monthly industrial production in the OECD and six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation and South Africa), which account for 75% of the IMF World EO estimate of global GDP. To obtain a quarterly index of the world industrial production, we computed 3-month-averages of monthly entries.

Table A.1: ***(Continued)***

Variable	**Sample**	**Definitions and sources**
Other variables		
Nominal GDP	1970:1–2016:4	Gross domestic product—expenditure approach, in U.S. dollars, current prices, current PPPs, seasonally adjusted. Data are from the OECD Quarterly National Accounts.
Real GDP	1970:1–2016:4	Gross domestic product—expenditure approach, in US dollars, volume estimates, fixed PPPs, OECD reference year, annual levels, seasonally adjusted. Data are from the OECD Quarterly National Accounts.
Short-term interest rate	1970:1–2016:4 1971:1–2016:4 (IT) 1981:2–2016:4 (KR) 1974:2–2016:4 (SE)	Short-Term Interest Rate, OECD Economic Outlook, Estimate, Calendar Adjusted, SA
Long-term interest rate	1970:1–2016:4 1983:1–2016:4 (KR)	Long-Term Interest Rate on Government Bonds, OECD Economic Outlook, Estimate, Calendar Adjusted, SA
Exports of goods and services	1970:1–2016:4	External balance of goods and services—Exports of goods and services, national currency, current prices, annual levels, seasonally adjusted. Data are from the OECD Quarterly National Accounts.
Imports of goods and services	1970:1–2016:4	External balance of goods and services—Imports of goods and services, national currency, current prices, annual levels, seasonally adjusted. Data are from the OECD Quarterly National Accounts.
Export deflator	1970:1–2016:4	External balance of goods and services—Deflator of the exports of goods and services, national currency. Data are from the OECD Quarterly National Accounts.
Import deflator	1970:1–2016:4	External balance of goods and services—Deflator of the imports of goods and services, national currency. Data are from the OECD Quarterly National Accounts.
Forecasts of US GDP	1970:1–2016:4	Survey of Professional Forecasters (SPF): SPF forecast of GDP one quarter ahead, provided by the Federal Reserve Bank of Philadelphia.

Notes: All definitions are from the original sources. The data set covers 13 countries: Australia (AU), Austria (AT), Canada (CA), Finland (FI), France (FR), Germany (DE), Italy (IT), Japan (JP), Norway (NO), South Korea (KR), Sweden (SE), the U.K., and the U.S. We exclude Spain from the analysis due to a much later starting date of the hours series in 1995:1. We exclude the outlier country—Ireland—from the analysis. The results for Ireland are available upon request.

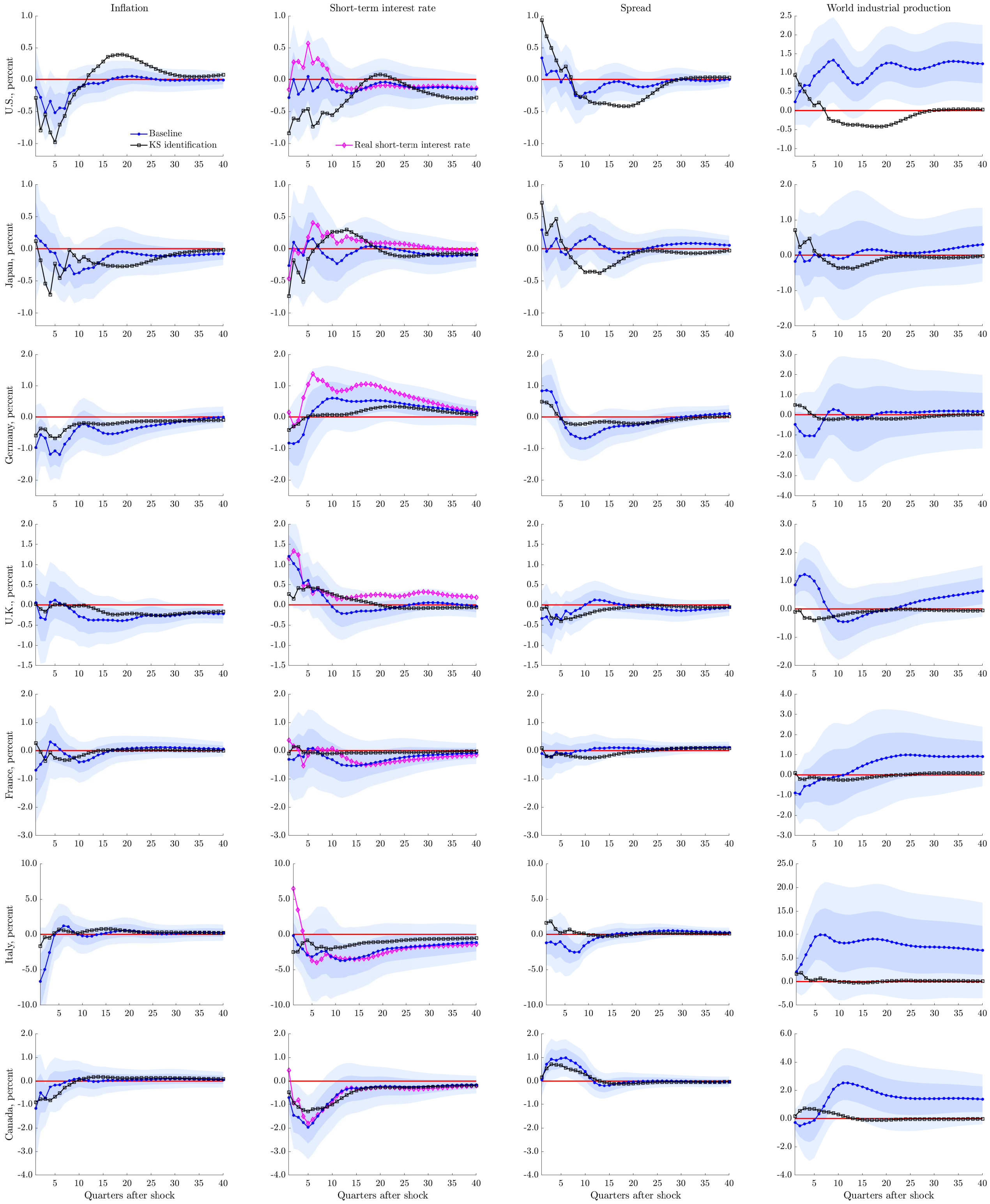
B Additional tables and figures

Table B.1: **Pairwise correlations of country-specific news shocks**

	World IP	US GDP	AU	AT	CA	FI	FR	DE	IT	JP	KR	NO	SE	UK	US
Australia	0.00	0.01	1.00												
Austria	0.00	0.00	0.12	1.00											
Canada	0.00	0.01	0.14	0.06	1.00										
Finland	-0.01	0.00	0.01	0.11	0.07	1.00									
France	-0.01	0.00	0.13	0.13	0.10	0.04	1.00								
Germany	-0.01	0.00	0.04	0.20	0.03	0.21	0.07	1.00							
Italy	0.01	0.01	0.11	0.02	0.11	0.10	0.04	-0.04	1.00						
Japan	0.00	0.00	-0.27	-0.02	0.00	0.02	0.02	0.09	0.05	1.00					
South Korea	0.00	0.00	0.20	-0.34	0.01	0.08	-0.07	-0.02	-0.15	0.02	1.00				
Norway	0.00	0.00	0.01	0.08	-0.25	0.16	-0.09	-0.03	-0.03	-0.13	-0.04	1.00			
Sweden	0.01	0.02	0.01	0.03	0.08	-0.02	-0.07	-0.07	0.11	0.04	-0.09	0.05	1.00		
U.K.	0.01	0.01	0.04	0.00	-0.01	-0.19	-0.17	-0.10	-0.05	-0.02	0.12	0.07	0.13	1.00	
U.S.	0.01	0.01	0.07	-0.04	-0.06	-0.06	-0.06	-0.03	0.12	0.07	-0.06	0.07	0.11	-0.02	1.00
Mean	0.00	0.00	0.04	0.03	0.02	0.04	-0.01	0.03	0.03	-0.01	-0.03	-0.01	0.03	-0.01	0.00
Std. dev.	0.01	0.01	0.12	0.14	0.10	0.10	0.10	0.10	0.08	0.10	0.14	0.11	0.08	0.10	0.07

Notes: This table reports the pairwise correlations of country-specific news shocks obtained by applying the baseline BER identification to 11-variable VARs. World IP is the world industrial production (Baumeister and Hamilton, 2019). Mean (std. dev.) are computed based on the 13 pairwise correlations of country-specific news shocks reported in this table.

Figure B.1: **Impulse responses to a news shock, baseline results**



Notes: This figure shows the IRFs to country-specific news shocks for the G7 countries. We obtain the IRFs by applying, respectively, the baseline BER and the KS identifications of news shocks to 11-variable VARs. The IRFs of the real short-term interest rate are obtained by subtracting the IRFs of inflation from the IRFs of the short-term interest rate. The magnitude of the news shocks is normalized to produce a 1% increase in output at a horizon of 40 quarters after the shock. Shaded areas are 68% and 95% confidence intervals based on the recursive-design wild bootstrap procedure (Gonçalves and Kilian, 2004).