The Role of Confidence Measures in European Unemployment Dynamics[*]

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First draft: October 2021
Current version: August 2024

Abstract

This paper explores the role of confidence measures in macroeconomic dynamics, focusing on their impact on unemployment in Europe. Using a mixed-frequency Panel FAVAR model with data from 22 European countries, we find that confidence shocks, which have no immediate effect on productivity or unemployment, are strongly correlated with non-technological shocks driving long-term unemployment dynamics. By applying a simultaneous identification approach with short- and long-run restrictions, we show that confidence shocks account for approximately 50% of unemployment variance in the medium run. These results support the "news" view of confidence and challenge both the traditional view that focuses solely on technological news and the conventional belief that technological news shocks are the primary drivers of business cycles, suggesting instead that confidence-related shocks linked to non-technological factors play a significant role. To validate our empirical findings, we develop a structural search and matching model, demonstrating that under adaptive learning, confidence shocks in the form of news can explain a substantial portion of unemployment fluctuations. This research shifts the focus from technological to confidence-related shocks, providing new insights into labor market dynamics.

Keywords: Confidence Shock, Unemployment Fluctuations, Consumer and Firms Survey Expectations, Panel Favar, Mixed-Frequencies.

JEL Classification: C32, D83, E24, E30

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[*]This paper should not be reported as representing the views of Bank of Spain. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Spain. This paper previously circulated under the title "The Effect of Non-Technological News Shocks on Unemployment Fluctuations: The Case of Europe". The paper has benefited from comments by Eric R. Sims, Francesco Zanetti and Enrique Martínez-García. We also thank participants at the IAAE 2024, 22nd annual SAET conference, University of Minnesota Macroeconomic Workshop, Alicante Macroeconomic PhD Workshop and the UAB MacroClub for helpful comments. This research has been greatly beneficial from founding provided by the European Research Council (ERC) under the project number 804989 (DYMOLAMO).

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1 Introduction

In recent years, there has been significant interest in understanding the role of expectations and confidence in macroeconomic dynamics. The debate centers on whether confidence measures reflect news about future economic developments or are driven by psychological waves of optimism and pessimism known as 'animal spirits" (Barsky and Sims (2012)). While the former view has predominantly focused on technological news (Beaudry and Portier (2006); Barsky and Sims (2011)), with the stock market widely accepted as a forward-looking variable, the applicability of confidence indicators remains uncertain (Barsky and Sims (2012); Beaudry and Portier (2014)). The academic literature on confidence is ambiguous about the nature of the shocks it reflects. Additionally, if these measures do convey news, as Barsky and Sims (2012) pointed out, it is not clear what type of fundamental news they contain. This paper addresses this gap by examining the informational content of confidence measures from both consumers and firms, and their implications for macroeconomic outcomes, particularly unemployment fluctuations.

Our study leverages on a rich dataset from the European Commission, which includes a wide array of expectational questions across different sectors of the economy, not just consumers. By doing so, we move beyond the traditional focus on consumer confidence alone, providing a more holistic view of the expectations of all economic agents. Specifically, we use data from 22 European countries spanning from 2000 to 2021 to identify and study the effect of confidence innovations on the European labor market. The surveys are conducted monthly across economic agents—manufacturing, construction, retail trade, services, and consumers—capturing expectations regarding future production, employment, and the overall state of the economy. For the empirical analysis, we employ a Mixed-Frequency Panel FAVAR model that allows us to combine variables at different frequencies—monthly (unemployment and surveys) and quarterly (real labor productivity)—and extract a country-specific factor that combines all survey data for each country, summarizing overall expectations for each economy.

First, using labor productivity, unemployment, and the confidence factor, we apply the sequential identification scheme of Beaudry and Portier (2006). We use their approach not as an identification, if not as a signaling scheme to ascertain two critical aspects: Firstly, whether the forward-looking variables could potentially contain news information. Secondly, it informs about the nature of the news —specifically, whether news are related to the technological or non-technological side of the economy.[1] We show that innovations to confidence, which have no contemporaneous effects on labor productivity or unemployment, are highly correlated (-0.95) with non-technological shocks that explain the long-run behavior of unemployment. However, this correlation does not hold with the technological shocks that drive the long-run behavior of labor productivity, as Beaudry and Portier (2006) found with innovations to the stock market. Given that such shocks explain the major share of

[1] We follow a similar approach to Gali (1999) to define the technological and non-technological sides of the economy.

the forecast error variance of confidence, these observations suggest that there is at least some truth to the news view of confidence in the same line of Barsky and Sims (2012). However, these news seem to be related to the non-technological side of the economy, moving away from the traditional technology news.

The sequential identification scheme developed by Beaudry and Portier (2006) (BP) encounters limitations in jointly identifying exogenous variations from fundamental components and confidence (potential news) shocks. Identified shocks tend to be correlated to each other preventing to know, for example, the contribution share of different shocks. Following this, we propose a simultaneous scheme to jointly identify uncorrelated shocks — technology, non-technology, and confidence shocks (non-technological news shocks) — whose restrictions are informed by the insights gained from the signaling scheme.[2] The simultaneous scheme relies on short and long-run identification schemes, showing that confidence shocks significantly affect unemployment, particularly in the medium to long run, accounting around 50% of its variance. Non-technology shocks emerge as the primary driver of unemployment fluctuations at the business cycle frequency. The longer-horizon implications for unemployment are far too large and significant for confidence innovations not to convey information about future fundamentals. These results suggest that there could be news shocks about future non-technological aspects of the economy, not reflected in current unemployment, which account for a major fraction of the variance in the confidence factor at any horizon. Our findings are connected with the paper of Schmitt-Grohé and Uribe (2012), who find that anticipated technology shocks do not play a major role in explaining business cycle fluctuations in output, investment, and employment. Instead, anticipated shocks, such as wage markup, government spending, and investment-specific shocks, can explain a significant portion of the variance in these variables.

After incorporating additional variables such as prices, investment, nominal and real wages, we find that our confidence shock consistently resembles a demand shock, leading to a persistent decrease in unemployment while simultaneously increasing prices, investment, and wages. Additionally, we show that the above results remain consistent when including the stock market to identify a technological news shock. Neither technological news nor technological shocks are the main drivers of unemployment throughout the business cycle, in line with the findings of Angeletos et al. (2020). This opens up a new perspective within the news literature, which has so far focused on technological news. Our findings suggest that, when it comes to the job market, the traditional story centered on technology news does not hold.

Finally, we provide a simple model to validate our empirical results, demonstrating that confidence shocks(non-technological news) can explain a significant proportion of unemployment fluctuations in the medium run. We present a search and match-

[2]Our identifying approach to news shocks is related to the family of "max-share" restriction approaches, but with much fewer restrictions. We do not take a stand on whether the contribution of our news shock should maximize the forecast-error variance of the targeted variable (in our case, unemployment) at a long but finite horizon.

ing model within a dynamic and stochastic framework, following Shimer (2005). In addition to the two standard shocks—productivity and separation rate shocks—we introduce a third shock representing news about a transitory shock that affects labor market tightness. This approach is motivated by our finding that confidence shocks Granger-cause labor market tightness but not vice versa. After calibrating the model to match the empirical impulse response functions, we find that if agents form expectations about future labor market tightness adaptively, the model can account for the share of the variance in unemployment explained by confidence (non-technological news) shocks. This is because the model incorporates a self-referential aspect. However, if agents form expectations rationally, such shocks play no role in unemployment fluctuations. This theory, based on informational frictions, not only validates our empirical results but also opens the door to the possibility that an important driver of unemployment is news related to the non-technological side of the economy.

Related literature. Our paper contributes to the literature that seeks to understand the role of confidence in macroeconomics. Theoretical developments often focus on how to empirically quantify confidence shocks and what information these shocks contain. As Barsky and Sims (2012) pointed out, there are at least two distinctive, although not exclusive, views on the role of confidence. The first, known as the "animal spirits" view, dates back to Pigou (1927), Keynes (1937), and Akerlof and Shiller (2010). This perspective posits that autonomous fluctuations in beliefs can causally affect economic activity. More recently, theories have focused on reformulating models to include economic sentiment as an endogenous variable, as seen in works by Angeletos and La'o (2013), Bacchetta and Van Wincoop (2013), Benhabib et al. (2015), and Acharya et al. (2021). The second view, the "information" or "news" view, suggests that confidence indicators contain information about the future states of the economy (Lamla et al. (2007); Barsky and Sims (2012); Beaudry and Portier (2014)).

Our paper provides new evidence supporting the second view. However, we differentiate our work by using a combination of confidence indicators from both firms and workers, while previous studies typically focus on the expectations of one type of agent. For instance, Lamla et al. (2007) utilize survey-based business expectations from firms in Germany, and Barsky and Sims (2012) and Beaudry and Portier (2014) employ consumer confidence measures in the U.S. Another distinction is that Barsky and Sims (2012) and Beaudry and Portier (2014) assume that consumer confidence measures should contain news about future technology. In contrast, our findings suggest that the news identified in our survey data pertains to the non-technological side of the economy. Additionally, Beaudry and Portier (2014) find that if stock prices are excluded from the system, confidence innovations do not significantly affect long-run TFP movements. This supports our finding that confidence shocks do not contain technological news. We observe that our confidence shocks, identified using short-run restrictions, are highly correlated with the shocks driving the long-run behavior of unemployment but not with those affecting long-run labor productivity. Furthermore, our results are robust to the inclusion or exclusion of stock prices.

This research builds on the existing empirical literature that provides evidence on the "news-driven business cycle hypothesis". The news literature posits that business cycles can emerge without contemporaneous changes in fundamentals. Since the seminal contribution of Beaudry and Portier (2006), this literature has primarily focused on identifying the effect of news about future productivity on the business cycle. In particular, they rely on forward-looking variables such as stock prices to identify technological news shocks.[3] They argue that stock prices reflect news about future changes in technology, as they are clearly forward-looking and free to jump in response to revised expectations. Subsequent works by Barsky and Sims (2011), Forni et al. (2014), and Barsky et al. (2015) have challenged these conclusions by using alternative identification strategies. Unlike the traditional literature focused on technology news, our findings suggest that in the context of the labor market, particularly unemployment, it is not technology news that plays a major role but rather news related to the non-technology aspects of the economy. This result aligns with the work of Schmitt-Grohé and Uribe (2012), who find that anticipated technology shocks do not play a major role in explaining business cycle fluctuations in output, investment, and employment. Instead, anticipated shocks, such as wage markup, government spending, and investment-specific shocks, can explain a significant portion of the variance in these variables. When we include the stock market and attempt to identify a technological news shock, we find similar evidence as Barsky and Sims (2011), Forni et al. (2014), and Barsky et al. (2015) that TFP is not mainly driven in the medium-to-long run by technological news shocks. Moreover, the inclusion of stock prices does not alter our main result. This reinforces our conclusion that confidence-related non-technological news shocks are significant drivers of labor market dynamics, especially in terms of unemployment fluctuations.

This work also contributes to the ongoing research investigating how to build simple macroeconomic models that robustly capture the idea of news-driven business cycles. News-driven models face a fundamental theoretical challenge. As Barro and King (1984) pointed out, in standard neoclassical models, technological news shocks do not produce the correct business cycle comovements. Moving away from traditional technological news shocks is even more challenging, as it explores new territory. To analyze the effect of news on unemployment, we use a dynamic and stochastic search and matching model. Similarly, Theodoridis and Zanetti (2016) introduces different types of news shocks in a search and matching model. However, they find that non-technological news—specifically shocks affecting the destruction rate and the efficiency of the matching function—and technological news shocks do not significantly explain unemployment fluctuations in their model. Hence, the dynamics of the unemployment rate are governed by surprises in the destruction rate and the efficiency of the matching function. Capturing the effect of non-technological news on unemployment requires departing from some standard modeling assumptions.

[3] A recent strand of papers use patent grants data to identify exogenous future technological improvements; see Cascaldi-Garcia and Vukotić (2022) and Lucke (2013).

We contribute to this literature by exploiting the synergies between the literature on informational frictions and adaptive learning in the spirit of Evans and Honkapohja (2012) with the literature on news. A framework where agents try to infer the future of the labor market by looking at current fundamentals gives rise to feedback effects, allowing non-technological news to have a long-lasting effect on unemployment, reproducing its empirical variance. Our model shares some similarities with Lorenzoni (2009) in terms of the introduction of imperfect information.[4] Lorenzoni emphasizes the role of consumer expectations and how noisy signals or news shocks about productivity lead to expectational errors, causing fluctuations in economic activity. These noise shocks act as demand-side disturbances, distinct from technological shocks. His model highlights how imperfect information can lead to demand shocks, which affect output, employment, and inflation. By incorporating these insights, our model allows for a more nuanced understanding of how non-technological news can drive business cycle dynamics, particularly in the labor market.

Structure. The remaining parts of this paper are organized as follows. Section 2 describes the data, its sources and transformations. Section 3 presents the econometric model, the signalling scheme of BP and the simultaneous identification scheme. Section 4 reports the main empirical findings and the results from the inclusion of stock prices. Section 5 presents the theoretical model. Section 6 provides a battery of extensions and robustness tests; and Section 7 provides some concluding comments.

2 Data: Sources, and Transformation

Sources. Data are gathered for the following countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Ireland, Latvia, Luxembourg, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom. The frequency of the data is monthly (M) and quarterly (Q). It spans the period 2000m1-2021m6. Data are collected from two main institutions: (i) the OECD Main Economic Indicators Database-gross domestic product per person employed (Q) and unemployment rate (M); (ii) European Commission - The Business and Consumer Survey. The business and consumer data are qualitative surveys reported as aggregated diffusion time series[5]. In particular, we use several business surveys related to expected production and employment. Concerning the households, we use surveys related to their expected financial and future economic situation in their country (in general terms and the number of unemployed people).[6]

[4]The paper of Lorenzoni (2009) belongs to the literature on dispersed information and social learning. Important contributions this literature include Zeira (1987), Zeira (1994), Banerjee (1992) and Chamley and Gale (1994). Additionally, there are excellent books by Chamley (2004) and Veldkamp (2011).

[5]The goal of this survey data is to provide overall perceptions and expectations (anticipations) of the short-term developments of the economic cycle. These surveys are conducted under the principle of harmonization to produce comparable data; for example, high frequency, timeliness, and continuous harmonization are among their main qualities.

[6]For more details, see Appendix B.

Transformations. Productivity is transformed into the Napierian logarithm. The unemployment is transformed as follows:

$$v = \ln\left(\frac{100 \times \text{Variable}}{100 - \text{Variable}}\right).$$

This transformation is necessary because it allows us to argue that v is defined as a non-stationary series unbounded above and below.[7] To construct the confidence indicator for each economic agent, we follow the methodology of the European Commission. Confidence indicators are the arithmetic average of the answers to the questions that we consider. All variables are already available in the seasonally adjusted form. Finally, data enter standardized in the mixed-frequencies Panel FAVAR since it helps us to reconstruct better, from quarterly to monthly, the labor productivity of each economy.

3 Econometric Methodology

In this section, we introduce the empirical model and its restrictions to understand the information contain in confidence measures. We first present the mixed-frequency Panel FAVAR model and describe the estimation procedure.[8] Second, we then explain the signalling scheme from Beaudry and Portier (2006) (BP), which tests whether confidence measures align with the "news" view and explores the nature of such news. We find that non-technology shocks, identified with long-run restrictions, and confidence shocks, identified with short-run restrictions, are highly correlated. This correlation suggests (i) that our confidence factor contains anticipated information as news, and (ii) such news are related to the non-technological part of the economy. However, the BP scheme cannot assess the relative explanatory power of each structural shock, as confidence and non-technological shocks are identified in different systems. Therefore, we propose a simultaneous short- and long-run identification that extends the signalling scheme, enabling joint identification of technological, non-technological, and confidence (news) shocks.

3.1 Mixed Frequency (MF) Panel FAVAR model

MF-Panel FAVARs have the same structure as VAR models in the sense that all variables—observable and unobservable—are assumed to be endogenous and interdependent. However, a cross-sectional dimension is added to the representation.

[7]These transformations are appropriate for us since most unemployment rates are I(1) processes using a standard unit-root test. See Farmer (2015) and Nicolau (2002) for more details.

[8]Our econometric approach takes general approach in the following aspect: Our VAR does not implicitly impose any cointegration relation on the different countries of analysis. In this sense, we estimate the model in log-levels, as suggested by Sims et al. (1990), instead of imposing an ad hoc number of co-integrating relationships in a VEC model as in Beaudry and Portier (2006). This approach allows us to (i) analyze countries where there exists a cointegration relationship between the variables, as well as countries where there is no such relationship, and (ii) avoid the problem of not having a unique solution that is emphasized by Kurmann and Mertens (2014). The augmented BP scheme and results are robust if variables enter in the model in stationary terms.

Formally, a panel FAVAR model comprises C units, which, in our case are countries. As for a standard VAR, each country includes N endogenous variables and p lags, defined over T periods. We consider an unbalanced panel with mixed frequencies—at a monthly and quarterly frequency. If one were to consider a VAR at a monthly-quarterly frequency, then the vector of dependent variables has two missing observations in every quarter.

Suppose a general panel FAVAR model where observable and non-observable variables are known a priori. In addition, also suppose that there is a single frequency. This model can be written, as a panel VAR, in the following way:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{C,t} \end{pmatrix} = \begin{pmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_C \end{pmatrix} + \begin{pmatrix} A_1^1 & 0 & \dots & 0 \\ 0 & A_2^1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & A_C^1 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{C,t-1} \end{pmatrix} + \dots \tag{1}$$

$$+ \begin{pmatrix} A_1^p & 0 & \dots & 0 \\ 0 & A_2^p & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & A_C^p \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{C,t-p} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \vdots \\ \epsilon_{C,t} \end{pmatrix},$$

and

$$\begin{pmatrix} \Sigma_1 & 0 & \dots & 0 \\ 0 & \Sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Sigma_C \end{pmatrix},$$

where $y_{i,t}$ is a vector that contains three variables, labor productivity, the unemployment rate, and the unobservable factor for country i, $\epsilon_{i,t}$ is a vector of random disturbances following $N(0, \Sigma_i)$, δ_i a vector of constants, and A_i^p represent the matrix of coefficients for country i and endogenous variables with p lags. We assume that $\mathcal{A}_i$, where $\mathcal{A}_i = \{A_i^1, ..., A_i^p\}$, are related across i units according to the specification:

$$\mathcal{A}_i = \bar{a} + a_i, \; a_i \sim N(0, \Omega)$$

where $\bar{a}$ and Ω represent a common mean and variance. This specification simply means that the C units of the model are characterized by heterogeneous VAR coefficients (i.e., $\mathcal{A}_i \neq \mathcal{A}_j$ if $i \neq j$), but that these coefficients are random processes sharing a common mean. Therefore, the parameters of interest, $\bar{a}$, are the (cross-sectional) average coefficients of the group.[9]

[9]Different European frameworks have also been studied under the lens of PANEL VARs; for example: (i) price differential in monetary unions, Canova and Ciccarelli (2004), (ii) responses to monetary policy shocks in different regions of the same monetary union, Jarociński (2010), and (iii) how the structure of housing finance affects the monetary transmission mechanism Calza et al. (2013).

Mixed-Frequencies FAVAR. The observed state-space FAVAR model of each country is

$$
\underbrace{\begin{bmatrix} LP_{i,t} \\ UN_{i,t} \\ HH_{i,t} \\ IND_{i,t} \\ SER_{i,t} \\ BUL_{i,t} \\ RE_{i,t} \end{bmatrix}}_{y_{i,t}} = \underbrace{\begin{bmatrix} 1/3 & 0 & 0 & 1/3 & 0 & 0 & 1/3 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,1} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,2} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,3} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,4} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,5} & 0 & 0 & 0 & 0 & \dots & 0 \end{bmatrix}}_{H_i} \underbrace{\begin{bmatrix} \hat{LP}_{i,t} \\ UN_{i,t} \\ \hat{F}_{i,t} \\ \hat{LP}_{i,t-1} \\ UN_{i,t-1} \\ \hat{F}_{i,t-1} \\ \hat{LP}_{i,t-2} \\ UN_{i,t-2} \\ \hat{F}_{i,t-2} \\ \dots \\ \hat{LP}_{i,t-p} \\ UN_{i,t-p} \\ \hat{F}_{i,t-p} \end{bmatrix}}_{\hat{y}_{i,t}} + \begin{bmatrix} 0 \\ 0 \\ v_{i,t}^3 \\ v_{i,t}^4 \\ v_{i,t}^5 \\ v_{i,t}^6 \\ v_{i,t}^7 \end{bmatrix}.
$$

This equation states two important relations: 1. When a quarterly observation for labor productivity ($LP_{i,t}$) is available, it is computed as an average of the unobserved monthly data on ($\hat{LP}_{i,t}$). 2. The five survey series—consumer, industry, service, construction, and retail confidence indicators—are mapped to a single latent variable that we called factor ($\hat{F}_{i,t}$), plus a specific error term. This mapping is done through the restricted matrix H_i that depends on the free parameters $h_{i,1}, \cdots, h_{i,5}$. On the other hand, when an observation for ($LP_{i,t}$) is unavailable, the state-space model changes to

$$
\underbrace{\begin{bmatrix} LP_{i,t} \\ UN_{i,t} \\ HH_{i,t} \\ IND_{i,t} \\ SER_{i,t} \\ BUL_{i,t} \\ RE_{i,t} \end{bmatrix}}_{y_{i,t}} = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,1} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,2} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,3} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,4} & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & h_{i,5} & 0 & 0 & 0 & 0 & \dots & 0 \end{bmatrix}}_{H_i} \underbrace{\begin{bmatrix} \hat{LP}_{i,t} \\ UN_{i,t} \\ \hat{F}_{i,t} \\ \hat{LP}_{i,t-1} \\ UN_{i,t-1} \\ \hat{F}_{i,t-1} \\ \hat{LP}_{i,t-2} \\ UN_{i,t-2} \\ \hat{F}_{i,t-2} \\ \dots \\ \hat{LP}_{i,t-p} \\ UN_{i,t-p} \\ \hat{F}_{i,t-p} \end{bmatrix}}_{\hat{y}_{i,t}} + \begin{bmatrix} v_{i,t}^1 \\ 0 \\ v_{i,t}^3 \\ v_{i,t}^4 \\ v_{i,t}^5 \\ v_{i,t}^6 \\ v_{i,t}^7 \end{bmatrix},
$$

where $var(v_{i,t}^1)$ is set to a large number. Notice that when observations of ($LP_{i,t}$) are missing, the first row of H_i is zero. Since we rely on the Kalman filter, this assumption effectively means that missing observations on ($LP_{i,t}$) are ignored when calculating the updated estimate of $(LP_{i,t})$. Therefore, the observation equation for this model changes over time depending on whether observations on $(LP_{i,t})$ are missing.

Hence, the unobserved state-space model of each country is a simple VAR with three variables (i.e., monthly labor productivity, unemployment rate, and the surveys-factor)

$$\hat{y}_{i,t} = c_i + A_{i,1}\hat{y}_{i,t-1} + A_{i,t-2}\hat{y}_{i,2} + \ldots + A_{i,p}\hat{y}_{i,t-p} + \epsilon_{i,t}. \tag{2}$$

Therefore, the observed and unobserved equations represent the joint transition equations in the state-space model. The initial conditions $y_{i,0:-p+1} = (y'_{i,0}, \cdots, y_{i,-p+1})$ are assumed to be distributed according to $y_{i,0:-p+1} \sim N(0, V(\mathcal{A}_i, \Sigma_i))$, where $V(\mathcal{A}_i, \Sigma_i)$ represents the unconditional variance of $y_{i,0:-p+1}$.

The priors for the VAR coefficients $\mathcal{A}_i = (A_{i,1}, \ldots, A_{i,p})$ and the covariance matrix Σ_i have a standard form, namely,

$$\begin{aligned} &p\left(\mathrm{vec}(\mathcal{A}_i) \mid \Sigma_i\right) = \mathcal{N}\left(\mathrm{vec}(\underline{\mathcal{A}_i}), \Sigma_i \otimes \underline{\Sigma_i}\right) I(\mathrm{vec}(\mathcal{A}_i)), \\ &p\left(\Sigma_i\right) = \mathcal{IW}\left(n+2, (n+2)\,\underline{\Sigma_i}\right), \end{aligned}$$

where $p\left(\Sigma\right) = \mathcal{IW}\left(n+2, (n+2)\,\underline{\Sigma}\right)$ denotes the inverse Wishart distribution with mode $\underline{\Sigma}$ and $n+2$ degrees of freedom, and $I(\mathrm{vec}(\mathcal{A}_i))$ is an indicator function that is equal to 0 if the VAR is explosive—some of the eigenvalues of $\mathcal{A}_i(L)$ are greater than 1—and to 1 otherwise.[10]

The same priors are shared for all countries. Hence, this prior structure exploits the structure of coefficients, given that the C units of the model are sharing a common mean. The prior for the VAR parameters, $\mathrm{vec}(\underline{\mathcal{A}})$, is a standard Minnesota prior with the hyperparameter for the overall tightness equal to the commonly used value of 0.2 (see Giannone et al. (2015)). The prior for the VAR parameters $\mathrm{vec}(\mathcal{A})$ are centered around zero, except for the "own-lag" parameter that is centered at 1 - this implies that the individual variables exhibit random walk behavior. The prior for the covariances Σ_i of the innovations, $\underline{\Sigma}$, is a relatively uninformative inverse Wishart distribution with just enough degrees of freedom (n+2) to have a well-defined prior mean, which is set to be a diagonal matrix. The prior for H_i is given by $p(h) = N(1, 0.5^2)$, the product of independent Gaussian distributions for each element $h_{i,1,\cdots,5}$ of the matrix H_i.[11] Turning to the initial conditions, all the country-specific $Y_{0:-p+1}$ have mean zero and standard deviations equal to one.

The state-space model is efficiently estimated with Bayesian methods using Kalman Filter, in conjunction with modern simulation smoothing techniques (Carter and Kohn (1994); Durbin and Koopman (2002)) that easily help us to accommodate

[10] The enforcement of the stationarity constraint on the model coefficients becomes relevant to avoid that the updated covariance matrix in the Kalman Filter algorithm becomes singular and hence precluding the computation of its inverse.

[11] Elements in the matrix H_i are updated using Metropolis-Hastings algorithm. This algorithm involves a scaling matrix that the researcher selects to obtain the appropriate acceptance ratio of proposals.

missing observations and draw the latent states. All results are based on 10,000 simulations, of which we discard the first 9,000 as burn-in draws.[12]

3.2 Signalling scheme of BP

This section explains the scheme of Beaudry and Portier (2006), that we interpret as a signalling scheme. Two orthogonalization schemes are used, imposing sequentially, not simultaneously, either impact or long-run (at eight year horizon) restrictions on the reduced-form moving average representation of the data. The disturbance of the confidence innovation is obtained by imposing impact restrictions (i.e., short-run) on the reduced-form residuals of equation 2,

$$\underbrace{\begin{pmatrix} \epsilon_t^{Prod} \\ \epsilon_t^{Un} \\ \epsilon_t^{F} \end{pmatrix}}_{\text{Reduced-form residuals}} = \underbrace{\begin{bmatrix} s_0^{11} & 0 & 0 \\ s_0^{21} & s_0^{22} & 0 \\ s_0^{31} & s_0^{32} & s_0^{33} \end{bmatrix}}_{\text{P}} \underbrace{\begin{pmatrix} w_{1t}{}^{\text{Shock 1}} \\ w_{2t}{}^{\text{Shock 2}} \\ w_{3t}{}^{\text{Confidence innovation}} \end{pmatrix}}_{\text{Structural Disturbances}}. \tag{3}$$

To be specific, let the mapping between reduced-form and structural disturbances be $\epsilon_t = Pw_t$, where $w_t \sim N(0, I_n)$ is a $n \times 1$ vector of structural disturbances with unit variance. In particular, P is the restriction implemented using Cholesky factorization on Σ; hence, P is a lower-triangular matrix, with at least n(n-1)/2 additional restrictions.[13] The confidence innovation affects the factor contemporaneously and with a lag on productivity and unemployment. Our interpretation of this shock is that it represents advanced information or a signal that agents receive about the future, affecting their expectations. Moreover, it is orthogonal to the other two innovations, shocks 1 and 2, which affect productivity and the unemployment rate contemporaneously, respectively. We leave the first two shocks without giving a formal interpretation.

On the other hand, by imposing long-run restrictions, at eight year horizon, on the reduced-form residuals of equation 2, we obtain the structural disturbances that have persistent effects on the variables of the system. To be specific, let the mapping between reduced-form and structural disturbances be $\epsilon_t = \tilde{P}w_t$, where $\tilde{w}_t \sim N(0, I_n)$ is a $n \times 1$ vector of structural disturbances with unit variance. In particular, $\tilde{P}$ has the following structure $C(1)^{-1}S$, where $C(1)$ represents the point estimate of the cumulated impulse responses in reduced form on the eight-year horizon, and S is

[12] To decreased the complexity and uncertainty of the model, given that the model needs to deal with missing observations, and draw the latent states, some shortcuts are taken. First, a Mixed-Frequency Favar model is estimated for each country using the same priors and initial conditions. Attempts to perform the estimation in stacked-form have been done, but the updated covariance matrix in the Kalman Filter algorithm becomes singular and hence precluding the computation of its inverse. Second, the posterior distributions of the reduced-form coefficients for each unit are averaged out across the entire cross-section of C units. This yields the posterior distributions of the (cross-sectional) average coefficients of the group. This estimation approach yields consistent estimates, initially proposed by Pesaran and Smith (1995). Intuitively, this estimation approach is equivalent as including a hyperprior on Ω, with a high value, allowing single country coefficients to differ between them, see Section 2.2 in Jarociński (2010).

[13] The errors are orthogonal $var(w_t) = var(P^{-1}\epsilon_t) = (P^{-1})\Sigma(P^{-1})' = P^{-1}\Sigma(P^{-1})' = P^{-1}(PP')(P^{-1})' = I_{(N)}$.

the restriction implemented using Cholesky factorization on $C(1)\Omega C(1)'$; hence, S is a lower-triangular matrix, with at least n(n-1)/2 additional restrictions.[14] We are interested in the first two disturbances affecting productivity and unemployment in the long-run since we want to identify technological and non-technological shocks. The interpretation of these shocks is in line with Gali (1999).[15]

$$\underbrace{\begin{pmatrix} \epsilon_t^{Prod} \\ \epsilon_t^{Un} \\ \epsilon_t^{F} \end{pmatrix}}_{\text{Reduced-form residuals}} = \underbrace{C(1)^{-1}\begin{bmatrix} s_0^{11} & 0 & 0 \\ s_0^{21} & s_0^{22} & 0 \\ s_0^{31} & s_0^{32} & s_0^{33} \end{bmatrix}}_{\tilde{P}} \underbrace{\begin{pmatrix} \tilde{w}_{1t}^{\text{Technological Shock}} \\ \tilde{w}_{2t}^{\text{Non-Technological Shock}} \\ \tilde{w}_{3t}^{\text{Shock 3}} \end{pmatrix}}_{\text{Structural Disturbances}}. \tag{4}$$

The first shock drives the long-run behavior of all the variables in the system. In this sense, it affects the long-run dynamics of the three variables. The second one can influence the long-run movements of the unemployment rate and the factor, but it does not alter the long-run dynamics of labor productivity. Finally, the last structural shock cannot affect the dynamics of the first two variables in the long-run.

Preliminary results. We begin by estimating a MF Panel FAVAR for LP, UN, HH, IND, SER, BUL, and RE with 5 lags and recover three orthogonalized shocks series corresponding to the w_t and $\tilde{w}_t$, as previously explained. That is, the orthogonal shocks w_t are recovered by imposing impact restriction, and the orthogonal shocks $\tilde{w}_t$ are recovered by imposing long-run restrictions on a 100 periods horizon. Figure 1 shows the correlation between the confidence innovation, w_{3t}, and the technological shock, $\tilde{w}_{1t}$, and non-technological shock, $\tilde{w}_{2t}$.

The striking observation is that long-run shocks appear to correlate with confidence innovations, particularly those related to the non-technological side of the economy (-0.95). More specifically, the dynamics associated with the w_{3t} shock - which by construction is an innovation in the estimated factor which is contemporaneously orthogonal to productivity and unemployment - seem to recover similar information to $\tilde{w}_{2t}$ - which by construction has long-lasting effects on unemployment. On the other hand, they also show a very modest correlation with changes in productivity, meaning that hardly any information is reflected in the factor before actually translating into productivity increases. In addition, we observe that the fraction of the forecast error variance of the confidence factor attributable to its own innovation exceeds 70 percent at any horizon.[16] These results point to the news view of confidence as in Barsky and Sims (2012). However, they do not seem to anticipate information related future technological developments, if not information related to the non-technological side of the economy.

One might wonder what potential explanatory power confidence (non-technological

[14] The errors are orthogonal $var(\tilde{w}_t) = var(\tilde{P}^{-1}\epsilon_t) = (\tilde{P}^{-1})\Sigma(\tilde{P}^{-1})' = S^{-1}C(1)\Sigma C(1)'(S^{-1})' = S^{-1}(SS')(S^{-1})' = I_{(n)}$.

[15] Examples of non-technology shocks found in the literature include labor supply shifters, preference shocks, and also typical demand shocks such as those induced by monetary policy, government spending, marginal efficiency of investment, discount factor and most financial shocks.

[16] See Figure C.8 in the Appendix.

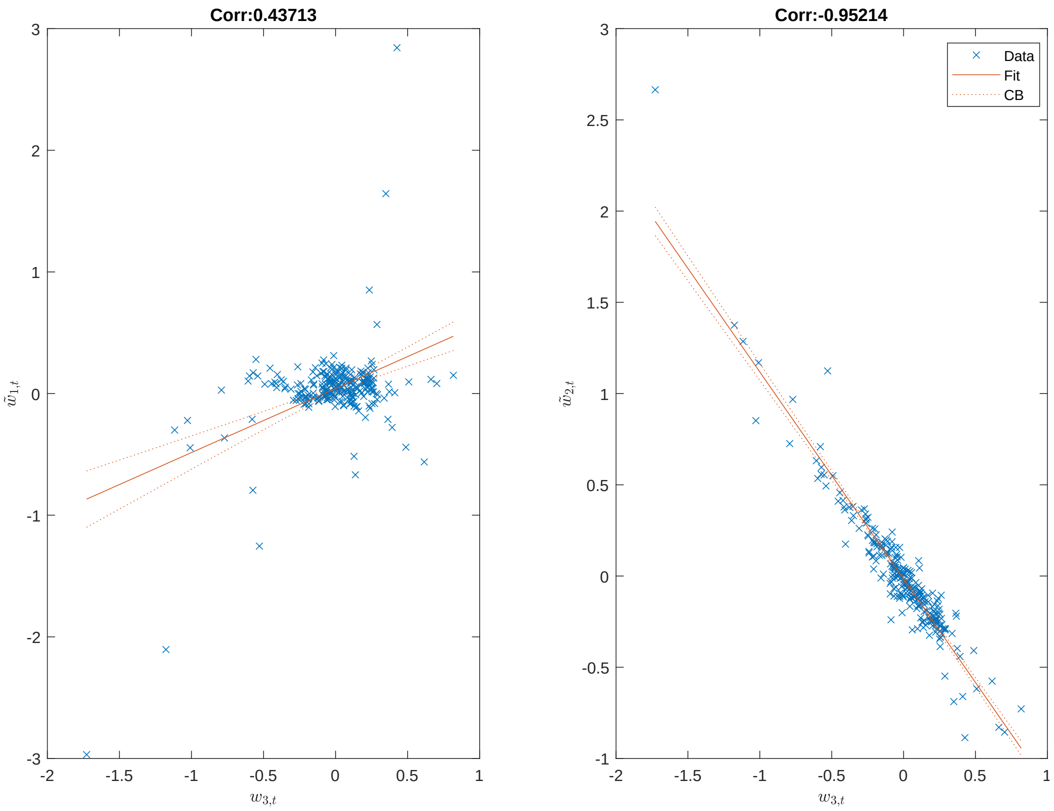


Figure 1: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel FAVAR with 5 lags

news) shocks have compared to other fundamental shocks. Notice that under the BP scheme, our shocks coming from different schemes are correlated; hence, we cannot explore the relative importance of each. Therefore, in the next subsection, we propose a simultaneous short- and long-run identification that enables us to jointly identify technological, non-technological, and confidence (non-technological news) shocks. This new structural identification will be consistent with the findings using the BP scheme.

3.3 Simultaneous Identification

The proposed identification scheme imposes, at the same time, short and long-run restrictions to help us to identify, under the same framework, (i) technological, (ii) non-technological, and (iii) news shocks. Equation 5 denotes the restricted elements of P (i.e. impact matrix) and L (i.e. long-run matrix). The implemented restrictions imply the following properties for the relationship between the variables in the system.

Assumption 1. Labor productivity can only be explained in the long-run by technological shocks. Moreover, technological shocks have contemporaneous and long-run effects on all the variables in the system.

Assumption 2. Non-technological shocks have contemporaneous effects on all the variables in the system, but they have no long-run effects on productivity.

Assumption 3. Confidence (Non-technological news) shocks do not immediately impact unemployment. However, they can have a contemporaneous effect on productivity. Furthermore, they only have the potential to explain the long-term dynamics of unemployment, as shown in Figure 1.

$$P = \begin{pmatrix} * & * & * \\ * & * & 0 \\ * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & 0 & 0 \\ * & * & * \\ * & * & * \end{pmatrix}. \tag{5}$$

Assumptions 1 and 2 follow common assumptions regarding productivity as a driving force of economic fluctuations. In particular, 1 is quite a natural representation - also reflected by a broad range of theoretical models - given that it resembles the standard long-run identification assumption, see Gali (1999); Galí (2004). Finally, assumption 3 combines (i) the standard properties of news shocks - that they do not have a contemporaneous impact on the variable of interest (in this case unemployment) - and (ii) the potential ability to explain long-run unemployment fluctuations based on our previous correlation results.

4 Empirical Results

In this section, first we analyze the responses of unemployment to technological, non-technological and confidence (news) shocks. Second, we expand our focus and include stock prices in the system of variables to properly capture technological news; following the central idea of Beaudry and Portier (2006).

4.1 How does unemployment respond to the different structural shocks?

Figure 2 reports unemployment's impulse response functions (IRFs) to positive innovations in the MF Panel FAVAR. Structural shocks are displayed on the columns. The horizontal axis measures time in months from impact to 150 months after innovations have occurred. The vertical axis represents the responses. All IRFs are displayed with 90% probability density intervals.

The unemployment rate responds negatively and significantly to news innovations and positively and significantly to non-technological innovations. Moreover, the effect of news shocks on unemployment is more persistent than the effect of non-technological shocks in the medium-term. In the case of the non-technological shock, it dies after 30 periods however when it comes to the confidence shock, it happens after 60 periods. This persistent effect on unemployment is far too large and significant for confidence innovations not to convey information about future fundamentals of the economy. In addition, the confidence (news) shock is the major driver of the factor, explaining on more than 80 percent of its forecast error variance at any horizon (see Figure C.10 in the Appendix). This last result reinforces the interpretation of the news view of confidence as in Barsky and Sims (2012). In the robustness section 6.2, we include capital investment and consumer prices, one at a time, to gain a deeper economic understanding of the confidence shocks. By adding these variables to the system, we find that our confidence shock resembles a demand shock, as it persistently decreases unemployment, increases the confidence factor, and raises both prices and investment.

Finally, although the median response of unemployment to a technology shock is negative after impact, it becomes slightly significant after 10 periods, though this effect is very transitory. In the medium run, however, the response reverses, leading to an increase in unemployment. This pattern may reflect heterogeneous responses across European countries, as indicated by the confidence bands and the slightly negative and positive effects along the responses. In some European countries, technological improvements might reduce the unemployment rate, while in others, they could disrupt certain job skills, resulting in higher unemployment.

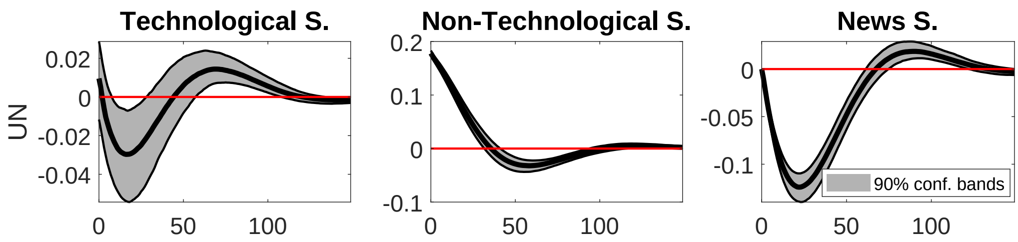


Figure 2: Response functions of unemployment to positive innovations from the MF PANEL FAVAR

Note: Posterior distributions of impulse response functions to a estimated shock of one standard deviation using short and long-run restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 3 plots the share of variance of the unemployment rate attributable to each shock in the system. In this sense, we can quantify the relative importance of the structural shocks under consideration - technological, non-technological and confidence (news) shocks. This exercise is done at different frequencies from impact to 150 months ahead. Similar to Justiniano et al. (2010), short-term fluctuations in unemployment can be attributed entirely to non-technological shocks.[17] However, as time progresses, the impact of news shocks becomes increasingly significant. Eventually, they become the primary driver of the unemployment's variance in the medium and long-term. Specifically, they are found to account for approximately 50% of the variance in the long-term.[18]

[17]In particular, in the model of Justiniano et al. (2010) a shock to desired wage markups (or, equivalently, to labor supply) explains a large fraction of the fluctuations in hours at very low frequencies.

[18]The complete results of the Figures 2 and 3 are reported in the Appendix, depicted in Figures C.9 and C.10.

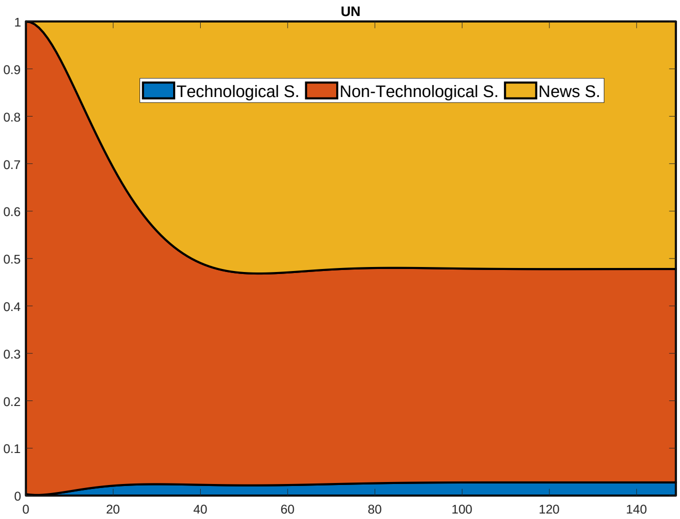


Figure 3: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of the unemployment rate at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 5.

4.2 Stock Prices and Technological News Shocks

Since surveys do not capture technological news, we increase our focus and explore the relevance of technological news to the labor market. Following the central idea in Beaudry and Portier (2006), that financial variables, especially stock prices, are likely to reflect news about future technological growth, we include stock prices in the system of variables. Moreover, two recent papers, Beaudry and Portier (2014) and Barsky et al. (2015), revisit how to identify news shocks that can influence fluctuations of future TFP. These two papers conclude that the inclusion of stock prices, in a small VAR, may drastically change the effects of news shocks in the system of variables. Hence, we follow the recommendations of these papers and include stock prices (SP) as our second variable in the system.

Following the previous procedure, we first apply the signaling scheme explained in Section 3.2 for the four variable case as follows:

Short-run restrictions

$$\underbrace{\begin{pmatrix} \epsilon_t^{Prod} \\ \epsilon_t^{SP} \\ \epsilon_t^{Un} \\ \epsilon_t^{F} \end{pmatrix}}_{\text{Reduced-form residuals}} = \underbrace{\begin{bmatrix} s_0^{11} & 0 & 0 & 0 \\ s_0^{21} & s_0^{22} & 0 & 0 \\ s_0^{31} & s_0^{32} & s_0^{33} & 0 \\ s_0^{41} & s_0^{42} & s_0^{43} & s_0^{44} \end{bmatrix}}_{\text{P}} \underbrace{\begin{pmatrix} w_{1t} \\ w_{2t} \\ w_{3t} \\ w_{4t} \end{pmatrix}}_{\text{Structural Disturbances}} .$$

Long-run restrictions

$$\underbrace{\begin{pmatrix} \epsilon_t^{Prod} \\ \epsilon_t^{SP} \\ \epsilon_t^{Un} \\ \epsilon_t^{F} \end{pmatrix}}_{\text{Reduced-form residuals}} = \underbrace{C(1)^{-1} \begin{bmatrix} s_0^{11} & 0 & 0 & 0 \\ s_0^{21} & s_0^{22} & 0 & 0 \\ s_0^{31} & s_0^{32} & s_0^{33} & 0 \\ s_0^{41} & s_0^{42} & s_0^{43} & s_0^{44} \end{bmatrix}}_{\tilde{P}} \underbrace{\begin{pmatrix} \tilde{w}_{1t} \\ \tilde{w}_{2t} \\ \tilde{w}_{3t} \\ \tilde{w}_{4t} \end{pmatrix}}_{\text{Structural Disturbances}} .$$

Upon incorporating stock market data into our analysis, we find that when implementing the BP scheme, w_{2t}, a shock that affects stock prices contemporaneously and with a lag to productivity, contains predictive information about $\tilde{w}_{1t}$, a shock that can only drive the long-run behavior of productivity. This is evidenced by the relatively high correlation (0.767) between w_{2t} and $\tilde{w}_{1t}$, as shown in Figure 4. Moreover, the correlation between w_{4t} -a shock that affects the factor contemporaneously and with a lag to unemployment- and $\tilde{w}_{3t}$ -a shock that can drive the long-run behavior of unemployment- is still significantly high (-0.81).

This finding prompts us to impose joint restrictions, as outlined in Eq. 6, at both the short-term (P) and long-term (L) in order to properly identify shocks related to technology, technological news shocks, non-technological shocks, and confidence (non-technological news) shocks.

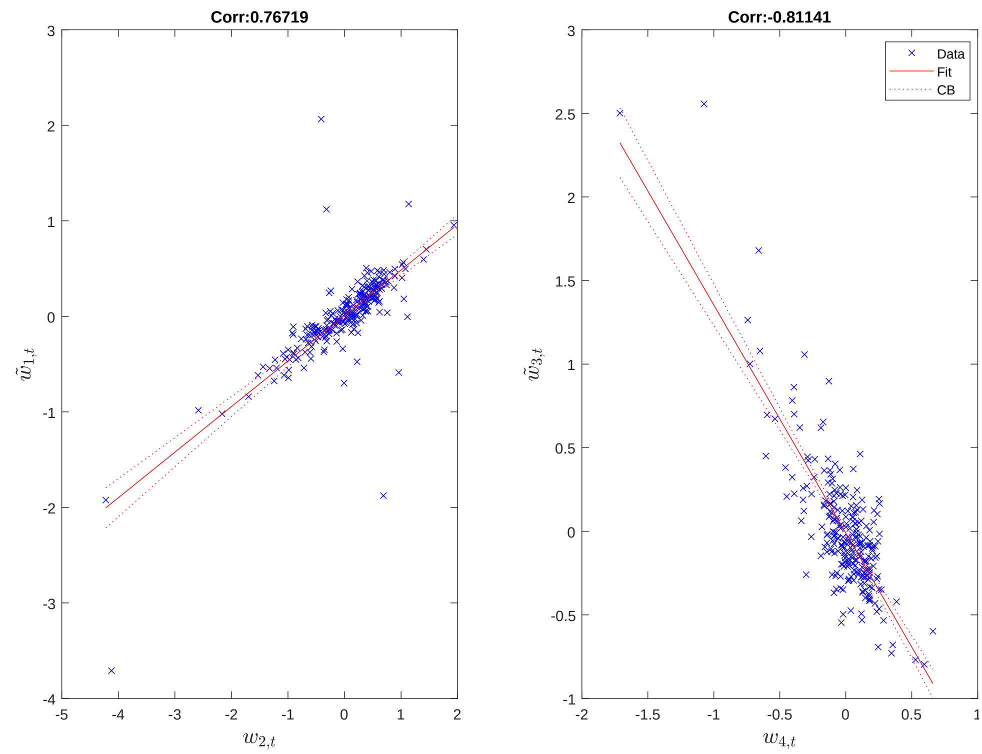


Figure 4: Plot of w_{2t} against $\tilde{w}_{1t}$ - left - and on the right w_{4t} against $\tilde{w}_{3t}$ in the MF Panel VAR with with stock prices.

Assumption 1. Productivity can only be explained in the long-run by technological and news shocks related to productivity. Moreover, technological innovations have contemporaneous and long-run effects on all the variables in the system. On impact, productivity responds with a lag to only news technological shocks.

Assumption 2. Technological news shocks do not have contemporaneous effects on productivity, but they can affect unemployment and their related news contemporaneously. Moreover, SP can affected by all shocks in the long-run. Technological news shocks only have the potential to explain the long-run dynamics of productivity - as it is suggested by Figure 4.

Assumption 3. Non-technological shocks have contemporaneous effects on all the variables in the system, but they have no long-run effects on productivity. On impact, unemployment is not affected by non-technological news shocks.

Assumption 4. Confidence (non-technological news) shocks do not have contemporaneous effects on the unemployment rate, but they can affect productivity and their related news contemporaneously. Moreover, they have the potential to explain the long-run dynamics of unemployment and the factor - as it is suggested by Figure 4.

$$P = \begin{pmatrix} * & 0 & * & * \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & 0 & * & * \\ * & 0 & * & * \end{pmatrix} \tag{6}$$

Figure 5 shows the IRFs of labor productivity and unemployment using the restrictions of Eq.6. We can see that positive technological news innovations have really persistent positive effects on productivity - first raw, second column -while they lead to increase unemployment in the short-term. This may be because positive productivity news lead to a reallocation of resources - labor for capital - within firms. This result is in line with Barsky and Sims (2011), who find that hours work decrease for 5 quarters after a positive technological news shock. In addition, Manuelli (2000) argues that an anticipated improvement in technology is likely to lead to an increase in the unemployment rate. Our results indicate that after 25 periods, the effect of a technological news shock on the unemployment is reversed, meaning that the initial loss of employment is recovered.

Moreover, the inclusion of the stock market and identification of a technological news shock seems to enhance the identification of a productivity shock. Since, now unemployment decreases significantly in the short-term after a positive productivity shock. This implies that, in Figure 2, the response of unemployment to productivity shocks is masking the effects of productivity and news productivity shocks. The effect of the remaining shocks on unemployment is unchanged, reinforcing the previous results.

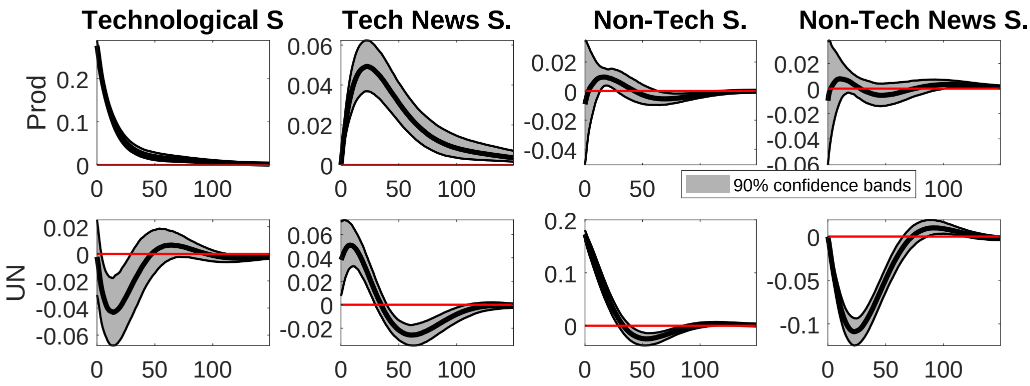


Figure 5: Response functions of unemployment to positive innovations from the MF PANEL FAVAR

Note: Posterior distributions of impulse response functions to a estimated shock of one standard deviation using short and long-run restrictions, as in Equation 6. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Regarding the variance decomposition, see Figure 6, technological news shocks explain about 15% of the variance of productivity in the long run. Hence, non-anticipated technological shocks are the main driver of productivity. This result is in line to Barsky and Sims (2011), Forni et al. (2014), and Barsky et al. (2015). With respect to the unemployment drivers, confidence (non-technological news) shocks continue to explain sizable fraction of its variance in the long run. This result is not significantly affected by the identification of technological new shocks. Moreover, anticipated and non-anticipated technological shocks together explain around 15% of the variance of unemployment at any horizon. Previously, non-anticipated technological shocks explained nearly zero.[19] These results align with the findings of Angeletos et al. (2020), who show that neither technological news nor technological shocks are the primary drivers of unemployment throughout the business cycle.

5 Model

In the previous section, we have provided empirical evidence that innovations in confidence measures, potentially in the form of non-technological news, have significant implications for unemployment. However, interpreting the effect of such shocks on unemployment is challenging without imposing additional structure and developing a theory to understand these dynamics. In this section, we first show that our confidence innovation Granger-causes job vacancies in Europe but not vice versa, indicating that our shock is useful for forecasting job vacancies in Europe. Second, we develop a structural model to help us understand the empirical findings. Based on the previous result, we incorporate "news" shocks that influence the expectation of the labor market tightness within a dynamic and stochastic search and

[19]The complete results of the Figures 5 and 6 are reported in the Appendix, depicted in Figures C.11 and C.12.

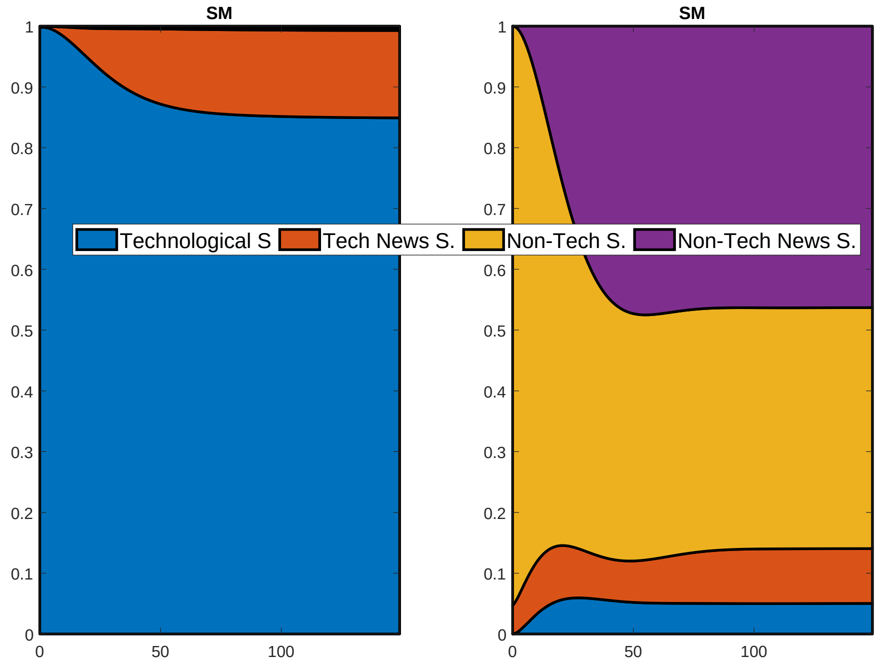


Figure 6: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of the unemployment rate at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 6.

matching model, in addition to the "usual" unanticipated disturbances affecting the labor market—such as labor productivity and separation shocks (see Shimer (2005)). This model is fairly standard in unemployment theory. Motivated by the findings of Theodoridis and Zanetti (2016), which suggest that in a standard search and matching model under full information, news shocks play no role in explaining the variance decomposition of unemployment, we analyze the variance decomposition of unemployment under two scenarios: (i) full information and (ii) informational frictions based on learning dynamics in the spirit of Evans and Honkapohja (2012). The previous mechanism generates a self-referential aspect in the economy.

5.1 Building a bridge between empirics and theory

In the simple search and matching model, an important endogenous variable that affects the evolution of unemployment is the labor market tightness, which impacts the probability of finding a job. High labor market tightness leads to higher hiring rates, thereby reducing unemployment. This tightness is defined as the ratio of vacancies to unemployment. In this model, today's labor market tightness is influenced by expectations of future tightness through the job creation condition. Firms make strategic decisions about posting vacancies based on anticipated future conditions, linking present and future labor market dynamics.

To investigate whether our estimated confidence (non-technological news) shock operates through this channel, we propose a Granger causality test between our confidence shock and job vacancies in Europe.[20]

Table 1 presents granger causality tests between the estimated news shocks and the job vacancies ratio (JV) - for two transformations of JV - with five lags.[21] On the left, the hypothesis that the confidence shocks do not Granger cause JV is rejected with a P-value less than 0.01, indicating strong evidence that information in the estimated shocks helps forecast the job vacancy rate one quarter later. Conversely, the right side of the table shows that the hypothesis JV does not help predict the estimated confidence shocks. It has a P-value of 51% without transforming JV and 22% if JV is expressed in quarterly differences. Therefore, we observe a robust unilateral causal relationship from confidence shocks to European job vacancies.

This finding supports the notion that confidence shocks influence labor market dynamics through the job creation condition, establishing an expectation channel. This channel allows firms to adjust their vacancy postings based on anticipated economic conditions, highlighting the significant role of news and information in driving labor market behavior.

Dependent variable: JV			Dependent variable: News		
Transformation JV	F-test	P-Value	Transformation JV	F-test	P-Value
None	14.94	2.7849e-04	None	0.44	0.51
Diff	10	1.8884e-04	Diff	1.51	0.22

Table 1: Granger causality tests

5.2 Environment

Following the standard literature, this economy is characterized by frictions in the labor market. These are captured by a Cobb-Douglas matching function, $M_t = Av_t^{1-\nu}u_t^{\nu}$, where $A > 0$ and $0 < \nu < 1$, which describes the number of successful matches between unemployed workers, u_t and vacancies, v_t, reflecting increasing and concave dependencies on its inputs. The labor market tightness, defined as $\theta = \frac{v}{u}$, influences the likelihood of filling vacancies, $q(\theta_t) = A\theta_t^{-\nu}$, and the matching probability for unemployed workers, $m(\theta_t) = A\theta_t^{1-\nu}$.

The unemployment rate increases when jobs are destroyed at a exogenous rate, λ_t, and decreases when workers find jobs. Thus,employment evolves according

$$n_{t+1} = (1 - \lambda)n_t + q(\theta_t)v_t, \tag{7}$$

[20]We obtain the job vacancy rate - defined as the number of job vacancies * 100 / (number of occupied posts + number of job vacancies) - from Eurostat. It is obtained as an aggregated measure for the EU 27 - individual weights are not available to calculate the joint job vacancy ratio for our 22 studied countries - from 2006.Q1 to 2021.Q2.

[21]The estimated news shocks are transformed to quarterly frequency by averaging every three observations. The Granger causality tests are run from 2006.Q1-2021.Q2 - when JV has no transformation - and 2006.Q2-2021.Q2 - when JV is expressed in quarterly differences.

where λ_t follows an iid process

$$\lambda_t = \lambda + \epsilon_t^{\lambda}, \tag{8}$$

$\epsilon_t^{\lambda} \sim N(0, \sigma_{\lambda}^2)$ denotes a shock, and λ the mean of the destruction rate.

Labor productivity is modeled as a stationary AR(1) process in logs

$$\ln(y_t) = (1-\rho)\ln(\overline{y}) + \rho\ln(y_{t-1}) + \epsilon_t, \;\; 0 < \rho < 1. \tag{9}$$

Where $\epsilon_t \sim N(0, \sigma^2)$ and ρ measures its persistence.

The Household. We consider an economy with a representative household of size one, where all workers are identical and risk-neutral, and there is perfect consumption insurance among the members. The expectation operator $E_t^{\mathcal{P}^w}$ is determined using a subjective probability measure $\mathcal{P}^w$. The household's decision-making can be represented by the following Bellman equation:

$$W(n_t, y_t) = w_t n_t + b(1-n_t) + \beta E_t^{\mathcal{P}^w} W(n_{t+1}, y_{t+1}), \tag{10}$$

subject to the law of motion for employment 7. $W(n_t, y_t)$ represents its current value. The household takes as given wages, w_t, and labor market tightness, θ_t. The period utility value from non-employment is represented by b, and β is the discount factor. The surplus from an additional member of the household being employed is captured by

$$\frac{\partial W(n_t, y_t)}{\partial n_t} = w_t - b + \beta(1 - \lambda_t - \theta_t q_t(\theta_t))\frac{\partial E_t^{\mathcal{P}^w} W(n_{t+1}, y_{t+1})}{\partial n_{t+1}}. \tag{11}$$

This equation reflects the net employment value plus the expected continuation value.

The Firm. A representative firm with a linear production function aims to maximize its profits by choosing the number of vacancies, v, to post in each period at a constant ongoing cost, c. The firm's profit maximization problem is subject to the evolution of employment and taking as given wages, w_t and the labor market tightness, θ_t. The problem is formalized as:

$$\Pi(n_t, y_t) = \max_{v_t \geq 0} \;\; y_t n_t - w_t n_t - c v_t + \beta E_t^{\mathcal{P}^f} \Pi(n_{t+1}, y_{t+1}) \;\; , \tag{12}$$

subject to

$$n_{t+1} = (1-\lambda_t) n_t + q(\theta_t) v_t, \tag{13}$$

where $\Pi(n_t, y_t)$ denotes the current value function. The expectation operator for firms, $E_t^{\mathcal{P}^f}$, is determined using a subjective probability measure $\mathcal{P}^f$. The first order condition is given by

$$\frac{\partial E_t^{\mathcal{P}^f} \Pi(n_{t+1}, y_{t+1})}{\partial n_{t+1}} = \frac{c}{\beta q(\theta_t)}, \tag{14}$$

setting the marginal cost of posting a vacancy to the discounted marginal gain from an additional employee. The net profit from hiring an additional worker, considering the expected continuation value, is:

$$\frac{\partial \Pi(n_t, y_t)}{\partial n_t} = y_t - w_t + (1 - \lambda_t)\frac{c}{\beta q(\theta_t)}. \tag{15}$$

This represents the direct profit impact of an additional employed worker plus the adjusted expected future benefits.

Wage Determination. Wages in this model are negotiated through a Nash bargaining process, where the wage w_t maximizes the joint surplus of a match between workers and firms, as represented by equations 11 and 15, respectively, with worker bargaining power $\alpha \in (0,1)$. By combining the surplus-sharing rules that form the solution to this problem, iterating forward, and using equations 11, 15, and 14, we derive the standard equilibrium wage:

$$w_t = \alpha(y_t + c\theta_t) + (1 - \alpha)b. \tag{16}$$

5.3 Beliefs and News Shocks

In this subsection we analyze the equilibrium determination of the labor market variables, in the case of rational expectations and in the case of imperfect information with adaptive learning.

5.3.1 Rational Expectation Equilibrium

Initially, we derive the Rational expectations equilibrium (REE) where the expectations of workers and firms align and are measure with a objective probability measure. We denoted this expectations by E_t. The equilibrium is characterized by the labor market tightness at which the representative firm is indifferent to opening an additional vacancy. This is captured by the free entry condition. By iterating forward the labor market tightness equation (15), and using the firm's first-order condition (14), the wage equation (16), and the expected constant separation rate ($E_t\lambda_{t+1} = \lambda$), we come up with:

$$\frac{c}{\beta q(\theta_t)} = (1 - \alpha)(E_t y_{t+1} - b) + \frac{(1 - \lambda)c}{q(\theta_{t+1})} - \alpha c E_t \theta_{t+1}. \tag{17}$$

Deviations from this condition prompt immediate adjustments in θ_t through changes in firm vacancy decisions. The labor market tightness today is affected by expectations of the value of a filled vacancy in the next period.

Considering the productivity process (9), agents solve the system of equations given by (17) and (9) and linearizing around steady state values for $\overline{\theta}$ and $\overline{y} = 1$. This yields the following equation:

$$\theta_t = \hat{\phi}_0 + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 E_t \theta_{t+1} + \hat{\phi}_1 \rho^{-1} \epsilon_t. \tag{18}$$

In this paper, we focus on the RE equilibrium that takes the form of the fundamental or minimum state variable solution (MSV).[22] This solution can be guessed to be of the form

$$\theta_t = \overline{A} + \overline{B} y_{t-1} + \overline{C} \epsilon_t, \tag{19}$$

where $\overline{A}$, $\overline{B}$, and $\overline{C}$ are time-invariant coefficients known to the agents, ensuring that no systematic errors occur in their expectations.[23]

Moreover, we assume that agents receive news, ϵ^{β}, about a transitory shock that will affect labor market tightness in the next period. This news shock is incorporated into the agents' one-period-ahead forecasts of labor market tightness. Specifically, the expectation of next period's labor market tightness is adjusted as follows:

$$E_t \theta_{t+1} = \overline{A} + \overline{B} y_t + \epsilon^{\beta}_{t-1}. \tag{20}$$

This anticipation influences current decisions on vacancy postings.

5.3.2 Agents' model of learning

We now relax the assumption of rational expectations by modeling agents as econometricians. We equipped agents with a perceived law of motion (PLM) that takes the form of MSV solution with unobserved coefficients:

$$\theta_t = A_t + B_t y_{t-1} + \nu_t. \tag{21}$$

Agents estimate equation (21), estimating and updating their coefficients every period as new data become available. For that, they use a recursive least squares algorithm. Letting $\hat{x}'_t = (\hat{A}_t, \hat{B}_t)$ and $z'_t = (1, y_t)$, the algorithm can be written in recursive terms as:

$$\begin{aligned} R_t &= R_{t-1} + g(z_{t-1} z'_{t-1} - R_{t-1}), \\ \hat{x}_t &= \hat{x}_{t-1} + g R_t^{-1} z_{t-1}(\theta_{t-1} - z'_{t-1}\hat{x}_{t-1}) + \epsilon^{\beta}_{t-1}. \end{aligned} \tag{22}$$

Where $\hat{x}_t$ denotes the current period's coefficient estimate, $g \in (0,1)$ denotes the constant gain, determining the rate at which older observations are discounted, and ϵ^{β}_t is a shock to the expected labor market tightness. In this case, ϵ^{β}_t represents the new information about the transitory component of the labor market received at the end of the previous period.[24] Therefore, we can interpret this shock as "news shocks" in the sense defined by Beaudry and Portier (2004) and others.

From (21) it follows that agents' one-period forecasts of labor market tightness in a given period are given by

$$E^{\mathcal{P}}_t \theta_{t+1} = \hat{A}_t + \hat{B}_t y_t. \tag{23}$$

[22] 18 can be written in ARMA(1,1) form. As Evans and Honkapohja (1986) point out, a complete listing of ARMA solutions brings into relief the problem of multiple equilibria. One selection rule has been proposed by McCallum (1983). His first principle is to choose a minimal set of state variables. One from which it is impossible to delete (i.e., set a coefficient of value zero) any single variable, or group of variables, while continuing to obtain a solution.

[23] Further details are provided in Appendix B showing how 19 can be obtained from 18.

[24] For further details and derivation see Appendix 6 from Adam et al. (2017).

Plugging (23) into (18) gives the actual law of motion (ALM) for labour market tightness

$$\theta_1 = \hat{\phi}_0 + \hat{\phi}_2 \hat{A}_t + \hat{\phi}_2(1-\rho)\hat{B}_t + (\hat{\phi}_2 \rho \hat{B}_t + \hat{\phi}_1) y_{t-1} + (\rho^{-1}\hat{\phi}_1 + \hat{\phi}_2 \hat{B}_t)\epsilon_t. \tag{24}$$

Following the method of Marcet and Sargent (1989) and Evans and Honkapohja (2012), we use the ALM (24) and the PLM (21) to formulate the function $T(\hat{A}_t, \hat{B}_t)$ that maps the agents' expectations about parameters A,B into their realised values

$$T(\hat{A}_t, \hat{B}_t) = [\hat{\phi}_0 + \hat{\phi}_2 \hat{A}_t + \hat{\phi}_2(1-\rho)\hat{B}_t,\ \hat{\phi}_2 \rho \hat{B}_t + \hat{\phi}_1]. \tag{25}$$

The fixed point in this mapping is a REE for the model mencioned in the subsection 5.3.1. The T-mapping determines the evolution of beliefs in transition to the long-run equilibrium.

Data Generating Process. Plugging (25) into (7) and (23), and solving delivers the actual data generating process

$$\mu_t = (\epsilon_t, \epsilon_t^{\lambda}, \epsilon_t^{\beta}) \ \sim N(0, \sigma_\mu^2 I_3), \sigma_\mu^2 = [\sigma^2, \sigma_\lambda^2, \sigma_\beta^2] \tag{26}$$

$$y_t = (1-\rho) + \rho y_{t-1} + \epsilon_t, \tag{27}$$

$$\lambda_t = \lambda + \epsilon_t^{\lambda}, \tag{28}$$

$$R_t = R_{t-1} + g(z_{t-1} z'_{t-1} - R_{t-1}), \tag{29}$$

$$\hat{x}_t = \hat{x}_{t-1} + g R_t^{-1} z_{t-1}(z'_{t-1}[T(\hat{A}_t, \hat{B}_t) - \hat{x}_{t-1} + V(\hat{B}_t)\epsilon_t] + \epsilon_{t-1}^{\beta}, \tag{30}$$

$$u_{t+1} = u_t + (1-u_t)\lambda_t - \mu(z'_t T(\hat{x}_t) + V(\hat{x}_t)\epsilon_t)^{1-\alpha} u_t. \tag{31}$$

5.4 Calibration

This section describes the calibration of the model parameters, which total 12. The parameterization approach adopted is two-pronged: it involves selecting a subset of parameters from the existing literature and estimating the remaining parameters through a process of matching impulse responses of unemployment.

Specifically, the parameter vector $\theta_1 = [\beta, \alpha, \nu, \rho]$ is directly obtained from the literature. We normalize the time period to one month. The steady state of productivity is normalized to 1 without loss of generality. The discount factor β is set to 0.96, implying an annual real interest rate of approximately 5%. Direct evidence on workers' bargaining power is scarce; however, according to Petrongolo and Pissarides (2001), acceptable values fall within the interval [0.5, 0.7]. Mortensen and Nagypal (2007) suggests a value of 0.5, which aligns with conventional thinking in the literature. Following Hosios (1990), we set the parameter in the Nash bargaining problem such that $\alpha = 1 - \nu$. The value of the persistence of the productivity, ρ, is computed as an average of the 22 European countries.

The remaining parameters, collected in the vector $\Theta = [c, \lambda, A, g, b, \sigma, \sigma^{\lambda}, \sigma^{\beta}]$, are calibrated to match the model's unemployment responses after the three shocks with those observed empirically in our FAVAR. We take the empirical impulse responses as interesting statistics that a well-specified structural model should be capable of matching. This calibration focuses on matching unemployment dynamics over horizons up to 60 months.[25]

Let $\hat{\gamma}$ denote the vector collecting the IRFs of unemployment to the three structural shocks. The objective function targeted for optimization is defined as:

$$\mathcal{L}(\Theta) = (\hat{\gamma} - \gamma(\Theta))'\Omega^{-1}(\hat{\gamma} - \gamma(\Theta)), \tag{32}$$

where $\gamma(\Theta)$ represents the vector of IRFs generated by the model, and Ω is a weighting matrix. Specifically, Ω is a diagonal matrix where each diagonal element represents the variance of the corresponding IRF, with zeros elsewhere. Table 3 summarizes the estimated parameters.

Variable	Description	Value	Source
α	bargaining power	0.50	Standard
β	discount factor	0.96	Annual real interest rate 0.05
ρ	persistence productivity	0.88	Empirical monthly productivity
ν	elasticity matching function	0.5	Hosios rule: $\alpha = 1 - \nu$

Table 2: Calibrated parameters from literature and data

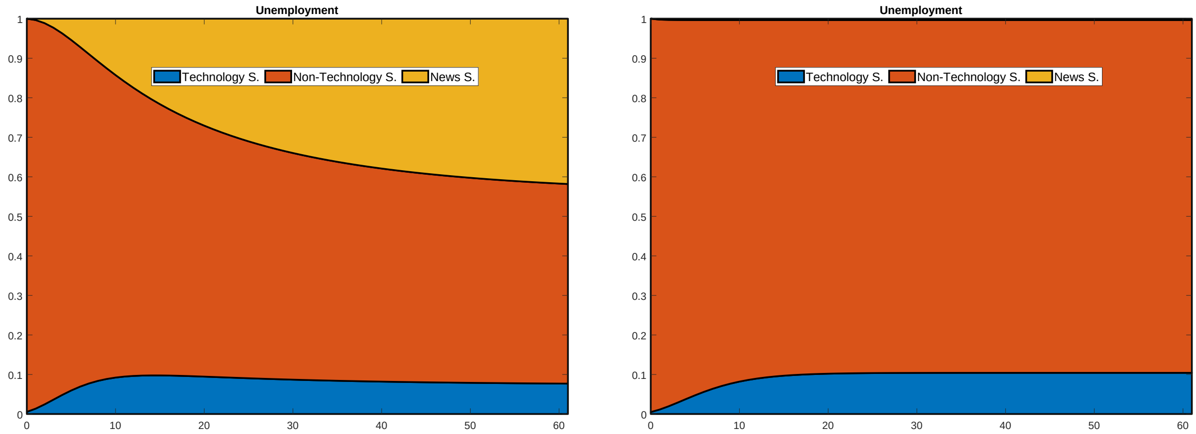
Variable	Description	Adap. Learning Estimates	RE Estimates wrt news shocks
c	cost of open a vacancy	0.29	0.32
μ	efficiency matching technology	0.11	0.11
g	constant gain	0.08	0.00
b	unemployment benefits	0.46	0.45
λ	separation rate	0.11	0.10
σ	Std. productivity shocks	0.0044	0.0049
σ^{λ}	Std. destruction rate shocks	0.0036	0.0040
σ^{β}	Std. news shocks	0.0031	0.0055

Table 3: Estimated monthly parameters from matching IRFs of unemployment

5.5 Theoretical Results

Figure 7 illustrates the share of unemployment variance attributed to each perturbation in the adaptive learning (AL) and rational expectations (RE) models. The AL model demonstrates an excellent fit, with short-term fluctuations in unemployment predominantly due to the destruction rate (i.e., non-technological shocks). Over time, the significance of news shocks grows, eventually accounting for a significant proportion of the medium-term variance, aligning with the empirical model (see Figure 3). In contrast, in the RE model, the contribution of news to the variance of unemployment is not different from zero at any time horizon. This result is in line with the findings of Theodoridis and Zanetti (2016). However, this fact is at odds

[25] Specifically, we aim to match the first 60 periods of the IRFs shown in Figure 2, which include the large and persistent effect of the confidence (news) shock on unemployment.



Adaptative Expectations Model Rational Expectations Model

Figure 7: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each shock to the forecast error variance contributions of the unemployment rate at horizons j = 0, 1, . . . , 60.

with our empirical results.[26] It is important to mention that the RE news shock's standard deviation is close to two times larger than in the AL model. This indicates that the effect generated in the AL model is not driven by a large standard deviation of such shock. Table 3 shows the standard deviations of each shock.

We show that a parsimoniously specified labor search and matching model under adaptive learning successfully replicates the empirical dynamics of unemployment in response to confidence (news) shocks who affects the forecast of the tightness of the labor market. Therefore, these shocks have a cavity in a theoretical framework, if we introduce them with a mechanism that enhances a self-referential feature.

6 Robustness Tests

In this section, we perform several extensions to the baseline specification and check the robustness of our results to a battery of sensitivity checks. We include all the figures related to this section in Appendix D. The MF Panel FAVAR model presented in the previous section is estimated using five lags, long-run restrictions are imposed on an 8.3-year horizon (i.e. 100 months horizon), and using (i) labor productivity, (ii) unemployment rate and (iii) estimated factor from surveys of households and firms - manufacturing, services, retail and construction. We include additional variables in the model to characterize the nature of a confidence (news) shock by analyzing the effect on these variables. In addition, we follow Schorfheide and Song (2021) to handle the extreme observations from the COVID-19 outbreak. Moreover, we generate data from a random generating process to test whether the BP signalling strategy used in this paper induces a high correlation between the estimated

[26]See Figure 13 in the Appendix for the IRFs.

structural shocks. Finally, we check whether our proposed augmented identification scheme of Beaudry and Portier (2006) is able to disentangle the different shocks when the data generating process is our theoretical model. We check the robustness of our results to changes in all of these specifications.

6.1 Alternative Long-Run Horizons, and Lag Specifications

In this subsection, we present the robustness of our baseline results to alternative long-run horizons and lag specifications. Figures D 16,17 present the correlation between w_{3t} against $\tilde{w_{1t}}$ and w_{3t} against $\tilde{w_{2t}}$ using the BP signalling scheme scheme and the IRFs under the joint identification scheme of equation 5.

Changing the horizon - to 50 and 150 periods - at which long-run restrictions are imposed does not affect the results presented in the previous section. The same is true if we use different lag specifications, 7 and 9 lags - see Figures D 14, 15.

6.2 More Variables

In this subsection, we expand our analysis by incorporating additional variables into the system one by one to assess the effect of confidence shocks on each of them individually. Specifically, we examine the IRFs of confidence shocks on capital investment, the GDP deflator as a measure of prices, and both nominal and real compensation of employees. These variables are introduced into the system as the last variable, allowing them to respond to all shocks in both the short and long term. The inclusion of these variables do not change the previous results.

The new joint short- and long-run restrictions are specified in Equation 33, which retain the same core assumptions as those in Equation 5. The only difference is that the additional shock has no long-term effects on productivity, unemployment, and the confidence factor.

Figure D 18 presents the impulse response functions of confidence shocks on the four variables discussed: capital investment, the GDP deflator, and nominal and real wages. The results show that investment increases following a positive confidence (non-technological news) shock, consistent with the presence of Pigou cycles. Additionally, both prices and wages —nominal and real— rise in response to the shock. The negative comovements between unemployment and these variables, including prices, investment, and compensation, suggest that our confidence shock behaves similarly to a demand shock. This is comparable to the dynamics observed between unemployment, inflation, and real wages following a monetary policy shock in Galí (2010) and a risk premium shock as detailed in the Appendix of Foroni et al. (2018).

$$P = \begin{pmatrix} * & * & * & * \\ * & * & 0 & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & 0 & 0 & 0 \\ * & * & * & 0 \\ * & * & * & 0 \\ * & * & * & * \end{pmatrix} \tag{33}$$

6.3 Handling extreme observations from the COVID-19 outbreak a la Schorfheide and Song (2021)

In line with Schorfheide and Song (2021), we exclude Covid crisis observations - March, April, and May - from the estimation sample, given that it is another way of modeling outliers. Figure D 19 shows that excluding a few months of extreme observations does not change our baseline results.

6.4 Spurious correlation between the estimated structural shocks

In this subsection, we present noisy simulated data to check whether the BP signalling strategy used in this paper induces a high correlation between the estimated structural shocks. If this spurious correlation were to happen with simulated data, we could not impose the long-run behavior of news labor market shocks on unemployment in equation 5.

Figure D 20 plot the correlation between w_3 against $\tilde{w}_1$ and w_3 against $\tilde{w}_2$ for three different simulated data groups. The correlation figures plot an obvious point cloud in each simulated group, pointing this identification system does not generate spurious correlations between w_3 against $\tilde{w}_1$ and w_3 against $\tilde{w}_2$.

6.5 Simulating data from the theoretical model

In this subsection, we present two robustness exercises using the theoretical model as our data generating process. First, we create artificial series of productivity, unemployment rate and the expectation of the labor market tightness using the three shocks in our model. Then, we run a standard VAR model and apply the augmented version of BP (i.e., signalling scheme and a joint identification scheme - equation 5) to our estimation. Figures D 21 and 22 show that our proposed augmented version of BP is able to fully identify the three shocks of interest. In our second robustness, we create a non-fundamentalness problem. This means that we create the same artificial series for productivity, unemployment rate and the expectation of the labor market tightness, but now only using the technological and non-technological shocks in our model. Figures D 23 and 24 show two important things. First, the signalling scheme of BP correctly picks that the forward looking variable (the expectation of the labor market tightness) does not contain news shocks. Second, we proceed by ignoring the result of signalling scheme and impose the joint identification scheme of equation

5. It can be seen that in Figure D 24 that the joint identification scheme does not identify any news shock. These robustness results make us confident with respect to the use of our proposed augmented version of BP.

7 Conclusion

This paper has attempted to address a longstanding question in economics: What kind of information is contained in consumer and firm confidence, and how important are these measures for the economy? By employing a mixed-frequency Panel FAVAR model, using surveys from various economic agents, and formulating a simultaneous identification scheme (with both long- and short-run restrictions), we present novel empirical evidence on the relationship between confidence innovations and unemployment fluctuations in Europe.

First, using sequential short- and long-run restrictions, we show that innovations in confidence, which have no contemporaneous effects on labor productivity or unemployment, are highly correlated (-0.95) with non-technological shocks that drive the long-run behavior of unemployment. Second, through simultaneous identification to jointly identify technological, non-technological, and confidence shocks, we found that confidence shocks are crucial in explaining unemployment, particularly in the medium to long run, accounting for around 50% of its variance. The longer-horizon implications for unemployment are far too large and significant for confidence innovations not to convey information about future fundamentals. However, these results indicate that the news captured in confidence measures is likely related to future non-technological aspects of the economy, challenging both the traditional view that focuses solely on technological news and the conventional belief that technological news shocks are the primary drivers of business cycles.

Moreover, we develop a structural search and matching model to validate our empirical results, highlighting the importance of expectations in labor market dynamics. Our analysis shows that under adaptive learning, confidence shocks can explain a significant portion of unemployment variance, thereby bridging the gap between empirical observations and theoretical modeling. This work contributes to the literature by shifting the focus from technological news to the broader implications of confidence-related shocks in the form of non-technological news, offering new insights into the mechanisms driving business cycles and labor market behavior.

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A A Gibbs Sampler for PANEL VARs

First, let me use the notation $z_{i,j:k}$ to denote the sequence $\{z_{i,j}, \ldots, z_{i,k}\}$ for a generic variable of a country $z_{i,t}$. The mixed-frequency Panel FAVAR, specified by the observed and unobserved equations in Section 3, is estimated using a Gibbs sampler, which involves the following blocks:

1. The first block involves draws from the joint distribution $y_{i,-p+1:T}, H_i \mid \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$, which is given by the product of the marginal posterior of $H_i \mid \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$ times the distribution of the initial observations $y_{i,-p+1:T} \mid H_i, \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$. The marginal posterior of $H_i \mid \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$ is given by:

$$p\left(H_i \mid \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}\right) \propto \mathcal{L}\left(y_{i,1:T} \mid H_i, \text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}\right) p(H_i)$$

where $\mathcal{L}\left(y_{1:T} \mid H_i, \text{vec}(\mathcal{A}_i), \Sigma_i, W_i\right)$ is the likelihood obtained by using the Kalman Filter in the state-space model specified in the observed equation. Since $p\left(H_i \mid \text{vec}(\mathcal{A}_c), \Sigma_i, W_i, y_{i,1:T}\right)$ does not feature a known form, this step involves a Metropolis-Hastings algorithm. Then, we use Carter and Kohn (1994) and Durbin and Koopman (2002)'s simulation smoother to obtain draws for the estimated factors $y_{i,-p+1:T}$, for given H_i and $\text{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$.

2. The second block involves the estimation of Equation 2, given $y_{i,-p+1:T}$. The posterior distribution of $\text{vec}(\mathcal{A}_i), \Sigma_i$ is given by:

$$p\left(\Sigma_i \mid y_{0:T}\right) = IW\left(\underline{\Sigma_i} + \hat{S}_{i,v}, (n+2) + T\right)$$
$$p\left(\text{vec}(\mathcal{A}_i) \mid \Sigma_i, y_{i,0:T}\right) = N\left(\text{vec}(\hat{\mathcal{A}}_i), \Sigma_i \otimes \left(X_i X_i' + \underline{\Sigma_i}^{-1}\right)^{-1}\right)$$

where $X_i = \left(y'_{i,-p+1}, \ldots, y'_{i,T-(p+1)}\right)'$, $\hat{S}_{i,v} = v_i v_i' + (\hat{\mathcal{A}}_i - \underline{\mathcal{A}_i})'\underline{\Sigma_i}^{-1}(\hat{\mathcal{A}}_i - \underline{\mathcal{A}_i})$, and
$\hat{\mathcal{A}}_i = \left(X_i X_i' + \underline{\Sigma_i}^{-1}\right)^{-1}\left(X' y_{i,1:T} + \underline{\Sigma_i}^{-1}\text{vec}(\underline{\mathcal{A}_i})\right)$,
and $v_i = y_i - \hat{\mathcal{A}}_i{}' X_i$ are the VAR residuals.

B European Commission - The Business and Consumer Survey

To calculate the aggregate confidence indicator of each economic agent, we follow the procedure in the Joint Harmonised EU Programme of Business and Consumer Surveys of the European Commission.

Industrial confidence indicator.
The industrial confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on production expectations, order books, employment expectations and stocks of finished products (the last with inverted sign).

Do you consider your current overall order books to be...?

- + more than sufficient (above normal)
- = sufficient (normal for the season)
- − not sufficient (below normal)

Do you consider your current stock of finished products to be...?

- + too large (above normal)
- = adequate (normal for the season)
- − too small (below normal)

How do you expect your production to develop over the next 3 months? It will...

- + increase
- = remain unchanged
- − decrease

How do you expect your firm's total employment to change over the next 3 months? It will...

- + increase
- = remain unchanged
- − decrease

Services confidence indicator.
The services confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on business climate and on recent and expected evolution of demand and employment.

How has your business situation developed over the past 3 months? It has...

- + improved
- = remain unchanged
- − deteriorated

How has demand (turnover) for your company's services changed over the past 3 months? It has...

- + increase
- = remain unchanged
- − decrease

How do you expect the demand (turnover) for your company's services to change over the next 3 months? It will...

- + increase
- = remain unchanged
- − decrease

How do you expect your firm's total employment to change over the next 3 months? It will...

- + increase
- = remain unchanged
- − decrease

Retail trade confidence indicator.
The retail trade confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on the present and future business situation, expected employment and on stocks (the last with inverted sign).

How has (have) your business activity (sales) developed over the past 3 months?

- + improved
- = remain unchanged
- − deteriorated

Do you consider the volume of stock currently hold to be...?

- + too large (above normal)
- = adequate (normal for the season)
- − too small (below normal)

How do you expect your business activity (sales) to change over the next 3 months? It (They) will...

- + improved
- = remain unchanged
- − deteriorated

How do you expect your firm's total employment to change over the next 3 months? It will...

- + increase

- = remain unchanged
- − decrease

Construction confidence indicator.
The construction confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on order book and employment expectations.

Do you consider your current overall order books to be...?

- + more than sufficient (above normal)
- = sufficient (normal for the season)
- − not sufficient (below normal)

How do you expect your firm's total employment to change over the next 3 months? It will...

- + increase
- = remain unchanged
- − decrease

Consumer confidence indicator.
The consumer confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on the past and expected financial situation of households, the expected general economic situation, the intentions to make major purchases over the next 12 months and expected unemployment (the last with inverted sign).

How has the financial situation of your household changed over the last 12 months? It has...

- ++ got a lot better
- + got a little better
- = stayed the same
- − got a little worse
- −− got a lot worse
- N don't know

How do you expect the financial position of your household to change over the next 12 months? It will...

- ++ got a lot better

- + got a little better
- = stayed the same
- − got a little worse
- −− got a lot worse
- N don't know

How do you expect the general economic situation in this country to develop over the next 12 months? It will...

- ++ got a lot better
- + got a little better
- = stayed the same
- − got a little worse
- −− got a lot worse
- N don't know

Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend...

- ++ much more
- + a little more
- = about the same
- − a little less
- −− much less
- N don't know

How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...

- ++ increase sharply
- + increase slightly
- = remain the same
- − fall slightly
- −− fall sharply
- N don't know

C Main Results - Complete Figures

In this section, we present the complete figures from the augmented identification scheme of the baseline model MF Panel Favar using (i) labor productivity, (ii) unemployment rate and (iii) estimated factor from surveys of households and firms - manufacturing, services, retail and construction.

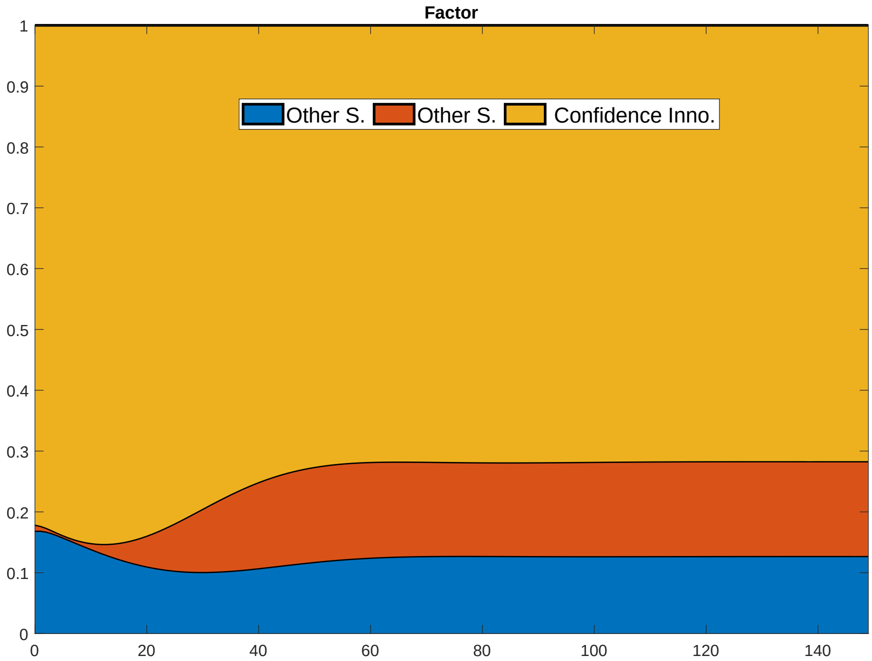


Figure 8: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of the factor at horizons j = 0, 1, . . . , 100 using short-run restrictions as in equation 3.

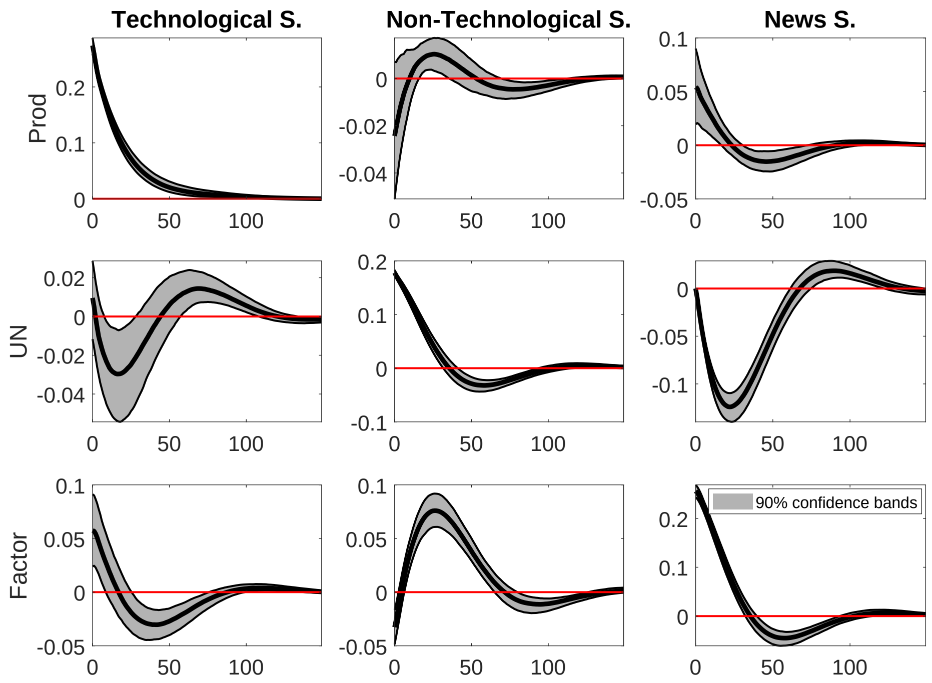


Figure 9: Response functions to positive shocks, as in Equation 5, from the whole the MF PANEL FAVAR

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

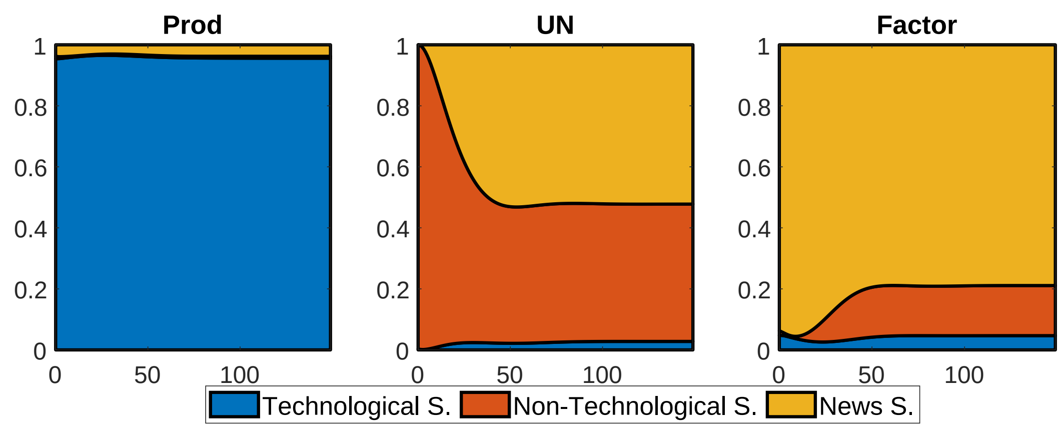


Figure 10: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of each variable at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 5.

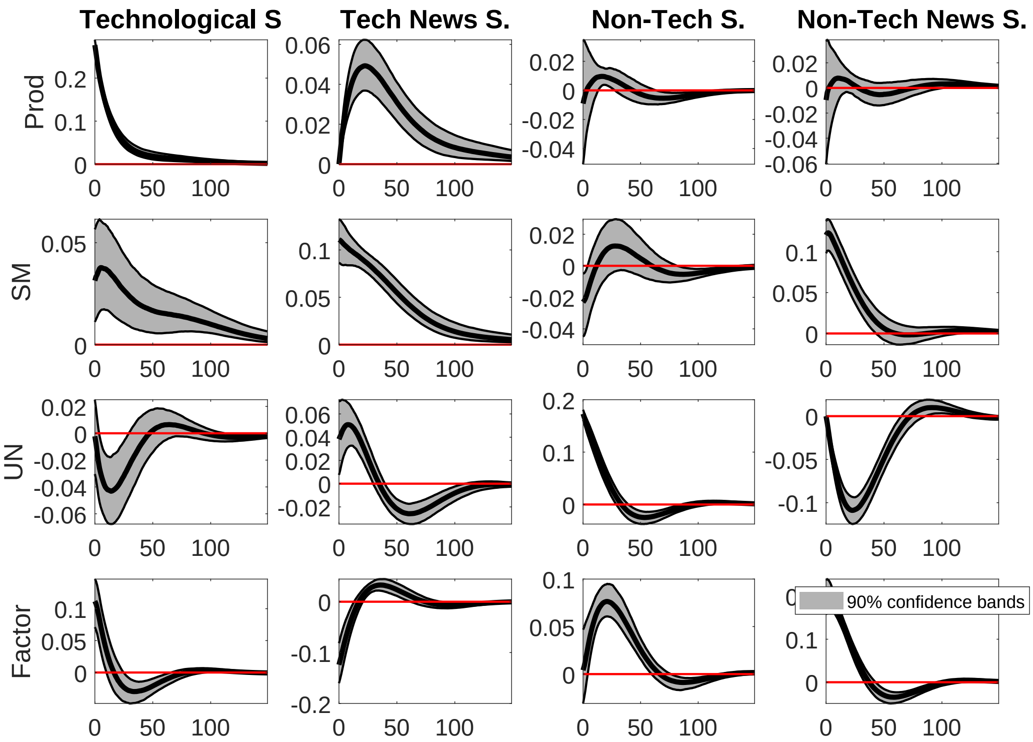


Figure 11: Response functions to positive shocks from the whole the MF PANEL FAVAR with stock prices

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 6. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

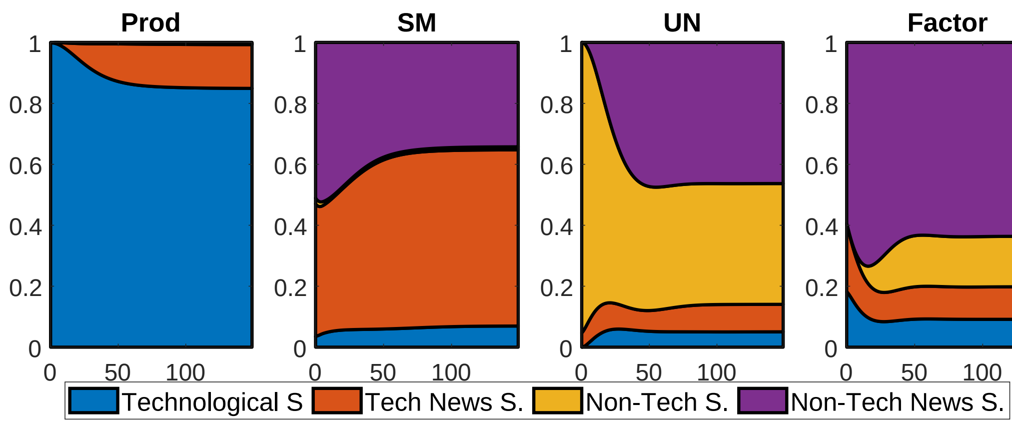
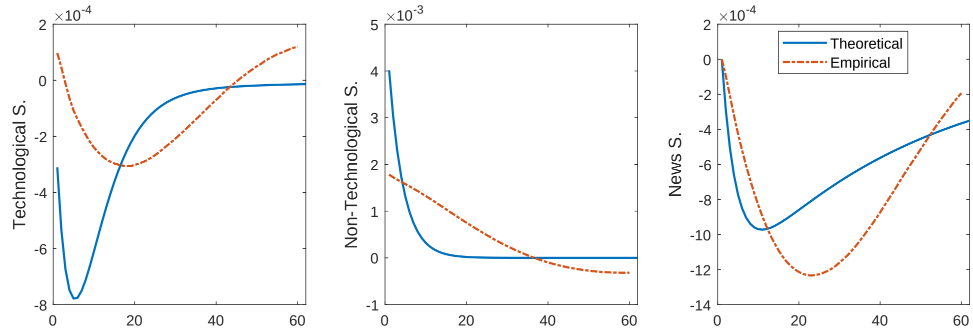
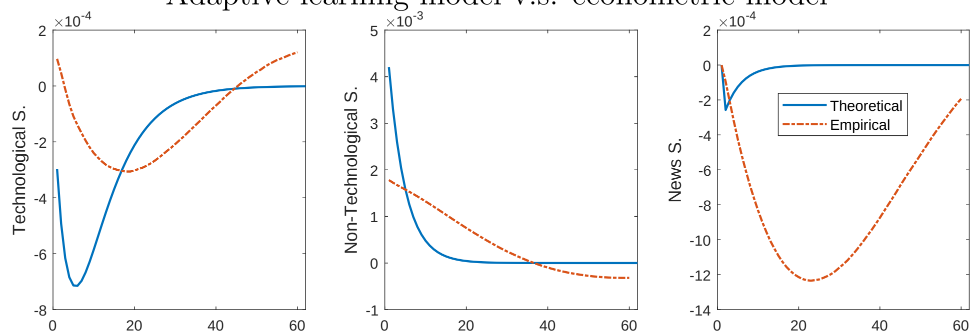


Figure 12: Variance decomposition at different frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of each variable at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 6.



Adaptive learning model v.s. econometric model



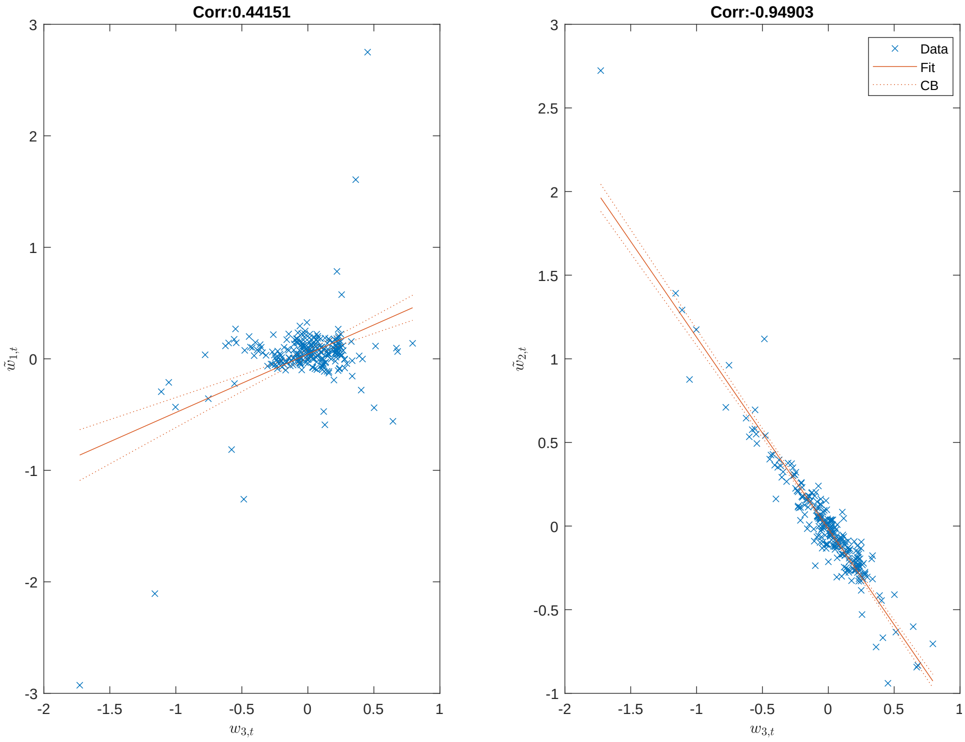
RE model v.s. econometric model

Figure 13: Impulse response functions of unemployment to positive innovations from the theoretical and econometric model

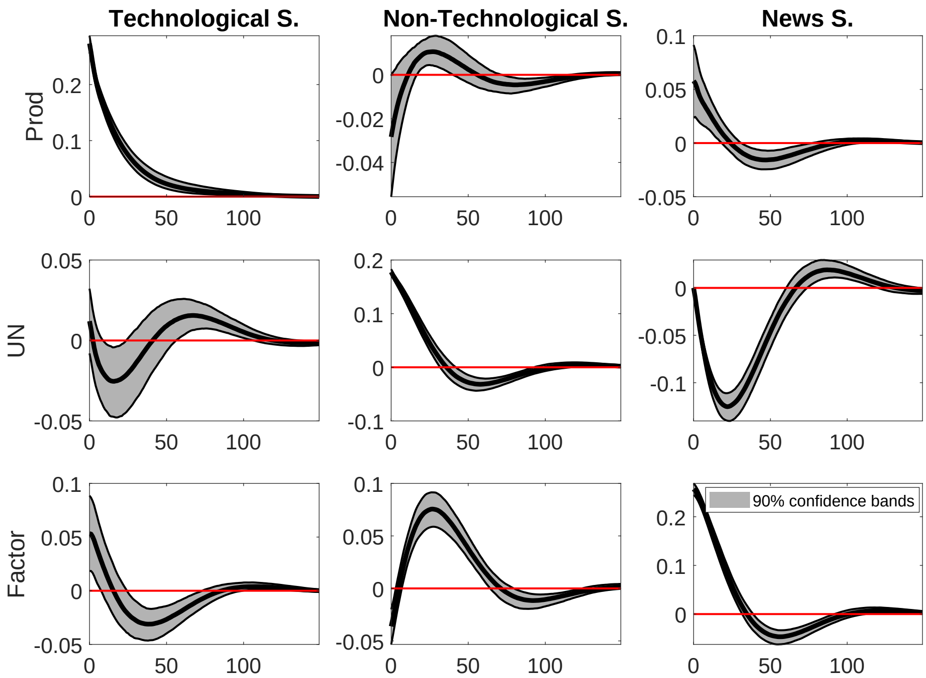
Note: The solid blue line corresponds to IRFs to the theoretical model, and dashed orange line to the median of the MF PANEL FAVAR.

D Robustness Figures

In this section, we present different the results of several extensions to the baseline model specification. We include figures using (i) 7 and 9 lags in the MF Panel Favar model, (ii) changing the long-run horizon imposed at the identification schemes to 4.1 years (50 periods) and 12.5 years (150 periods), (iii) enlarging the model with more variables investment, (iv) control for the extreme observations from the COVID-19 outbreak, (v) generate dummy data to show that the identification scheme does not generate spurious results, and (vi) simulating data from the theoretical model.



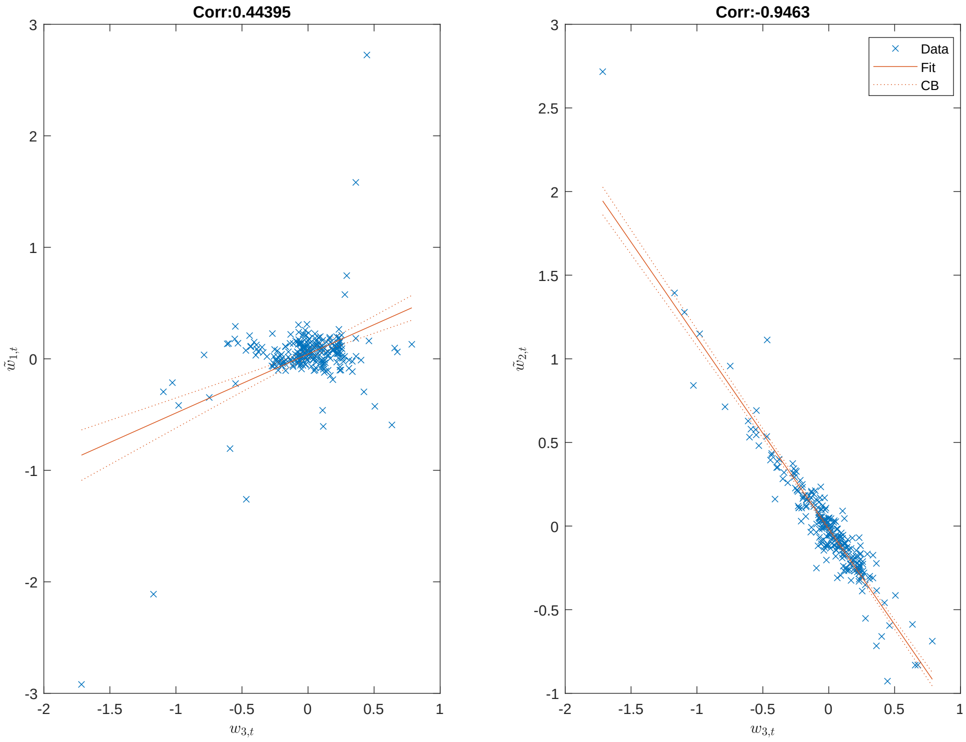
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 7 lags.



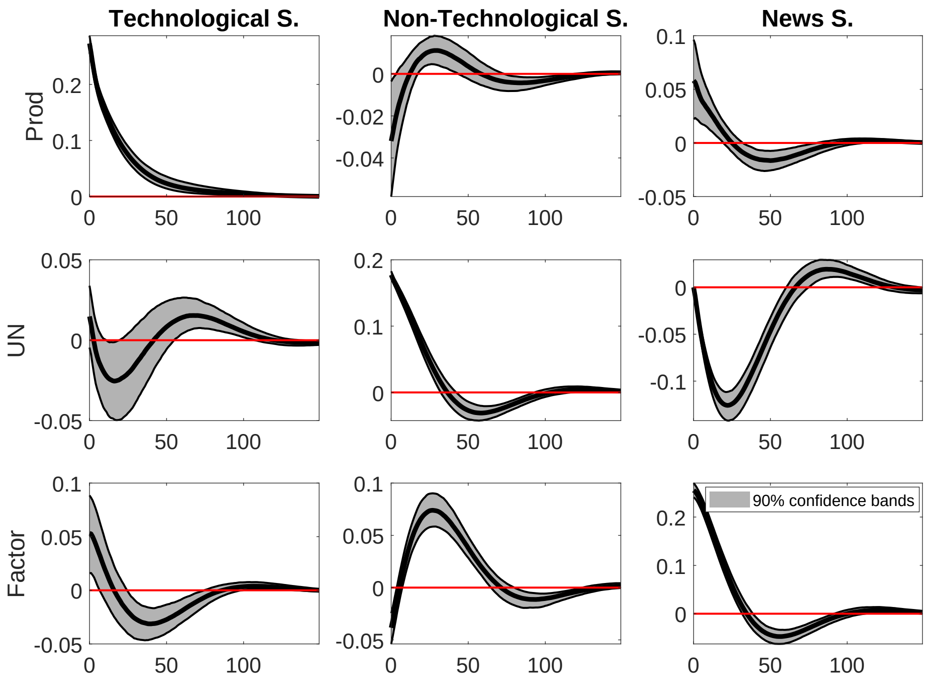
Response functions to positive shocks from the whole the MF Panel VAR with 7 lags.

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 14: MF Panel VAR with 7 lags



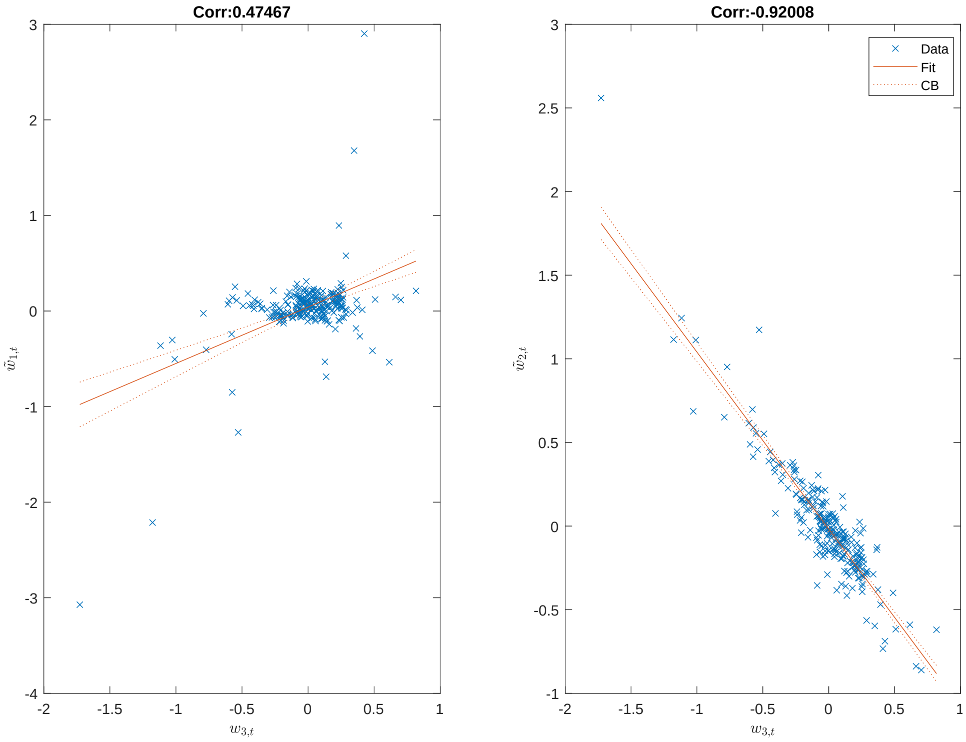
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 9 lags.



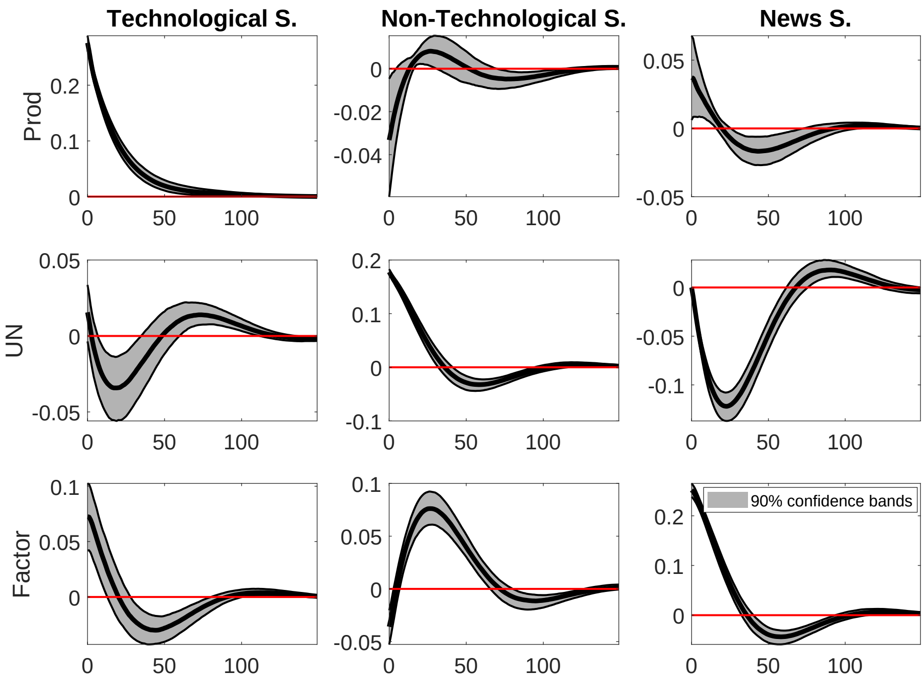
Response functions to positive shocks from the whole the MF Panel VAR with 9 lags.

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 15: MF Panel VAR with 9 lags



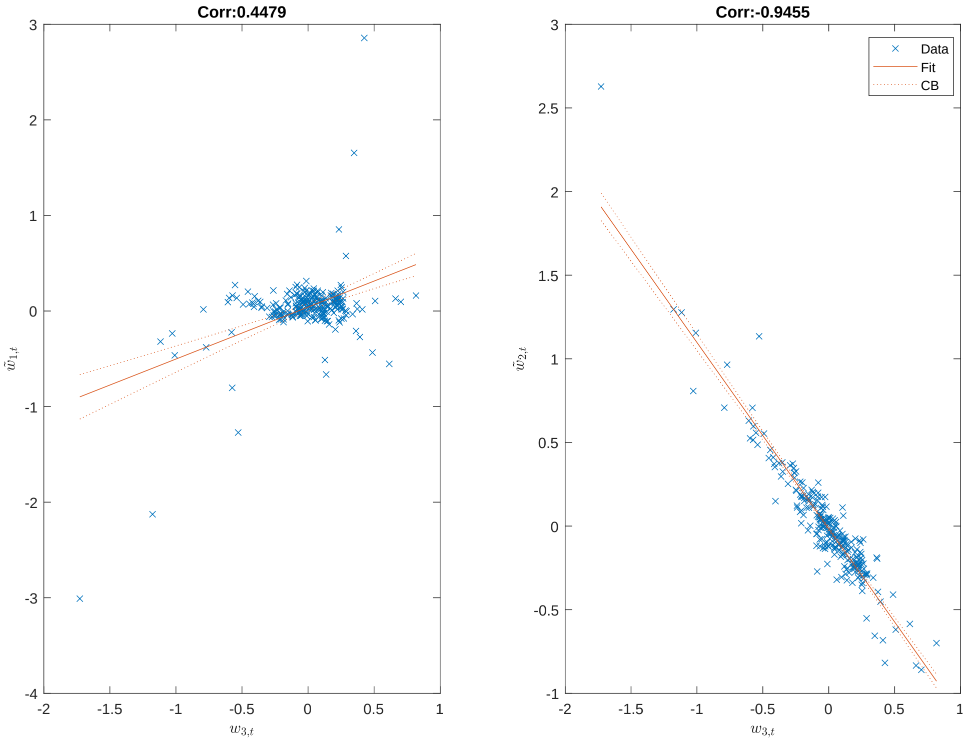
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 5 lags. Long-run shocks are imposed to be neutral at 50 periods horizon.



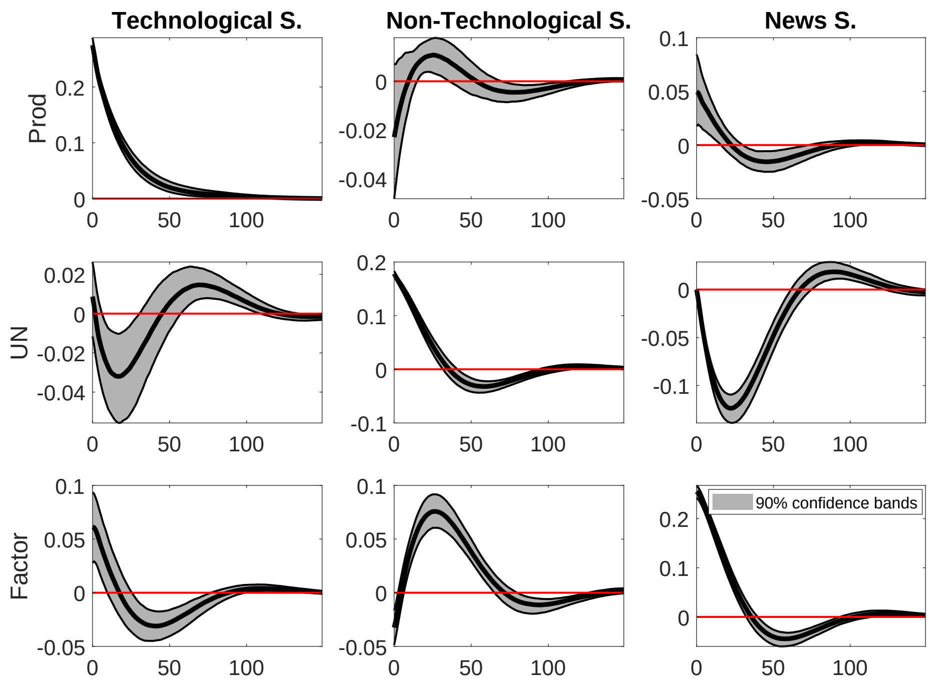
Response functions to positive shocks from the whole the MF PANEL FAVAR imposing long-run horizon at 50 periods.

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 16: Long-run horizon imposed on a 50 periods



Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 5 lags. Long-run shocks are imposed to be neutral at 150 periods horizon.



Impulse response functions from the whole the MF PANEL FAVAR imposing long-run horizon at 150 periods.

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 5. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 17: Long-run horizon imposed on a 150 periods

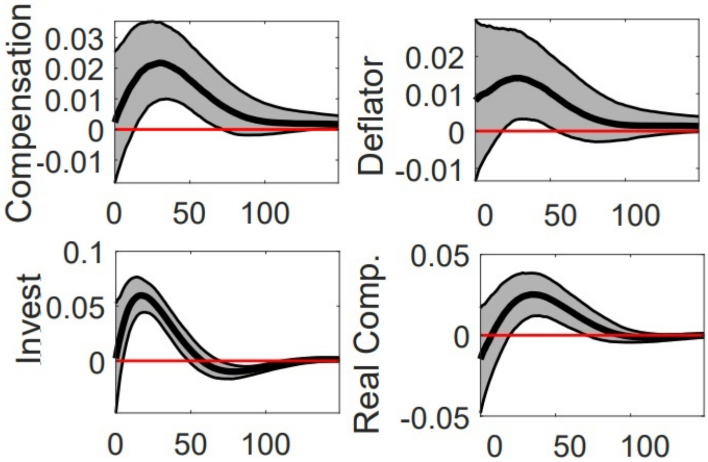
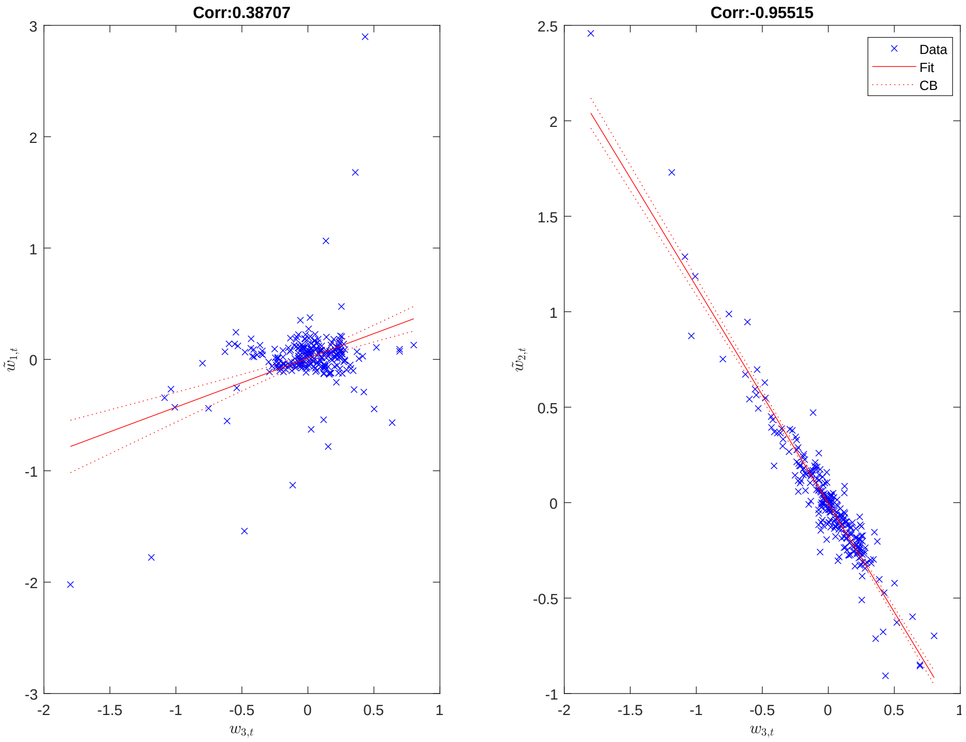
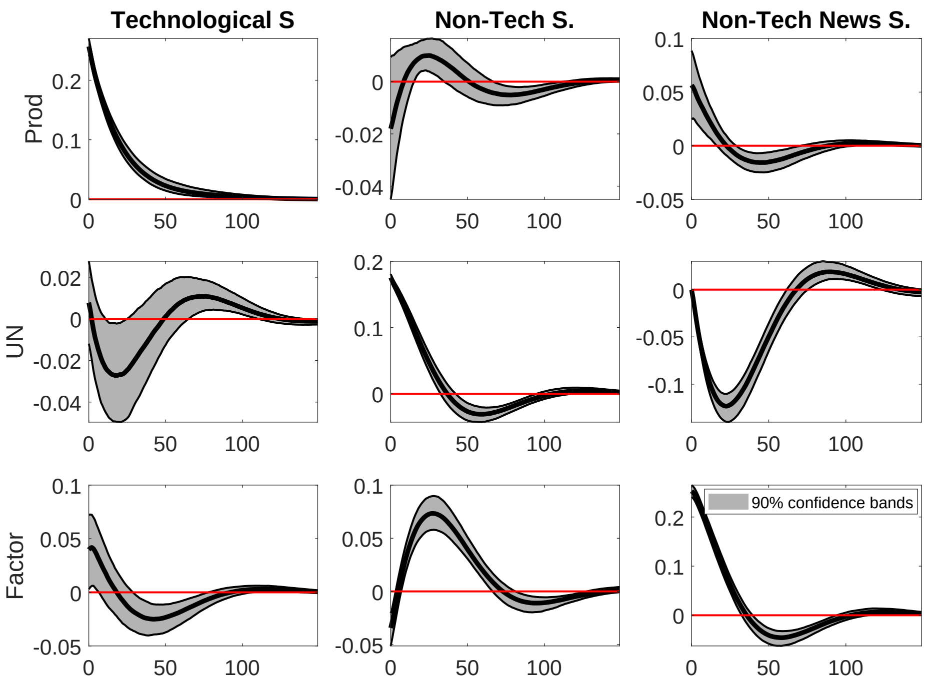


Figure 18: Response functions of nominal compensation, prices (measured as GDP deflator), capital investment and real compensation to a positive confidence (non-technological news) shocks

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 6. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.



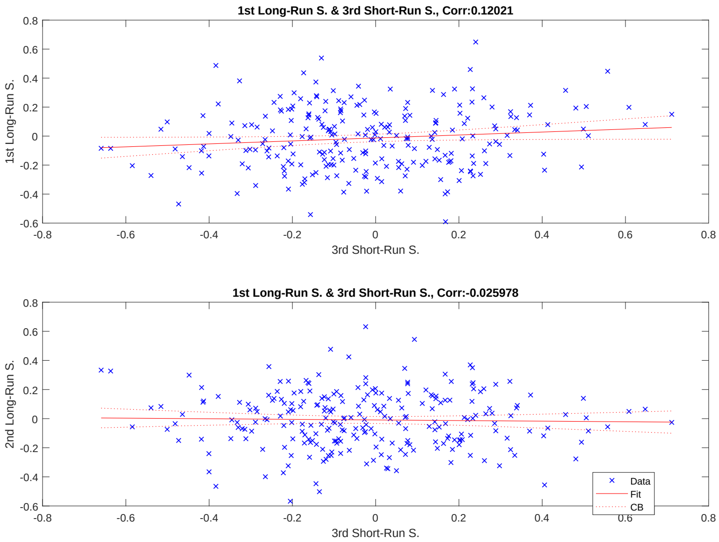
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR excluding observations from March, April and May 2020



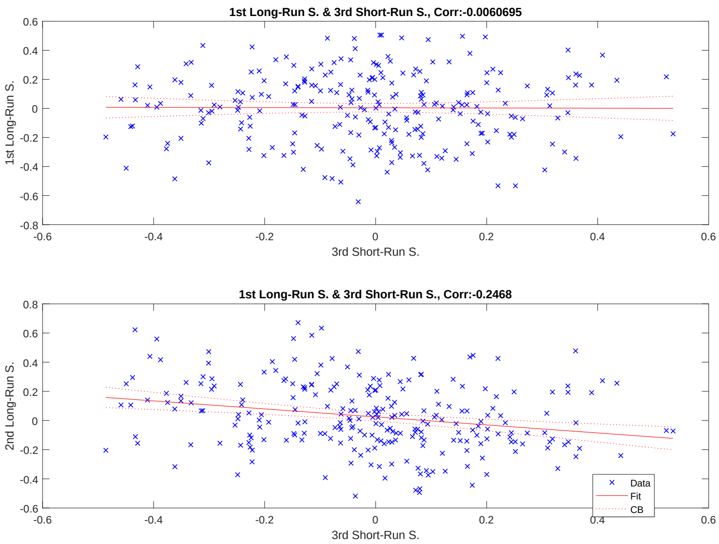
Response functions to positive shocks from the whole the MF PANEL FAVAR with excluding observations from March, April and May 2020

Note: Posterior distributions of cumulative impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 6. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

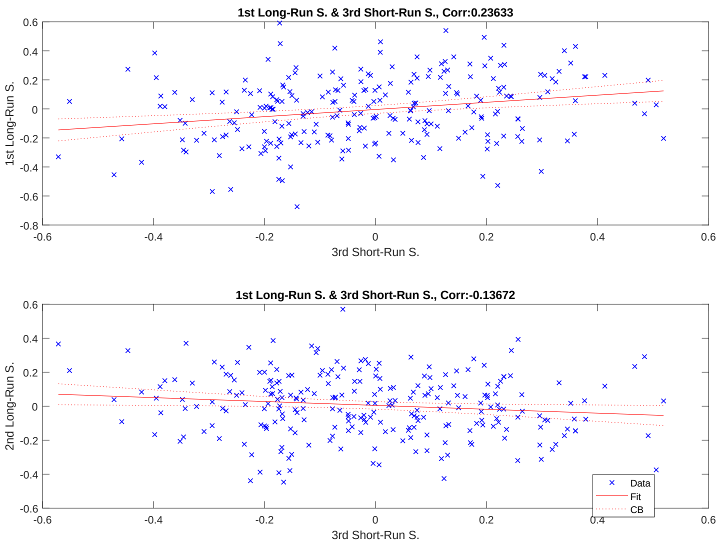
Figure 19: MF PANEL FAVAR with excluding observations from March, April and May 2020



Simulated data, group 1.



Simulated data, group 2.



Simulated data, group 3.

Figure 20: Plot of w_3 against $\tilde{w}_1$ - left - and $\tilde{w}_2$ -right. Shocks are obtained from the trivariate specification with five lags.

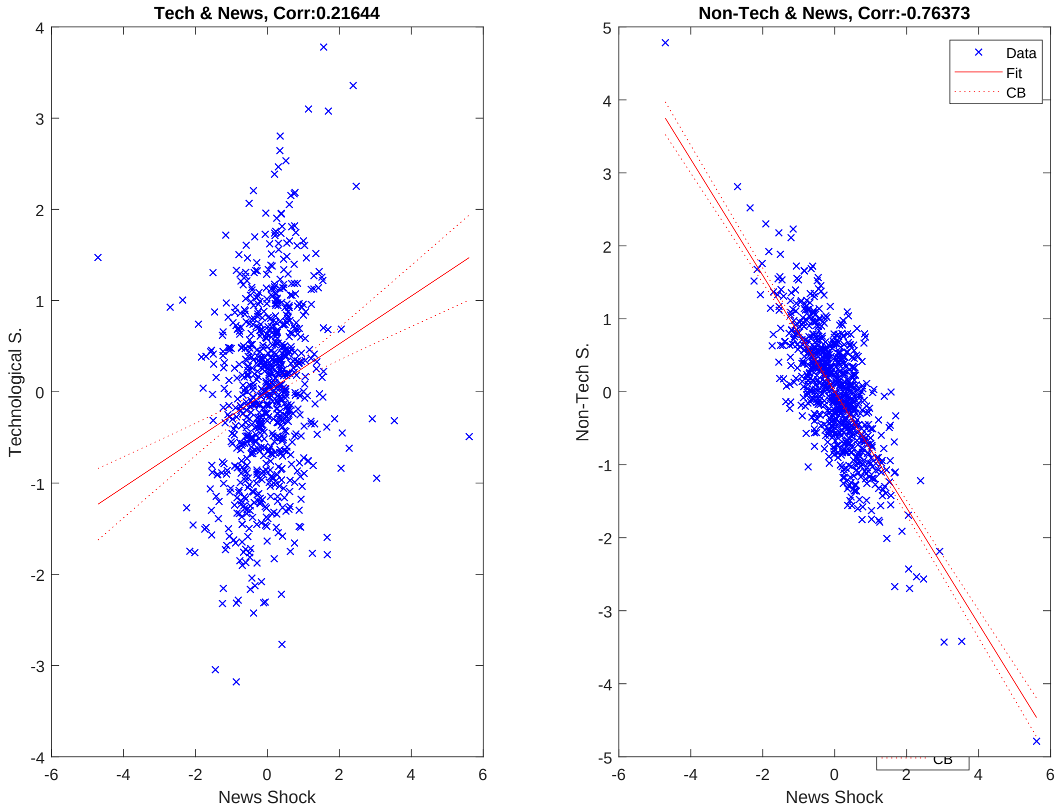


Figure 21: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$, using data generated from the theoretical model. The three shocks are active.

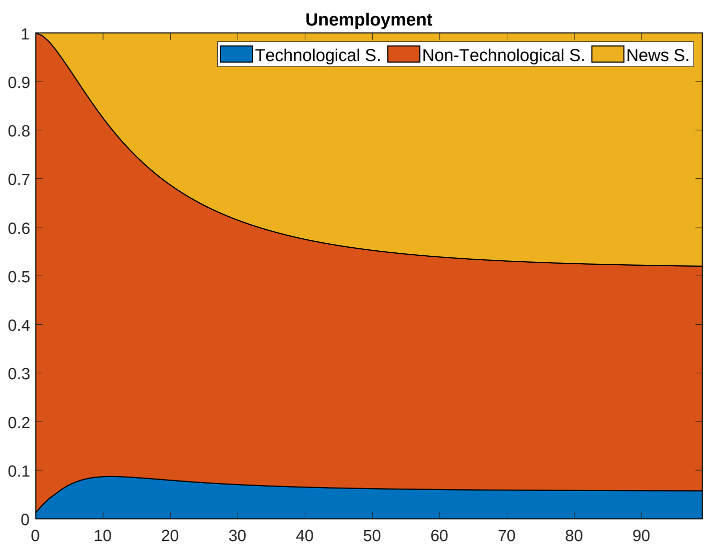


Figure 22: Variance decomposition at different frequencies of the unemployment rate - using data generated from the theoretical model. The three shocks are active.

Note: The colored areas represent the point-wise median cumulative contributions of each identified shock to the forecast error variance contributions of each variable at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 5.

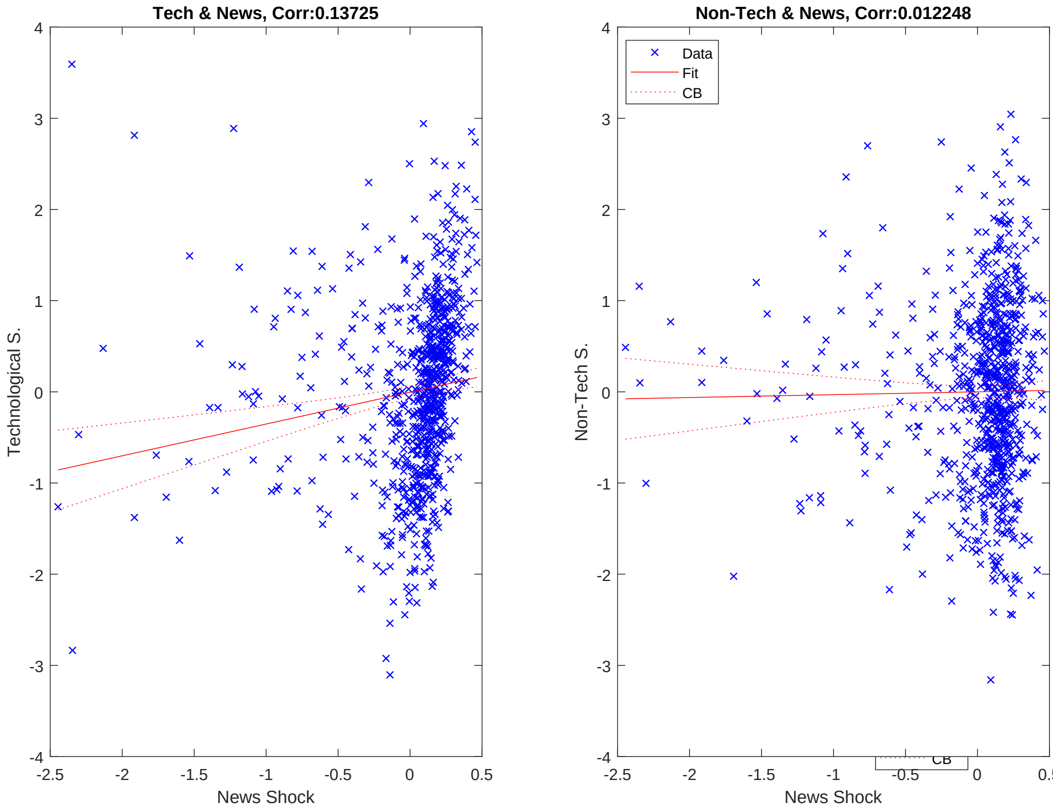


Figure 23: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$, using data generated from the theoretical model. Only technological and non-technological shocks are active.

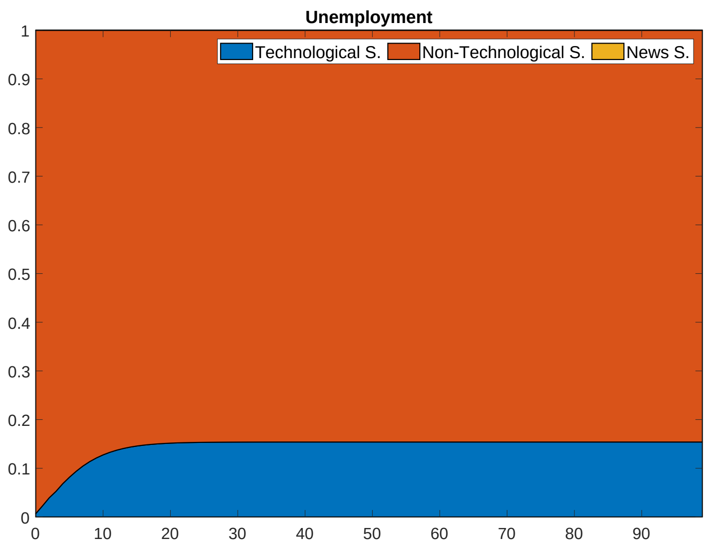


Figure 24: Variance decomposition at different frequencies of the unemployment rate - using data generated from the theoretical model. Only technological and non-technological shocks are active.

Note: The colored areas represent the point-wise median cumulative contributions of each identified shock to the forecast error variance contributions of each variable at horizons j = 0, 1, . . . , 100 using joint short and long-run restrictions as in equation 5.

E Linearisation of the job creation condition

We linearize the job creation condition applying a first-order Taylor polynomial of this equation at the steady state $\theta = \overline{\theta}$ and $y = \overline{y} = 1$. The job creation condition is represented by the following equation:

$$\frac{c}{\beta q(\theta_t)} = (1-\alpha)(E_t y_{t+1} - b) + \frac{(1-\lambda)c}{q(\theta_{t+1})} - \alpha c E_t \theta_{t+1}. \tag{34}$$

We take the first-order Taylor polynomial of each component of the previous equation:

$$\frac{c}{\beta q(\theta_t)} = \frac{c}{\beta q(\overline{\theta})} - \frac{c}{\beta q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (\theta_t - \overline{\theta}) \tag{35}$$

$$(1-\alpha)(E_t y_{t+1} - b) = (1-\alpha)(1-b) + (1-\alpha)(E_t y_{t+1} - b) \tag{36}$$

$$\frac{c(1-\lambda)}{q(E_t\theta_{t+1})} = \frac{c(1-\lambda)}{q(\overline{\theta})} - \frac{c(1-\lambda)}{q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (E_t\theta_{t+1} - \overline{\theta}) \tag{37}$$

$$\alpha c E_t \theta_{t+1} = \alpha c \overline{\theta} + \alpha c (E_t \theta_{t+1} - \overline{\theta}) \tag{38}$$

We can write equation (35) as:

$$\begin{aligned} \frac{c}{\beta q(\overline{\theta})} - \frac{c}{\beta q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (\theta_t - \overline{\theta}) &= (1-\alpha)(1-b) + (1-\alpha)(E_t y_{t+1} - b) \\ &+ \frac{c(1-\lambda)}{q(\overline{\theta})} - \frac{c(1-\lambda)}{q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (E_t\theta_{t+1} - \overline{\theta}) - \alpha c \overline{\theta} + \alpha c (E_t \theta_{t+1} - \overline{\theta}) \end{aligned} \tag{39}$$

We subtract the steady state of equation (35) from both sides of equation (40):

$$\begin{aligned} -\frac{c}{\beta q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (\theta_t - \overline{\theta}) &= (1-\alpha)(E_t y_{t+1} - b) \\ -\frac{c(1-\lambda)}{q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} &(E_t\theta_{t+1} - \overline{\theta}) - \alpha c (E_t \theta_{t+1} - \overline{\theta}) \end{aligned} \tag{40}$$

In the next step, we plug the functional form of $q(\overline{\theta}) = \mu \overline{\theta}^{-\nu}$

$$\begin{aligned} \frac{c\nu \overline{\theta}^{\nu-1}}{\beta\mu} (\theta_t - \overline{\theta}) &= (1-\alpha)(E_t y_{t+1} - b) \\ -\frac{c(1-\lambda)\nu\overline{\theta}^{\nu-1}}{\mu} &(E_t\theta_{t+1} - \overline{\theta}) - \alpha c (E_t \theta_{t+1} - \overline{\theta}) \end{aligned} \tag{41}$$

Then θ_t can be written as:

$$\theta_t = \phi_0 + \phi_1 E_t y_{t+1} + \phi_2 E_t \theta_{t+1} \tag{42}$$

where

$$\phi_0 = \overline{\theta} - \phi_2\overline{\theta} - \phi_1 \tag{43}$$

$$\phi_1 = \frac{(1-\alpha)\beta\mu}{c\nu\overline{\theta}^{\nu-1}} \tag{44}$$

$$\phi_2 = \beta(1-\lambda) - \frac{\beta\alpha\mu}{\nu\overline{\theta}^{\nu-1}} \tag{45}$$

Next, we plug in the previous equation, the expectation if the productivity in the next period, that under rational expectations is $E_t y_{t+1} = (1-\rho) + \rho y_t$. Therefore, we come up with:

$$\theta_1 = \hat{\phi}_0 + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 E_t\theta_{t+1} + \hat{\phi}_1\rho^{-1}\epsilon_t, \tag{46}$$

where

$$\hat{\phi}_0 = \phi_0 + (1-\rho)(1+\rho)\phi_1 \tag{47}$$

$$\hat{\phi}_1 = \rho^2\phi_1 \tag{48}$$

$$\hat{\phi}_2 = \phi_2 \tag{49}$$

$$\tag{50}$$

F Rational expectation coefficients

The Rational Expectation Equilibrium (REE) correspond to fixed points of the T-mapping. The T-mapping of this model is represented by the following vector:

$$T(\hat{A}_t, \hat{B}_t) = [\hat{\phi}_0 + \hat{\phi}_2\hat{A}_t + \hat{\phi}_2(1-\rho)\hat{B}_t, \hat{\phi}_2\rho\hat{B}_t + \hat{\phi}_1]. \tag{51}$$

Therefore, the REE is defined by the set of coefficients $(\overline{A}, \overline{B})$ such that

$$\begin{pmatrix} \overline{A} \\ \overline{B} \end{pmatrix} = \begin{pmatrix} \hat{\phi}_0 \\ \hat{\phi}_1 \end{pmatrix} + \begin{pmatrix} \hat{\phi}_2 & \hat{\phi}_2(1-\rho) \\ 0 & \hat{\phi}_2\rho \end{pmatrix} \begin{pmatrix} \overline{A} \\ \overline{B} \end{pmatrix} \tag{52}$$

Solving the previous system, we come up with

$$\overline{B} = \frac{\hat{\phi}_1}{1-\hat{\phi}_2\rho}, \tag{53}$$

$$\overline{A} = \frac{1}{1-\hat{\phi}_2}[\hat{\phi}_0 + \hat{\phi}_2(1-\rho)\frac{\hat{\phi}_1}{1-\hat{\phi}_2\rho}]. \tag{54}$$

The coefficient $\overline{C}$ in ecuation (19) is just a function of $\overline{B}$:

$$\overline{C} = \hat{\phi}_1(\rho^{-1} + \frac{\hat{\phi}_1}{1-\hat{\phi}_2\rho}). \tag{55}$$

We can now define E-stability for determining the stability of the REE under least squares learning. E-stability determines the stability of the REE under a stylized learning rule in which the PLM parameters (A, B) are adjusted slowly in the direction of the implied ALM parameters. The REE $(\overline{A}, \overline{B})$ is E-stable if small displacements from $(\overline{A}, \overline{B})$ are returned to $(\overline{A}, \overline{B})$ under this rule. It follows that the REE is E-stable if and only if the eigenvalues of $\begin{pmatrix} \hat{\phi}_2 & \hat{\phi}_2(1-\rho) \\ 0 & \hat{\phi}_2\rho \end{pmatrix}$ are < 1. The two eigenvalues are $\lambda_1 = \hat{\phi}_2$ and $\lambda_2 = \hat{\phi}_2\rho$.