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Abstract

This paper draws from two observations in the literature. First, that shocks to entrepreneur or household confidence matter for economic outcomes. Second, that it is hard to explain the extent of cyclical comovement between economies taking into account their trade links only. We check empirically to what extent confidence fluctuations matter for business cycles and in particular for their comovement between economies. We focus on a large (euro area) and a small, nearby economy (Poland). Our results show that confidence fluctuations account for approximately 40% of business cycle fluctuations in the euro area. Spillovers of confidence shocks are also large. Our main finding is that the their direct impact (i.e. not via trade but through the cross-border spread of news and business sentiment) accounts for almost 40% of business cycle fluctuations in Poland.

JEL: C32, E32, F44

Keywords: International spillovers, animal spirits, sentiments, business cycle

1 Introduction

Cyclical economic fluctuations can originate in (possibly nonfundamental) shifts in expectations about economic activity. This idea goes back at least to Pigou (1927) and Keynes (1936), who postulated that waves of optimism or pessimism might influence current economic conditions. For many years mainstream macroeconomic models have largely ignored the role of such factors as drivers of business cycles. More recent literature, both empirical and theoretical, attempts to formalize and quantify the impact of fluctuations in moods. As will be shown below, most studies document a highly significant role of such factors.

An important, related and highly relevant question is, whether confidence also spills over borders and affects cyclical fluctuations abroad. The importance and relevance of this question stems from two observations. First, that economic fluctuations between countries are highly correlated, so that obviously business cycles spill over borders. Second, that the literature (with special emphasis on structural macroeconomic models) has a clear problem with explaining where such high correlation comes from. Neither the international real business cycle model (Backus et al., 1992) nor new Keynesian models (Justiniano and Preston, 2010) can explain the high correlation of business cycles, unless productivity shocks are assumed to be correlated. Trade seems by far not sufficient to explain comovement, adding financial factors helps somewhat (Olivero, 2010; Brzoza-Brzezina et al., 2018), but international correlations still remain a puzzle. This paper investigates the role of confidence in driving the international comovement of economies.

As mentioned, the literature on the role of confidence in driving cyclical fluctuations is abundant. Let us start with defining the main concepts. Contemporaneous papers (at least a substantial share) distinguish two types of confidence shocks (see eg. Barsky and Sims 2012).

The first relates to new information about future technology that is orthogonal to current technology. In the literature such shocks are usually called “technology news shocks”, and we will stick to this convention throughout the paper. One can think for instance of innovations that have already been invented (and are known to agents), but due to implementation lags have not yet been implemented and thus do not increase productivity yet. These shocks have a supply-side flavor - ultimately they are supposed to increase productivity and, as a result, are expected to have a permanent impact on output. The related literature originates from the papers of Beaudry and Portier (2006), who empirically document the existence of a shock (derived from stock price data) that causes a boom in investment and consumption and significantly precedes the growth of productivity. Beaudry and Portier (2004) include this type of shock (a signal about future technology) into an RBC model. Fujiwara et al. (2011) estimate a New Keynesian model with technology news shocks and Blanchard et al.

(2013) additionally consider noise (i.e. false) shocks about future technology. Schmitt-Grohe and Uribe (2012) generalize the concept to a wider range of shocks. They estimate a DSGE model with several news shocks and confirm a very important role of anticipated shocks in driving main business cycle variables. Kamber et al. (2017) estimate VAR models for four developed, small, open economies and documents that technology news shocks explain a substantial part of output fluctuations (between 6% in New Zealand and 40% in the UK). Further contributions to the empirical stream in the literature include i.a. Barsky and Sims (2011), who estimate a new Keynesian type of model that allows for technology news shocks and show that their contribution to explaining the variance of consumption and investment, while negligible in the short run, increases to 50% in the long run. On the theoretical front Jaimovich and Rebelo (2009) discuss the conditions under which news shocks can generate comovement of main macrovariables characteristic for business cycle fluctuations. Their main conclusion is that wealth effects must be weak, since otherwise positive news shocks reduce current labor supply and, hence current output. Eusepi and Preston (2011) develop a model that departs from the rational expectations assumption towards learning, in which self-fulfilling expectations arise in response to technology shocks.

The second type of confidence shocks relates to nonfundamental shifts in demand (consumption, investments), due to expectations about future prospects of the economy. It bears similarities Keynes' notion of "animal spirits" that influence entrepreneurs willingness to undertake investment activity and, hence, drive cyclical fluctuations. Following part of the literature we will refer to such shocks as "sentiment shocks".[1] These shocks are purely demand-driven, and, as such are expected to have only a temporary impact on economic activity. Again, both empirical and theoretical studies exist that deal with these shocks. Angeletos and La'O (2013) provide a model in which limited communication between agents provides an environment in which shocks to believes (sentiments) have real effects that resemble boom-bust phenomena. Angeletos et al. (2014) derive a main business cycle factor from US data and show that its properties differ from shocks known in the structural literature. In particular, the factor moves output, hours worked, consumption and investments in the same direction, without affecting technology. Then, the paper constructs and estimates a DSGE model with a shock to agent's believes about other agents perception of business conditions. This shock is interpreted as a sentiment shock and has properties similar to the empirically derived factor and is shown to explain 40-50% of the variance of output, consumption and investment. Milani (2017) estimates a DSGE model with learning and shows that sentiment fluctuations are responsible for over forty percent of business fluctuations in the United States. On the other hand, according to the Barsky and Sims (2011) estimation, sentiment shocks have a negligible impact on output and consumption for both short and long horizons (technology news is what counts).

[1]Some papers call this type of shock "confidence shock". We call it "sentiment", while leaving the term "confidence" to encompass both sentiment and news innovations.

Three papers (to our knowledge) dealt explicitly with the role of confidence in explaining international business cycle correlations. Beaudry et al. (2011) extend the model of Beaudry and Portier (2004) to a two-country setting. They show that technology news shocks can drive cross-country synchronization of cycles even in a flexible price economy. Levchenko and Pandalai-Nayar (2015) take an empirical approach to assess the spillover of confidence shocks between the US and Canada. They identify both technology news and sentiment shocks and show that the Canadian business cycle is driven to a large extent by US confidence. DeGrauwe and Ji (2017) construct a two-country model with agents switching endogenously between two forecasting rules (fundamentalist and extrapolative). In this framework small spillovers via trade channels are amplified by the animal spirit mechanism resulting from agents becoming extrapolative in case of boom or bust.

Our paper deals directly with the last issue: whether and to what extent does confidence affect the international transmission of business cycles. We estimate an SVAR/VECM model based on data from Poland and the euro area (a small open economy and its large neighbor). The contribution of our paper to the literature is twofold. First, we check whether the earlier findings for US-Canada (Levchenko and Pandalai-Nayar (2015)) spillovers are universal, in that they also hold for a large-small economy pair in a different part of the world. Second, and more importantly, our paper distinguishes between indirect (via trade linkages) and direct (via cross-border spread of news) spillovers of confidence. As a consequence we offer a contribution to the cited above literature searching for the "missing transmission channel" between countries.

Our main findings are as follows. First, we confirm the important role of confidence in driving the business cycle in the euro area. At the 12 quarter horizon (the peak of the frequency response function for GDP) confidence shocks account for 38% of forecast error variance decomposition of GDP in the euro area. Second, spillovers from the euro area to Poland do matter as well: by the same metric foreign confidence shocks determine 74% of GDP fluctuations in Poland. Our distinction of direct and indirect effects shows that they divide roughly half-by-half. In other words approximately 38% of the variance of Polish GDP is explained by direct spillovers of confidence (news and sentiment) from the euro area. This is our account of the "missing channel" in the structural business cycle literature. Third, we analyze historical shock decompositions. These show periods where confidence shocks were particularly important. In the euro area sentiment shocks played a significant role in generating the slowdowns during the financial and sovereign default crises, as well as positive effects from the ECBs promise to do "whatever it takes" to save the euro. These events contributed to business cycle fluctuations in Poland as well.

The rest of the paper is organized as follows. Section 2 discusses the estimation strategy and the data, Section 3 the results, Section 4 offers a number of robustness checks and Section 5 concludes.

2 Model, data and estimation

2.1 Model

We investigate the international spillovers of technology and sentiment shocks using a structural vector autoregression (SVAR) framework. We follow the approach proposed initially by Uhlig (2004)and applied in the confidence literature by Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015) and identify the structural shocks by imposing so called medium-run restrictions on the impact matrix.

Our basic VAR model includes seven variables for the large economy (euro area): total factor productivity (TFP), real GDP, hours worked, short term nominal interest rate, investments, private consumption and GDP forecasts and GDP for the small open economy (Poland) - in this order. We identify three structural shocks in the model, all stemming from the euro area, which also affect Poland as the economy tightly integrated with the euro area.

The method we apply relies on the sequential identification of the subsequent shocks. We extract the respective shocks conditional on the values of the previous shocks. As a first step we extract two technology shocks in the euro area in the spirit of Barsky and Sims (2011). The first one will be called surprise technology shock and corresponds to the reduced form innovation to the TFP equation in the VAR model with the TFP variable ordered first. The second one is a news shock about future TFP which we identify as having no contemporaneous impact on TFP but explaining the maximum of the forecasts error variance of the TFP series after accounting for the impact of the surprise technology shock. This approach reflects the assumption that TFP in the euro area is affected by these two shocks only:

$$TFP_t = \lambda_1^{TFP}\epsilon_t^{sur} + \lambda_2^{TFP}\epsilon_{t-k}^{news} \tag{1}$$

where TFP_t is TFP in the euro area and ϵ_t^{sur} and ϵ_t^{news} are the surprise and news technology shocks respectively.

Finally we identify the sentiment shock in the euro area. Our identification procedure follows Levchenko and Pandalai-Nayar (2015) who estimate a model for spillovers of news and sentiment shocks between the United States and Canada. Sentiment is identified as the shock which maximizes the forecasts error variance of the GDP forecasts after accounting for surprise and news technology shocks:

$$GDP_t^{F,EA} = \lambda_1^F\epsilon_t^{sur} + \lambda_2^F\epsilon_{t-k}^{news} + \lambda_3^F\epsilon_t^{sent} + \zeta_t \tag{2}$$

where ϵ_t^{sent} is the sentiment shock in the euro area while ζ_t is another shock (or combination of structural shocks) affecting the expectations of future economic activity in the euro area $GDP_t^{F,EA}$ not related to technology or sentiment. Hence, our approach does not exclude that some other shocks may also affect agents expectations about future economic activity.

A similar approach has also been applied by Angeletos et al. (2014)[2] who identify sentiment shocks in the US from a DSGE model and show that their estimated structural sentiment shock is closely related to a main business cycle shock extracted from a VAR model. Not only do these shocks share the same properties (in terms of impulse responses they generate), but they also have very similar time series. After the estimation has been done, we cross-check whether the estimated shock shares the main properties with the structural sentiment shocks of Angeletos et al. (2014).

In what follows the identification procedure is described in detail. We start with the reduced form VAR(p) model:

$$A(L)Y_t = u_t \tag{3}$$

where Y_t is the $k \times 1$ vector of observable variables in levels and u_t is a vector of reduced form disturbances.

The moving average representation of model (3) is:

$$Y_t = B(L)u_t. \tag{4}$$

We assume that the reduced form disturbances u_t are linear combinations of structural shocks ϵ_t with the impact matrix C_0:

$$u_t = C_0\epsilon_t \tag{5}$$

Therefore the structural representation of the VAR(p) model is:

$$Y_t = C(L)\epsilon_t \tag{6}$$

where $C(L) = B(L) \cdot C_0$. We assume that the structural shocks ϵ_t are orthogonal to each other and have unit variance, which implies that:

$$C_0C_0' = \Sigma \tag{7}$$

where Σ is the covariance matrix of reduced form innovations u_t.

As is well known there is an infinite number of matrices satisfying condition (7). For

[2] The main difference is that Angeletos et al. (2014) maximize the variance of output and hours worked while Levchenko and Pandalai-Nayar (2015) rely on forward-looking variables.

example the Cholesky decomposition of Σ provides a lower triangular matrix which fulfills condition (7) and this matrix, denoted as $\tilde{C}_0$ is the starting point for the structural decomposition with medium run restrictions.

As a next step we specify matrix D, which satisfies the restriction $DD' = I$ and which defines the impact matrix C_0 as $C_0 = \tilde{C}_0 D$.

The subsequent columns of matrix D correspond to the identified structural shocks. The identification of the respective columns of matrix D is based on the assumption that the structural shocks ϵ_t explain the maximum variance of the forecast error of selected variables in the VAR(p) model. Below we discuss the subsequent steps of our decomposition.

The h-steps ahead forecasts error from the VAR(p) model can be derived as:

$$Y_{t+h} - \hat{Y}_t(h) = \sum_{i=0}^{h} B_i u_{t+h-i} = \sum_{i=0}^{h} B_i C_0 \epsilon_{t+h-i} = \sum_{i=0}^{h} B_i \tilde{C}_0 D \epsilon_{t+h-i}, \tag{8}$$

where $\hat{Y}_t(h)$ is the h-steps ahead forecast of Y_t while B_i is the respective coefficient matrix in the moving average representation of VAR(p).

Accordingly the h-step ahead forecast error of variable k in vector Y_t is:

$$Y_{k,t+h} - \hat{Y}_{k,t}(h) = \sum_{i=0}^{h} B_{k,i} \tilde{C}_0 D \epsilon_{t+h-i}, \tag{9}$$

where $B_{k,i}$ is the k-th row of matrix B_i. Then the forecast error variance of variable k at horizon h is:

$$\Omega_k(h) = \sum_{i=0}^{h} B_{k,i} \Sigma B'_{k,i} \tag{10}$$

Let $\Omega_{i,k}(h)$ denote the contribution of the structural shock i to the forecast error variance of variable k at horizon h:

$$\Omega_{i,k}(h) = \frac{\sum_{i=0}^{h} B_{k,i} \tilde{C}_0 d_j d'_j \tilde{C}'_0 B'_{k,i}}{\sum_{i=0}^{h} B_{k,i} \Sigma B'_{k,i}}. \tag{11}$$

Without loss of generality let us assume that the first two structural shocks are the euro area surprise and news technology shocks and the third one is the euro area sentiment shock. The baseline of the identification proposed by Barsky and Sims (2011) and adopted in our paper is the assumption expressed by (1) that only two technology shocks influence TFP for the euro area. This assumption implies:

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \; \forall h. \tag{12}$$

The surprise technology shock is the reduced form innovation in the TFP equation in model (3) while the news technology shock is the shock, which maximizes the forecast error variance of TFP over H^{news} horizon after accounting for the impact of the surprise technology shock.

The maximization problem can be written as follows (see Barsky and Sims, 2011):

$$d_2 = \text{argmax} \sum_{h=0}^{H^{news}} \Omega_{1,2}(h) = \text{argmax} \sum_{h=0}^{H^{news}} \left(\frac{\sum_{i=0}^{h} B_{1,i} \tilde{C}_0 d_2 d_2' \tilde{C}_0' B_{1,i}'}{\sum_{i=0}^{h} B_{1,i} \Sigma B_{1,i}'} \right). \tag{13}$$

s.t.

$$\tilde{C}_0(1,i) = 0 \; \forall i \neq 1$$

$$d_2(1) = 0$$

$$D'D = I$$

where d_2 is the second column of D matrix, which specifies the second structural shocks interpreted here as the news technology shock. Therefore $\tilde{C}_0 d_2$ is the impact vector of this shock. The first two restrictions guarantee that the news shock does not have a contemporaneous effect on TFP. The third constraint ensures that vector d_2 is a column of an orthonormal matrix.

Uhlig (2004)shows that the maximization problem defined by (15) is equivalent to finding the eigenvector (which is a non-zero portion of d_2) associated with the largest eigenvalue of the lower $(k-1)\times(k-1)$ submatrix of matrix Λ^{news}, which is a weighted sum of the matrices $\left(B_{1,i}\tilde{C}_0\right)' \left(B_{1,i}\tilde{C}_0\right)$over H^{news}:

$$\Lambda^{news} = \sum_{i=0}^{H^{news}} \left(H^{news} + 1 - \max(1,i)\right) \left(B_{1,i}\tilde{C}_0\right)' \left(B_{1,i}\tilde{C}_0\right). \tag{14}$$

Next we identify the euro area sentiment shock, assumed to maximize the remaining forecast error variance of the euro area GDP forecast over H^{sent} horizons after accounting for the contribution of surprise and news technology shocks. The forecast horizon set for the identification of the sentiment shock is assumed to be shorter than the horizon chosen to identify the technology shocks since the impact of the sentiment shock on GDP is supposed to be temporary (this is a demand shock). As already mentioned we assume that the euro area GDP forecast is ordered seventh in the VAR(p) model while the sentiment shock is the third structural shock. It is worth to note that the identification of the sentiment shock does not alter two technology shocks specified in the previous step. Thus the contribution of these shocks to the forecast error variance of GDP forecast is fixed for all horizons.

To identify the sentiment shock we derive vector d_3 by solving the following equation:

$$d_3 = \operatorname{argmax} \sum_{h=0}^{H^{sent}} \Omega_{7,3}(h) = \operatorname{argmax} \sum_{h=0}^{H^{news}} \left(\frac{\sum_{i=0}^{h} B_{7,i} \tilde{C}_0 d_3 d_3' \tilde{C}_0' B_{7,i}'}{\sum_{i=0}^{h} B_{7,i} \Sigma B_{7,i}'} \right) \tag{15}$$

s.t.

$$\tilde{C}_0(1,i) = 0 \ \forall i \neq 1$$

$$D(:, 2) = \hat{d}_2$$

$$D'D = I.$$

The vector d_3 defining the euro area sentiment shock is thus the third column of matrix D. We solve equation (15) subject to the constraints that the second column of matrix D is fixed and equal to the impact vector corresponding to the news shock $\hat{d}_2$ identified in the previous step. Numerically we find vector d_3 by proceeding as follows:

1. We form a matrix $D^{news} = \begin{bmatrix} 1 & 0 \\ 0 & \tilde{D}^{news} \end{bmatrix}$, where the subsequent columns of matrix $\tilde{D}^{news}$ are the eigenvectors associated with the eigenvalues (set in descending order) being the solution to problem (13).

2. We derive matrix Λ^{sent}, as:

$$\Lambda^{sent} = \sum_{i=0}^{H^{sent}} \left(H^{sent} + 1 - \max(1, i)\right) \left(B_{7,i} \tilde{C}_0 D^{news}\right)' \left(B_{7,i} \tilde{C}_0 D^{news}\right). \tag{16}$$

3. We calculate the eigenvectors corresponding to the eigenvalues of the lower $(k-2) \times (k-2)$ submatrix of matrix Λ^{sent}. These eigenvectors are set to be the subsequent columns of $(k-2) \times (k-2)$ matrix $\tilde{D}^{sent}$.

4. We derive a $k \times k$ matrix $D^{sent} = D^{news} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \tilde{D}^{sent} \end{bmatrix}$.

5. The vector d_3 which corresponds to the euro area sentiment shock is the third column of D^{sent} matrix.

2.2 Data

As already mentioned we estimate the model for the euro area (EA) and Poland (PL). Poland is strongly integrated with the euro area (which buys almost 60% of its exports). At the same time it is relatively small - at current prices Polish GDP amounts to less than 5% of the euro area. They are close in geographic and political terms (both are part of the European Union). Moreover, existing research documents a high level of business cycle correlation (e.g. Stanisic, 2013). Summing up, Poland and the euro area seem to be ideal candidates to look for a significant role of confidence spillovers between a large and small economy. Moreover, GDP per capita and productivity in Poland were in our sample much lower than in the euro area. For instance GDP per capita measured at purchasing power standards increased from 42% of the EA level in 2000 to 67% in 2016. This means that in the period under consideration Poland can be treated as an importer of technology rather than innovator, validating our decision to identify technology shocks only in the euro area.

The estimated model consists of eight variables: total factor productivity (EA), real GDP (EA and PL), hours worked (EA), real investments (EA), real private household consumption (EA), GDP forecast of professional forecasters (EA) and the short term nominal interest rate (EA). We use GDP forecasts from the Survey of Professional Forecasters (SPF) ranging two quarters ahead. Given that the euro area hit the zero lower bound on interest rates we decided to use the shadow rate calculated using the method of Wu and Xia (2016) (series available from Cyntia Wu's web page) until 2004 and EURIBOR3M before. Total factor productivity (adjusted for capacity utilization) is calculated by the European Commission (Havik et al., 2014) and has been interpolated to quarterly frequency using quadratic frequency conversion filter. The model is estimated with quarterly data from 1Q1999 until 4Q2016. The beginning of our sample is motivated both by the creation of the euro area and introduction of inflation targeting in Poland.

2.3 Estimation

We are now ready to estimate the model and extract the structural shocks. We specify the model as a Vector Error Correction Model (VECM) to capture the long run relationships between the variables. We set the maximum lag order in the VECM equal to 1 as indicated by BIC information criterion. The Johansen's trace and maximum eigenvalue tests suggest that the number of cointegrating vectors spanning the cointegrating space is between three and five. We were able to identify four economically justified long-run relationships and so decided to set the number of cointegrating relations to four. Accordingly we impose restrictions on the cointegrating vectors to identify the whole cointegrating space. We identify the first cointegrating vector as a one-factor production function for the euro area and we restrict GDP as a function of TFP (with unit elasticity) and hours worked. The estimated long run elasticity of GDP with respect to hours worked estimates close to 0.8. The second cointegrating relation links the GDP forecast for the euro area to current GDP. The estimate of the respective parameter in the cointegrating vector is above one, which suggests that forecasters had a slight upward bias in our sample. The third cointegrating vector relates euro area GDP to private consumption and investments. The last cointegrating vector constitutes a long term transmission channel from the euro area to Poland. According to our specification GDP in Poland depends in the long run on GDP in the euro area with the long run elasticity estimated slightly above one, which is consistent with the real convergence process present in our sample. The whole set of restrictions imposed on the cointegrating space has not been rejected by likelihood test for binding restrictions. The detailed estimation results for the VECM are presented in Table 1.

We use the residuals from the estimated VECM model to specify the structural shocks. To this end we impose the restrictions on the impact matrix as described above. We set $H^{news} = 40$ and $H^{sent} = 2$ in line with Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015) respectively. This allows to identify the three structural shocks in the euro area - surprise and news technology shocks as well as the sentiment shock.

3 Confidence and its spillovers

This Section presents our main findings - how the estimated structural shocks work and what role they play in driving the business cycles in the euro area and in transmitting it to Poland. We begin by checking how the shocks work, and in particular, whether the reaction of the respective variables in the model to the sentiment shock is in line with the findings of Angeletos et al. (2014). Next we investigate the role of the shocks in driving the business cycle in the euro area and analyze the transmission of shocks to Poland. We draw our main conclusions on the role of respective shocks by investigating the forecasts error variance decomposition of GDP in the euro area and in Poland. We also split the impact of the euro area sentiment and news shocks on Poland's GDP into its direct and indirect effect. Finally we conduct a historical decomposition of GDP developments in both countries.

3.1 Impulse responses

The impulse response analysis has two goals. First the validation of our model . We check whether responses to the identified shocks are in line with economic intuition and, in particular, whether the sentiment shock has the desired properties. Second, we see if and how the spillovers work.

Figure 1 presents the impulse responses of all model variables to a surprise technology shock. As should be expected the reaction of TFP is immediate and keeps increasing for the next 28 quarters. This translates into higher consumption, investments and GDP in the euro area. For all these variables the reaction is highly persistent. In contrast, the interest rate does not rise, if anything, we observe a slight (though insignificant) decline. This seems to be in line with the specifics of a positive technology shock, which raises output but lowers inflation, sending contradictory signals to the central bank. Regarding spillovers, we observe a relatively strong reaction of Polish GDP, comparable in size to euro area GDP change. However, interestingly and in line with economic intuition, the response of the Polish economy is lagged - the reaction becomes significant only after 3 years. The transfer of technology takes time and this model feature can be considered as a positive validation of our identification strategy.

Impulse responses to the news technology shock are shown on Figure 2. As in the previous case TFP, GDP, consumption and investments increase persistently. However, now the reactions are lagged even in the euro area, which is consistent with TFP increasing later. In the short run responses are relatively weak. Consumption increases and hours worked decline somewhat. This seems in line with a weak income effect from higher future expected output: households consume more and take more leisure. These two forces cancel out so that GDP does not change initially and increases only in the medium term. Interestingly, the immediate reaction of Polish GDP is stronger than that in the euro area. This suggests that economic news are transmitted not only via real economic linkages. Since we have only one variable for Poland we are not able to distinguish whether it is rather an effect on consumption or investment in anticipation of higher output that drives the result.

Last but not least, we analyze the reactions to the euro area sentiment shock. This shock can be thought of as demand-type and thus should be expected to generate rather short-term reactions. This is indeed the case. The positive reaction of output, consumption, investments and hours is short-lived and dies out after approximately two years. There is a clear and fast spillover to Polish GDP which follows a very similar pattern. We observe a negative reaction of TFP to the sentiment shock - something that could be worrying. However, in economic terms the reaction is negligible (0.01%), something confirmed by the variance decompositions discussed later.

As promised, we use the impulse responses to the sentiment shock to validate our identification strategy. In Angeletos et al. (2014) the sentiment shock generates a comovement of GDP, consumption, investments and hours worked - this is also the case in our model. It explains approximately half of the forecast error variance of GDP - something we find as well (shown later). As pointed out by Angeletos et al. (2014) the reactions are not typical for other demand shocks known from the structural (New Keynesian DSGE) literature. For instance a time preference shock pushes consumption and investments in opposite directions, an expansionary monetary policy shock would lower the interest rate (which increases in our case) and a government spending shock would raise GDP but crowds out private expenditure.[3] Our shock generates a short-lived economy-wide expansion, something hard to achieve with standard shocks in structural economic models, but easy to imagine in case of a positive swing in moods (sentiments). These considerations make us confident that what we identify is indeed a shock to economy-wide sentiments.

3.2 Variance dempositions

As a next step we discuss the forecast error variance decomposition (FEVD) of selected variables with respect to the contribution of the identified shocks. It will be convenient to synthetise the information in the text instead of presenting the whole series of dempositions. In order to concentrate on the most relevant information we generate the spectral density function of GDP and identify its peak. This is found at approximately 10-14 quarters, therefore in what follows we will often refer to the decomposition at the 12-quarter horizon as representative for the business cycle. Obviously a single number will mask variation over time, but in tables and figures we present the detailed decomposition related to different horizons.

[3] Financial shocks could possibly act in a similar fashion. However, as we show in Section 4 its inclusion does not change our main findings.

In line with our expectations the forecasts error variance of TFP is affected almost entirely by technology shocks (Table 2). The contribution of the surprise technology shock to the variance of the forecast error amounts to 97% in the short horizon (4 quarters) and decreases to 68% in the long run (10 years). In line with our earlier findings the news shock has a negligible impact on TFP in the short run, with lengthening of the forecast horizon its role increases to 30% for the 10 years ahead forecast.

What is more interesting is the decomposition of euro area GDP (Table 3). Here the situation is more nuanced. In the long run technology shocks dominate - in the 10 year horizon they explain almost 85% of the variance (with the surprise shock being more important than the news shock). However, at business cycle frequencies the bulk of GDP variability is driven by confidence. In the 12-quarter horizon the sentiment shock is responsible for 37% of output variance and the news technology shock for 2%. It sums to 39%, this being our synthetic measure of the role played by confidence shocks in the euro area.

From this paper's point of view the most interesting results come now. The variance decomposition of Polish GDP (Table 4) reveals a number of findings. First, and not very surprisingly, the three shocks identified as coming from the euro area account for 70-90% of the variance. This shows that the role played by foreign developments in driving the Polish business cycle is huge. Second, confidence shocks play a pronounced role in generating spillovers. In the 12-quarter horizon approximately 70% of output variance is driven by the sentiment and news shocks (divided roughly half-half). Their role declines only in the longer term to slightly below 20%.

Let us now turn to the motivation of this paper. As shown in the Introduction the structural business cycle literature, in spite of modeling properly and carefully international trade relationships, is not able to come close to the scale of business cycle synchronization between countries. We hypothesized that the spillovers are to some extent due to confidence spreading in the ether - via media (including social ones) for example. The results presented thus far do not have a saying whether the spillovers are due to trade or other channels. It could be that they are entirely the effect of confidence shocks affecting euro area GDP and then impacting Poland via trade linkages. In such case our paper would say something new about the type of shocks that affect Poland, but not about the channels.

The next experiment sheds light on this issue. We calculate the FEVD of Polish GDP with respect to the confidence shocks after switching off their impact on euro area variables. Technically this amounts to setting selected elements of the impact matrix C_0 to zero, so that either the sentiment or the news shock has no impact on the euro area variables. Figures 4 and 5 present the FEVD to the news and sentiment shock divided into the direct (i.e. the one just calculated) and indirect (i.e. remaining, transmitted via euro area variables) impact on Polish GDP. The channels divide roughly half-by-half. In the 12-quarter horizon 18% of Polish GDP is driven by the direct spillover of euro area technology news, 21% by the direct spillover of euro area economic sentiments. Together this gives 39% of GDP variance and is our measure of an important channel entirely missing in structural macroeconomic models of international business cycles.

3.3 Historical decompositions

Variance decompositions speak about the average role of shocks in the sample. In contrast, historical decompositions allow to investigate the role played by various shocks in shaping model variables in each and single quarter. Below we discuss the historical decompositions of euro area and Poland's GDP, concentrating on the most important developments. On the one hand this analysis sheds light on the factors that drove the business cycles with a particular emphasis on confidence shocks. On the other, the findings can also be seen as another form of validating our modeling strategy.

Let us first focus on euro area GDP. Figure 6 presents its decomposition into the contributions of all shocks (unidentified shocks have been grouped and labeled "other"). As already shown in the previous Subsection, the most important shock at business cycle frequency is the sentiment shock. This is also clear from the historical decomposition. To facilitate its interpretation Figure 7 plots the Economic Sentiment Indicator in the euro area (note that this variable was not used in the estimation process). Contribution of the sentiment shock to GDP growth was positive until 2001 and negative between 2002 and 2005. The first event can be related to very positive moods during the growth of the dot-com bubble, while the downward swing in moods followed the stock market crash and the subsequent recession. Sentiment became again a driver of output between 2006 and 2008, probably following the record readings of the sentiment indicator and the booming housing markets. The onset of the global financial crisis is identified by the model as the occurrence of a large and persistent negative sentiment shock. This shock has negative contribution to GDP since the mid-2008 until the end of 2010. In the next few quarters it remains in general neutral for economic growth and then drags economic growth down again in 2012 - this coincides with a sharp deterioration in moods following the euro area debt crisis. The last event with an interesting economic interpretation is the positive contribution of sentiment shocks to GDP in 2013-14 which most probably follows Mario Draghi's promise to do "whatever it takes" to save the euro and the announcement of the OMT program which limited the growth of sovereign bonds yields and were perceived as having prevented the collapse of the euro area.

Turning to the surprise technology shock, its contribution to euro area GDP is mainly time (plus the lag between the shock and its strongest impact on GDP of approximately 3 years). In 2010 the contribution of this shock started to be negative as a consequence of the financial crisis which affected investment plans of the corporate sector. The most significant and negative impact of the news shock is identified in years 2014-2016 which may be associated with supply-side problems known as “secular stagnation” and the reversal of the globalization process.

When interpreting the impact of the news technology shock it should be born in mind that its transmission to the real economy is much slower that in case of the two previous shocks - the impact on GDP begins only after 2 years. Hence, its contribution to GDP is the consequence of past shocks. In this spirit we interpret its generally positive contribution to GDP between 2001 and 2010 as positive pre-crisis expectations of future technology improvements related to the forces described above the were driving current productivity. After the crisis expectations of future productivity improvements became much more bleak, and the shock stared to exert a negative impact on output.

Turning to the decomposition of Polish GDP (Figure 8) it has to be born in mind that all structural shock in our model come from the euro area and only their transmission to Polish GDP differs somewhat from the transmission to EA GDP. As a result it is not very surprising that the factors behind the Polish business cycle are similar to those described above. As in the case of the euro area we can observe the boom-bust swing in sentiments shortly before and immediately after the crisis and the more persistent effects of current and expected future technology improvements.

4 Robustness

This Section investigates the robustness of our results to various assumptions. We begin with checking whether our choice of the forward-looking variable matters substantially for the findings. To this end we substitute the GDP forecast with the Purchasing Managers Index (PMI) for the euro area. The variance decomposition of EA and Polish GDP for selected horizons is presented in Table (5). While the specific numbers differ from our baseline estimation, the main message remains unchanged - confidence shocks matter both for fluctuations in the euro area and for the spillover to Poland. The direct spillover is weaker than in our baseline case, but with a 20% share in GDP FEVD can still be considered substantial.

Second, as written in Section 3.1, our sentiment shock could possibly be confused with a financial shock. While ex ante it seems hardly plausible that financial shocks could explain such a share of business cycle fluctuations, below we offer a formal investigation into this matter. Given the limited sample size our baseline model with eight variables should be considered large and we would not feel comfortable extending it for any additional variables that might be necessary to identify financial shocks. Instead we decided to proceed as follows - we dropped three variables that do not seem crucial to extract the technology and sentiment shock (consumption, investments and the interest rate) but were rather used to validate them. On their place we include a variable that contains information about financial frictions (ordered third) and reestimate the model. Then we identify four shocks - first the two technology shocks, than a financial shock that (given the previous shocks) maximizes the FEVD of the financial variable and finally the sentiment shock that given the previous shocks maximizes the FEVD of the GDP forecast.

We use two alternative financial variables: the VIX index and the Euribor-Overnight Index Swap spread. Both are standard indicators of financial tensions, the first with a more global flavor, the second euro area oriented. Table (5) presents selected aspects of the variance decomposition. The financial shock matters somewhat for cyclical fluctuations explaining up to 15% of GDP variance in the euro area (and slightly less in Poland). Regarding spillovers, changing the model is not completely innocuous. However, the main findings remain valid - at the 12-quarter horizon the sentiment shock explains approximately half of the FEVD of Polish GDP. Direct spillovers of confidence shocks account for 37-52% of GDP fluctuations. It should also be noted that modifying the identification method did not influence the sentiment shock as such. For instance the correlation between the sentiment shock identified in the baseline model and in the model including the VIX is 0.85.

All in all, our two robustness checks, while changing somewhat the specific numbers, do not undermine our main finding - confidence shocks matter a lot for business cycle fluctuation and their international spillovers.

5 Conclusions

How important are confidence fluctuations for business cycles? And how important are they for spillovers of cyclical fluctuations between economies? These questions seem fundamental to understand the nature of business cycle fluctuations. They relate to the old idea of Pigou (1927) and Keynes (1936) that fluctuations in moods have a potential to drive business cycles. This view has recently gained substantial attention in the literature and most existing research point to a very important role of confidence fluctuations. In this area we offer rather new data than new ideas. More importantly, we believe that moods can also travel across borders, thus strengthening the international correlation of business cycles. This idea has so far been almost untested in the literature and we believe to have a genuine contribution in this area.

This paper offers an empirical approach to answering the two above questions. We estimate a VAR/VECM model for the euro area and Poland (a large and a small, neighboring economy) and carefully identify shocks related to confidence fluctuations. We distinguish two types of confidence shocks. The first type relates to the supply side of the economy and can be interpreted as expectation of future improvements in technology (it is called technology news). The second type has a demand flavor and can be interpreted as fluctuations in moods about future economic performance, unrelated to technological advance (we call it sentiment).

Regarding the first question, we confirm what was already stated for other countries. Confidence shocks play an important role both in the euro area and in Poland. For instance, in the 12-quater horizon they account for almost 40% of forecast error variance decomposition of GDP in the euro area and their spillover to Poland accounts for over 70% of its GDP variability. We also divide the international transmission of confidence into a direct and indirect effect. The latter operates by first affecting euro area variables and then transmitting to Poland (probably mainly via trade). The former affects Poland directly, presumably due to spreading news (e.g. via media). The direct channel is responsible for approximately 50% of the confidence spillovers or, in other words, for almost 40% of Polish GDP variance. We put this result at the forefront of our findings, since it points to an important role of a channel that has, so far, been neglected in the structural international business cycle literature.

Last but not least our paper offers a clear and interpretable historical decomposition of GDP fluctuations, accentuating the role of confidence shocks. For instance we show that sentiment shocks played an important role during the financial crisis and during the euro area sovereign debt crisis.

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Tables and Figures

Table 1: Estimation results of the cointegrating relationships

Dependent variable	GDP_t^{EA}	GDP_t^{PL}	$GDPF_t^{EA}$	GDP_t^{EA}
TFP_t	1	-	-	-
GDP_t^{EA}	-	1.052 (0.242)	1.087 (0.016)	-
$HOURS_t^{EA}$	0.815 (0.048)	-	-	-
INV_t^{EA}	-	-	-	0.100 (0.025)
$CONS_t^{EA}$	-	-	-	0.622 (0.064)
LR test for binding restrictions: chi2(4) = 15.68 (0.154)				

Note: Standard errors in parentheses.

Table 2: Forecast error variance decomposition of euro area TFP

TFP				
quarters	Surprise technology	News technology	Sentiment	Other
4	0.966	0.024	0.001	0.010
8	0.928	0.055	0.003	0.014
12	0.891	0.090	0.006	0.012
24	0.792	0.201	0.003	0.004
40	0.681	0.307	0.005	0.006

Table 3: Forecast error variance decomposition of euro area GDP

EA GDP				
quarters	Surprise technology	News technology	Sentiment	Other
4	0.110	0.042	0.748	0.101
8	0.202	0.029	0.508	0.261
12	0.329	0.019	0.365	0.287
24	0.665	0.038	0.130	0.166
40	0.727	0.115	0.057	0.100

Table 4: Forecast error variance decomposition of Poland's GDP

Poland's GDP				
quarters	Surprise technology	News technology	Sentiment	Other
4	0.009	0.369	0.501	0.122
8	0.014	0.386	0.433	0.167
12	0.037	0.364	0.376	0.224
24	0.337	0.194	0.222	0.247
40	0.674	0.108	0.071	0.148

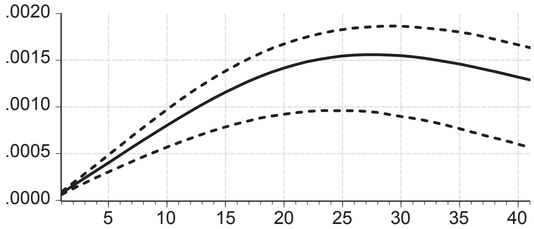
Table 5: EA & Poland's GDP FEVD - robustness checks

	Baseline (8 variables incl. GDP forecast)			PMI			VIX				OIS			
EA GDP														
h	Surprise	News	Sentiment	Surprise	News	Sentiment	Surprise	News	Financial	Sentiment	Surprise	News	Financial	Sentiment
4	0.110	0.042	0.748	0.100	0.019	0.671	0.142	0.182	0.152	0.478	0.227	0.181	0.035	0.519
12	0.329	0.019	0.365	0.414	0.012	0.297	0.396	0.101	0.089	0.274	0.470	0.089	0.024	0.275
24	0.665	0.038	0.130	0.786	0.006	0.092	0.652	0.048	0.054	0.138	0.728	0.039	0.010	0.118
Poland's GDP														
h	News	Sentiment	Dir. conf. spill.	News	Sentiment	Dir. conf. spill.	News	Financial	Sentiment	Dir. conf. spill.	News	Financial	Sentiment	Dir. conf. spill.
4	0.369	0.501	0.542	0.447	0.293	0.318	0.122	0.080	0.609	0.509	0.182	0.065	0.614	0.654
12	0.364	0.376	0.386	0.432	0.256	0.207	0.101	0.055	0.493	0.369	0.174	0.072	0.508	0.521
24	0.194	0.222	0.209	0.397	0.242	0.191	0.070	0.048	0.268	0.140	0.102	0.038	0.268	0.227

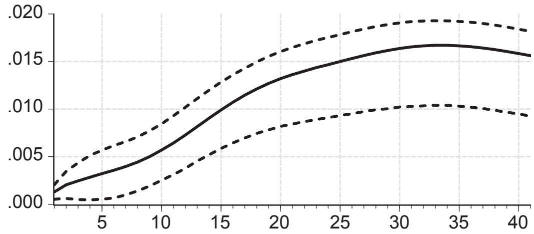
Note: The table presents selected forecast error variance decompositions for GDP in the euro area and in Poland in our baseline model and for three robustness checks.

Figure 1: The impulse responses to surprise technology shock.

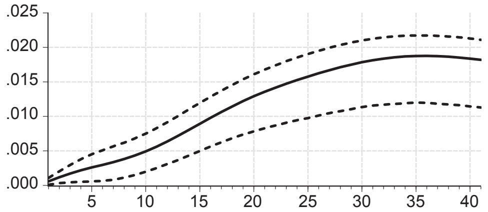
a) Response of EA TFP to surprise technology shock



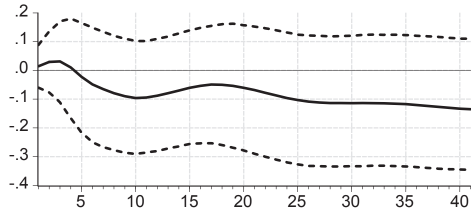
b) Response of EA GDP to surprise technology shock



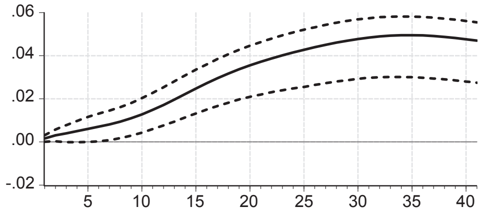
c) Response of EA HOURS to surprise technology shock



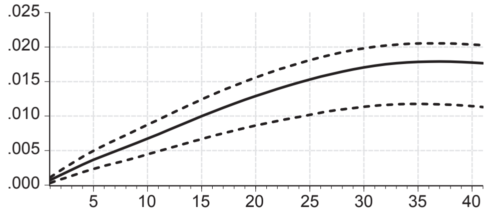
d) Response of EA INT. RATE to surprise technology shock



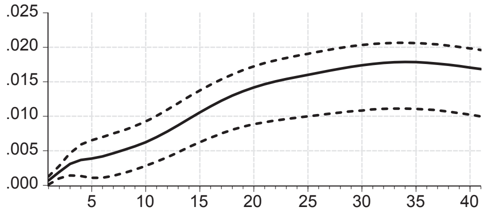
e) Response of EA INV to surprise technology shock



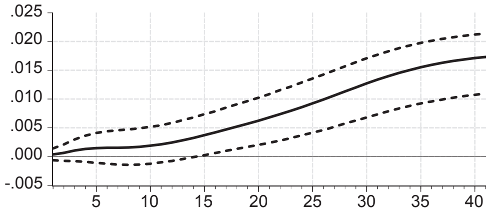
f) Response of EA CONS to surprise technology shock



g) Response of EA GDPF to surprise technology shock

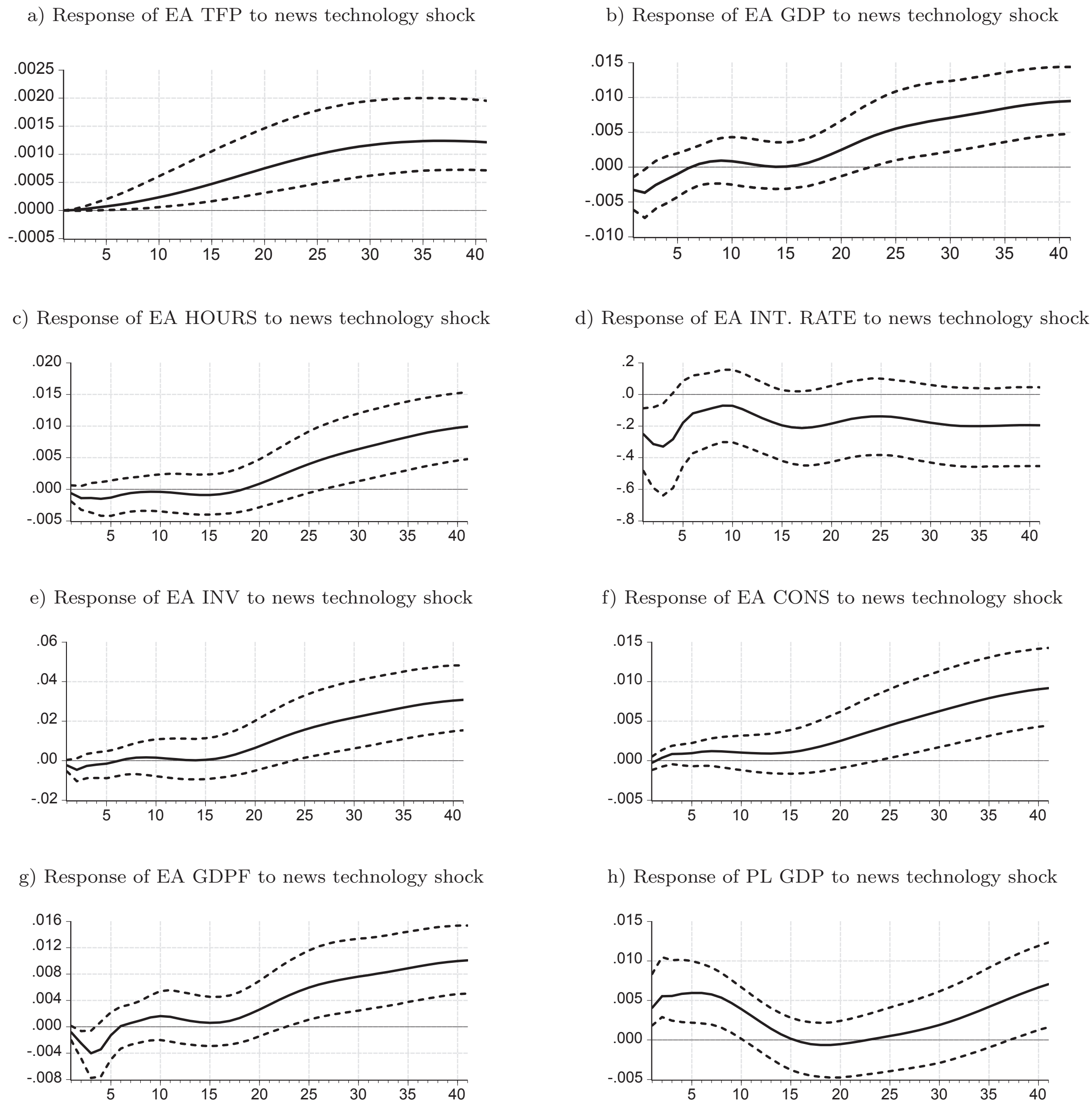


h) Response of PL GDP to surprise technology shock



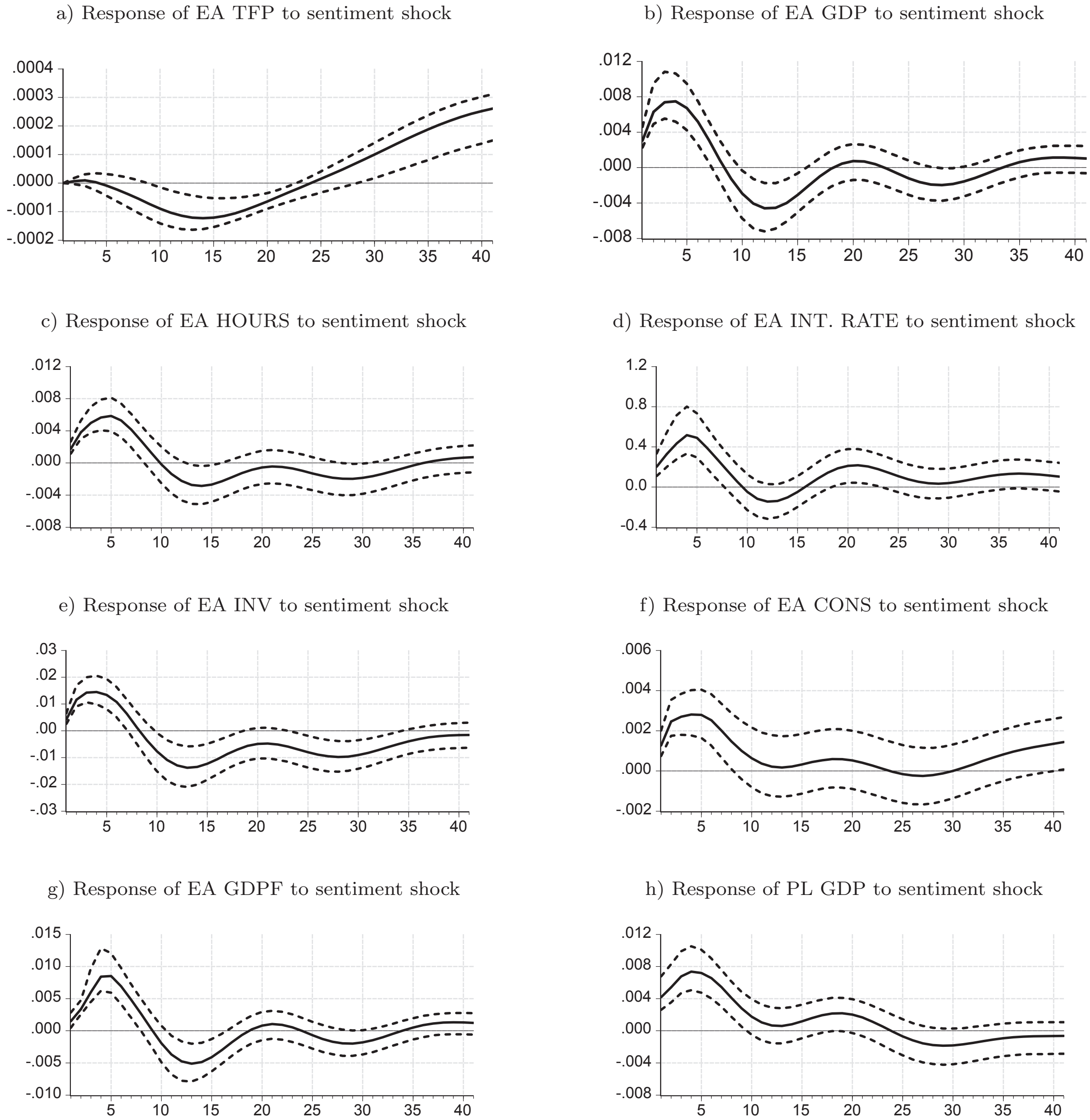
Note: Dotted lines represent the 90 percent bootstrap confidence bands calculated with 10 000 replications, using the approach proposed by Hall (1992).

Figure 2: The impulse responses to news technology shock.



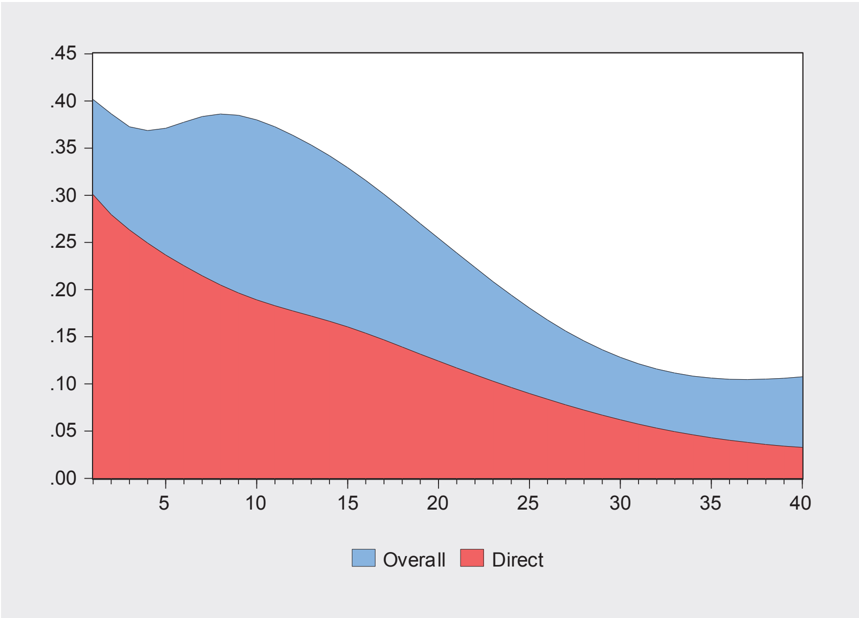
Note: Dotted lines represent the 90 percent bootstrap confidence bands calculated with 10 000 replications, using the approach proposed by Hall (1992).

Figure 3: The impulse responses to sentiment shock.



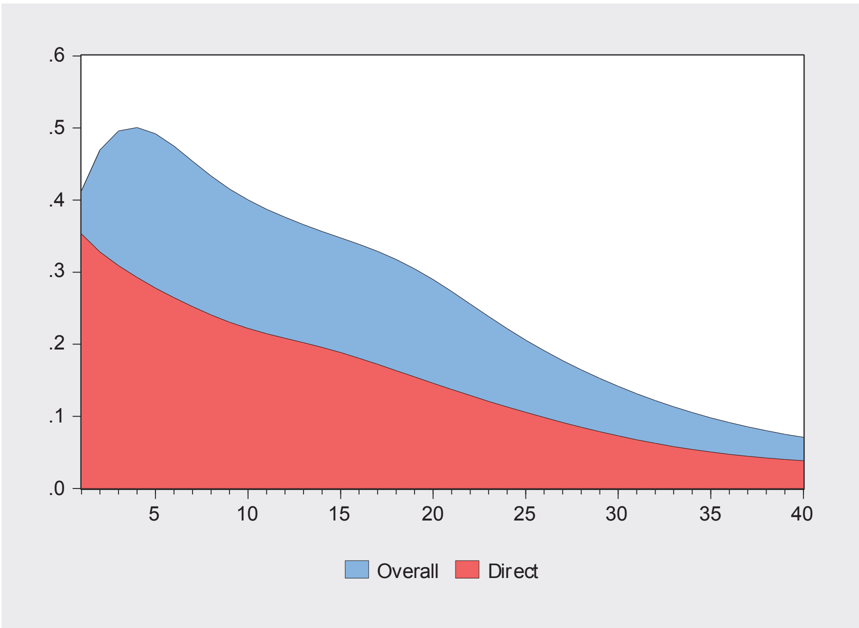
Note: Dotted lines represent the 90 percent bootstrap confidence bands calculated with 10 000 replications, using the approach proposed by Hall (1992).

Figure 4: Direct vs indirect impact of the news shock on the variability of Poland's GDP.



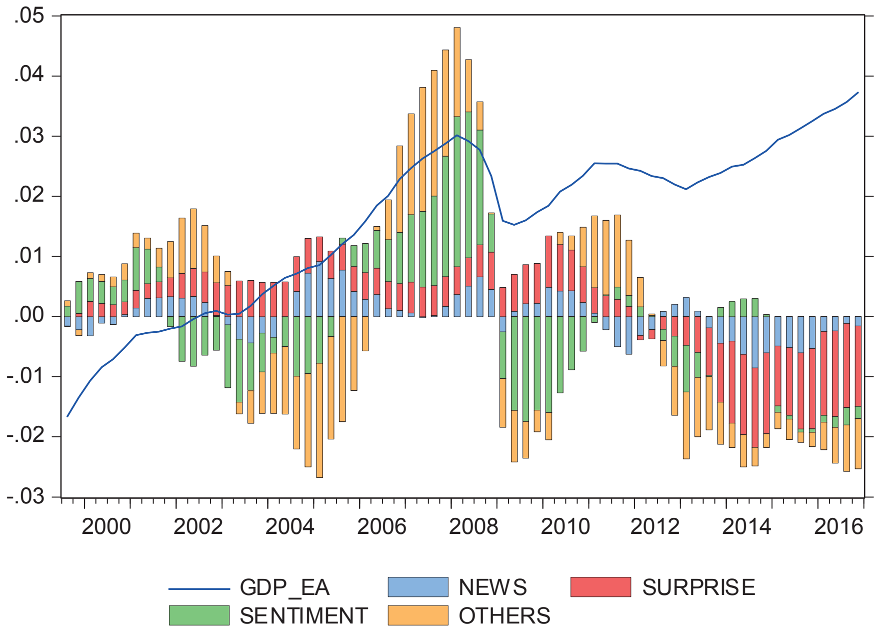
Note: The plot presents the contribution of the euro area news shock to Poland's GDP FEVD decomposed into its direct and indirect effects.

Figure 5: Direct vs indirect impact of the sentiment shock on the variability of Poland's GDP.



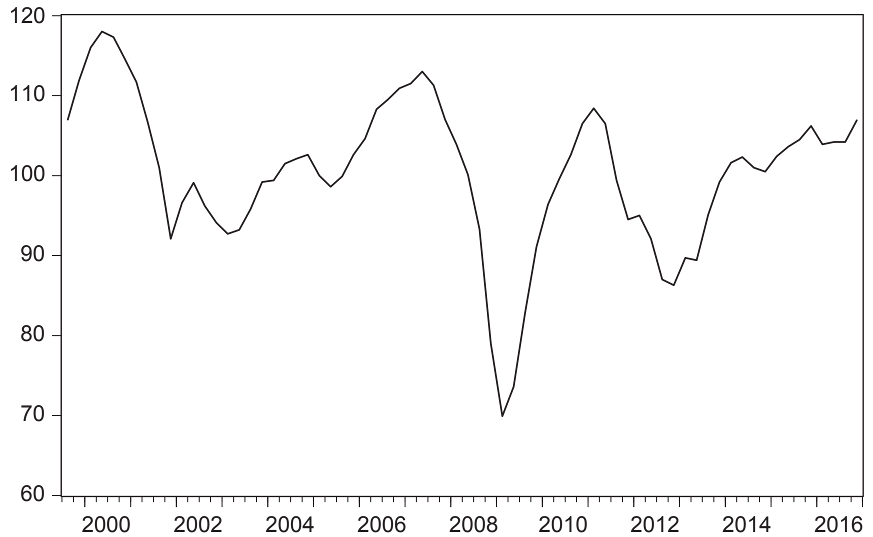
Note: The plot presents the the contribution of the euro area sentiment shock to Poland's GDP FEVD decomposed into its direct and indirect effects.

Figure 6: Historical decomposition of euro area GDP.



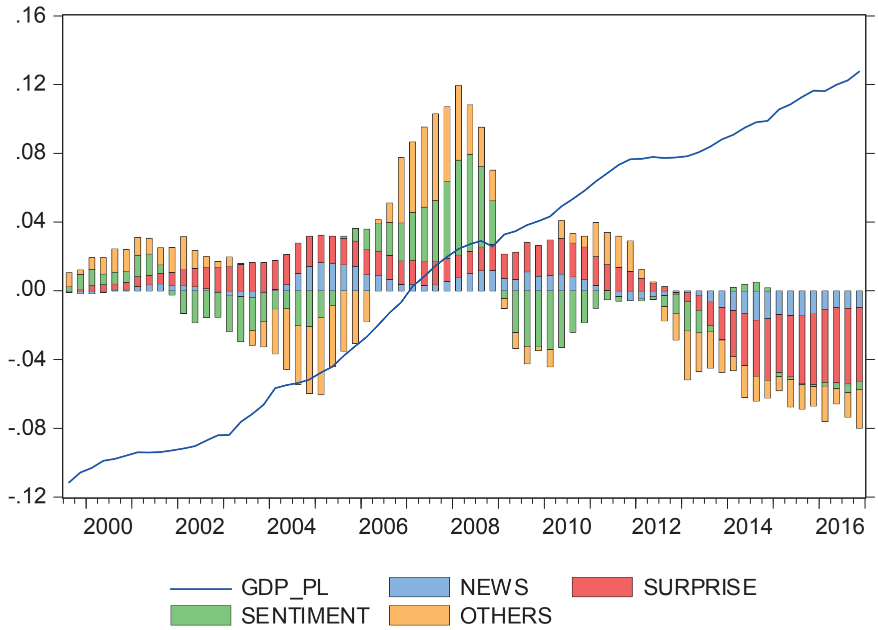
Note: The plot presents the historical decomposition of euro area GDP with respect to structural shocks.

Figure 7: Economic sentiment indicator in the euro area



Note: The plot presents the Economic Sentiment Indicator in the euro area (Source: European Commission).

Figure 8: Historical decomposition of Poland's GDP.



Note: The plot presents the historical decomposition of Poland's GDP with respect to structural shocks.

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