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Abstract

We show that the joint behaviour of confidence measures and unemployment in a panel of European countries favours a view of labour market fluctuations driven largely by a shock that does not affect unemployment contemporaneously but affects it persistently over business-cycle horizons and explains the major share of the forecast error variance of confidence measures. This shock is captured in firm and household surveys and is almost perfectly correlated (-0.95) with non-technological disturbances driving the long-run behaviour of unemployment, but only modestly correlated with shocks affecting long-run productivity. One structural interpretation is that it represents news about future non-technological fundamentals, which is first captured in confidence measures. This shock accounts for 50% of unemployment variance at business-cycle frequency. It behaves as a mildly inflationary transitory demand shock – raising investment, wages, interest rates, fiscal surplus, and vacancies – is orthogonal to identified monetary policy shocks, and induces professional forecasters to revise unemployment expectations downward.

Key words: Non-technological news shocks, unemployment fluctuations, confidence measures, panel favar, mixed-frequencies.

JEL classification: C32, D83, E24, E30.

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1 Introduction

What information do consumer and firm confidence measures contain, and does that information matter for the macroeconomy? Consumer and firm confidence measures are closely monitored by policymakers and financial markets, yet the information embedded in these indicators remains imperfectly understood. Under the view that confidence is a forward-looking variable containing information about future economic fundamentals, it remains unclear whether confidence measures primarily anticipate technological developments that shape future productivity or instead capture non-technological forces.[1] Using confidence measures from firms and households in a panel of European countries, this paper shows that confidence innovations are related primarily to non-technological forces and play an important role in unemployment fluctuations over the business cycle.

The empirical strategy we adopt is to extend the sequential identification approach of Beaudry and Portier (2006)—originally applied to stock prices and TFP in the United States—to a system containing labor productivity, unemployment, and a latent confidence factor extracted from firm and household surveys across 22 European countries.[2] We perform two separate orthogonalizations on the reduced-form residuals of a mixed-frequency Panel FAVAR: one imposing short-run (impact) restrictions, the other imposing long-run restrictions.[3] The short-run scheme recovers a disturbance that represents innovations in confidence measures that is contemporaneously orthogonal to productivity and unemployment. The long-run scheme recovers two disturbances that drive long-run movements in productivity and in unemployment. The confidence innovation from the first scheme and the disturbances from the second are identified in separate systems and are therefore not constrained to be mutually orthogonal—yet examining their correlation is informative about the nature of the information embedded in confidence measures.

The main observation we uncover is that the confidence innovation from the short-run scheme and the disturbance driving long-run unemployment — when isolated separately without imposing orthogonality — are found to be almost perfectly correlated (-0.95). In contrast, the correlation between the confidence innovation and the disturbance driving long-run productivity is only 0.44. This is the mirror image of the finding in Beaudry and Portier (2006), where stock price innovations are almost perfectly correlated with the disturbance driving long-run TFP. In our setting, confidence innovations line up not with the technological side of the economy but

[1]A broad literature debates whether fluctuations in confidence reflect autonomous shifts in beliefs or information about future fundamentals. See, among others, Pigou (1927), Keynes (1937), Akerlof and Shiller (2010) for the former view, and Beaudry and Portier (2006), Barsky and Sims (2011), Barsky and Sims (2012) for the latter.

[2]The model aggregates diverse forward-looking indicators from firms and households into a country-specific confidence factor. 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.

[3]Our use of restrictions at a long but finite horizon follows the spirit of Uhlig (2004) medium-run identification approach.

with the non-technological side — the side that governs long-run unemployment dynamics.[4] Moreover, the confidence innovation explains the major share of the forecast error variance of the confidence factor at all horizons, suggesting that there is at least some truth to the news view of confidence in the same line of Barsky and Sims (2012).

Since the shocks identified under the two sequential schemes are not mutually orthogonal, their individual variance contributions are not directly comparable. To address this issue, we propose a simultaneous identification scheme that jointly disentangles technological shocks, non-technological shocks, and confidence shocks interpreted as non-technological news shocks within a unified system. We refer to this disturbance throughout as either the confidence shock or the non-technological news shock, using both terms interchangeably. The scheme combines short- and long-run restrictions, informed by the evidence from the sequential results.[5] Under this identification, we find that confidence shocks generate a persistent decline in unemployment at business-cycle frequencies, peaking around three to four years after impact, and account for roughly 50% of its forecast-error variance. These shocks also raise the confidence factor, while having a limited short-run effect on labor productivity in the baseline specification. In addition, they explain a substantial share of the forecast-error variance of the confidence factor and are associated with persistent responses in other macroeconomic variables, features that are more consistent with a news-based interpretation of confidence innovations than with animal spirits or noise (Barsky and Sims, 2012). By contrast, non-technological shocks account for most unemployment fluctuations at horizons shorter than one year. These results are in line with Schmitt-Grohé and Uribe (2012), who show that anticipated technology shocks play only a limited role in business-cycle fluctuations, whereas anticipated wage-markup, government-spending, and investment-specific shocks account for a substantial share of the variance of output, investment, and employment.

In an augmented specification that includes prices, investment, real wages, three-month bond yields, the fiscal balance, and unfilled vacancies, the confidence shock resembles a mildly inflationary transitory demand shock, lowering unemployment persistently while increasing prices, investment, vacancies, wages, the fiscal surplus, and interest rates. We also show that our results are robust to the inclusion of stock prices, which allows us to separately identify a technological news shock. Under this specification, neither technological news shocks nor surprise technological shocks emerge as the main drivers of unemployment over the business cycle, in line with Angeletos et al. (2020).[6] In addition, we regress forecast revisions for

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

[5] Our approach is related to "max-share" identification schemes, but it imposes fewer restrictions. In particular, we do not require the confidence shock to maximize the forecast-error variance of unemployment at any finite horizon, and we identify several structural shocks jointly rather than through partial identification.

[6] Angeletos et al. (2020) identify their shock by maximizing the share of unemployment variance at business-cycle frequencies, whereas we identify confidence shocks from a joint measure of household and firm surveys, impose no contemporaneous effect on unemployment, and leave the

unemployment from professional forecasters on lagged confidence shocks and find that positive shocks lead to net downward revisions in expected unemployment. This provides independent support for the news interpretation: professional forecasters—who play no role in constructing the confidence measures—appear to treat these shocks as containing genuine information about future unemployment. The shock is also orthogonal to monetary policy shocks, suggesting that it captures distinct informational content. Our findings are further robust to alternative measures of productivity.

Finally, we interpret our empirical findings through a simple search-and-matching model with adaptive learning. The purpose of the model is not to identify the exact structural source of the shock, but rather to illustrate a mechanism through which non-technological news can matter for unemployment. In the benchmark model under rational expectations, non-technological news that enters through expectations of future labor market tightness are neutral in equilibrium. Under adaptive learning, however, such news can propagate through belief updating and vacancy-posting decisions, producing persistent unemployment responses in line with the data.

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)).

A natural concern when interpreting confidence innovations is whether they reflect genuine information about the future—news—or merely noisy signals that lead agents to mistaken beliefs. Chahrour and Jurado (2018) show that this distinction cannot be resolved on purely empirical grounds: news and noise representations of agents' beliefs are observationally equivalent, so any belief-driven process admits both representations and no identification scheme can separate them from observables alone. We take this equivalence result seriously and do not claim to disentangle news from noise in a strict representational sense. Several features of our results, however, lead us to favor a news interpretation of the confidence innovations we recover. First, the shocks account for a substantial share of the forecast-error variance of the confidence factor and generate persistent responses in other macroeconomic variables—patterns that Barsky and Sims (2012) associate with genuine news rather

long-run impact matrix unrestricted.

than animal spirits or pure noise. Second, regressing professional forecasters' revisions of expected unemployment on lagged confidence shocks yields net downward revisions following positive shocks: forecasters who play no role in constructing the confidence measures treat these innovations as containing information about future labor market conditions. Third, the shocks are orthogonal to identified monetary policy shocks, suggesting that they carry distinct informational content rather than reactions to policy surprises.

With this interpretation in hand, our paper provides new evidence in support of the news 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. Our results also speak to the role of stock prices emphasized by Beaudry and Portier (2014). They find that once stock prices are removed from the system, confidence innovations no longer have significant long-run effects on TFP. Our confidence shocks correlate strongly with the long-run drivers of unemployment but not of labor productivity, and this holds whether or not stock prices enter the system. Our confidence measures therefore do not appear to carry technological news, reinforcing the interpretation that their informational content concerns the non-technological side of the economy.

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.[7] 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

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

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 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. Building on the insights of Barro and King (1984), technological news shocks in standard neoclassical models fail to generate the appropriate business cycle comovements. The seminal work of Jaimovich and Rebelo (2009) addresses this issue by incorporating news about future technological advancements through various channels, such as variable capital utilization, adjustment costs, and specific preferences that allow for modeling short-run wealth effects on labor supply. 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 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. 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.[8] 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.[9] 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.

Structure. Section 2 describes the data, its sources and transformations. Section 3 presents the econometric model, the scheme of BP and the simultaneous

[8] Di Pace et al. (2021) and García-Rodríguez (2026) show, under adaptive learning and internal rationality, respectively, that learning about wages in a search-and-matching model improves the model's ability to match the data.

[9] 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).

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 concludes.

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[10]. 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).[11]

Productivity measure. Our measure of productivity is real gross domestic product per person employed, obtained at quarterly frequency. Labor productivity is a natural choice for our setting: it is available in a harmonized form for all 22 countries over the full sample period, and it is the productivity concept most directly linked to hiring decisions and labor market dynamics. However, it is not a pure measure of technology, as it also reflects changes in capital intensity and factor utilization. To address this, we show in Section 6.2 that our results are robust when using a standard Solow residual and the utilization-adjusted TFP series following (Comin et al., 2025).

Transformations. Productivity is transformed into the Napierian logarithm. The unemployment rate, u_t is transformed using a logit (log-odds) transformation:

$$v_t = \ln\left(\frac{100 \times u_t}{100 - u_t}\right).$$

This transformation maps the unemployment rate, which is bounded between 0 and 100, onto the entire real line $(-\infty, +\infty)$, yielding a variable that can exhibit non-stationary dynamics unbounded above and below.[12]

[10]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.

[11]For more details, see Appendix B.

[12]These transformations are appropriate for our setting because standard unit-root tests suggest that unemployment rates are $I(1)$ for most, though not all, countries in the sample. Applying the transformation ensures that the resulting variable can be treated as $I(1)$ uniformly across countries in the panel. See Farmer (2015) and Nicolau (2002) for more details.

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.[13] Second, we then explain the BP scheme, 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 scheme of BP, 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. A cross-sectional dimension is added to the representation with a total of C units, which, in our case are countries. The model is given by two key equations: the measurement equation 1 and transition equation 2, whose vectors of variables and matrices are indexed by i and t, referring to countries and time periods.

Equation 1 links the observed data $(y_{i,t})$ to the latent state vector $(\widehat{y}_{i,t})$ through the matrix (H_i) and a measurement error term $(v_{i,t})$, with $v_{i,t} \sim \mathcal{N}(0, W_i)$. For each

[13] 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). Under this approach, the estimates remain consistent without requiring the variables to be rendered stationary beforehand. Moreover, transformations such as first-differencing may remove important features of the data that contain information about the co-movement among the variables. 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.

country $i = 1, \ldots, C$ we observe (i) unemployment $UN_{i,t}$ at monthly frequency, (ii) five monthly confidence series ($HH_{i,t}$, $IND_{i,t}$, $SER_{i,t}$, $BUL_{i,t}$, $RE_{i,t}$)—consumer, industry, service, construction, and retail confidence indicators—, and (iii) labor productivity $LP_{i,t}$ at quarterly frequency. To combine monthly and quarterly information in a single system, we treat monthly labor productivity as latent and link the observed quarterly series to the latent monthly series through an aggregation restriction.

Let the observed vector ($y_{i,t}$) and latent monthly vector ($x_{i,t}$) be

$$y_{i,t} \equiv \begin{bmatrix} LP_{i,t} \\ UN_{i,t} \\ HH_{i,t} \\ IND_{i,t} \\ SER_{i,t} \\ BUL_{i,t} \\ RE_{i,t} \end{bmatrix}, \qquad x_{i,t} \equiv \begin{bmatrix} \widehat{LP}_{i,t} \\ UN_{i,t} \\ \widehat{F}_{i,t} \end{bmatrix},$$

where $\widehat{LP}_{i,t}$ is latent monthly labor productivity and $\widehat{F}_{i,t}$ is a latent confidence factor. Then, by stacking the latent monthly vector $\widehat{y}_{i,t} \equiv \left(x'_{i,t}, x'_{i,t-1}, \ldots, x'_{i,t-p}\right)'$, the observation equation can be read as

$$y_{i,t} = H_i \, \widehat{y}_{i,t} + v_{i,t}, \tag{1}$$

where the observed error term vector is

$$v_{i,t} \equiv \begin{bmatrix} v_{i,t}^{LP} \\ 0 \\ v_{i,t}^{HH} \\ v_{i,t}^{IND} \\ v_{i,t}^{SER} \\ v_{i,t}^{BUL} \\ v_{i,t}^{RE} \end{bmatrix}.$$

The mapping matrix H_i is restricted to encode the following relations: (i) unemployment is observed without measurement error; (ii) the five survey series load on the common factor $\widehat{F}_{i,t}$ with country-specific loadings ($h_{i,1}, \ldots, h_{i,5}$); and (iii) when a quarterly observation of $LP_{i,t}$ is available (i.e., in the last month of each quarter), it is linked to the latent monthly series via the temporal aggregation restriction

$$LP_{i,t} = \tfrac{1}{3}\left(\widehat{LP}_{i,t} + \widehat{LP}_{i,t-1} + \widehat{LP}_{i,t-2}\right) + v_{i,t}^{LP},$$

which corresponds to the first row of H_i selecting ($\widehat{LP}_{i,t}, \widehat{LP}_{i,t-1}, \widehat{LP}_{i,t-2}$) with weights $(1/3, 1/3, 1/3)$. When $LP_{i,t}$ is observed we set $\mathrm{var}(v_{i,t}^{LP}) = 0$ (so the aggregation holds exactly). When $LP_{i,t}$ is not observed (the first two months of each quarter), we treat it as missing by setting the first row of H_i to zero and setting $\mathrm{var}(v_{i,t}^{LP})$ to a very large number. 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.

The transition equation for the latent monthly variables is a VAR with p lags and three endogenous variables ($n = 3$):

$$x_{i,t} = c_i + \sum_{j=1}^{p} A_{i,j}\, x_{i,t-j} + \epsilon_{i,t}, \qquad \epsilon_{i,t} \sim \mathcal{N}(0, \Sigma_i), \tag{2}$$

where c_i is a vector of country-specific constants, $A_{i,j}$ are country-specific VAR coefficient matrices, and $\epsilon_{i,t}$ are country-specific reduced-form innovations. We assume that $\mathcal{A}_i$, where $\mathcal{A}_i = (A_{i,1}, \ldots, A_{i,p})$, are related across units i according to

$$\text{vec}(\mathcal{A}_i) = \bar{a} + a_i,\ a_i \sim \mathcal{N}(0, \Omega). \tag{3}$$

Here, $\bar{a}$ and Ω represent a common mean and variance across countries. This specification implies that countries are characterized by heterogeneous VAR coefficients (i.e., $\mathcal{A}_i \neq \mathcal{A}_j$ if $i \neq j$), while allowing these coefficients to be random draws around a common mean. Therefore, the parameters of interest, $\bar{a}$, are the (cross-sectional) average coefficients of the group.[14]

The initial conditions $\widehat{y}_{i,0:-p+1} = (\widehat{y}'_{i,0}, \cdots, \widehat{y}_{i,-p+1})$ are assumed to be distributed according to $\widehat{y}_{i,0:-p+1} \sim N(0, V(\mathcal{A}_i, \Sigma_i))$, where $V(\mathcal{A}_i, \Sigma_i)$ represents the unconditional variance of $y_{i,0:-p+1}$. The priors for the VAR coefficients $\mathcal{A}_i$ and the covariance matrix Σ_i have a standard form, namely,

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

where $p\left(\Sigma\right) = I\mathcal{W}\left(n+2, (n+2)\, \underline{\Sigma}\right)$ denotes the inverse Wishart distribution with mode $\underline{\Sigma}$ and $n+2$ degrees of freedom, and $I(\text{vec}(\mathcal{A}_i))$ 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.[15]

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, $\text{vec}(\underline{\mathcal{A}})$, is a standard Minnesota prior with the hyperparameter for the overall tightness equal to the commonly used value of 0.2 (see Giannone, Lenza and Primiceri (2015)). The prior for the VAR parameters $\text{vec}(\mathcal{A})$ are centered around zero, except for the "own-lag" parameter that is centered at 1 - this implies that the individual variables exhibit random walk

[14]Different European frameworks have also been studied using panel VARs; for example: (i) price differentials in monetary unions, Canova and Ciccarelli (2004), (ii) responses to monetary policy shocks across 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).

[15]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.

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.[16] Turning to the initial conditions, all the country-specific $\widehat{y}_{i,0:-p+1}$ 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 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.[17]

3.2 BP scheme

This section explains the scheme of Beaudry and Portier (2006). 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,

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

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.[18] The confidence innovation affects the factor contemporaneously and with a lag on productivity and unemployment. Our interpretation of this shock is

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[16] 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.

[17] 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).

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

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.[19] 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 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.[20] 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).[21]

$$\underbrace{\begin{pmatrix} \epsilon_t^{Prod} \\ \epsilon_t^{Un} \\ \epsilon_t^{F} \end{pmatrix}}_{\text{Reduced-form residuals}} = \underbrace{C(1)^{-1} \begin{bmatrix} s_0^{11} & 0 & 0 \\ s_0^{21} & s_0^{22} & 0 \\ s_0^{31} & s_0^{32} & s_0^{33} \end{bmatrix}}_{\tilde{P}} \underbrace{\begin{pmatrix} \tilde{w}_{1t}^{\text{Technological Shock}} \\ \tilde{w}_{2t}^{\text{Non-Technological Shock}} \\ \tilde{w}_{3t}^{\text{Shock 3}} \end{pmatrix}}_{\text{Structural Disturbances}}. \tag{5}$$

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

[19] Our use of restrictions at a long but finite horizon follows the spirit of Uhlig (2004) medium-run identification approach and is motivated by the concerns raised by Erceg et al. (2005) and Uhlig (2004) about the estimation uncertainty associated with exact infinite-horizon long-run restrictions.

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

[21] 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.

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.[22] 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.

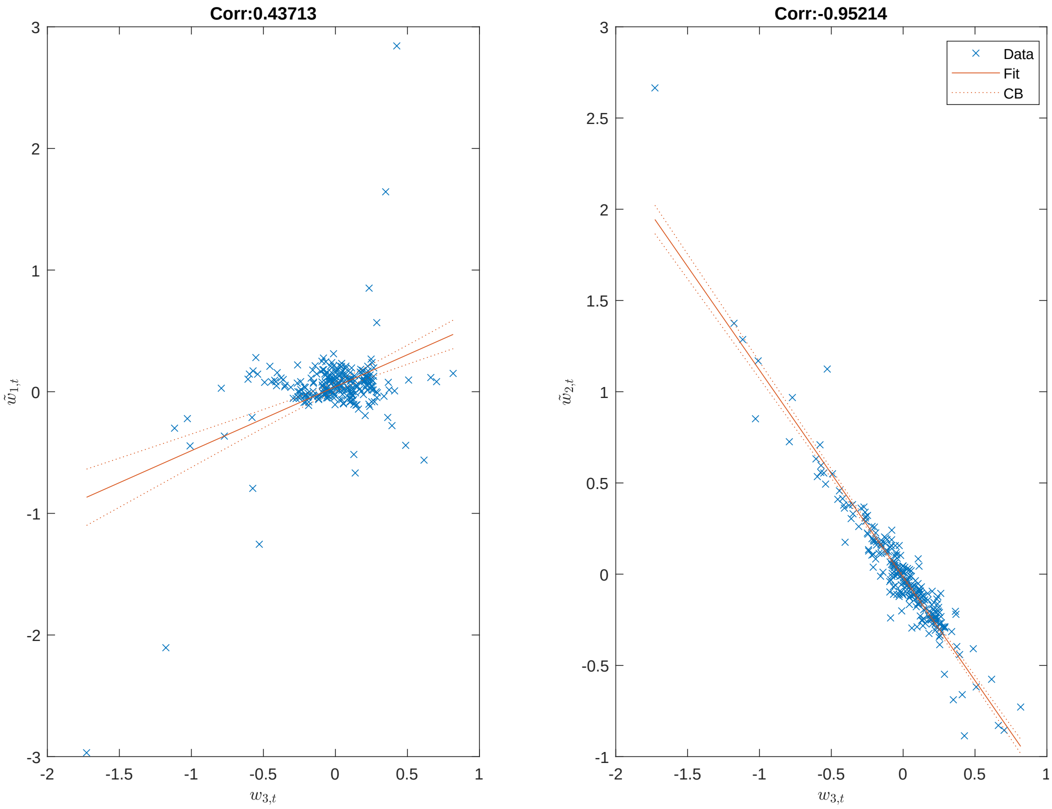

Figure 1: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel FAVAR with 5 lags

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

[22]See Figure C.7 in the Appendix.

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 6 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.

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

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 shows the impulse response functions (IRFs) of the unemployment rate to positive structural shocks in the MF Panel FAVAR, with each column corresponding to a different positive shock. The horizontal axis measures months from impact up to 150 months, and the vertical axis shows the response magnitude. Shaded areas denote 90% probability density intervals.

The unemployment rate responds significantly and negatively to confidence (non-technological news) shocks, and significantly and positively to non-technological shocks. Moreover, confidence shocks exhibit high persistence, with the unemployment response remaining significant for approximately 60 months, compared to roughly 30 months for non-technological shocks. This persistence suggests that confidence innovations convey information about future economic fundamentals.

Confidence shocks also dominate the latent confidence factor, explaining over 80% of its forecast error variance at all horizons (see Figure C.9 in the Appendix). In Section 6.5, we regress professional forecasters' unemployment-forecast revisions on lags 1–5 of the confidence shock and find that positive news shocks induce net downward revisions in unemployment expectations. A regression on contemporaneous and lead shocks confirms that forecasters do not anticipate these innovations. These results reinforce the "news view" interpretation of our confidence shocks, as articulated in Barsky and Sims (2012).

In Section 6.3, we augment the VAR system one variable at a time—adding capital investment, the GDP deflator (prices), nominal and real compensation, the three-month bond yield, fiscal balance (revenue minus expenditures), unfilled vacancies, and government spending—to further characterize confidence shocks. We find that confidence shocks resemble mildly inflationary transitory demand shocks: they persistently reduce unemployment, elevate the confidence factor, productivity shows a short-lived uptick, and increase investment, prices, wages, interest rates, and government spending. Unfilled vacancies and fiscal balance also rise on impact, implying higher vacancy creation (as implied in our theoretical model in Section 5) and a temporary fiscal surplus driven by lower unemployment-benefit payments and higher tax revenues.

These dynamics closely mirror those of the Main Business-Cycle (MBC) shock in Angeletos et al. (2020), as both shocks produce a transitory boost to real activity measures, while imparting only a mild, short-lived inflationary impulse, a procyclical rise in interest rates, and negligible effects on productivity. Whereas Angeletos et al. (2020) isolate the MBC shock by maximizing the unemployment-variance share at business-cycle frequencies, we extract confidence shocks from a joint measure of household–firm surveys and impose no contemporaneous effect on unemployment.

Figure 3 plots the share of variance of the unemployment rate attributable to

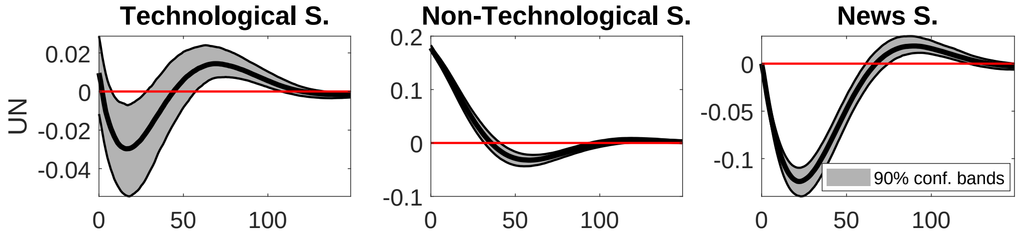

Figure 2: Response functions of unemployment to positive innovations from the MF PANEL FAVAR

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

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. At short-term horizons (below 12 months), unemployment

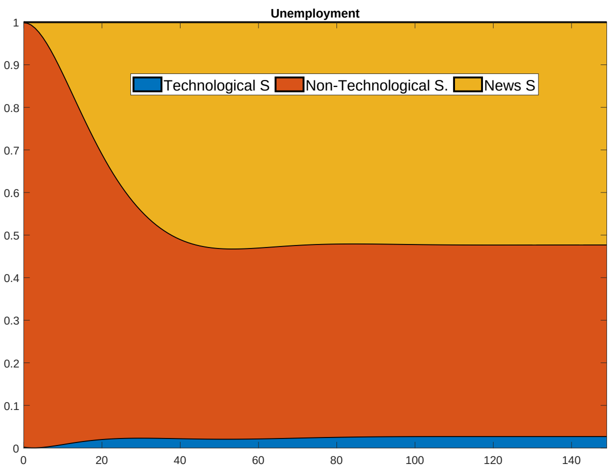

Figure 3: Variance decomposition of the variable unemployment at different frequencies

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

dynamics are primarily driven by non-technological shocks. As we move to business-cycle periodicities (18–96 months), the contribution of confidence shocks steadily increases, becoming the main driver around the 40-month horizon. Technological shocks, by contrast, account for only about 4 % of the variance at business-cycle frequencies.

These results bear a similar flavor to those of Justiniano et al. (2010) for U.S. data, where wage-markup shocks explain over 90 % of unemployment fluctuations below the 12-month horizon and then drop significantly at business-cycle frequencies; their technology shock explains about 4 % at these frequencies; and their investment-specific shock accounts for roughly 50 % at business-cycle periodicities.[23]

4.2 Stock Prices and Technological News Shocks

The baseline model described in the previous section indicates that our confidence factor mainly captures non-technological news rather than news about future productivity. To account for technological news, we augment the system with stock prices (SP). This follows Beaudry and Portier (2006) and subsequent work (Beaudry and Portier (2014) and Barsky et al. (2015)) showing that stock prices may embed forward-looking information about future productivity growth.[24]

We first revisit the BP logic in the four-variable system $(Prod, SP, UN, F)$.[25] Two results stand out. First, the shock that affects stock prices contemporaneously and productivity with a lag is strongly correlated with the shock that drives the long-run behavior of productivity (correlation = 0.767), suggesting that stock prices contain information about future productivity. Second, the confidence (non-technological news) shock, which affects the factor contemporaneously and unemployment with a lag, remains strongly correlated with the shock that drives the long-run behavior of unemployment (correlation = −0.81), indicating that the confidence factor continues to capture non-technological news. Figure C.10 in the Appendix summarizes these correlations.

These findings motivate a joint identification scheme, as outlined in Eq. 7, that separates four shocks in a single system: technology shocks, technological news shocks, non-technological shocks, and confidence shocks. The key identifying assumptions are straightforward. A.1: Only technology and technological news shocks may affect productivity in the long run, and they do not affect unemployment and the confidence factor in the long run. A.2: Technological news shocks do not affect productivity on impact. A.3: Non-technological shocks have no long-run effect on productivity. A.4: Confidence shocks do not affect unemployment contemporaneously, but they may affect unemployment in the long run.

$$P = \begin{pmatrix} * & 0 & * & * \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & 0 & * & * \\ * & 0 & * & * \end{pmatrix} \tag{7}$$

[23]The model of Justiniano et al. (2010) is a medium-scale DSGE of the New Neoclassical Synthesis, featuring Calvo-style sticky prices and wages under monopolistic competition, endogenous capital utilization with adjustment costs, habit formation, and variable investment efficiency. In their model, there is no search-and-matching frictions, so there is no explicit unemployment margin to model. Instead, labor enters the model only on the intensive margin—households choose hours worked. Their investment-specific shock generates a "boom-and-bust" cycle: investment surges on impact before unwinding over the following year; output and hours follow hump-shaped paths; and nominal variables exhibit mild, hump-shaped upticks.

[24]As shown by (Beaudry and Portier (2014) and Barsky et al. (2015), the inclusion of stock prices, in a small VAR, may drastically change the effects of news shocks in the system of variables.

[25]The BP scheme for the four-variable system is reported in the Appendix; see Equation (7).

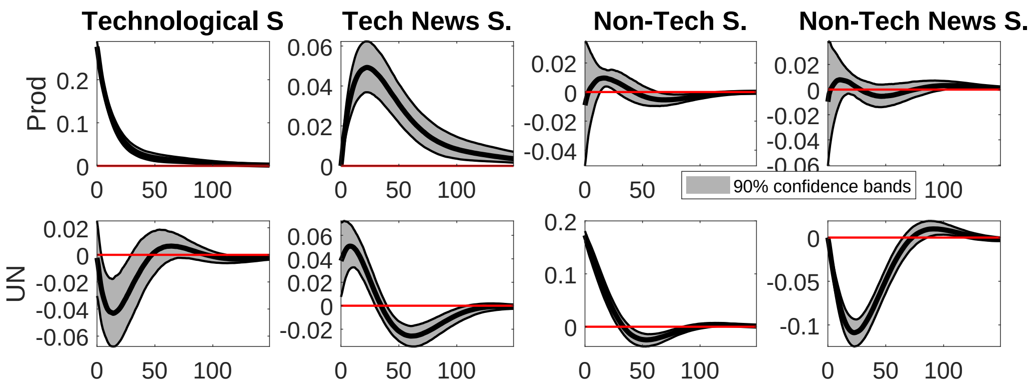

Figure 4: Response functions of labor productivity (first) and unemployment (second) to positive innovations from the MF PANEL FAVAR

Note: Posterior distributions of impulse response functions to the estimated shocks of one standard deviation using short and long-run restrictions, as in Equation 7. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

Figure 4 reports the IRFs of labor productivity and unemployment. A positive technological news shock has a persistent positive effect on productivity—first row, second column—and raises unemployment in the short run. One possible explanation is that favorable news about future productivity induces firms to reallocate resources from labor toward capital. This interpretation is consistent with Barsky and Sims (2011), who find that hours worked decline for five quarters following a positive technological news shock. Likewise, Manuelli (2000) argue that anticipated technological improvements may increase unemployment in the short run. In our results, this effect reverses after about 25 months, so the initial employment loss is eventually undone.

Including stock prices also sharpens the identification of the technology shock itself, compared to the baseline specification. This suggests that the baseline technology shock partly mixed together unanticipated technology shocks and technological news shocks. By contrast, the responses to non-technological and confidence shocks are broadly unchanged. The main message from the baseline model therefore survives the richer specification.

The variance decomposition in Figure 5 reinforces this conclusion. Technological news shocks explain around 15% of long-run productivity variance, implying that anticipated technology matters for productivity but is not its main driver. This result is in line to Barsky and Sims (2011), Forni et al. (2014), and Barsky et al. (2015). For unemployment, however, confidence (non-technological news) shocks remain the dominant force at business-cycle frequencies. Anticipated and unanticipated technology shocks together account for only a modest share of unemployment fluctuations. [26] This is in line with Angeletos et al. (2020), where technology and

[26] The complete results of the Figures 4 and 5 are reported in the Appendix, depicted in Figures C.11 and C.12.

technology-news shocks also play only a limited role in unemployment fluctuations. Overall, adding stock prices helps identify technological news, but it does not overturn our main result.

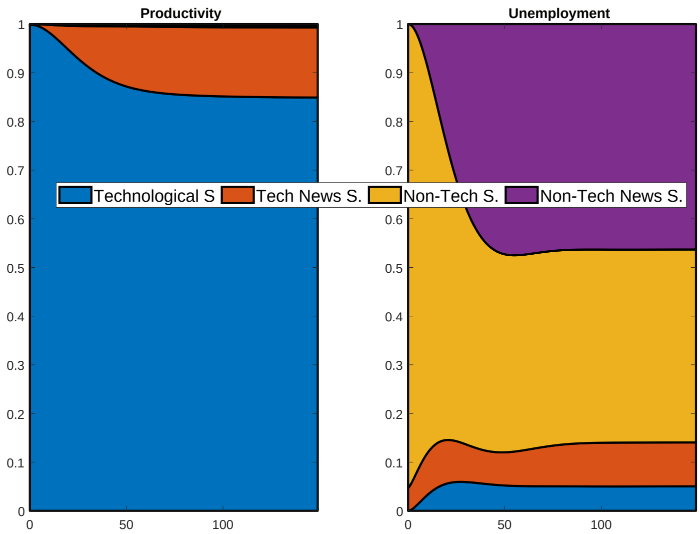

Figure 5: Variance decomposition of productivity (left) and unemployment (right) at different frequencies

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 7.

5 Model

In the previous section, we provided empirical evidence that innovations in confidence measures, potentially in the form of non-technological news, have significant implications for unemployment. In this section, we ask whether the effects of such shocks on unemployment can be rationalized within a simple theoretical environment, while remaining agnostic about the specific non-technological fundamental that the news shock represents.

We first show that our confidence innovation Granger-causes job vacancies in Europe but not vice versa, suggesting that the shock operates through the expectation channel embedded in the job creation condition. Motivated by this finding, we develop a dynamic search-and-matching model that incorporates news shocks about future labor market tightness alongside the usual unanticipated productivity and separation shocks. We then compare the implications of this environment under rational expectations and under adaptive learning, in the spirit of Evans and Honkapohja (2012), which represents a minimal departure from the rational-expectations benchmark.[27]

[27]Related contributions include Di Pace et al. (2021) and García-Rodríguez (2026).

The distinction between the two expectation-formation assumptions is central for our purposes. Under rational expectations, anticipated shocks affect equilibrium outcomes only insofar as they enter through an explicit structural channel. This requires the modeler to take a stand on the exact object about which agents receive news.[28] By contrast, under adaptive learning, shocks that are not tied to a fully specified structural margin can still matter because they influence agents' beliefs about future labor market conditions, and these beliefs feed back into vacancy posting and unemployment. We therefore use adaptive learning not as a literal identification of the underlying shock, but as a disciplined mechanism through which the type of non-technological news suggested by the data may acquire real effects.

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.[29]

Table 1 reports Granger-causality tests between the estimated confidence (non-technological news) shocks and the job vacancy ratio (JV), considering two transformations of JV and five lags.[30] The left panel rejects the null that confidence shocks do not Granger-cause JV at the 1% level, indicating that the estimated shocks contain useful information for predicting the job vacancy rate one quarter ahead. In contrast, the right panel indicates that we cannot reject the null hypothesis, that JV does not help predict the estimated confidence shocks, with p-values of 51%

[28] However, Theodoridis and Zanetti (2016) consider a search-and-matching DSGE model under RE with several anticipated disturbances, including non-technological news channels such as preference, matching-efficiency, and job-destruction shocks. While their model allows news shocks to matter for labor-market dynamics more broadly, they conclude that news has only a limited overall role in explaining unemployment.

[29] We obtain the job vacancy rate—defined as the number of job vacancies multiplied by 100 and divided by the sum of occupied posts and job vacancies—from Eurostat. The series is available only as an aggregate for the EU-27, since individual country weights are not available to construct a corresponding measure for our sample of 22 countries. The data cover the period from 2006.Q1 to 2021.Q2.

[30] The estimated confidence (non-technological news) shocks are converted to quarterly frequency by averaging every three monthly observations. The Granger-causality tests are conducted over 2006.Q1–2021.Q2 when the job vacancy rate is used in levels, and over 2006.Q2–2021.Q2 when it is expressed in quarterly differences.

when JV is in levels and 22% when it is expressed in quarterly differences. Taken together, these findings indicate a robust one-way predictive 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, $m(\theta_t) = A\theta_t^{1-\nu}$.

Employment evolves according to

$$n_{t+1} = (1 - \lambda_t)n_t + q(\theta_t)v_t, \tag{8}$$

where λ_t denotes the exogenous job-destruction rate. We assume

$$\lambda_t = \lambda + \epsilon_t^{\lambda}, \qquad \epsilon_t^{\lambda} \sim N(0, \sigma_{\lambda}^2), \tag{9}$$

with λ the mean separation rate. Labor productivity follows a stationary AR(1) process in logs:

$$\ln y_t = (1 - \rho)\ln \bar{y} + \rho \ln y_{t-1} + \epsilon_t, \qquad 0 < \rho < 1, \qquad \epsilon_t \sim N(0, \sigma^2). \tag{10}$$

Households are risk neutral and perfectly insure their members against idiosyncratic employment risk. As in the standard Mortensen-Pissarides environment, the worker's outside option is denoted by b, and wages are determined by Nash bargaining.[31]

[31] The detailed household problem is reported in the appendix E.

A representative firm with linear technology chooses vacancies to maximize

$$\Pi(n_t, y_t) = \max_{v_t \geq 0} \left\{ y_t n_t - w_t n_t - c v_t + \beta E_t^{\mathcal{P}^f} \Pi(n_{t+1}, y_{t+1}) \right\}, \tag{11}$$

subject to (9). Here c denotes the per-period vacancy posting cost, and $E_t^{\mathcal{P}^f}$ is the expectation operator used by firms. Under rational expectations, $\mathcal{P}^f$ coincides with the objective probability measure; under adaptive learning, it is generated by the perceived law of motion described below.

The first-order condition with respect to vacancies is

$$\frac{\partial E_t^{\mathcal{P}^f} \Pi(n_{t+1}, y_{t+1})}{\partial n_{t+1}} = \frac{c}{\beta q(\theta_t)}, \tag{12}$$

and the associated envelope condition implies

$$\frac{\partial \Pi(n_t, y_t)}{\partial n_t} = y_t - w_t + (1 - \lambda_t) \frac{c}{q(\theta_t)}. \tag{13}$$

Wages are determined by Nash bargaining between workers and firms, with worker bargaining power $\alpha \in (0, 1)$. Using the standard surplus-sharing conditions, the equilibrium wage can be written as

$$w_t = \alpha(y_t + c\theta_t) + (1 - \alpha)b. \tag{14}$$

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 Expectations Equilibrium

We begin with the rational-expectations equilibrium (REE), in which workers and firms form expectations using the objective probability measure, denoted by E_t. The equilibrium is determined by the level of labor-market tightness consistent with the free-entry condition. Combining the linearized equilibrium condition with the productivity process, labor-market tightness can be written as[32]

$$\theta_t = \hat{\phi}_0 + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 E_t \theta_{t+1} + \hat{\phi}_1 \rho^{-1} \epsilon_t. \tag{15}$$

To examine whether anticipated non-technological news can matter under rational expectations, consider the case in which agents receive at time t a signal about a disturbance that may affect labor-market tightness in period $t + 1$. Since this signal

[32] See Appendix E for the derivation.

belongs to agents' information set at the time forecasts are formed, we allow it to enter the one-step-ahead forecast and assume that

$$E_t\theta_{t+1} = \bar{A} + \bar{B}y_t + \bar{d}\,\epsilon^{\beta}_{t-1}, \tag{16}$$

where ϵ^{β}_{t-1} denotes the anticipated signal observed at time t, and $\bar{d}$ measures its effect on expected future labor-market tightness.

Following the minimum-state-variable approach,[33] we conjecture that current labor-market tightness follows

$$\theta_t = \bar{A} + \bar{B}y_{t-1} + \bar{C}\epsilon_t + \bar{d}\,\epsilon^{\beta}_{t-1}. \tag{17}$$

Matching coefficients after substituting (23) into (15) yields a system of fixed-point conditions for the coefficients of the solution.[34] In particular, the coefficient on the anticipated signal must satisfy

$$\bar{d} = \hat{\phi}_2\bar{d}. \tag{18}$$

Hence,

$$(1 - \hat{\phi}_2)\bar{d} = 0. \tag{19}$$

Under the E-stability condition for the REE, $|\hat{\phi}_2| < 1$, so the only admissible fixed point is

$$\bar{d} = 0. \tag{20}$$

Therefore, in the baseline search-and-matching model, anticipated news that enters only through expectations has no effect on labor-market tightness under rational expectations. The REE therefore collapses to the standard minimum-state-variable representation driven only by fundamentals. This result motivates the adaptive-learning mechanism developed next, where expectations play a role.

5.3.2 Agents' model of learning

We now relax the assumption of rational expectations and model agents as econometricians who form forecasts using a perceived law of motion and update their beliefs over time as new data arrive. This departure is motivated by the result of the previous subsection: under rational expectations, anticipated news that enters only through forecasts is neutral in equilibrium. Adaptive learning provides a simple mechanism through which such news can instead affect labor-market outcomes by shifting beliefs about future labor-market tightness.

Agents are endowed with a parsimonious perceived law of motion (PML) for labor-market tightness. This specification is intentionally simple. It reflects the idea

[33] 15 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.

[34] The derivation of the fixed-point conditions, the expressions for the REE coefficients, and the associated stability conditions are provided in Appendix G.

that agents do not separately identify all structural disturbances affecting the labor market, but instead summarize them through a reduced-form forecasting model.

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

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:

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

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. To allow non-technological news to affect beliefs, we assume that the learning rule is perturbed by an anticipated signal received at the end of the previous period, ϵ^{β}_{t-1}. Economically, this shock captures new information about the transitory component of labor-market conditions that agents cannot fully map into structural fundamentals.[35] 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

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

Plugging (23) into (15) 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 (8) and (23), and solving delivers

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

the actual data generating process

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

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

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

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

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

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

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.[36]

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.

[36]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.

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: α=1-ν

Table 2: Calibrated parameters from literature and data

Variable	Description	Adap. Learning Estimates
c	cost of opening a vacancy	0.29
μ	efficiency of matching technology	0.11
g	constant gain	0.08
b	unemployment benefits	0.46
λ	separation rate	0.11
σ	std. productivity shocks	0.0044
σ^{λ}	std. destruction-rate shocks	0.0036
σ^{β}	std. news shocks	0.0031

Table 3: Estimated monthly parameters from matching IRFs of unemployment

5.5 Theoretical Results

Figure 6 illustrates the share of unemployment variance attributed to each perturbation in the adaptive learning (AL) model. The 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).This result contrasts with the findings of Theodoridis and Zanetti (2016). In their estimated search-and-matching DSGE model, agents receive anticipated shocks to a broad set of macroeconomic and labor-market fundamentals, including stationary and non-stationary TFP, investment-specific productivity, preferences, matching efficiency, and job destruction. Although they find that news shocks matter for macroeconomic fluctuations and for some labor-market variables, their quantitative results suggest that news plays only a limited role in explaining unemployment, especially in the case of news shocks unrelated to the technological process. By contrast, in our framework, once beliefs are allowed to evolve under adaptive learning, news shocks become an important source of unemployment fluctuations at medium horizons.

Importantly, this result does not rely on assigning a disproportionately large variance to the news shock. The estimated standard deviation of the AL news shock is in fact smaller than that of the other shocks in the model. This contrasts with part of the quantitative news literature, where anticipated shocks are often calibrated or estimated to be substantially more volatile than fundamental disturbances.

We show that a search and matching model under adaptive learning successfully replicates the empirical dynamics of unemployment in response to confidence (non-technological news) shocks who affects the forecast of the tightness of the labor

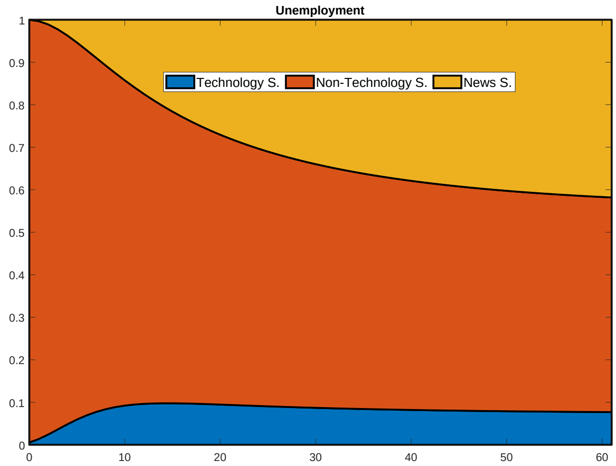

Figure 6: Variance decomposition of unemployment at different frequencies, under the adaptative expectations model

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.

market. Therefore, these shocks have a cavity in a theoretical framework, if we introduce them for instance 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 scheme used in this paper induces a high correlation between the estimated 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 scheme and the IRFs under the joint identification scheme of equation 6. 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 Alternative Productivity Measures: Solow Residual and Utilization-Adjusted TFP

Our baseline model uses labor productivity (GDP per person employed) as the productivity measure. A potential concern is that labor productivity conflates genuine technological change with variations in capital intensity and factor utilization, which could affect the identification of technological versus non-technological shocks. To ensure that our results are not driven by the choice of productivity measure, we re-estimate the model using two alternative TFP concepts.[37]

Since both alternative measures are available in quarterly frequency only for a subset of countries, we restrict the sample to the five largest Euro Area economies: Germany, France, Spain, Italy, and the Netherlands. These countries jointly represent approximately 80% of Euro Area GDP. We re-estimate the MF Panel FAVAR with the same specification as the baseline—five lags, with long-run restrictions imposed at a 100-month horizon—and apply the simultaneous identification scheme of Equation 6.[38]

Solow residual. We first replace labor productivity with a standard Solow residual constructed under the assumptions of constant returns to scale and competitive factor markets. The Solow residual is computed as $\Delta \ln \mathrm{TFP}_t = \Delta \ln Y_t - \alpha \Delta \ln K_t - (1-\alpha)\Delta \ln L_t$, where α denotes the capital share.

Utilization-adjusted TFP (EUROPROD-UA). A well-known limitation of the Solow residual is that it captures not only genuine technological change but also cyclical variation in factor utilization, potentially biasing the identification of technology shocks. To address this, we employ the utilization-adjusted TFP growth series from the EUROPROD-UA database.[39] These series adjust the Solow residual for changes in factor utilization using capacity utilization surveys and for non-zero profits, following the methodology of Comin et al. (2025).

[37] Standard cross-country TFP measures for Euro Area countries are generally available only at annual frequency and are not fully harmonized in their construction. We therefore rely on the quarterly, cross-country harmonized series provided by Comin et al. (2025) for the five largest Euro Area economies. Their dataset ensures comparability across countries by constructing TFP measures consistently using both a standard Solow residual approach and their own utilization-adjustment methodology.

[38] We first verify that the baseline results hold for this five-country subsample using labor productivity. The IRFs and variance decompositions are qualitatively unchanged relative to the full 22-country panel.

[39] The data are available at https://doi.org/10.53479/DS-europrod-ua.

Both TFP measures are transformed into log-levels and incorporated into our MF Panel FAVAR in place of labor productivity. The resulting impulse response functions are reported in Figure 18 for the Solow residual and Figure 19 for the utilization-adjusted measure, respectively. The confidence (non-technological news) shock continues to generate a persistent and statistically significant decline in unemployment, with the magnitude and shape closely matching the baseline results. Taken together, these findings indicate that our results are not driven by the specific use of labor productivity in the baseline.[40]

6.3 More Variables

In this subsection, we extend our analysis by incorporating additional variables into the VAR system one at a time to assess the effect of confidence shocks on each variable individually. Specifically, we examine the impulse response functions of confidence shocks on capital investment, the GDP deflator (as a measure of prices), nominal and real compensation, the nominal interest rate (measured by the three-month bond yield), fiscal balance (defined as government revenue minus total expenditures), unfilled vacancies, and government spending.[41] These variables are added as the last endogenous variable in the system, allowing them to respond to all shocks in both the short and long run. The inclusion of these variables does not alter our previous results.

The new joint short- and long-run restrictions are specified in Equation 33 and maintain the core identifying assumptions of Equation 6. The only modification is that the additional shock is assumed to have no long-term effect on productivity, unemployment, or the confidence factor.

Figure D20 presents the IRFs of confidence shocks for each added variable. A positive confidence (non-technological news) shock leads to an increase in investment, consistent with Pigou-cycle dynamics. Prices, nominal and real wages, nominal interest rates, and government spending also rise in response to the shock. The negative comovement between unemployment and these variables, along with the IRF dynamics, suggests that the confidence shock behaves similarly to a transitory demand shock, exhibiting only mild inflationary effects, as in Angeletos et al. (2020). Moreover, unfilled vacancies and the fiscal balance respond positively on impact, indicating that total vacancies increase—as implied in our theoretical model—and that a fiscal surplus arises, likely due to reduced unemployment-benefit payments and increased tax revenue.

These demand dynamics differ from those documented following an increase in the risk-premium shock in the Appendix of Foroni et al. (2018) or a positive monetary policy shock in Galí (2010). In the theoretical model of Foroni et al. (2018), a positive risk-premium shock leads households to demand a higher return on safe bonds, prompting them to increase saving, which depresses aggregate demand and, on im-

[40]The correlations reported in Figure 1 are also robust to these alternative measures.
[41]Data on unfilled vacancies are available for only ten countries.

pact, results in lower output and prices, higher unemployment, fewer vacancies, and a contraction in real wages. By contrast, in our case, a positive confidence shock also raises nominal interest rates—akin to an increase in the risk-premium shock—but unemployment begins to decline after the impact period.

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

6.4 Coincident Real Activity Measures

A potential concern with our baseline identification is that the zero-impact restriction on unemployment may not be very informative for isolating an exogenous confidence shock, since unemployment is well known to lag the business cycle. In particular, one may worry that what we label a confidence shock is in fact a shock that contemporaneously raises real activity, with confidence increasing only as a consequence. If so, the restriction that the shock has no impact effect on unemployment would be too weak, because unemployment typically adjusts more slowly than variables such as GDP or industrial production.

To address this concern, we augment the baseline model with a coincident indicator of real economic activity—real consumption and industrial production in separate specifications—and impose that the confidence (non-technological news) shock has no contemporaneous effect on this additional variable either. We refer to these variables as coincident, because they are standard coincident indicators of aggregate activity. Instead of including GDP directly, we add real consumption because our productivity measure is defined as GDP per person employed and we want to avoid mechanical collinearity. In both cases, the additional variable is placed last in the ordering and the model is extended to a four-variable system.

The joint short- and long-run restrictions are designed to preserve the interpretation of the first three shocks while fully identifying the system, without assigning a structural interpretation to the fourth shock. Specifically:

Assumption 1. Productivity can only be affected in the long run by the technology shock. Technological innovations may have contemporaneous and long-run effects on all variables.

Assumption 2. Non-technology shocks may have contemporaneous effects on all variables, but they have no long-run effect on productivity. On impact, unemployment is not affected by confidence (non-technology news) shocks.

Assumption 3. Confidence (non-technology news) shocks do not have contemporaneous effects on the unemployment rate or on the coincident activity indicator included in the system (industrial production or consumption), but they may affect productivity contemporaneously. They are allowed to affect the long-run dynamics of unemployment, the confidence factor, and the coincident activity variable.

Assumption 4. The fourth shock (which we do not attempt to interpret) may have contemporaneous effects on all variables, but it does not affect the long-run

dynamics of productivity and unemployment.
In terms of the impact and long-run restriction matrices, this corresponds to

$$P = \begin{pmatrix} * & * & * & * \\ * & * & 0 & * \\ * & * & * & * \\ * & * & 0 & * \end{pmatrix}, \qquad L = \begin{pmatrix} * & 0 & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \\ * & * & * & * \end{pmatrix}. \tag{34}$$

The resulting impulse responses to a confidence (non-technological news) shock are reported in Figure 21 for the specification with consumption and in Figure 22 for the specification with industrial production. The results confirm the robustness of our findings. Industrial production does not react on impact to the confidence shock, but rises shortly thereafter and displays a hump-shaped response, closely resembling the pattern obtained in the robustness exercise with investment in Section 6.3. For consumption, the median response is also positive and hump-shaped, although significance across horizons is more limited. Crucially, the responses of unemployment and the confidence factor remain very similar to those in the baseline model. These findings make it less likely that the identified confidence shock is simply capturing a contemporaneous real activity shock that then feeds into confidence.

As an additional robustness exercise, we also consider an alternative identification in which the confidence shock is restricted not to affect productivity contemporaneously, rather than in the long run. The corresponding restriction matrices are

$$P = \begin{pmatrix} * & * & 0 & * \\ * & * & 0 & * \\ * & * & * & * \\ * & * & 0 & * \end{pmatrix}, \qquad L = \begin{pmatrix} * & 0 & * & 0 \\ * & * & * & 0 \\ * & * & * & * \\ * & * & * & * \end{pmatrix}. \tag{35}$$

The results, reported in Figures 23 and 24, remain qualitatively unchanged under this alternative specification, further supporting our interpretation of the identified disturbance as a non-technological news shock rather than a generic contemporaneous real activity shock.

6.5 Confidence Shocks and Professional Forecast Revisions

A central question in interpreting confidence shocks is whether they reflect genuine information about future fundamentals — i.e., news shocks — or instead represent non-fundamental shifts in beliefs, commonly referred to as animal spirits. While both types of shocks can affect real outcomes in the short run, their underlying mechanisms differ.

The confidence shock is retrieved from households and firms across Europe. To better understand the nature of this shock, we examine how a distinct group of agents, for instance professional forecasters at the ECB, respond to it. Specifically, we ask: do professional forecasters revise their expectations of future unemployment when a confidence shock hits?

If the shock conveys genuine information then other agents with no direct role in generating the shock should also take it into account. If, on the other hand, the shock simply reflects non-informative mood swings in the household and firm sectors, it is unlikely that forecasters would systematically adjust their forecasts. In this way, the behavior of professional forecasters serves as an independent test of whether the shock is perceived more broadly as news or merely belief noise.

We use forecast data from the ECB Survey of Professional Forecasters (SPF), which provides one- and two-year-ahead forecasts of euro area unemployment. We construct a measure of forecast revision as the change in the forecast for unemployment in year $t+1$, that is, the difference between the one-year-ahead forecast made in quarter q of year t and the two-year-ahead forecast for the same target year $t+1$ made in quarter q of year $t-1$.

$$FR_t = E_{q,t}[u_{t+1}] - E_{q,t-1}[u_{t+1}]. \tag{36}$$

The forecast revision captures how agents update their views about the near-term labor market outlook. We then estimate the dynamic response of forecast revisions to previous confidence shocks using the following regression specification:

$$FR_t = \alpha + \sum_{i=1}^{5} \beta_i z_{t-i} + \varepsilon_t \tag{37}$$

where z_t denotes the identified structural confidence shock. Under the news hypothesis, we expect to observe a significant and negative cumulative response: that is, a positive confidence shock should cause professional forecasters to revise expected unemployment downward.

As shown in Table D4, the cumulative response of forecast revisions to the confidence shock is large and statistically significant. The sum of coefficients is –2.58, with a joint p-value below 0.001. This suggests that professional forecasters do interpret the shock as carrying relevant information, leading them to update their expectations of the labor market accordingly. The fact that these agents — who are not taken into account as a source for the estimated confidence measures — revise their forecasts in a consistent direction reinforces the interpretation that the confidence shock is perceived more broadly as news, rather than being confined to household-level or firm-level sentiment dynamics.

To validate the timing and surprise nature of the shock, we estimate a placebo regression, where forecast revisions are regressed on contemporaneous and future values of the confidence shock:

$$FR_t = \bar{\alpha} + \sum_{i=0}^{4} \gamma_i z_{t+i} + \eta_t. \tag{38}$$

This placebo test functions as an exogeneity and anticipation check. If forecasters had prior knowledge of the shock — for example, through correlated variables outside our VAR — they might begin revising their forecasts before the shock actually occurs. In that case, coincident and lead values of the shock would predict current forecast revisions, violating the identification assumption.

As shown in Table D5, the results confirm that this is not the case: the coefficients on future shocks are small and jointly insignificant. This supports the interpretation that the confidence shock is unanticipated, and that forecast revisions are true responses to the arrival of new information, not driven by reverse causality.

Taken together, these results suggest that the confidence shock, although identified from household and firm surveys, is perceived by external agents — such as professional forecasters — as containing useful information. The pattern of forecast revisions supports the view that the shock contains genuine information.

6.6 Correlation with Identified Monetary and Information Shocks

To ensure that our estimated confidence shocks capture distinct informational content—rather than simply reflecting standard monetary policy actions or central bank information shocks—we examine their correlation with two benchmark shock series: the monetary policy shocks and the central bank information shocks identified by Jarociński and Karadi (2020). These shocks are widely used in the literature to disentangle the effects of unexpected policy rate changes from those related to information revealed by the central bank about economic fundamentals.

In Appendix Table D6, we report the correlations between our confidence shocks and both components of ECB communication (pure monetary policy shocks and information shocks), using two different identification strategies: (i) the original approach by Jarociński and Karadi (2020), and (ii) a simplified method based on sign restrictions, which they refer to as the "Poor Man's" approach.

The low correlation coefficients across the comparisons suggest that our confidence shock are not simply repackaging existing monetary policy or central bank information surprises. Instead, they appear to encapsulate distinct, forward-looking information.

6.7 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 25 shows that excluding a few months of extreme observations does not change our baseline results.

6.8 Spurious correlation between the estimated structural shocks

In this subsection, we present noisy simulated data to check whether the BP scheme 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 6.

Figure D 26 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 $\tilde{w_2}$.

6.9 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 BP scheme and simultaneous identification approach - equation 6. Figures D 27 and 28 show that our method 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 29 and 30 show two important things. First, the BP scheme correctly picks that the forward looking variable (the expectation of the labor market tightness) does not contain news shocks. Second, we proceed by ignoring this result and impose the joint identification scheme of equation 6. It can be seen that in Figure D 30 that the joint identification scheme does not identify any news shock. These robustness results make us confident with respect to the use BP scheme and simultaneous identification approach.

7 Conclusion

This paper has asked what kind of information is contained in consumer and firm confidence measures, and whether that information matters for unemployment dynamics. Our evidence suggests that it does. Innovations in confidence are strongly linked to the forces that drive unemployment over the medium run, while being only weakly related to shocks shaping long-run productivity. In this sense, confidence measures appear to contain information about future non-technological fundamentals rather than future technology.

When jointly identified with other structural shocks, confidence shocks generate a persistent decline in unemployment at business-cycle frequencies, peaking around three to four years after impact, and account for roughly 50% of the forecast-error variance of unemployment. The implications for unemployment are too large and too significant for confidence innovations not to convey information about future fundamentals. While we do not claim to distinguish news from noise sharply, we favor a news interpretation because these shocks explain a substantial share of confidence fluctuations, generate persistent responses in macroeconomic variables, and are followed by downward revisions in expected unemployment by professional forecasters, who play no role in the construction of the confidence measures.

The main implication is that survey-based confidence measures are not just descriptive indicators: they help reveal the non-technological forces that matter for labor market dynamics in Europe. Our theoretical framework reinforces this interpretation by showing that, under adaptive learning, news about future labor market conditions can generate the persistent unemployment responses observed in the data.

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

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

where $\mathcal{L}\left(y_{1:T} \mid H_i, \operatorname{vec}(\mathcal{A}_i), \Sigma_i, W_i\right)$ is the likelihood obtained by using the Kalman Filter in the state-space model specified in the observed equation. Since $p\left(H_i \mid \operatorname{vec}(\mathcal{A}_c), \Sigma_i, W_i, y_{i,1:T}\right)$ 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 $\operatorname{vec}(\mathcal{A}_i), \Sigma_i, W_i, y_{i,1:T}$.

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

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

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

A.1 BP scheme - Four-Variable System

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

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

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.

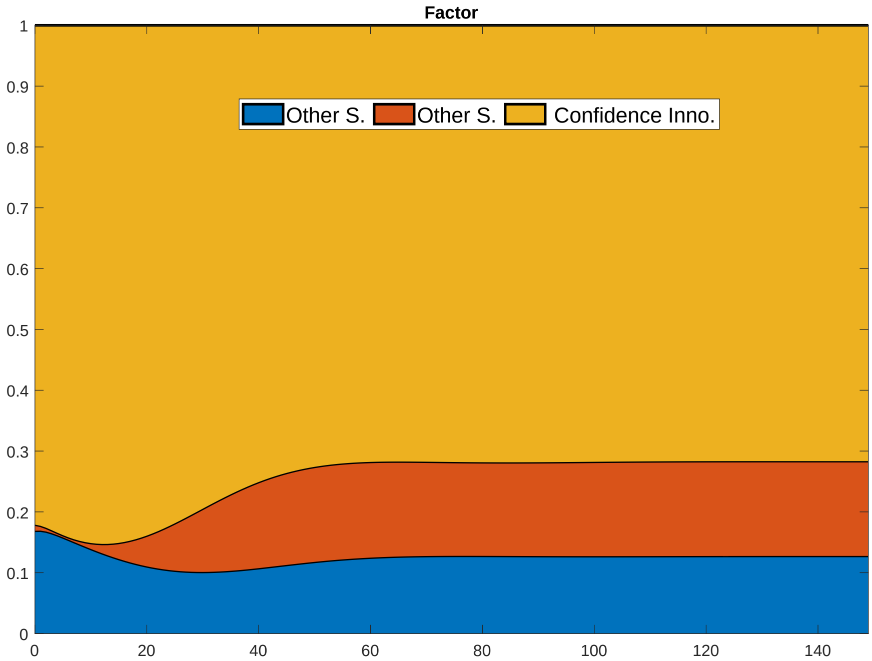


Figure 7: Variance decomposition at different frequencies

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 4.

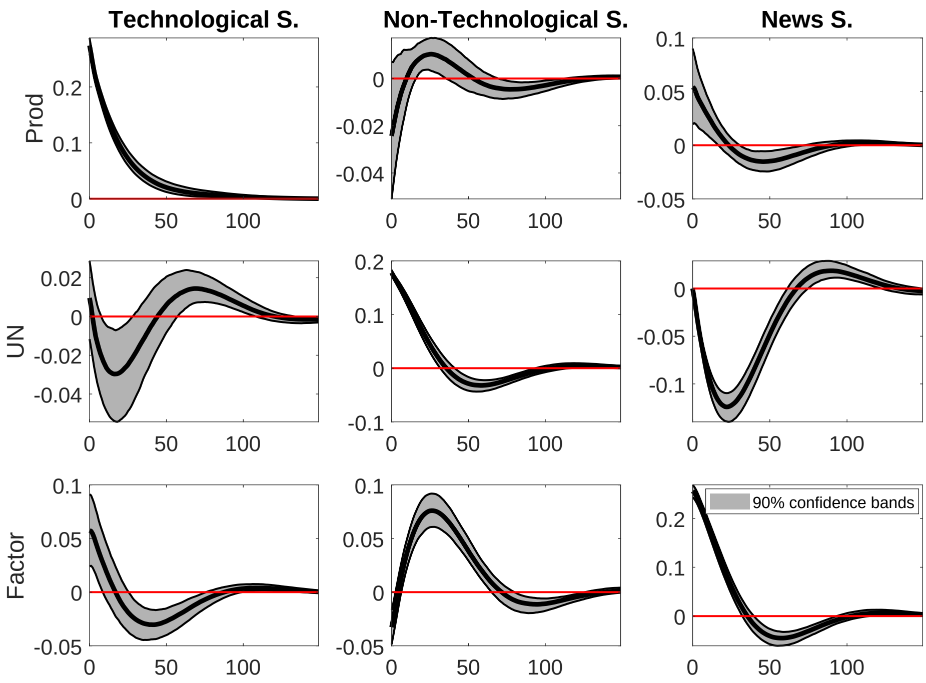


Figure 8: Response functions to positive shocks, as in Equation 6, from the whole the MF PANEL FAVAR

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

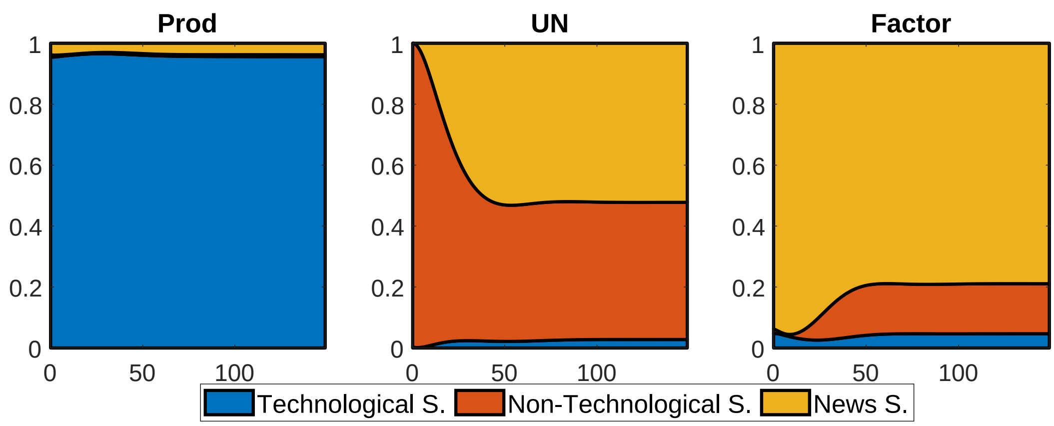


Figure 9: Variance decomposition at different frequencies

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.

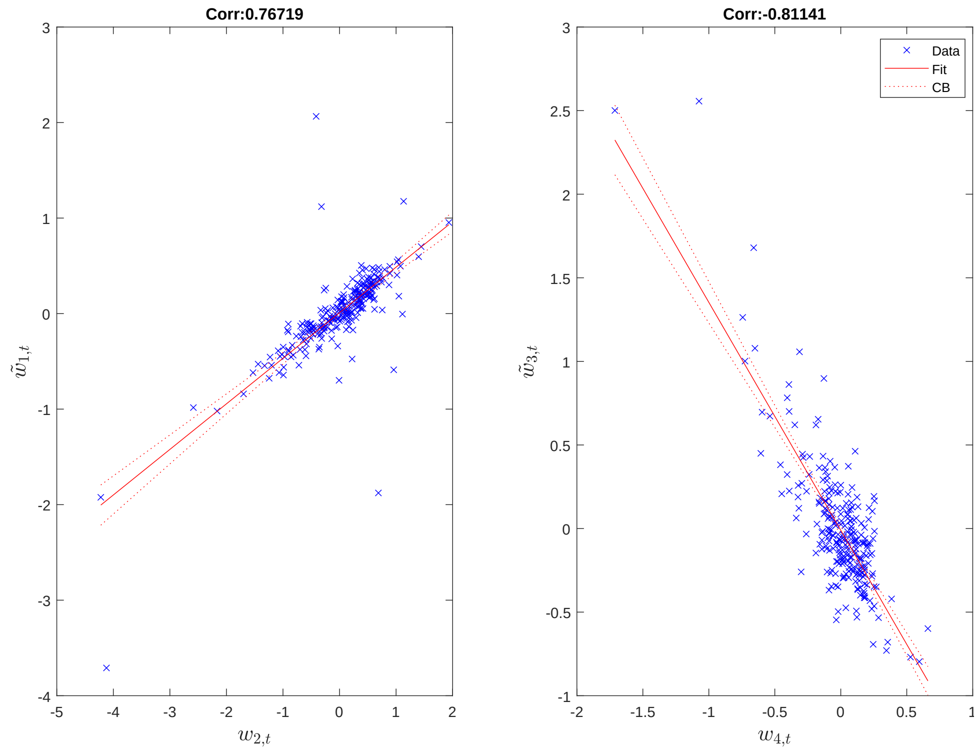


Figure 10: Plot of w_{2t} against $\tilde{w}_{1t}$ - left - and on the right w_{4t} against $\tilde{w}_{3t}$ in the MF Panel VAR with with stock prices.

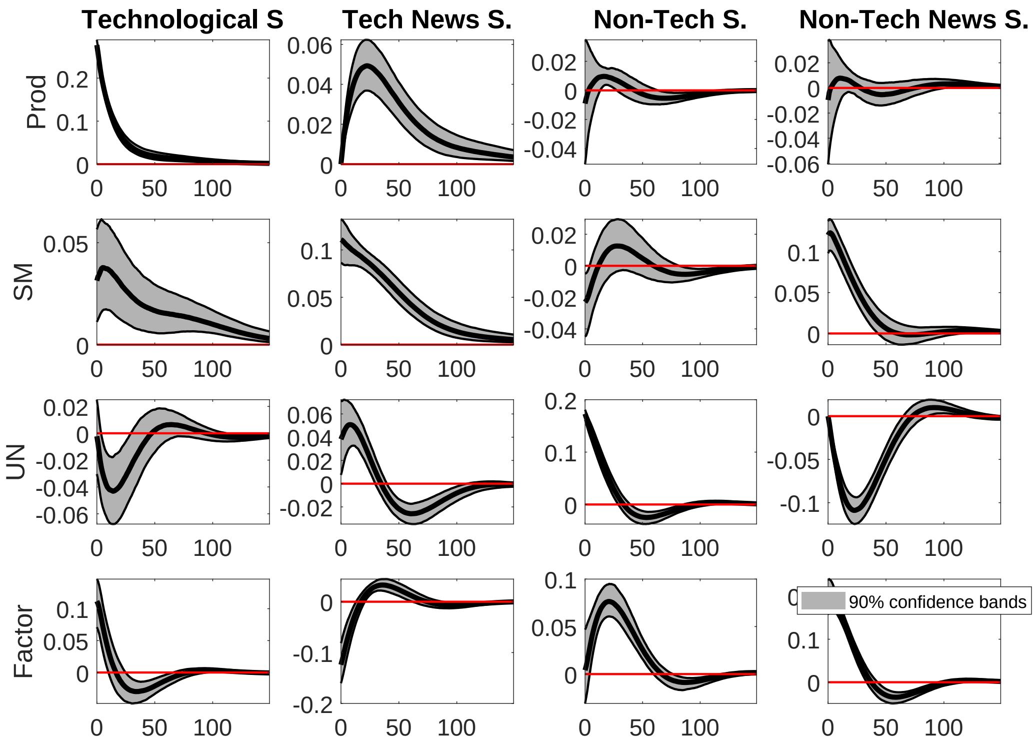


Figure 11: Response functions to positive shocks from the whole the MF PANEL FAVAR with stock prices

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 7. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

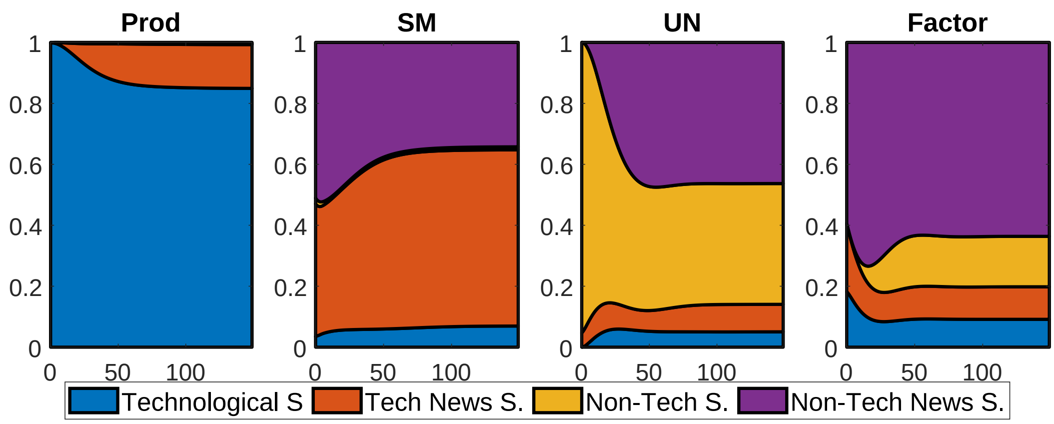
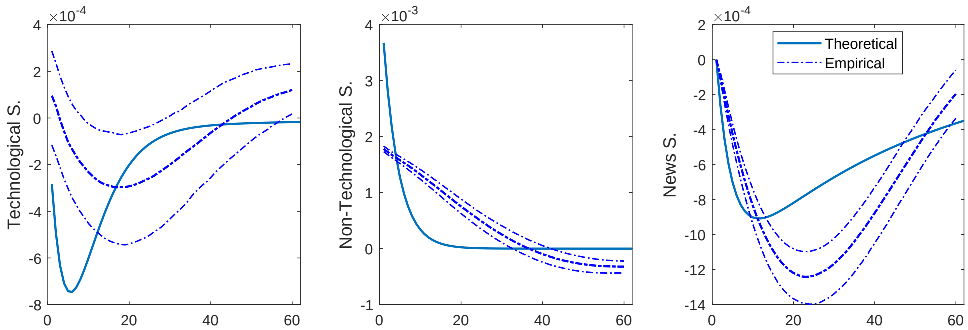


Figure 12: Variance decomposition at different frequencies

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 7.



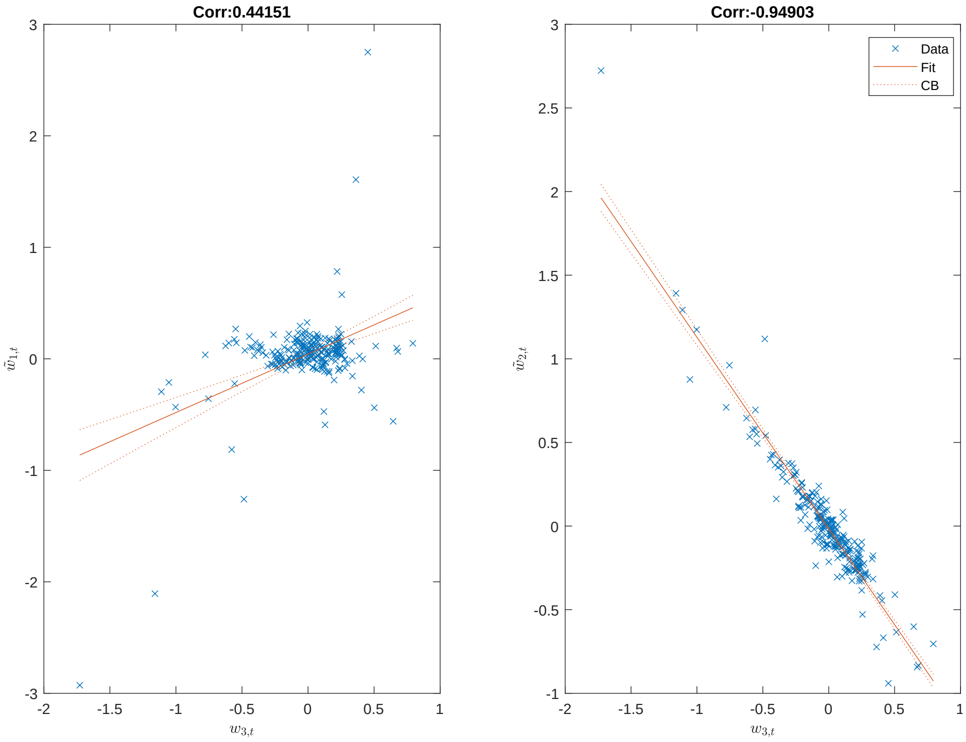
Adaptive learning model v.s. econometric model

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

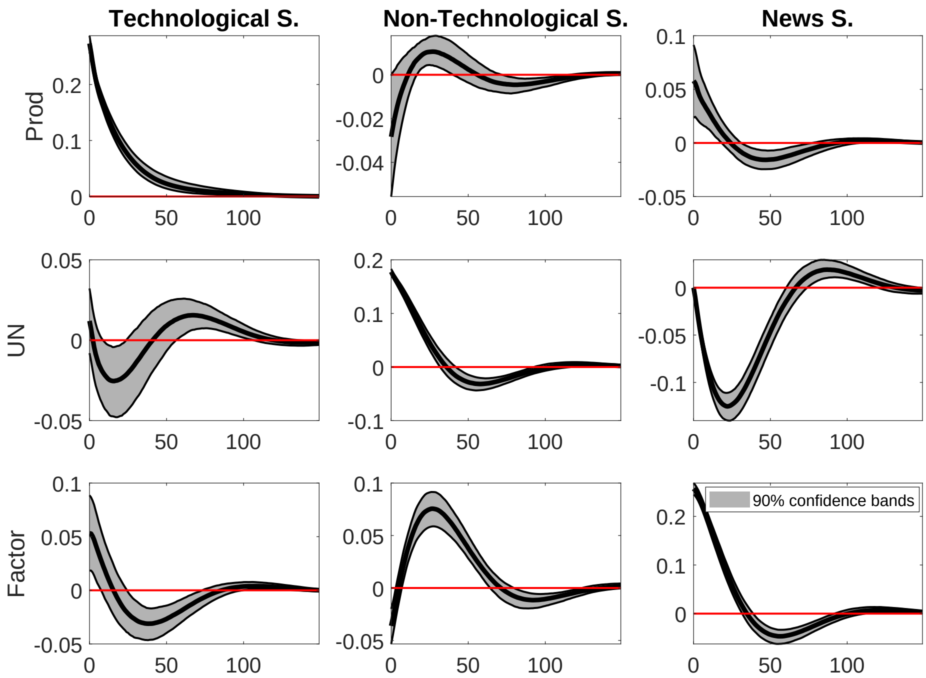
Note: The solid blue line corresponds to IRFs to the theoretical model, and dashed blue lines to the median and 90% probability density intervals of the MF PANEL FAVAR.

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.



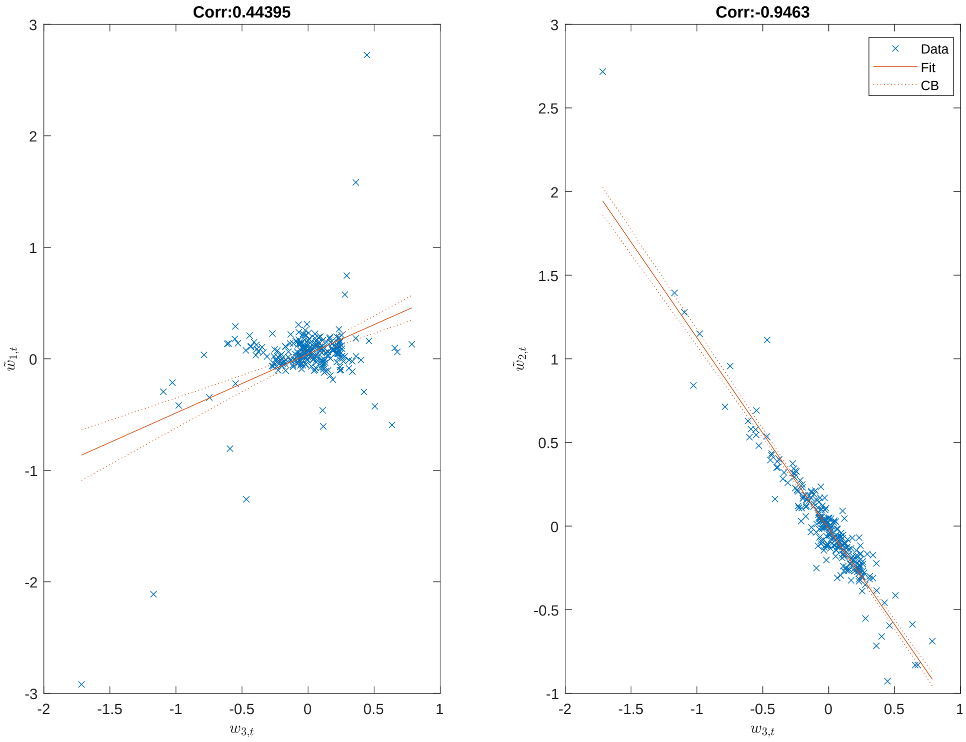
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 7 lags.



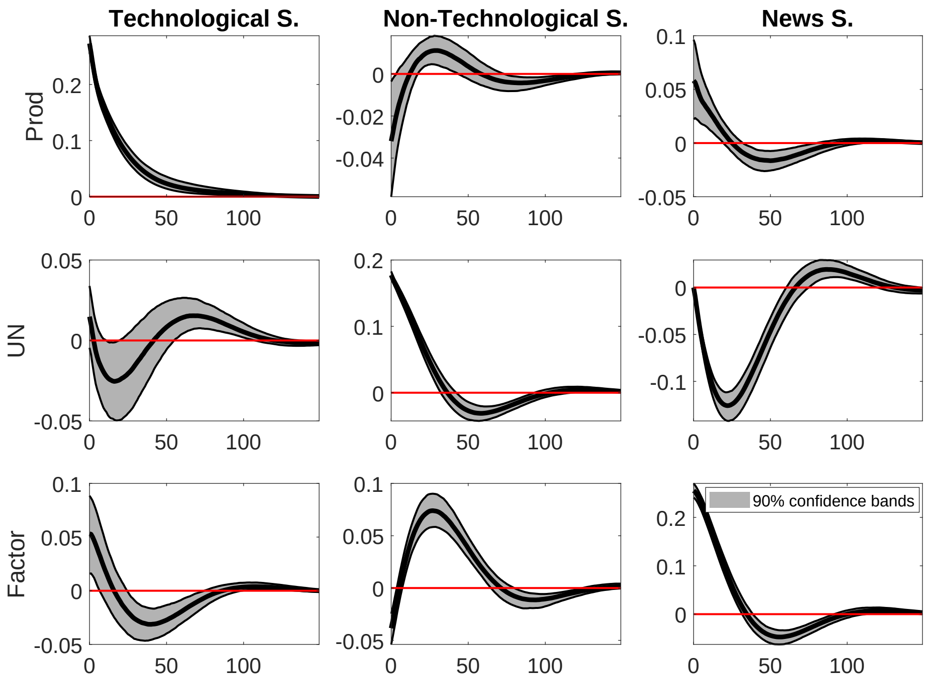
Response functions to positive shocks from the whole the MF Panel VAR with 7 lags.

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

Figure 14: MF Panel VAR with 7 lags



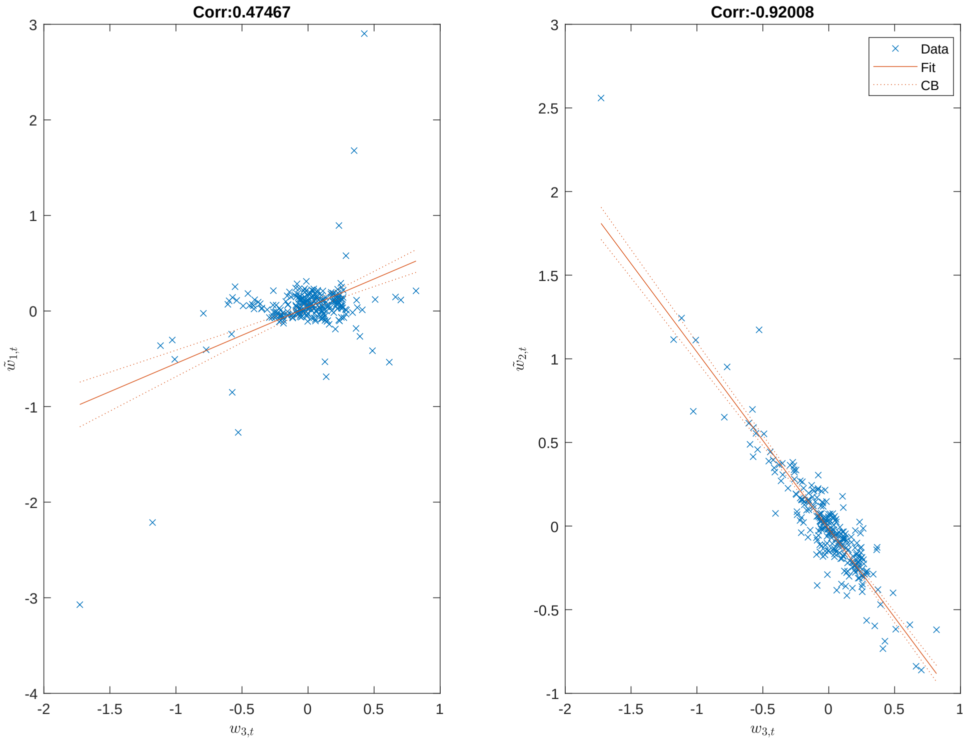
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 9 lags.



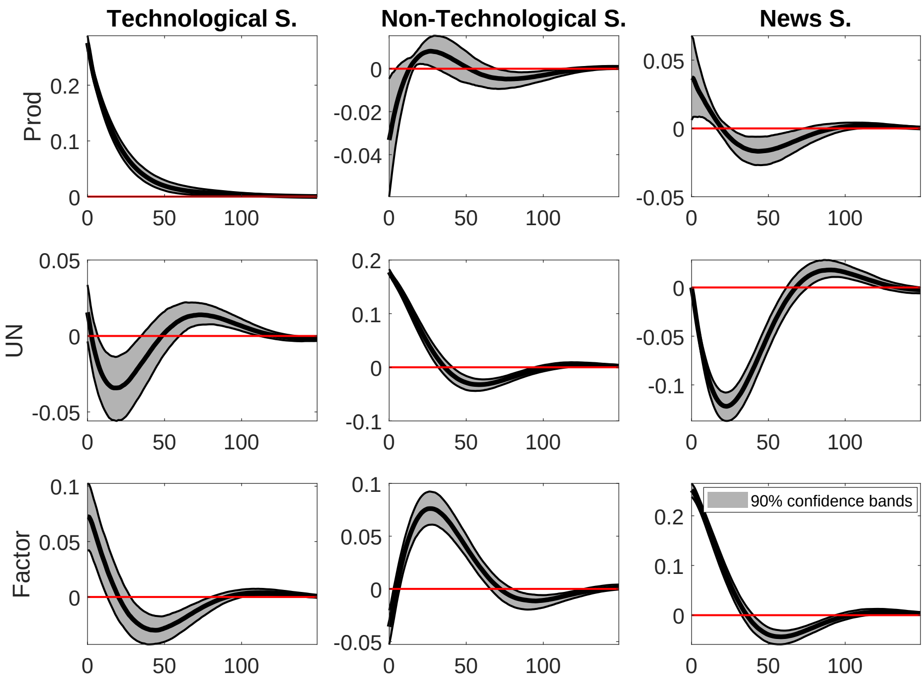
Response functions to positive shocks from the whole the MF Panel VAR with 9 lags.

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

Figure 15: MF Panel VAR with 9 lags



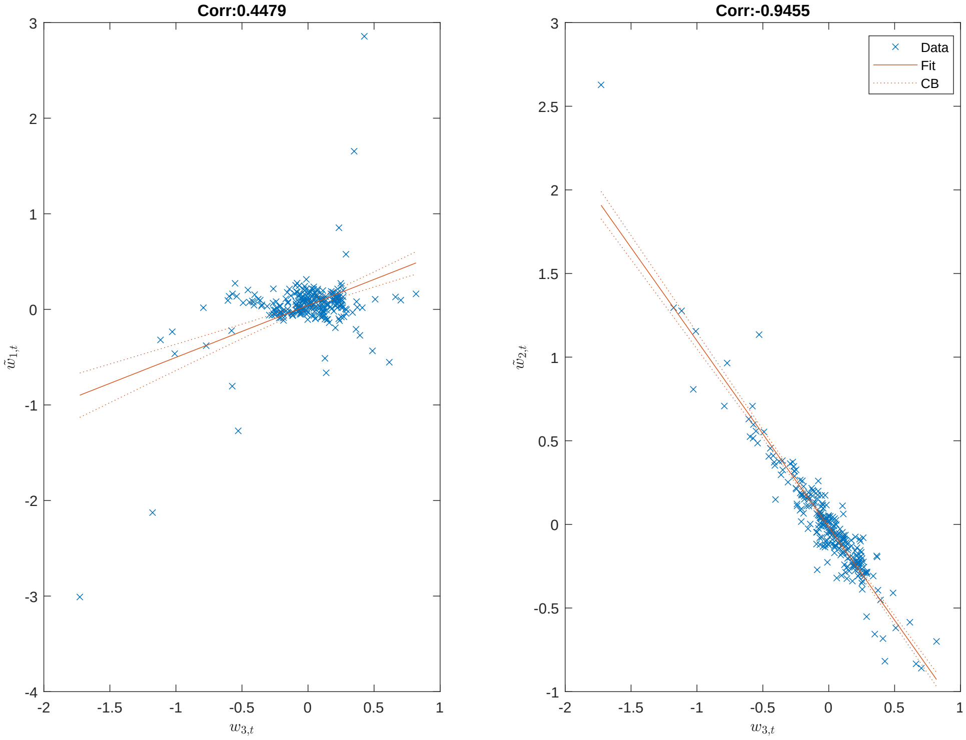
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR with 5 lags. Long-run shocks are imposed to be neutral at 50 periods horizon.



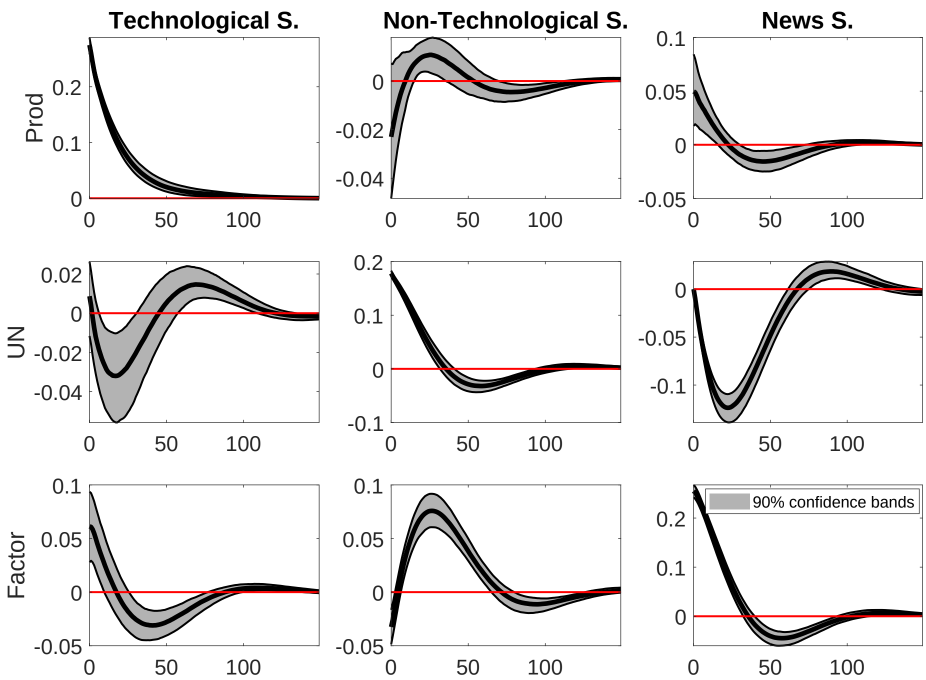
Response functions to positive shocks from the whole the MF PANEL FAVAR imposing long-run horizon at 50 periods.

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 6. 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 6. 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

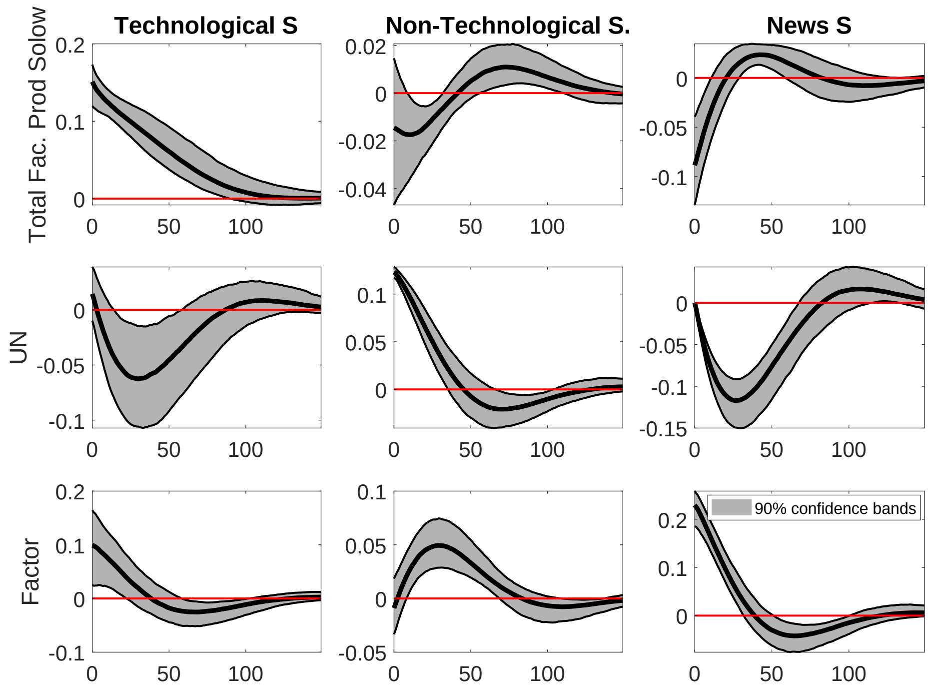


Figure 18: Response functions to positive shocks from the MF Panel FAVAR using the Solow residual as the productivity measure (five Euro Area countries: Germany, France, Spain, Italy, and the Netherlands)

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

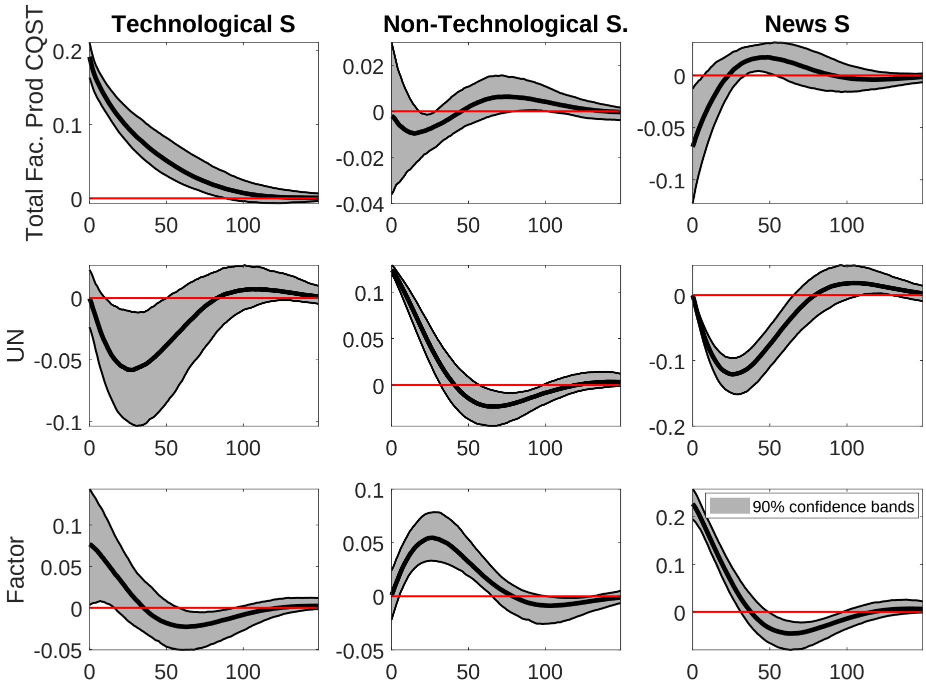


Figure 19: Response functions to positive shocks from the MF Panel FAVAR using utilization-adjusted TFP from EUROPROD-UA as the productivity measure (five Euro Area countries: Germany, France, Spain, Italy, and the Netherlands)

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

	β_1	β_2	β_3	β_4	β_5
Estimate	-0.14438	0.69816	-0.44363	-0.18815	-2.50280
(Std. Error)	(0.31601)	(0.37175)	(0.37992)	(0.39090)	(0.34866)
Model fit: $N = 82$, RMSE $= 0.664$, $R^2 = 0.579$, $F(5, 76) = 20.9$, $p = 4.26 \times 10^{-13}$					
Cumulative effect: $\sum_{i=1}^{5} \hat{\beta}_i = -2.5807$, **Wald** $\chi^2(1) = 34.63$, $p < 0.001$					

Table 4: Impact of Past Confidence Shocks on Unemployment Forecast Revisions

Note: Regression of the one-period-ahead forecast revision $FR_t = E_{q,t}[u_{t+1}] - E_{q,t-1}[u_{t+2}]$ *on confidence-shock lags* z_{t-1} *through* z_{t-5}*, showing individual coefficients, model fit, and the cumulative five-period effect.*

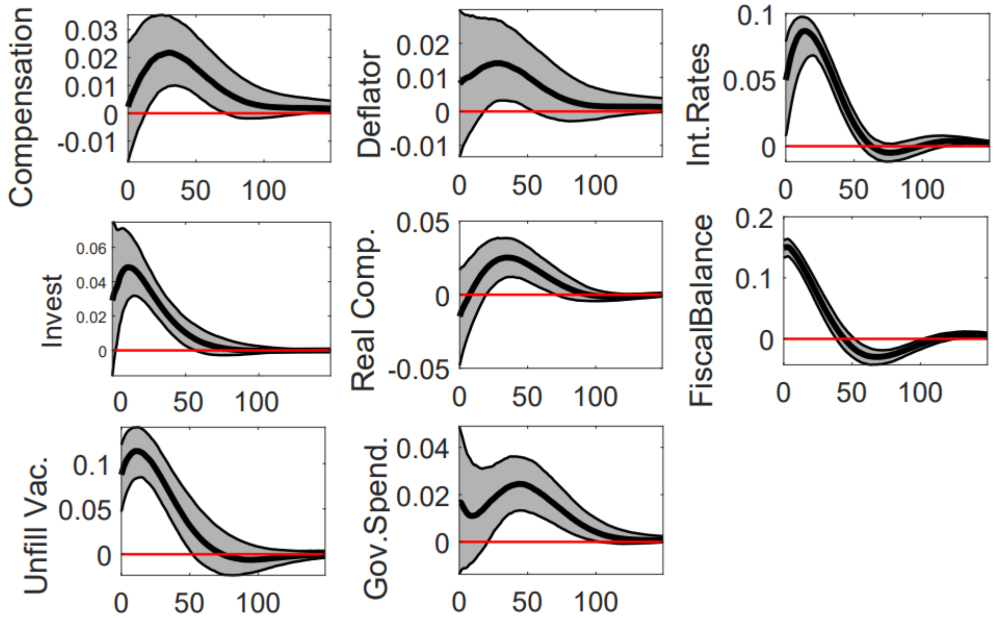


Figure 20: Response functions of nominal compensation, prices (measured as GDP deflator), nominal interest rate (measured as three bill rate), capital investment, real compensation, fiscal balance (measured as the difference between a government's total revenue and its total expenditures), number of unfilled vacancies, and government spending 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 7. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

	γ_0	γ_1	γ_2	γ_3	γ_4
Estimate	0.51549	0.19945	0.45178	0.16522	-0.06290
(Std. Error)	(0.52034)	(0.57325)	(0.55768)	(0.54515)	(0.46377)
Model fit: $N = 79$, RMSE $= 0.973$, $R^2 = 0.0752$, $F(5, 73) = 1.19$, $p = 0.324$					

Table 5: Placebo Test for Anticipation of News Shocks

Note: Regression of the one-period-ahead forecast revision $FR_t = E_{q,t}[u_{t+1}] - E_{q,t-1}[u_{t+2}]$ on contemporaneous and lead news shocks z_t through z_{t+4}, showing individual coefficients, model fit, and the joint F-test of the null that all coefficients equal zero.

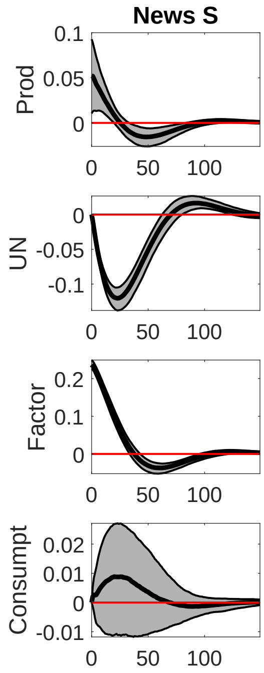


Figure 21: Consumption

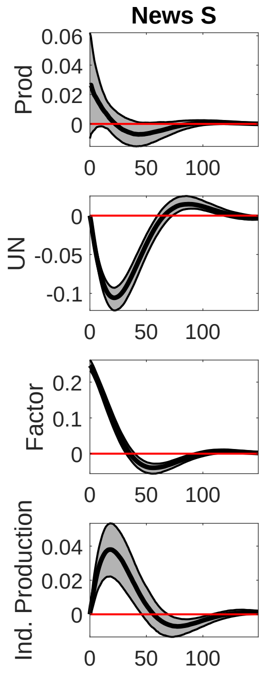


Figure 22: Industrial Production

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short and long-run restrictions (eq 34). Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

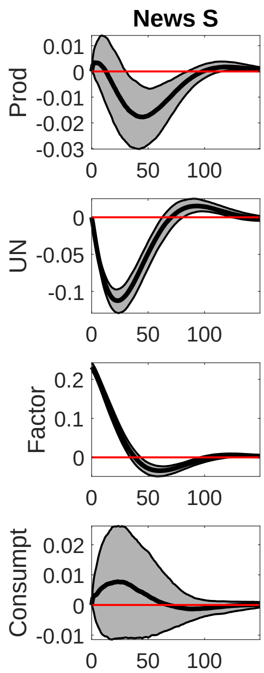


Figure 23: Consumption

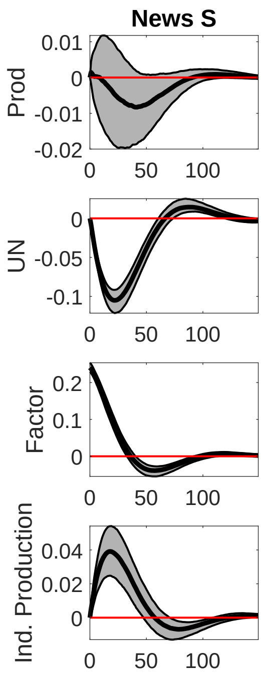


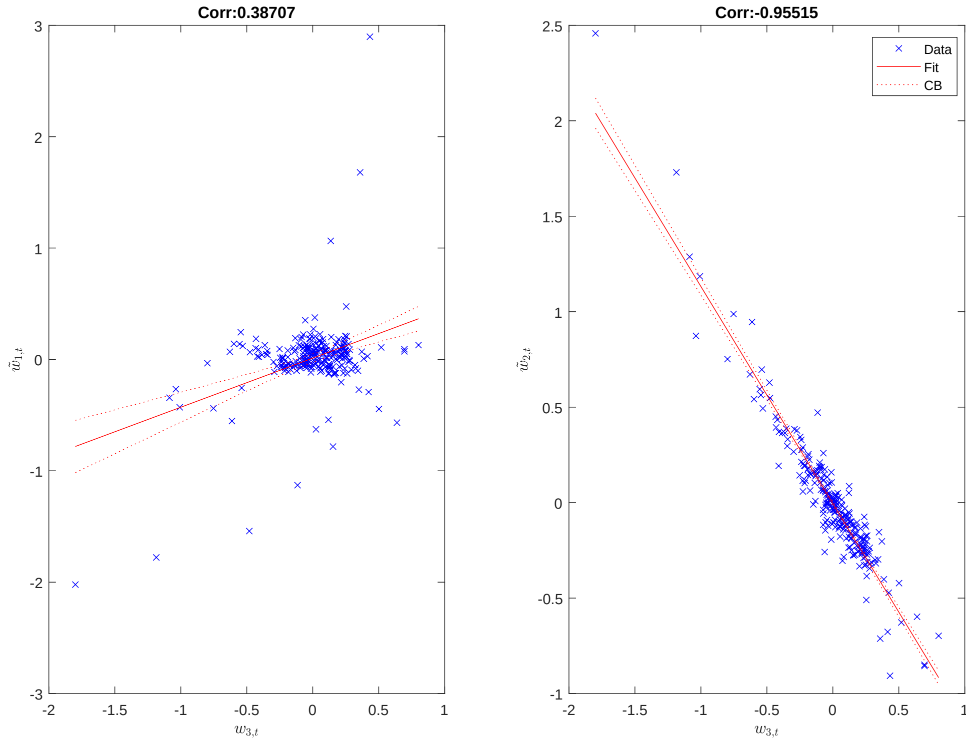
Figure 24: Industrial Production

Note: Posterior distributions of impulse response functions to an estimated shock of one standard deviation using short and long-run restrictions (eq 35). Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

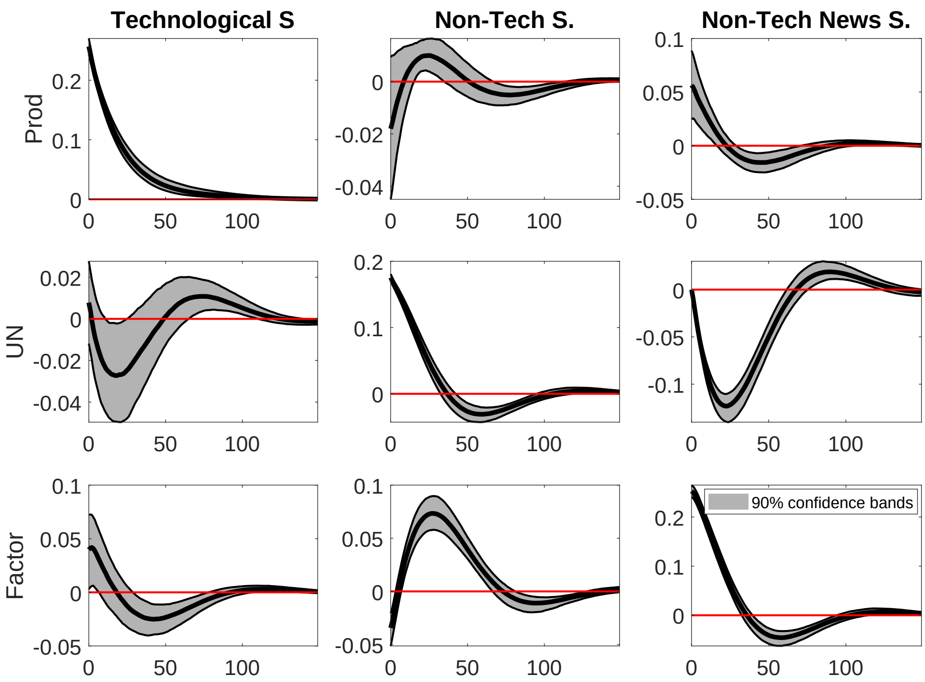
Shock Type	**Monetary Policy Shock**	**Central Bank Information Shock**
Jarociński and Karadi (2020)	-0.2971	0.1548
"Poor Man's" Sign Restrictions	-0.2215	0.0994

Table 6: Correlation between News Shock and ECB Monetary Policy Shocks

Note: The table reports correlations between the confidence shocks identifying in 3.3 and the two structural components of ECB monetary policy surprises: monetary policy shocks and central bank information shocks, coming from Jarociński and Karadi (2020). The "Poor Man's" approach refers to a simplified identification based on sign restrictions without using forecast revisions.



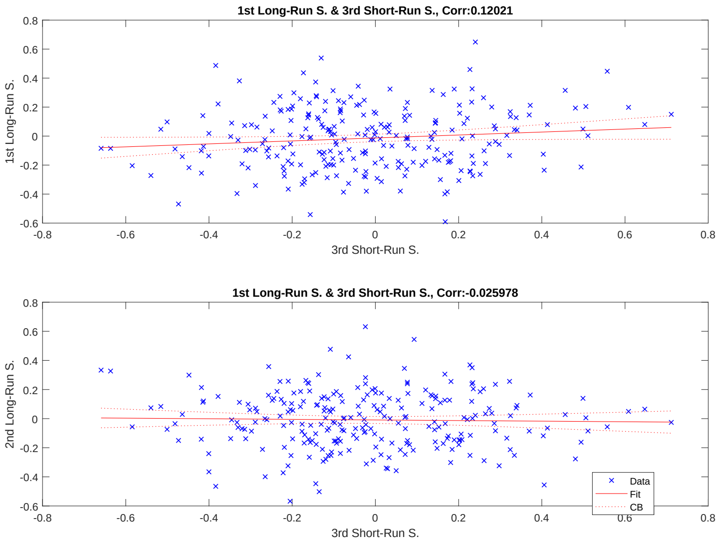
Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$ in the MF Panel VAR excluding observations from March, April and May 2020



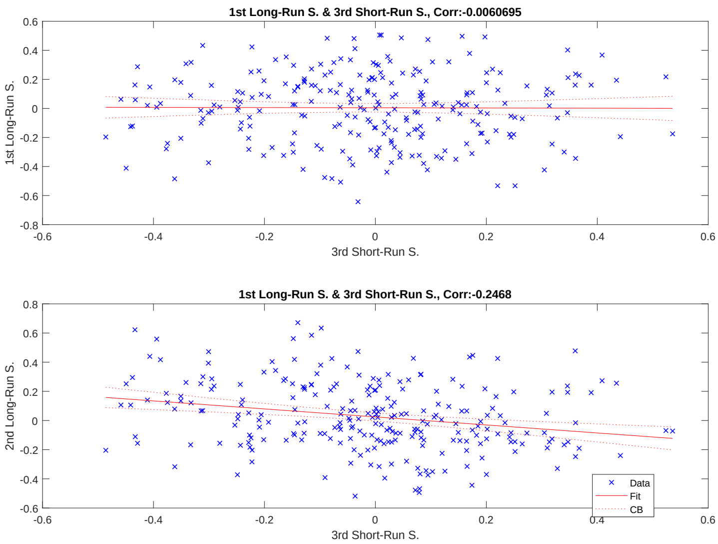
Response functions to positive shocks from the whole the MF PANEL FAVAR with excluding observations from March, April and May 2020

Note: Posterior distributions of cumulative impulse response functions to an estimated shock of one standard deviation using short-long restrictions, as in Equation 7. Median (solid line) and 90% probability density intervals (shaded area) based on 10,000 draws.

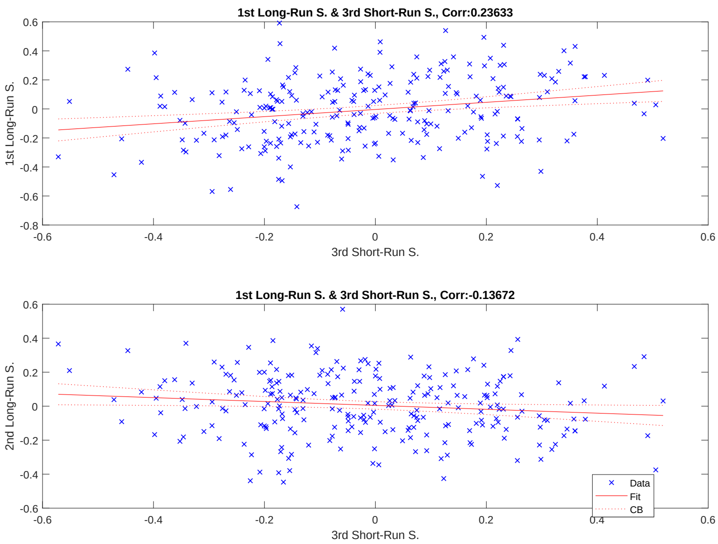
Figure 25: MF PANEL FAVAR with excluding observations from March, April and May 2020



Simulated data, group 1.



Simulated data, group 2.



Simulated data, group 3.

Figure 26: Plot of w_3 against $\tilde{w}_1$ - left - and $\tilde{w}_2$ -right. Shocks are obtained from the trivariate specification with five lags.

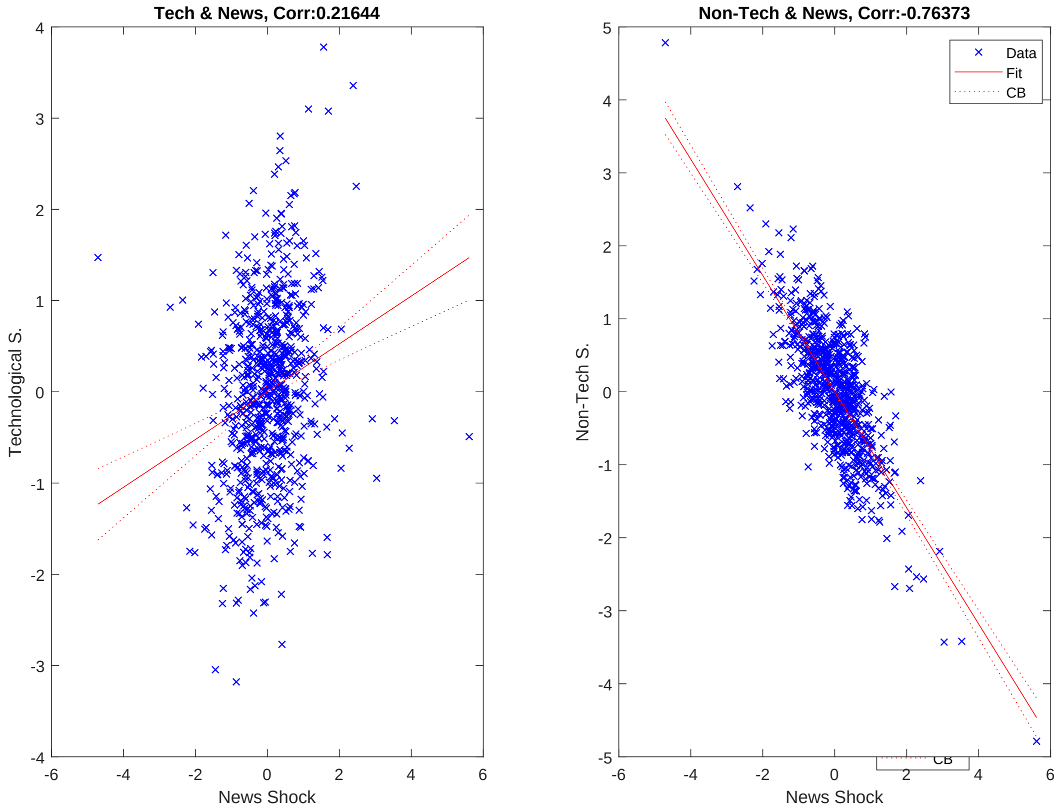


Figure 27: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$, using data generated from the theoretical model. The three shocks are active.

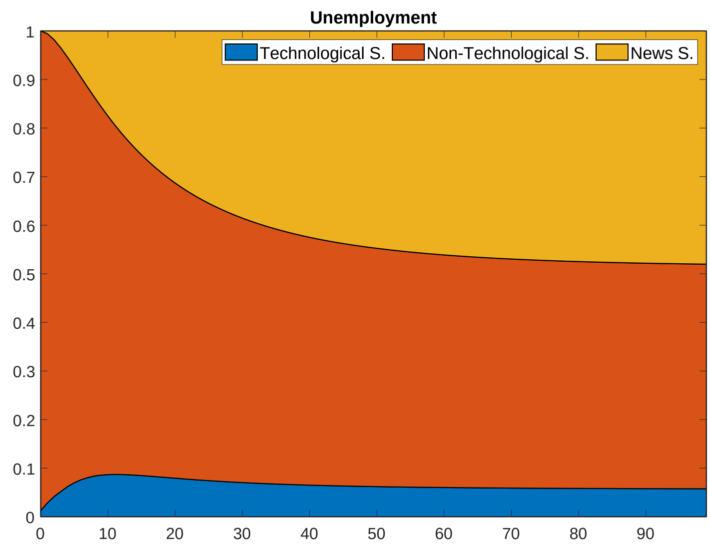


Figure 28: Variance decomposition at different frequencies of the unemployment rate - using data generated from the theoretical model. The three shocks are active.

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 6.

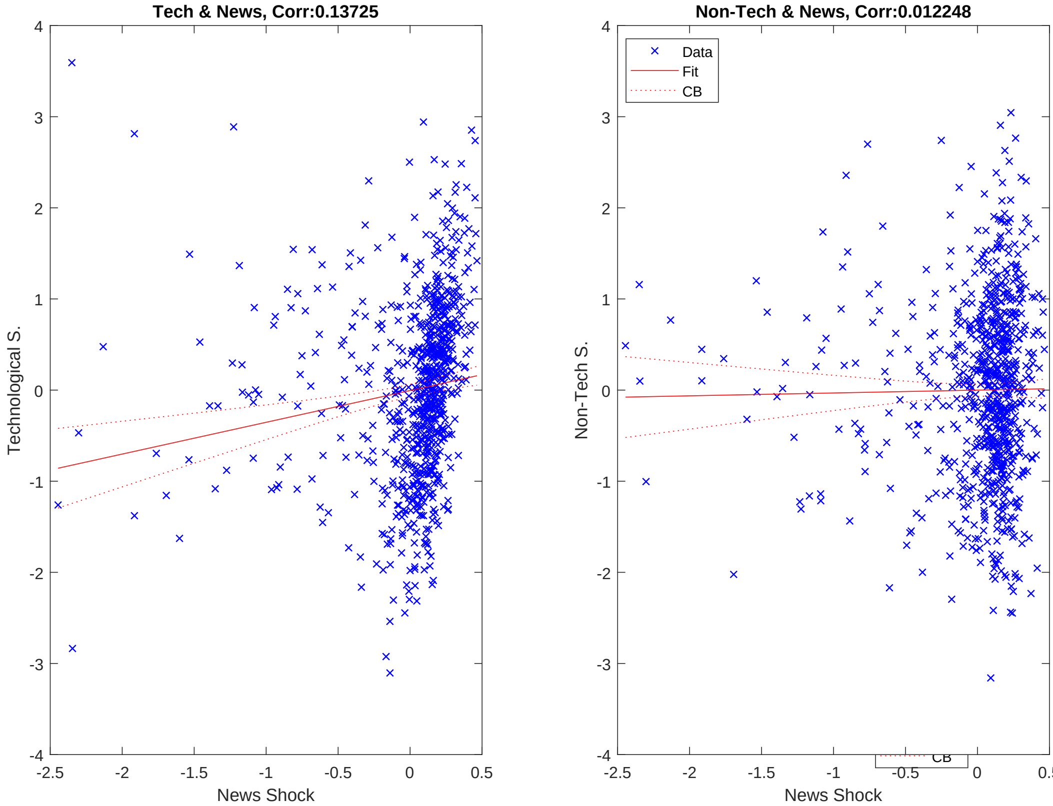


Figure 29: Plot of w_{3t} against $\tilde{w}_{1t}$ - left - and on the right w_{3t} against $\tilde{w}_{2t}$, using data generated from the theoretical model. Only surprise technological and non-technological shocks are active.

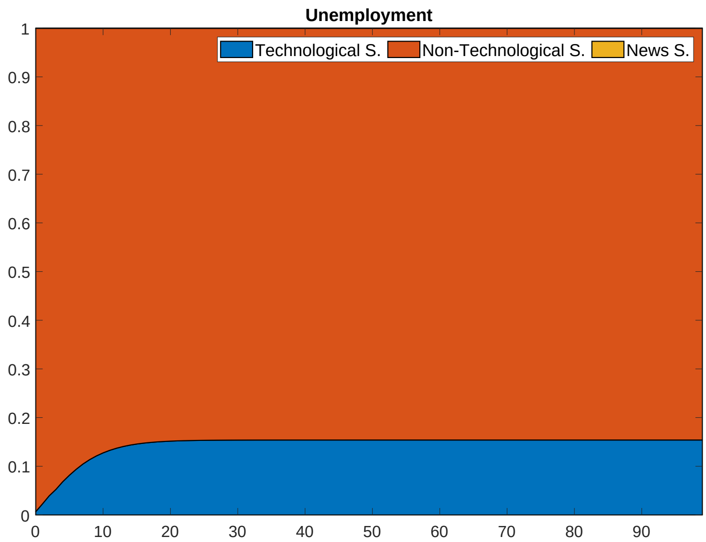


Figure 30: Variance decomposition at different frequencies of the unemployment rate - using data generated from the theoretical model. Only surprise technological and non-technological shocks are active.

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 6.

E 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:

$$W(n_t, y_t) = w_t n_t + b(1 - n_t) + \beta E_t^{\mathcal{P}^w} W(n_{t+1}, y_{t+1}), \tag{39}$$

subject to the law of motion for employment 8. $W(n_t, y_t)$ 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

$$\frac{\partial W(n_t, y_t)}{\partial n_t} = w_t - b + \beta(1 - \lambda_t - \theta_t q_t(\theta_t)) \frac{\partial E_t^{\mathcal{P}^w} W(n_{t+1}, y_{t+1})}{\partial n_{t+1}}. \tag{40}$$

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

F Linearisation of the job creation condition

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 (13), and using the firm's first-order condition (12), the wage equation (14), and the expected constant separation rate ($E_t\lambda_{t+1} = \lambda$), we come up with:

$$\frac{c}{\beta q(\theta_t)} = (1 - \alpha)(E_t y_{t+1} - b) + \frac{(1 - \lambda)c}{q(\theta_{t+1})} - \alpha c E_t \theta_{t+1}. \tag{41}$$

We linearize previous equation applying a first-order Taylor polynomial of this equation at the steady state $\theta = \overline{\theta}$ and $y = \overline{y} = 1$. Taking the first-order Taylor polynomial of each component:

$$\frac{c}{\beta q(\theta_t)} = \frac{c}{\beta q(\overline{\theta})} - \frac{c}{\beta q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (\theta_t - \overline{\theta}) \tag{42}$$

$$(1 - \alpha)(E_t y_{t+1} - b) = (1 - \alpha)(1 - b) + (1 - \alpha)(E_t y_{t+1} - 1) \tag{43}$$

$$\frac{c(1 - \lambda)}{q(E_t\theta_{t+1})} = \frac{c(1 - \lambda)}{q(\overline{\theta})} - \frac{c(1 - \lambda)}{q(\overline{\theta})^2} \frac{\partial q(\overline{\theta})}{\partial \overline{\theta}} (E_t\theta_{t+1} - \overline{\theta}) \tag{44}$$

$$\alpha c E_t \theta_{t+1} = \alpha c \overline{\theta} + \alpha c (E_t \theta_{t+1} - \overline{\theta}) \tag{45}$$

We can write equation (35) as:

$$\frac{c}{\beta q(\overline{\theta})} - \frac{c}{\beta q(\overline{\theta})^2}\frac{\partial q(\overline{\theta})}{\partial \overline{\theta}}(\theta_t - \overline{\theta}) = (1-\alpha)(1-b) + (1-\alpha)(E_t y_{t+1} - 1) \tag{46}$$
$$+\frac{c(1-\lambda)}{q(\overline{\theta})} - \frac{c(1-\lambda)}{q(\overline{\theta})^2}\frac{\partial q(\overline{\theta})}{\partial \overline{\theta}}(E_t\theta_{t+1} - \overline{\theta}) - \alpha c\overline{\theta} + \alpha c(E_t\theta_{t+1} - \overline{\theta})$$

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

$$-\frac{c}{\beta q(\overline{\theta})^2}\frac{\partial q(\overline{\theta})}{\partial \overline{\theta}}(\theta_t - \overline{\theta}) = (1-\alpha)(E_t y_{t+1} - 1) \tag{47}$$
$$-\frac{c(1-\lambda)}{q(\overline{\theta})^2}\frac{\partial q(\overline{\theta})}{\partial \overline{\theta}}(E_t\theta_{t+1} - \overline{\theta}) - \alpha c(E_t\theta_{t+1} - \overline{\theta})$$

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

$$\frac{c\nu\overline{\theta}^{\nu-1}}{\beta\mu}(\theta_t - \overline{\theta}) = (1-\alpha)(E_t y_{t+1} - 1) \tag{48}$$
$$-\frac{c(1-\lambda)\nu\overline{\theta}^{\nu-1}}{\mu}(E_t\theta_{t+1} - \overline{\theta}) - \alpha c(E_t\theta_{t+1} - \overline{\theta})$$

Then θ_t can be written as:

$$\theta_t = \phi_0 + \phi_1 E_t y_{t+1} + \phi_2 E_t\theta_{t+1} \tag{49}$$

where

$$\phi_0 = \overline{\theta} - \phi_2\overline{\theta} - \phi_1 \tag{50}$$
$$\phi_1 = \frac{(1-\alpha)\beta\mu}{c\nu\overline{\theta}^{\nu-1}} \tag{51}$$
$$\phi_2 = \beta(1-\lambda) - \frac{\beta\alpha\mu}{\nu\overline{\theta}^{\nu-1}} \tag{52}$$

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:

$$\theta_t = \hat{\phi}_0 + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 E_t\theta_{t+1} + \hat{\phi}_1\rho^{-1}\epsilon_t, \tag{53}$$

where

$$\hat{\phi}_0 = \phi_0 + (1-\rho)(1+\rho)\phi_1 \tag{54}$$
$$\hat{\phi}_1 = \rho^2\phi_1 \tag{55}$$
$$\hat{\phi}_2 = \phi_2 \tag{56}$$
$$\tag{57}$$

G Rational expectation coefficients

This appendix derives the coefficients of the rational expectations equilibrium (REE) and shows that, in the baseline model, anticipated news that enters only through expectations has no effect in equilibrium.

Starting from the linearized equilibrium condition (53),

$$\theta_t = \hat{\phi}_0 + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 E_t \theta_{t+1} + \hat{\phi}_1 \rho^{-1} \epsilon_t, \tag{58}$$

consider the conjectured minimum-state-variable solution

$$\theta_t = \bar{A} + \bar{B} y_{t-1} + \bar{C} \epsilon_t + \bar{d}\, \epsilon^{\beta}_{t-1}. \tag{59}$$

Since ϵ^{β}_{t-1} belongs to the information set at time t, the corresponding one-step-ahead forecast is

$$E_t \theta_{t+1} = \bar{A} + \bar{B} y_t + \bar{d}\, \epsilon^{\beta}_{t-1}. \tag{60}$$

Using the productivity process

$$y_t = (1-\rho) + \rho y_{t-1} + \epsilon_t, \tag{61}$$

and substituting (60) into (58), we obtain

$$\begin{aligned} \theta_t = \hat{\phi}_0 + \hat{\phi}_2 \bar{A} + \hat{\phi}_2 (1-\rho) \bar{B} + \left(\hat{\phi}_1 + \hat{\phi}_2 \rho \bar{B}\right) y_{t-1} \\ + \left(\hat{\phi}_1 \rho^{-1} + \hat{\phi}_2 \bar{B}\right) \epsilon_t + \hat{\phi}_2 \bar{d}\, \epsilon^{\beta}_{t-1}. \end{aligned} \tag{62}$$

The Rational Expectations Equilibrium (REE) corresponds to the fixed point of the T-mapping. The T-mapping of this model is represented by

$$T(\hat{A}_t, \hat{B}_t, \hat{d}_t) = \begin{bmatrix} \hat{\phi}_0 + \hat{\phi}_2 \hat{A}_t + \hat{\phi}_2 (1-\rho) \hat{B}_t \\ \hat{\phi}_1 + \hat{\phi}_2 \rho \hat{B}_t \\ \hat{\phi}_2 \hat{d}_t \end{bmatrix}. \tag{63}$$

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

$$\begin{pmatrix} \bar{A} \\ \bar{B} \\ \bar{d} \end{pmatrix} = \begin{pmatrix} \hat{\phi}_0 \\ \hat{\phi}_1 \\ 0 \end{pmatrix} + \begin{pmatrix} \hat{\phi}_2 & \hat{\phi}_2(1-\rho) & 0 \\ 0 & \hat{\phi}_2 \rho & 0 \\ 0 & 0 & \hat{\phi}_2 \end{pmatrix} \begin{pmatrix} \bar{A} \\ \bar{B} \\ \bar{d} \end{pmatrix}. \tag{64}$$

Solving for the coefficients on the fundamental states yields

$$\bar{B} = \frac{\hat{\phi}_1}{1 - \hat{\phi}_2 \rho}, \tag{65}$$

$$\bar{A} = \frac{\hat{\phi}_0 + \hat{\phi}_2 (1-\rho) \bar{B}}{1 - \hat{\phi}_2}. \tag{66}$$

The fixed-point condition for the anticipated-news coefficient is

$$\bar{d} = \hat{\phi}_2 \bar{d}. \tag{67}$$

Hence,

$$(1-\hat{\phi}_2)\bar{d}=0. \tag{68}$$

The coefficient on the contemporaneous productivity innovation is then

$$\bar{C}=\hat{\phi}_1\rho^{-1}+\hat{\phi}_2\bar{B}. \tag{69}$$

We now define E-stability for determining the stability of the REE under least-squares learning. The REE is E-stable if small deviations of $(\hat{A}_t, \hat{B}_t, \hat{d}_t)$ from the fixed point converge back to the fixed point under the notional-time learning dynamics induced by T. The Jacobian of the T-mapping is

$$DT=\begin{pmatrix}\hat{\phi}_2 & \hat{\phi}_2(1-\rho) & 0\\ 0 & \hat{\phi}_2\rho & 0\\ 0 & 0 & \hat{\phi}_2\end{pmatrix}. \tag{70}$$

Since this matrix is upper triangular, its eigenvalues are

$$\lambda_1=\hat{\phi}_2, \qquad \lambda_2=\hat{\phi}_2\rho, \qquad \lambda_3=\hat{\phi}_2. \tag{71}$$

Therefore, the REE is E-stable if these eigenvalues are smaller than one in modulus. Since $0<\rho<1$, this condition reduces to

$$|\hat{\phi}_2|<1. \tag{72}$$

Under this condition, the fixed-point restriction above implies

$$\bar{d}=0. \tag{73}$$