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Towards Technology-News-Driven Business Cycles*

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Abstract

We identify an inflationary technology news shock as the leading source of business cycle variations for the postwar U.S. economy. This shock acts like a demand shock: it induces strong positive comovement in real quantities - GDP, consumption, investment - and weak positive comovement between real quantities and inflation, contrary to the view that anticipated technological innovations reduce inflation. The technology news shock became the predominant source of the business cycle from the 80's. The reason is that anticipated improvements in future technology lead to improvements in financing conditions. The monetary policy response to these anticipations is contractionary in the short run, independently of the sample period. However, the response is more short-lived from the 80's than before and with respect to other non-technology shocks. Finally, the inclusion of sentiment, uncertainty and TFP measurement error shocks does not affect the importance of the technology news shock.

JEL Codes: E20, E31, E32, E44, E52, O33
Keywords: total factor productivity, business cycle, technology news shocks, demand shocks, financial sector transmission, monetary policy.

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1 Introduction

What drives business cycle fluctuations? The modern analysis of business cycles is centered around the study of "shocks". Shocks are considered to be exogenous forces that cause business cycle variation and are distinguished based on their origination (technology, policy, financial, etc...) and whether they are anticipated or unanticipated.

During the last five decades, the study of economic fluctuations has focused mostly on unanticipated shocks as the main cause of these variations. The idea that business cycles may be driven not only by surprises but also by shocks to expectations about future fundamentals has a long history. However, only during the last two decades these ideas have resurged. The seminal empirical work by Beaudry and Portier (2006) assigns a leading role to the technology (TFP) news shock as the driver of the business cycle, because it can generate strong positive correlation among real macroeconomic quantities and hours worked. Since then, research on news-driven business cycles has been not only empirical, but also model-based.[1] Using estimated DSGE models it is difficult to generate significant technology news-driven business cycles (Fujiwara et al. (2011), Khan and Tsoukalas (2012), Schmitt-Grohé and Uribe (2012)). In addition, other empirical studies (Barsky and Sims (2011), Forni et al. (2014), Kurmann and Sims (2017)) find that the technology news shock cannot be the main source of economic fluctuations, since it does not generate comovement among macroeconomic quantities and hours worked.

In this paper, we show that the major U.S. business cycle shock for the post World War II period is an anticipated technology shock. Differently from the aforementioned literature, the technology news shock we identify behaves like a demand shock. It induces strong positive comovement among real macroeconomic quantities - output, consumption, investment - and weak positive comovement among these real quantities and inflation. This shock established its prominence from the 80's. Before the 80's, based on the forecast error variance decomposition, it was as important as other technology or non-technology shocks. We argue that the technology news shock is more important for the business cycle from the 80's because its transmission through the financial sector is strengthened. A positive technology news shock eases financing conditions only from the 80's, as found also by Gambetti et al. (2018). In particular, the Baa corporate spread falls after a positive technology news shock from the 80's, and does not react before the 80's. At the same time, the response of monetary policy in the short run is found to be contractionary, independently of the period of study. However, the response of the real rate is more short-lived from the 80's compared to the period before the 80's and to the non-TFP shocks.

[1] For an extensive literature review, see Lorenzoni (2011) and Beaudry and Portier (2014).

The period before the 80's in the U.S. was characterized by strict financial regulation. In 1980 the Depository Institutions Deregulation and Monetary Control Act was signed. This act gradually phased out restrictions for banks, while also improving the Federal Reserve's control of monetary policy, by extending reserve requirements to depository institutions.[2] These changes in the monetary and financial regulatory environment may have played a role in the improved transmission of the technology news shock to the real economy.

Methodologically, the current paper extends, modifies and enriches the structural vector error correction model initially studied by Beaudry and Portier (2006). To be more specific, we consider a core vector error correction model with four variables: TFP, consumption, output, investment.[3] With this core system we identify four shocks based on zero short-run and long-run restrictions. The first two shocks are technology shocks, the surprise technology shock and the technology news shock, and the other two shocks are non-technology shocks, one of which is allowed to affect permanently all real macroeconomic quantities. The identification of the surprise technology shock is based on long-run restrictions á la Blanchard and Quah (1989). The technology news shock is assumed to have no impact effect on TFP but is allowed to affect it in the long run.

Compared to Beaudry and Portier (2006), we identify the technology news shock through consumption instead of stock prices. The reasons for this choice are the following. First, the use of stock prices is problematic due to the statistical properties of the series, that change around the 80's.[4] This is not the case for the series of consumption. Second, as explained by Ramey (2016), current stock prices do not necessarily react positively to news about future TFP improvements. This is the case when major technological innovations make the existing technology less valuable, hence may have a negative effect on stock prices. Moreover, innovations that take place in small private companies take time to be reflected in the stock market index S&P 500, that represents large companies. Hence, we choose to identify "news" through consumption. Cochrane (1994) was the first to do so and Beaudry and Portier (2014) have done it as robustness. Indeed, consumption contains information about future fundamentals, because it aggregates the behaviour of forward-looking consumers.[5]

[2]For more information on the act and its impact on the Federal Reserve, see McNeill and Rechter (1980) and https://www.federalreservehistory.org/essays/monetary_control_act_of_1980.

[3]We show that our core system does not suffer from serious non-fundamentalness problems.

[4]As discussed in Di Casola and Sichlimiris (2018), the series of real per-capita stock prices behaves like a unit root without drift up to the 80's and like a unit root with drift from the 80's. Using stock prices in a VEC model requires to account for a structural break and makes the identification of the news shock sensitive to the data period used for the analysis.

[5]"Ask a consumer about next year's GDP and he will answer 'I don't know.' But he may know that his factory is closing, and hence he is consuming less. This idiosyncratic shock is correlated with future GDP. Summing over consumers, aggregate consumption can reveal information about future aggregate activity, although neither consumers in the economy nor economists who study it can name what the crucial pieces of information are" (Cochrane (1994), pag. 350).

Through the core system we establish that the technology news shock is the main driver of the business cycle, since it accounts for two thirds of the variation of output. As mentioned above, this shock became the dominant driving force of the business cycle from the 80's. In order to highlight the changes in the propagation of this shock, we extend our core model. We do so by including variables connected to prices (e.g CPI inflation), interest rates (e.g. real Treasury bill) and financial sector conditions (e.g. corporate Baa spread). Based on these extensions, we find that the technology news shock behaves like a demand shock.

Our empirical study is the first one to obtain the positive response of inflation after a technology news shock. The empirical literature on news shocks (Barsky and Sims (2011), Forni et al. (2014), Kurmann and Sims (2017) and Fève and Guay (2018)) obtains a negative response. The negative response is at odds with standard New Keynesian models and has motivated research that adds features into the canonical model to reproduce the empirical finding. Most notable work in this direction comes from Jinnai (2013), Kurmann and Otrok (2014), Barsky et al. (2015). The fact that our identified technology news shock is inflationary means that the empirical evidence need not necessarily be at odds with standard New Keynesian models.

Kurmann and Sims (2017) and Bouakez and Kemoe (2017) have highlighted the potential problems coming from measurement errors in utilization-adjusted TFP. We further investigate whether measurement problems can produce an upward bias in the importance of the news shock, by introducing a TFP measurement error shock. We find that our results carry on to this modified system. In addition, our results regarding the dynamics of the news shock are robust to introducing confidence and uncertainty shocks.

Finally, our results show that the second most important shock for the business cycle is a non-technology, non-inflationary permanent shock, that accounts for 25-30% of the output variation. Given that this shock is assumed not to affect technology, but it has a permanent effect on output and hours worked, one candidate explanation is that it represents a labour supply shock, as first described in Shapiro and Watson (1988). Indeed, we find support for this interpretation for two main reasons. First, it is a significant source of variation of hours worked in the long run. Second, it does not behave like a demand shock. We conclude that business cycle fluctuations can have a parsimonious two-shock representation: the technology news shock and the labour supply shock. The latter one becomes less important for the business cycle over time. Therefore, we are heading towards technology-news driven business cycles.

Related literature and comparison. As we have already mentioned, there are various shocks that have been studied as possible causes of the business cycle. It is beyond our scope to summarize this research. We refer the reader to recent and past attempts to summarize these developments (Cochrane (1994), Ramey (2016)). Due to the fact that the technology news shock is responsible for two thirds of the variation in output, we will focus most of our discussion on papers that identify technology news shocks and may or may not identify other shocks.

We date the beginning of the modern literature on technology news shocks to Beaudry and Portier (2006). Afterwards, one strand of the literature has tried to gauge the importance of news shocks with estimated DSGE models and another strand with VAR-based approaches. The distinction would not be important, if these two different approaches were not producing contradictory findings. To be more specific, the VAR-based approach to news shocks led more support to the view that technology news shocks matter for the business cycle. In contrast, the DSGE-based approach cannot find support for the the technology news shock. Fujiwara et al. (2011) and Khan and Tsoukalas (2012) use a New Keynesian model, while Schmitt-Grohé and Uribe (2012) rely on a real business cycle model. They find that news shocks are important for the business cycle, but not the ones about technology.[6] There is one recent notable exception, Görtz and Tsoukalas (2017). They find that technology news shocks matter for the business cycle based on a New Keynesian model with financial frictions, estimated on post-1990 data. The crucial difference with other estimated DSGE models is that the transmission of the technology news shock is amplified through a financial intermediation channel. This line of thought can be consistent with our empirical evidence. We have argued that the financial propagation of the technology news shock is key for the technology news-driven business cycle. Thus, we are heading towards a consensus between evidence coming from (cointegrated) VAR systems and estimated DSGE models.

In terms of VAR models, two main approaches have emerged. The first one, pioneered by Beaudry and Portier (2006), relies on cointegration assumptions and hence the use of structural vector error correction models. This approach has the advantage of taking full account of the non-stationary properties of the series and is able to disentangle the short-run from the long-run dynamics. To distinguish the surprise technology shock from the anticipated one they impose zero short-run and long-run restrictions. The main variables of their analysis are TFP and stock prices. The news shock is orthogonal to TFP but affects it in the long-run like a surprise technology shock.[7] Beaudry and Portier (2014) argue that the news shock is the main driver of the business cycle, generating comovement among

[6]However, in her overview of the literature, Ramey (2016) shows that often the news shocks generated by estimated DSGE models are not unanticipated.

[7]For the systems that contain three or more variables the results from the original work of Beaudry and Portier (2006) cannot be replicated as pointed out by Kurmann and Mertens (2014). Following this critique, Beaudry and Portier (2014) propose a modification of their original identification strategy to extend it to a larger system, but do not provide a full identification for more than 3 variables.

output, consumption, investment and hours worked. The news shock accounts for more than half of the forecast error variance decomposition of these variables. However, the response of TFP to the news shock is not only delayed, but actually turns negative for the first two years, making the news shock rather unimportant for TFP at business cycle frequencies. Subsequent work from Beaudry and Lucke (2010) finds that the technology news shock is the dominant force, even when it competes with other technology or non-technology shocks.[8] Fève and Guay (2018) obtain similar conclusions when they introduce sentiment shocks in a VEC model. Our paper does not find a major role for the technology news shock before the 80's. However, its relevance for the macroeconomic quantities from the 80's is accompanied by a high relevance for TFP as well.

The second approach has its origins in the work of Barsky and Sims (2011) and is based on the maximization of the forecast error variance decomposition of TFP at some horizon, together with the assumption of orthoganality to TFP innovations. The authors argue that the news shock is not the main driver of the business cycle, because it does not generate comovement among the main macroeconomic variables. Their methodology has been modified in various ways by the following literature, inspired also by Francis et al. (2014). Forni et al. (2014) and Kurmann and Sims (2017) partially confirm the original findings. Kurmann and Sims (2017) find that the technology news shock cannot be the main source of business cycle variations, as it does not generate positive comovement on impact between output and hours worked. However, it seems to account well for the forecast error variance decomposition at medium to longer frequencies.

Kurmann and Otrok (2013) and Görtz et al. (2016) find a large role for the technology news shock and show that credit spread indicators fall and the slope of the yield curve rises after a technology news shock, respectively. Gambetti et al. (2018) show that news shocks have a different effect on yields and spreads before and after 1980 and relate it to the conduct of monetary policy. They also argue that the news shock identified after the 1980 looks more similar to the one identified in Beaudry and Portier (2006). However, unlike us, they find a negative response of inflation to the news shock. Bouakez and Kemoe (2017) show that the identification strategy in Barsky and Sims (2011) is sensitive to the presence of measurement errors in TFP. These errors may explain why the identified surprise technology shocks induce an increase in inflation. This is important, since news shocks are identified to be orthogonal to the surprise shocks. Using a modified approach, Bouakez and Kemoe (2017) find a prominent role for the news shock, while the disinflationary puzzle disappears. Inflation falls after a surprise technology shock, while it is almost

[8]A comment from Fisher (2010) shows that the results in Beaudry and Lucke (2010) are sensitive to the cointegration assumptions. That would not have been a problem, if the number of cointegrated relationships of the system was not largely debatable from a theoretical standpoint.

unchanged after the news technology shock.

A contemporaneous study on the main driver of the business cycle is Angeletos et al. (2018). The authors use a methodology for the identification of the shocks, based on the maximization of the volatility of a macroeconomic variable at different horizons. The results point towards a non-inflationary demand shock as the main driver of the business cycle volatility, despite not being the most important for consumption. This main business cycle shock is not the most important driver of the long-run behaviour. On the contrary, the technology news shock we identify looks like a demand shock and it is the source of fluctuations at business-cycle frequencies and in the long run.

The paper is structured in the following way. Section 2 describes the data and its properties. Section 3 describes the vector error correction model and the identifying assumptions for the structural shocks. Sections 4 describes the dynamics after the identified shocks and their contribution to the business cycle. Section 5 discusses the propagation of the technology news shocks across different sample periods. Section 6 provides additional results and section 7 concludes.

2 Data and its characteristics

We base our analysis on a core vector error correction model with four variables. Later, we extend the model to additional variables to better understand the transmission of the identified shocks.

2.1 Core variables

For our analysis we utilize quarterly U.S. data for the period 1948:01-2017:03. The main variables of interest consist of a measure of total factor productivity, output, consumption and investment. To be able to identify technology shocks (anticipated and unanticipated ones) we need a measure of total factor productivity (TFP). We consider the widely used real-time measure of TFP produced by Fernald (2014), that corrects for capital utilization based on the methodology proposed by Basu et al. (2013). Since the correction is based on annual data, Fernald cannot reproduce the exact same correction with quarterly data, but takes into account the most important elements and this is why the measure is commonly used in the literature on technology news shocks.[9] For the macroeconomic variables, we

[9]The series is continuously updated and available for download at https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/. We use the December 2017 vintage. Kurmann and Sims (2017) discuss the changes in the series, due to the revision in the utilization measurement carried out in March 2014, when Fernald switched from following Basu et al. (2006) to Basu et al. (2013). This revision motivated the comment by Cascaldi-Garcia (2017b) to Kurmann and Otrok (2013).

consider the real chain-weighted measures of GDP (output), personal consumption expenditure (consumption) and gross private domestic investment (investment) provided by the Bureau of Economic Analysis[10] (BEA). We transform the series in per-capita terms by dividing them with the series of civilian noninstitutional population of 16 years and above provided by the Bureau of Labor Statistics (BLS). Finally, we consider the logarithmic transformation of all these variables.

2.2 Additional variables

The variables mentioned below enrich the core model in order to highlight the transmission of the shocks. The corporate spread corresponds to the difference between Moody's Baa and Aaa corporate bond yield and is available in FRED database.[11] It is available at monthly frequency and we transformed it to quarterly series by taking the average value for each quarter. Inflation is measured as the annual growth rate of the consumer price index, provided by BLS. Results are available also for an alternative measure usually considered in the literature, that is the annual growth rate of the GDP deflator (BLS). Using the annual rate of inflation, we can rule out any problem related to seasonal adjustment. The interest rate used is the 3-month Treasury bill yield, deflated with actual CPI inflation. The Treasury yield is available at monthly frequency and we take averages of each quarter to make it quarterly.

Hours worked refers to the nonfarm business sector and the measure is also provided by BLS. We transform it in per-capita terms with the same population series used above. Confidence is measured as the index of consumer sentiment from the Michigan Survey of Consumers, available only from 1960.[12] Uncertainty is measured as the second factor representing financial uncertainty in Jurado et al. (2015) and it is available only from 1960q3.[13]

2.3 Unit roots testing

Unit root tests[14] cannot reject the hypothesis that the core variables are non-stationary, in particular they are unit roots with a drift. Based on these tests, the corporate spread, the interest rate, CPI inflation, confidence and uncertainty are stationary, while results are mixed for the growth rate of the GDP deflator and hours worked. Indeed, there is an ample

[10]More precisely, they correspond to Table 116.

[11]FRED data are available for download at https://fred.stlouisfed.org/. We have considered also the spread measured as difference between the Baa corporate bond yield and the 10-year Treasury bond yield for robustness.

[12]The data are available for download here: http://www.sca.isr.umich.edu/.

[13]The data are available for download from one of the authors' website: https://www.sydneyludvigson.com/data-and-appendixes/.

[14]Results from the tests are not reported here but they are available from the authors upon request.

debate on whether hours worked is stationary or not and we will discuss the issue when we introduce the variable in our model.

3 Model and Identification

In this section we analyze the presence of cointegration among our core variables. We describe the vector error correction model used in the analysis and the assumptions behind the zero short and long-run restrictions used to identify the shocks. The choice of having this system as a core rests on the need to incorporate as much information as possible to avoid non-fundamentalness issues, while being parsimonious.

3.1 Cointegration

We have mentioned above that our main series of interest, TFP, output, consumption and investment, are unit roots. Now we study the presence of cointegration among them, implying that linear combinations of these variables may be stationary. It is indeed very plausible that output, consumption and investment co-move in the long-run in a stationary way, given the national account identity. In fact, King et al. (1991) have already exploited the presence of cointegration among them in their analysis. Here, we also consider the relationship among these variables and TFP. Hence, we expect to find two cointegrating relationships for the system of four variables. We use the Johansen trace test of cointegration. The test for lag selection suggests 3 lags. Since we use quarterly data with seasonally adjusted series, it is useful to have at least 4 lags, hence one full year of past data, to account for possible seasonality left in the series. Finally, we use 6 lags in order to rule out the presence of autocorrelation in the residuals. The results for cointegration are similar with 4 lags. We assume the presence of a linear trend in the long-run relationship, because this is the most general assumption about the deterministic components.[15] The test, reported in Table 1, suggests the presence of two cointegrating relationships. Therefore, we proceed by assuming two cointegrating relationships and estimate a vector error correction model. As we will see, the trend enters the cointegrating vector in a significant way, hence we keep it.[16]

[15]See Juselius (2006) for the importance of the deterministic components for cointegration tests. The cointegration test relies on the assumption on the deterministic components and the inference about the deterministic components depends on the assumed cointegration. Hence, Juselius (2006) suggests to start from the most general case, i.e. the trend in the cointegrating vector, test for cointegration and then check the significance of the trend. If it is not significant, the second most-general assumption should be made about the determistic components and so on with the test.

[16]We have conducted a sensitivity analysis on the presence of the linear trend and found similar results for the identification of the news shock without it.

Given that our model contains the main macroeconomic variables and TFP, we find the results of the Johansen test in line with theory and proceed with two cointegrating relationships.

Cointegration test					
p-r	r	Eig.Value	Trace	Frac95	P-Value
4	0	0.118	80.349	63.659	0.001
3	1	0.102	46.063	42.770	0.022
2	2	0.033	16.709	25.731	0.445
1	3	0.027	7.552	12.448	0.299

Table 1: Johansen trace test of cointegration for TFP, output, consumption and investment series with restricted trend and 6 lags. The table reports the eigenvalues, the trace statistic test, the 5% critical value and the p-value for the null hypothesis of r cointegrating relationships.

3.2 Vector Error Correction Model

Our four-variable vector error correction model (VECM) takes the following form.

$$\Delta X_t = \Pi X^*_{t-1} + \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_p \Delta X_{t-p} + \Theta D_t + \epsilon_t, \tag{1}$$

where X_t is the vector containing TFP, consumption, output and investment, X^*_{t-1} is the cointegrating vector containing the lagged variables and the deterministic terms, p is the lag chosen, D_t contains the deterministic terms outside the cointegrating vector. If it contains a constant term, it means that we have a linear trend in levels outside the cointegrating relationship. In case of cointegration, the matrix Π has reduced rank and can be decomposed as:

$$\Pi = \alpha\beta'. \tag{2}$$

As suggested by Johansen test above, it has rank 2, so α has size 4×2, while β has size $(4+1) \times 2$, because we have included a trend in the cointegrating relationship. The vector β is the cointegrating vector and it defines the two stationary cointegrating relations, $\beta' X^*_{t-1}$. The vector α contains the loading coefficients, defining how the system adjusts to the long-term relationship among the variables. The other coefficient matrices of the VEC model define the short-term dynamics of the series.

Table 2 reports the loading coefficients for the two cointegrating relationships. We can see that TFP and investment are adjusting in a significant way to the long-run relationships, while consumption and output are weakly exogenous, since the coefficients in front of both cointegrating vectors are not significant. Table 3 reports the estimates of the β vector, after normalization.[17] All the variables enter significantly, including the linear trend, although with a small coefficient. A way to interpret the cointegrating vectors is to consider them in first difference. The first vector implies that the growth rate of output is proportional to the growth rate of consumption and investment plus a constant. The second vector implies that the growth rate of output is proportional to the growth rate of TFP and consumption plus a constant.[18] We can interpret the linear trend as representing an additional variable missing from the system.

	$\alpha(1)$	$\alpha(2)$
DLTFP	-0.243	0.250
	(-3.773)	(4.085)
DLC	-0.045	0.010
	(-0.741)	(0.173)
DLY	0.063	0.051
	(0.938)	(0.793)
DLI	1.075	-0.514
	(3.828)	(-1.927)

Table 2: Loading coefficients for the model with TFP, output, consumption and investment series, with linear trend inside the two cointegrating vectors and 6 lags. Sample period is 1948-2017.

	LTFP	LC	LY	LI	Trend
$\beta'(1)$	0.000	1.000	-0.806	-0.079	-0.001
	(.NA)	(.NA)	(-13.201)	(-4.081)	(-3.970)
$\beta'(2)$	-0.126	1.000	-0.833	0.000	-0.001
	(-3.309)	(.NA)	(-13.651)	(.NA)	(-3.986)

Table 3: Cointegrating vectors for the model with TFP, output, consumption and investment series, with linear trend inside the cointegrating vectors and 6 lags. Sample period is 1948-2017.

Figure A.1 and A.2 in Appendix A report the graphs of the two cointegrating vectors. We can notice that they look stationary.

3.3 Identifying Assumptions

In order to structurally identify the VEC model, we introduce the Beveridge-Nelson MA representation of a K-dimension VEC model with p lags, derived by Johansen (1995).

$$X_t = \Xi \left(\sum_{i=1}^{t} u_t + \Theta t \right) + \sum_{j=0}^{\infty} \Xi_j^* L^j u_t + X_0^*, \tag{3}$$

[17]Note that the normalization does not affect the results.

[18]But the growth rate of TFP is also related to the growth rate of investment by transitivity.

where $\Xi = \beta_\perp \left(\alpha'_\perp (I_K - \sum_{i=1}^{p-1} \Gamma_i)\beta_\perp\right)^{-1} \alpha'_\perp$ and has rank $K - r$. The element $\Xi \left(\sum_{i=1}^{t} u_t + \Theta t\right)$ is non-stationary and contains the long-run effects of the shocks and the deterministic components. The matrices Ξ_j^*'s contain transitory effects and constitute the stationary component. The relationship between the original structural shocks ϵ_t and the reduced-form shocks u_t is given by:

$$u_t = B\epsilon_t. \tag{4}$$

The matrix B is called the "impact matrix" and defines the short-run relationship between the structural shocks and the variables. The long-run effects of the shocks on the variables are defined by the long-run impact matrix, ΞB. In order to identify the responses of the variables to the structural shocks, we need to place some restrictions on one or both matrices.

Notice that for the full identification of a K-variables system, we need $K(K-1)/2$ restrictions. However, the assumption of cointegration implies that there are at least two permanent innovations in the system. The matrix of long-run effects contains only two linearly independent rows. Hence, each column of zeros in the long-run matrix ΞB represents only two $(K - r)$ independent restrictions, requiring us to make additional assumptions in the impact matrix B.We consider the variables ordered in the following way:

$$X_t = \begin{bmatrix} TFP_t \\ Consumption_t \\ Output_t \\ Investment_t \end{bmatrix}$$

For our identification we use zero short-run and long-run restrictions. First, we distinguish between technology and non-technology shocks, by assuming that non-technology shocks cannot affect TFP in the long run. This is equivalent to imposing zero restrictions on the first element of the third and fourth column of matrix ΞB, so that the first two shocks are technology shocks. Zero long-run restrictions to identify shocks in VAR models were first proposed by Blanchard and Quah (1989) and applied to the context of technology shocks by Galì (1999). We further assume that only technology shocks can affect TFP in the short-run, imposing zero in the first elements of the third and fourth column of matrix B. To distinguish between surprise (first) and news technology shocks (second), we follow Beaudry and Portier (2006) and assume that only the surprise shock can affect TFP in the short run, imposing a zero in the first element of the second column of matrix B. This is in line with the idea that the technology news shock hits the economy before TFP changes actually take place.

We are left with two non-technology shocks. Using Blanchard and Quah (1989)'s type of restrictions, we assume that the fourth shock is a temporary one and cannot affect investment in the long run. This implies a zero in the last element of the fourth column of matrix ΞB. As explained above, due to the assumption of two cointegrating relationships, two zeros in a column of matrix ΞB imply a column of zeros. Hence, our assumption is equivalent to assuming that the fourth shock has no long-run effect also on consumption and output. These assumptions imply the zero short and long-run restrictions reported below.

$$B = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \tag{5}$$

$$\Xi B = \begin{bmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & 0 \end{bmatrix} \tag{6}$$

Therefore, ϵ_1 is the surprise technology shock, ϵ_2 is the news technology shock, ϵ_3 is a permanent non-technology shock, ϵ_4 is a temporary non-technology shock. We can summarize our assumptions in the following way.

Assumption 1. *Only the surprise technology shock can affect TFP on impact and in the long run.*

Assumption 2. *The news technology shock is allowed to affect TFP only in the long run.*

Assumption 3. *The non-technology shocks cannot affect TFP on impact or in the long run. Moreover, the fourth shock is temporary.*

When discussing the impulse response functions in the next section, we will show that the first two shocks indeed look like a technology surprise and news shock. Notice that the third shock is allowed to affect the macroeconomic quantities in the long run, while not being a technology shock. Later we will show that it looks like a labor supply shock, in the spirit of Shapiro and Watson (1988).

With respect to Beaudry and Portier (2006), we have replaced the variable of stock prices with the variable of consumption to identify news shocks. There are two reasons for this choice. First, the statistical properties of the series raise doubts about its inclusion in a VEC model. As discussed in Di Casola and Sichlimiris (2018), the series behaves like unit root without drift up to the 80's and with drift from the 80's. Therefore, systems that contain stock prices need to account for a structural break to identify the cointegrating relationship in the data. The identification of news shocks in a VEC model with stock prices are sensitive to the data period used for the analysis. Such problems disappear when the consumption series is used instead. Second, the use of stock prices relies on the assumption that the stock market reacts positively on impact to the arrival of news on future technological improvements. As explained in Ramey (2016), this is not necessarily the case if the technological changes make current technology less valuable or happen in private companies not yet traded in the stock market. The idea of using consumption to study news shock was first proposed by Cochrane (1994), although he does not identify pritimive structural shocks. The measure of consumption aggregates the behaviour of all the consumers, who, individually, possess information about the future fundamentals that affect their life.

4 Dynamics and Contribution to the Business Cycle

In this section we document the dynamics induced by the identified two technology and two non-technology shocks on the main macroeconomic variables. After commenting on the dynamic behaviour of the shocks, we discuss their contribution for each macroeconomic variable based on the forecast error variance decomposition. The technology news shock is the dominant source of business cycle variation. We show that the news shock explains 60-70% of the unexplained variation in output, more than 70% of consumption and around 80% of investment. Importantly, it explains almost half of the unexplained variance of TFP within 40 quarters.

4.1 Impulse Responses from the core SVECM

Figure 1 displays the impulse responses from our core structural vector error correction model.

The (permanent) surprise technology shock

The first column of Figure 1 displays the responses of the surprise technology shock, that is the shock that can affect all the variables of the system both in the short and in the long run. The shock has a permanent effect on TFP and the macroeconomic variables. All the variables stabilize at a higher level after around two years. Even if this shock has a strong effect on TFP, it does not have a strong permanent effect on consumption, output and

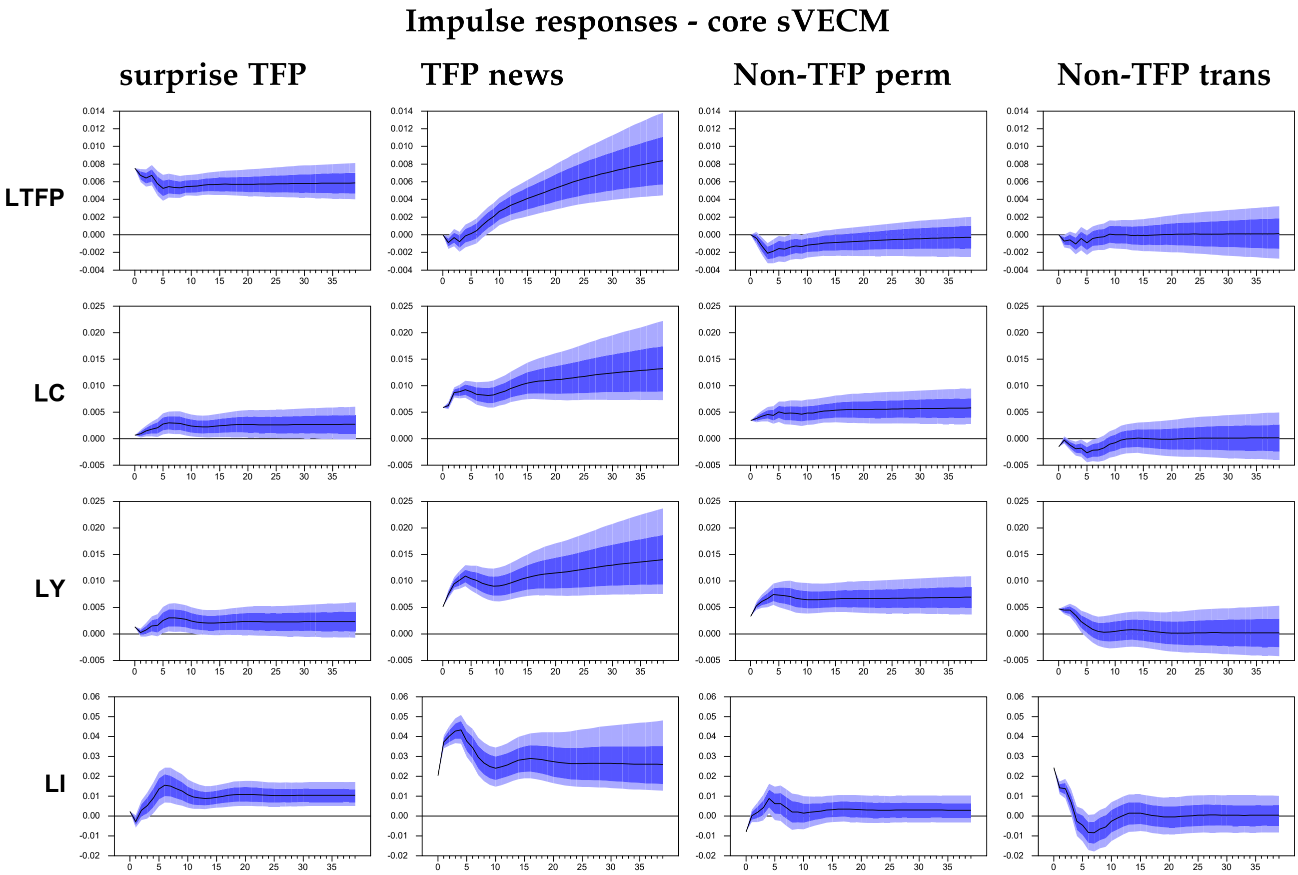

Figure 1: Impulse response functions for the 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY) and investment (LI), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the four shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

investment. In fact, we will see in section 5.3 that hours worked fall after this technology shock.

The (permanent) technology news shock

The second column of Figure 1 displays the impulse responses after the so-called news shock. As we have discussed previously, the technology news shock is identified following Beaudry and Portier (2006)'s identification paradigm. Even if this shock is not allowed to affect TFP on impact, it has a sizable effect on TFP starting from the eighth quarter. In the first eight quarters its effect on TFP is not significantly different from zero, in line with the idea of a delayed technological diffusion process, as theorized in Beaudry and Portier (2006).[19] Due to the dynamics induced on TFP, we follow the naming convention

[19] Notice that the effect of the news shock on TFP in the first quarters is actually found to be negative and significant in Beaudry and Portier (2006), Beaudry and Portier (2014) and positive and significant in Barsky and Sims (2011). This is in contrast with the idea of a delayed response after the news shock.

of the literature on news shocks and we call it technology news shock. This shock has a permanent strong impact on all the macroeconomic variables included in our system. The response for all the variables is initially hump-shaped and then converges towards its long-run value. One may wonder why the effect of a surprise technology shock on the macroeconomic variables is not as strong as for the news shock, despite a strong effect on productivity. The answer lies on the propagation mechanism, as we show in section 5.

The permanent non-technology shock

The third shock in our system is a non-technology shock in the sense that it cannot affect TFP neither in the short run nor in the long run. On the other hand, it is allowed to have an effect on all other macroeconomic variables. The responses are displayed in the third column of Figure 1. This shock induces a permanent positive effect on all the macroeconomic quantities. However, it seems that the effect on output and consumption is stronger than the effect on investment. We have identified a non-technology shock that can induce positive correlation among the macroeconomic variables. In section 5.3 we discuss the propagation of this shock and argue that it can be interpreted as a labor supply shock in the spirit of Shapiro and Watson (1988).

The transitory non-technology shock

The last shock we identify from our core system is a shock that is not allowed to affect TFP neither in the short run nor in the long run. In addition, it can affect the macroeconomic quantities only in the short run. This shock has a temporary positive effect on output and investment, but reduces consumption mildly for the first quarters.

From the description of the impulse responses one can conclude that we have three shocks that can induce comovement in the macroeconomic quantities. Among these three shocks, the technology news shock stands out. In the next subsection, we document the forecast error variance decomposition after the four aforementioned shocks for TFP and the macroeconomic quantities.

4.2 Forecast Error Variance Decomposition from the core sVECM

The purpose of this section is to show that the news shock is the major source of variation of the core macroeconomic variables we have included in the system.

4.2.1 Technology News matter for TFP at Business Cycle Frequencies

The literature on technology news shocks that follows Beaudry and Portier (2006)'s paradigm has struggled to make technology news shocks important drivers of TFP at medium, business cycle frequencies. In fact, in their literature review on news shocks, Beaudry and Portier (2014) find that technology news shocks explain only 4% of the movements in TFP four years ahead. In Figure 2 we show that the technology news shock explains a significant part of the variation in TFP at the 5-10 years horizon (up to 45%). A similar result is obtained by Fève and Guay (2018). The rest of the movements in TFP are vastly explained by the surprise technology shock as one would expect, given that the other two shocks that we identify are non-TFP shocks.

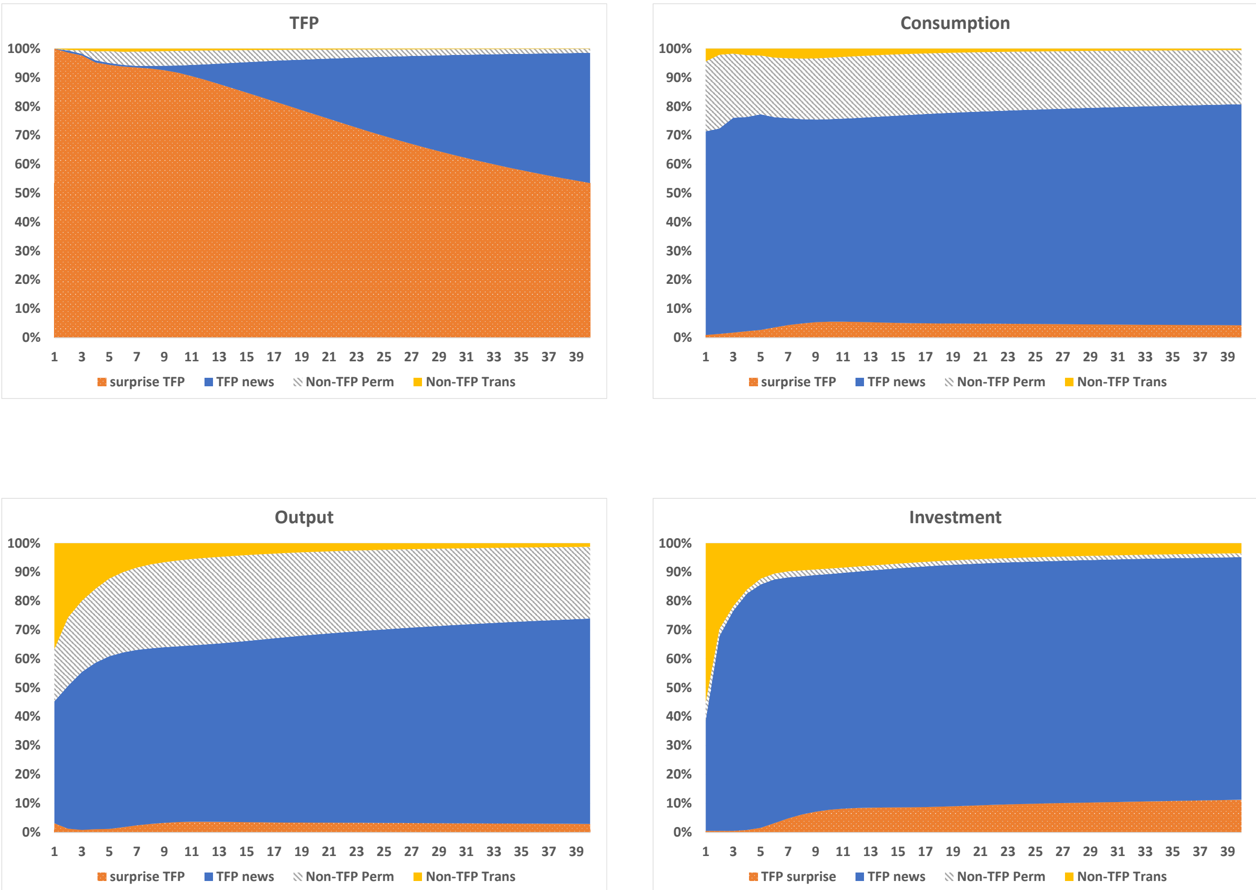

Figure 2: Forecast error variance decomposition for the 4-variable VEC model with TFP, consumption, output and investment, including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the contribution of the surprise TFP shock (dotted orange), the TFP news shock (blue), the non-TFP permanent shock (striped grey) and the non-TFP transitory shock (yellow).

4.2.2 Technology News shocks: the main source of economic fluctuations in the short run and the long run

Having discussed the sources of variation in TFP, we show the sources of variation of the macroeconomic variables up to 40 quarters ahead. The technology news shock is responsible for most of the unexplained variation of the macroeconomic quantities at any frequency (Figure 2). At the 5-10 year horizon, the share due to the news shock ranges between 65% and 84% for output, consumption and investment. A smaller portion is explained by the permanent non-technology shock at any business cycle frequency. The surprise technology explains around 3% at any frequency. Finally, the transitory non-technology shock accounts for some movements in the very short run. A similar leading role for the technology news shock is found also in Beaudry and Lucke (2010), Beaudry and Portier (2014) and Fève and Guay (2018). This performance of our identified technology news shock is remarkable, given that it competes with two additional shocks that are allowed to have permanent effects on the real quantities.

5 On the propagation of the technology news shock

Up to now, we have shown that there are three shocks that can induce positive comovement in real economic activity: the two technology shocks and the permanent non-technology shock. The technology news shock explains the bulk of the variation in the macroeconomic quantities at any frequency. The permanent non-technology shock is the second most important one. In this section we extend our core system with a fifth variable in order to understand why the news shock is the leading source of business cycle fluctuations among these three candidates. Therefore, we place at the center of our analysis the propagation mechanism of the news shock and how that distinguishes it from the other shocks. The fifth variable will be related to CPI inflation, the financial conditions and the monetary policy response, one at a time.

From the estimated VEC model that contains inflation we show that the technology news shock behaves like a demand shock. Then, we show that the propagation of the technology news shocks was relatively weaker before the 80's due to the weaker financial transmission accompanied by relatively more persistent monetary policy response. To illustrate this argument, we estimate a VEC model that contains the corporate Baa spread and the real rate as a fifth variable respectively.

5.1 The inflationary technology news shock and the non-inflationary non-technology shock

The first variable we consider important to include in our system is inflation. The reason is that, inflation can inform us about the potential nature of the shock, whether it is a supply shock or a demand shock.[20] The inflation (annual) rate is included in the vector error correction model like all other variables, but we restrict its coefficient in the cointegrated vector to be zero. Hence, we maintain the same cointegrating vectors as in the 4-variable system. Inflation is allowed to adjust to the long-run relationship among TFP, output, consumption and investment, but it is not allowed to affect it. Fève and Guay (2018) have followed a similar approach in their VEC model. Adding CPI inflation to the core system allows us to identify one more shock, which can serve as a robustness check for the results that we have already presented. The fifth shock is not allowed to affect any variable of the core system on impact, but is allowed to affect them in the long run.

$$B = \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & * & * & 0 \\ * & * & * & * & 0 \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \tag{7}$$

$$\Xi B = \begin{bmatrix} * & * & 0 & 0 & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & 0 & * \\ * & * & * & * & * \end{bmatrix} \tag{8}$$

We consider these identification assumptions conservative, because we allow for one more shock to impact all the variables permanently. In Figure 3 we show the responses of the variables after the five identified shocks.

After a surprise technology shock the response of inflation is negative for the first two quarters and then it becomes not significantly different from zero. Hence, the surprise technology shock looks indeed like a supply shock. The significance of our structural VEC model to identify well the surprise technology shock together with the technology news shock cannot be overlooked. In fact, Bouakez and Kemoe (2017) show that models based on Barsky and Sims (2011)'s identification of news shocks usually obtain a positive response of inflation after a surprise technology shock. The same is obtained in Gambetti et al. (2018) and Fève and Guay (2018). Given that the technology news shock is constructed to be orthogonal to the surprise technology shock, problems with the identification of the latter raise doubts about the identification of the former.

[20]We call supply shock the type of shock that causes negative comovement in quantities and prices and demand shock the one that causes positive comovement in quantities and prices.

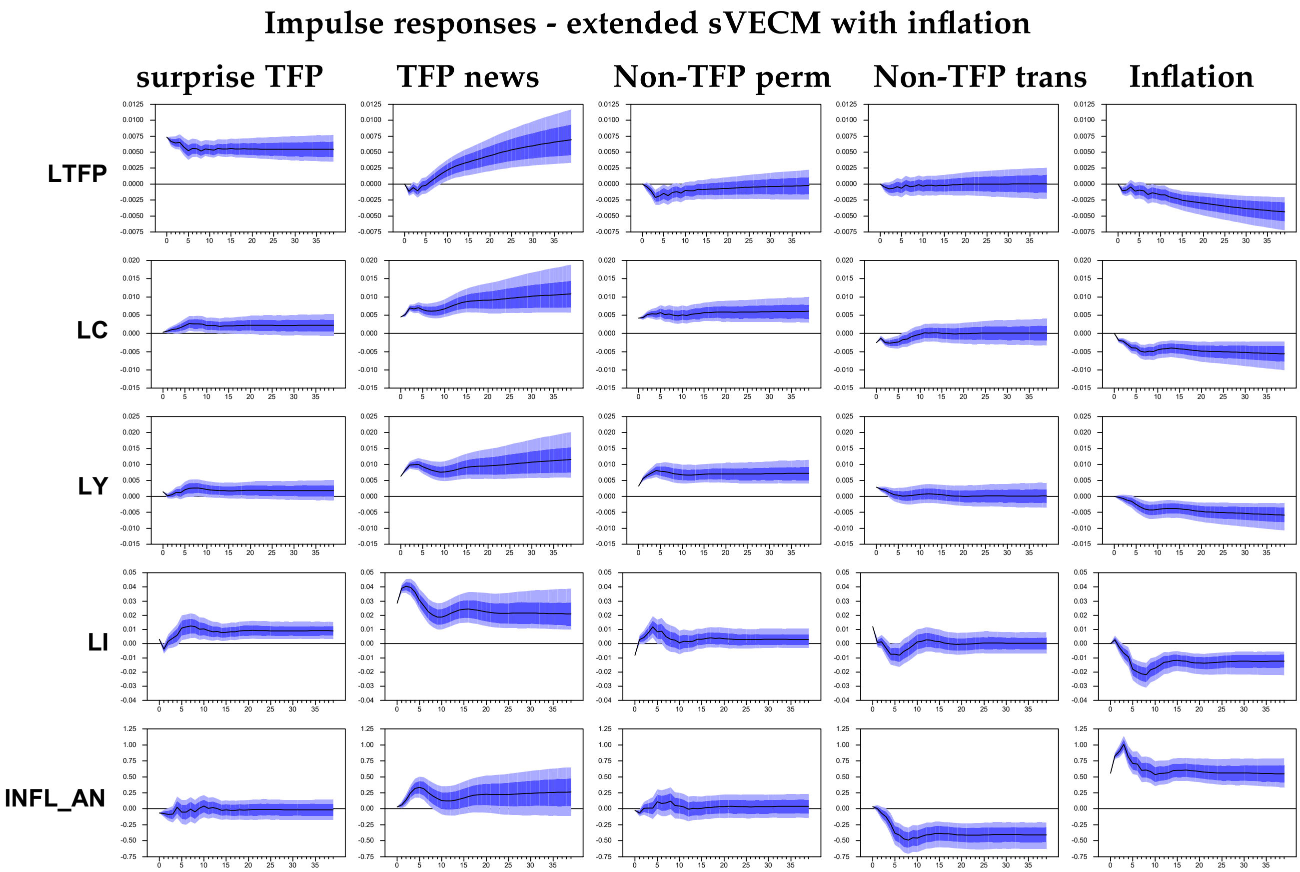

Figure 3: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and annualized inflation(INFL_ AN), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Inflation. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

After a news shock the response of inflation is weakly positive on impact, then it is hump-shaped and remains persistently positive. The literature on news shocks usually finds a negative response on impact and in the medium run (Barsky and Sims (2011), Görtz et al. (2016), Kurmann and Sims (2017), Gambetti et al. (2018)). In Bouakez and Kemoe (2017) this "disinflation puzzle" disappears and the response of inflation is not significant. The positive response we obtain indicates that our identified news shock behaves more like a demand shock rather than a supply shock. Finally, the second most important shock in the system is the permanent non-technology shock. The response of inflation after this shock is not significantly different from zero.

Due to the behavior of CPI inflation after a technology news shock and the permanent non-technology shock, we investigate whether these results are dependent on the measure of inflation that we use. Therefore, we replace inflation in the five variable VECM with the GDP deflator growth. We report these results in Figure B.1 in Appendix B. We confirm that the response of the GDP deflator growth is the same as for the CPI inflation after a technology news shock. However, the response is different for the non-technology permanent shock, becoming negative. This result implies that the third shock may be a supply shock that does not affect TFP in the long run, but affects output in the long run. At this point we conjecture that this shock may be the labor supply shock described in Shapiro and Watson (1988). In section 5.3 we report the response of hours worked and notice that the permanent non-technology shock increases hours worked and is its main driver in the long run.

We can conclude that the most important source of the business fluctuations is an inflationary technology news shocks and the second most important source is a non-technology non-inflationary shock.

5.2 When do technology news shocks matter?

In this section, we show that the financial transmission of the technology news shock is weak before the 80's. In addition, monetary policy does not restrain its propagation as much as before the 80's and compared to non-TFP shocks. To illustrate our argument, we consider a shorter sample period that spans from 1948:01 to 1979:01 in order to investigate different periods of the recent U.S. economic history. The choice of the end date for the short sample is not random. In July 1979 Volcker's era began as Volcker was appointed chairman of the Federal Reserve Board. The same month the U.S. Congress discussed the bill "Depository Institutions Deregulation and Monetary Control Act of 1980". This act gradually phased out restrictions for banks while also improving the Federal Reserve's control of monetary policy, by extending reserve requirements to depository institutions.[21] These two events are considered pivotal for the U.S. economic history after World War II. Finally, we estimate our model up to 2008:03 and find no significant impact of the Great Recession on the dynamic response of the identified shocks.

The response of technology news shocks across the three subsamples.

We revisit the core system and we estimate it across the three different sample periods. We keep the number of cointegration relationships and the number of lags constant across different sample periods. In Figure 4 we plot the responses of the four macroeconomic variables after a technology news shock. The response of TFP is different for the short sample compared to the extended samples. For the short sample TFP increases and stabilizes at a higher level after 10 quarters. In the extended samples TFP keeps increasing,

[21] For more information on the act, see McNeill and Rechter (1980). Strahan (2003) discusses the impact of the act on the real economy, due to the improved functioning of the banking system.

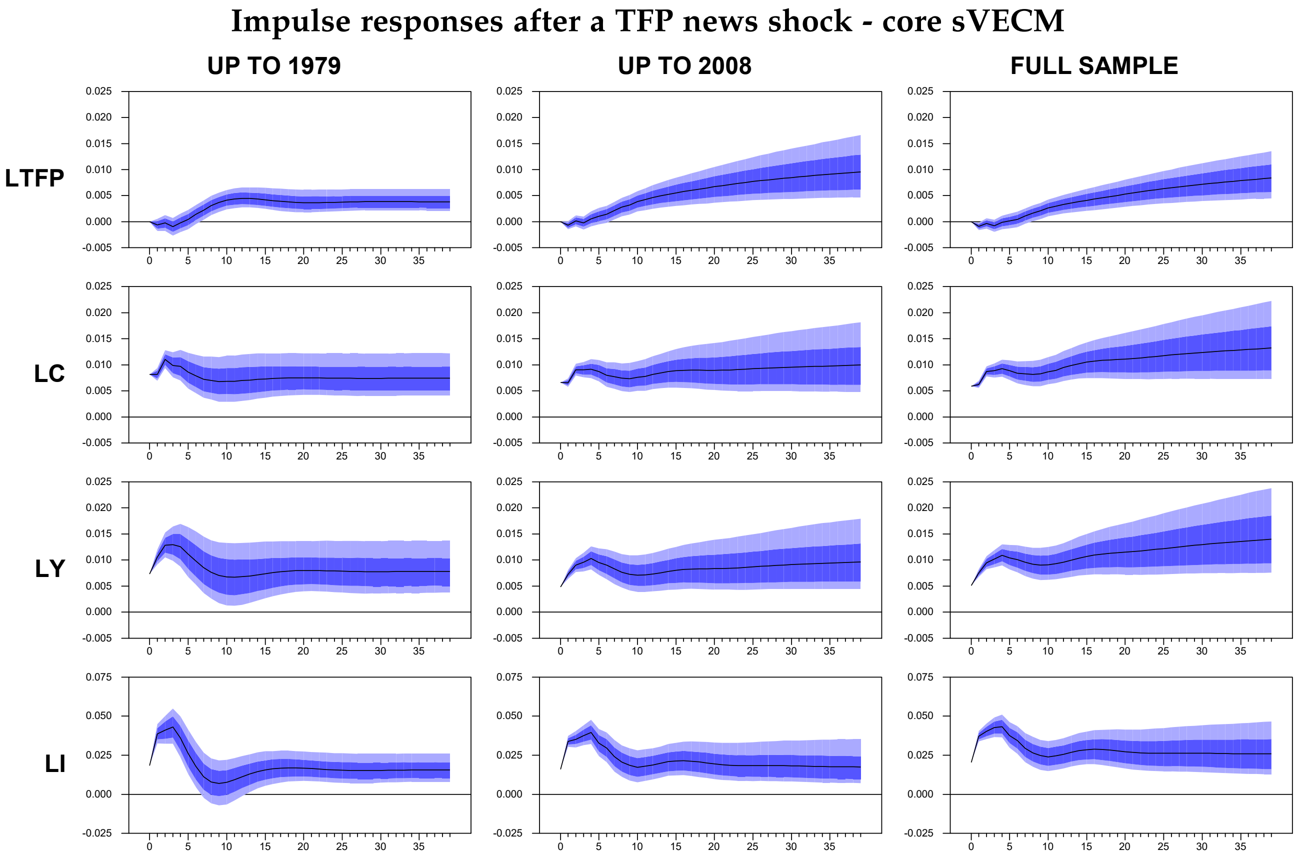

Figure 4: Impulse response functions for the 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY) and investment (LI), including 2 cointegrating relationships and 6 lags. In the rows we represent the variables and in the columns are the three different sample periods: 1948-1979q1, 1948-2008q3, 1948-2017q3. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

quarter by quarter. The response of the macroeconomic variables - consumption, output and investment - is similar across sample periods. To understand what drives the differences in the news shock, we look at the surprise technology shock and the permanent non-technology shock across different subsamples (see Figure B.2 in Appendix B). The response of the macroeconomic variables after the permanent non-technology shock does not change significantly. However, the strong response of the macroeconomic variables after a surprise technology shock that characterizes the short sample weakens substantially in the full sample. In Table 4 we display the forecast error variance decomposition of output for the full sample and the short sample. The bulk of the gains in forecast error variance decomposition for the technology news shock in the full sample comes from the weaker role of the surprise technology shock going from the short sample to the full sample.

Horizon	Surprise TFP		TFP News		Non-TFP Perm		Non-TFP Trans	
	full	short	full	short	full	short	full	short
4	1,0	2,2	57,6	63,6	25,6	33,9	15,8	0,3
8	2,9	14,0	60,7	46,2	29,0	39,6	7,4	0,2
24	3,2	32,4	66,6	25,0	27,7	42,4	2,4	0,1
40	2,9	36,0	71,1	20,2	24,8	43,8	1,3	0,1

Table 4: Forecast error variance decomposition of output in 4-variable model with TFP, consumption, output and investment, including 2 cointegrating relationship and 6 lags. "Full" refers to the full sample period, 1948:01-2017:03. "Short" refers to the period 1948:01-1979:01.

We still have to answer the question on why anticipated technological improvements became the dominant force of business cycle. For this purpose, we investigate the transmission of the shocks across the different sub-samples. Two natural candidates are available: the response of monetary policy and the financial transmission. We argue that the financing conditions allowed a stronger transmission of anticipations about future technological changes to the real economy.

The role of monetary policy in the propagation of technology news shocks

We estimate the five-variable model with the measure of inflation that we have presented in the previous section for the different sub-samples. For the sample that ends before the Great Recession, we do not observe substantial differences in the dynamic response of the variables across different shocks compared to the full sample. However, for the short sample the response of inflation is significantly positive for the first 10 quarters after a permanent non-technology shock (Figure B.3 in Appendix B). In the full sample this was not the case. At the same time, the response of inflation after the technology news shock differs across subsamples (Figure 5). Inflation falls not only on impact, but also in the long-run in the short sample. Hence, the news shock up to 1979:01 behaves like a supply shock. Does this different response of inflation imply a substantially different response of monetary policy? To shed light on this question, we estimate a five-variable system that includes the core variables and a measure of real rate. The real rate is defined as the difference between the Treasury 3-month bill rate and current inflation.[22] Using current inflation to deflate the nominal rate means that we are assuming that current inflation is a good predictor of next period's inflation. Since the next period for us is one quarter ahead, it is a reasonable assumption. The identifying assumptions for the fifth shock, the shock to the real rate, are the same as the ones used for inflation.

[22]Our choice of Treasury bill instead of the Federal funds rate is driven by the larger data series availability, since the series of Fed funds rate starts in 1954. In our case losing 7 years of observations is really important, because we estimate a long-run relationship and need as long time series as possible.

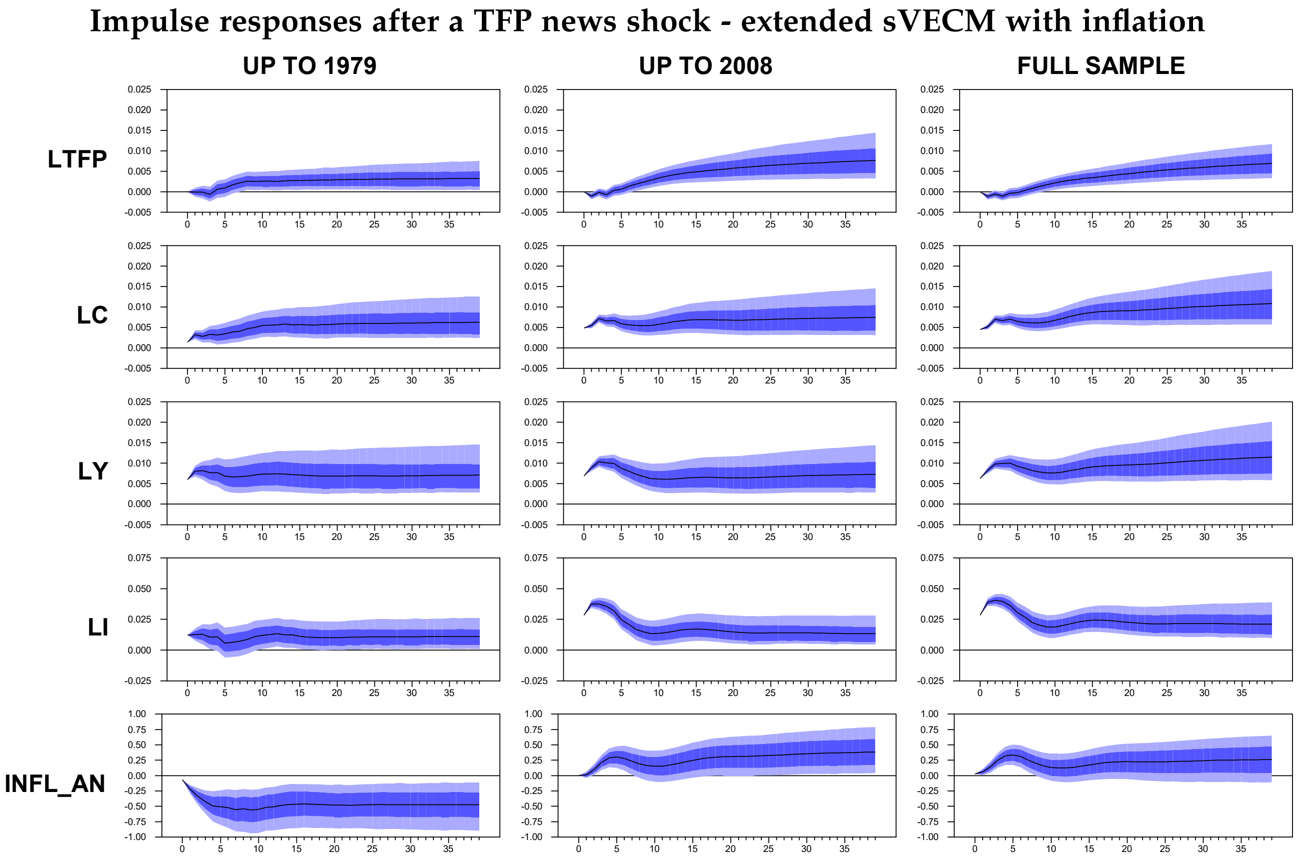

Figure 5: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and annualized inflation(INFL_ AN), including 2 cointegrating relationships. In the rows we represent the variables and in the columns are the three different sample periods: 1948-1979q1, 1948-2008q3, 1948-2017q3. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

From Figure 6 we see that the response of the real rate after a positive technology news shock is always positive on impact, but it is more persistent in the short sample, while it's short-lived in the second sample. Hence, in the short run the response of monetary policy to the news shock is equally contractionary, incentivizing a saving behaviour. Savings can become productive investment with a well-functioning financial intermediation. However, monetary policy has a different relation with inflation across the sample periods. In the short sample the increase in real rate coincides with a decrease in inflation, while in the full sample inflation increases. These different responses indicate that the monetary policy was more concerned with fighting inflationary pressures from the 80's rather than before, as argued in Clarida et al. (2000), Orphanides (2003). This result stands in contrast to the findings in Gambetti et al. (2018), where the Federal Reserve is found to be more restrictive towards inflation before the 80's rather than afterwards.

Figure B.4 and B.5 in Appendix B report the response of the real rate to all the shocks for the full and the short sample, respectively. The response to the surprise technology

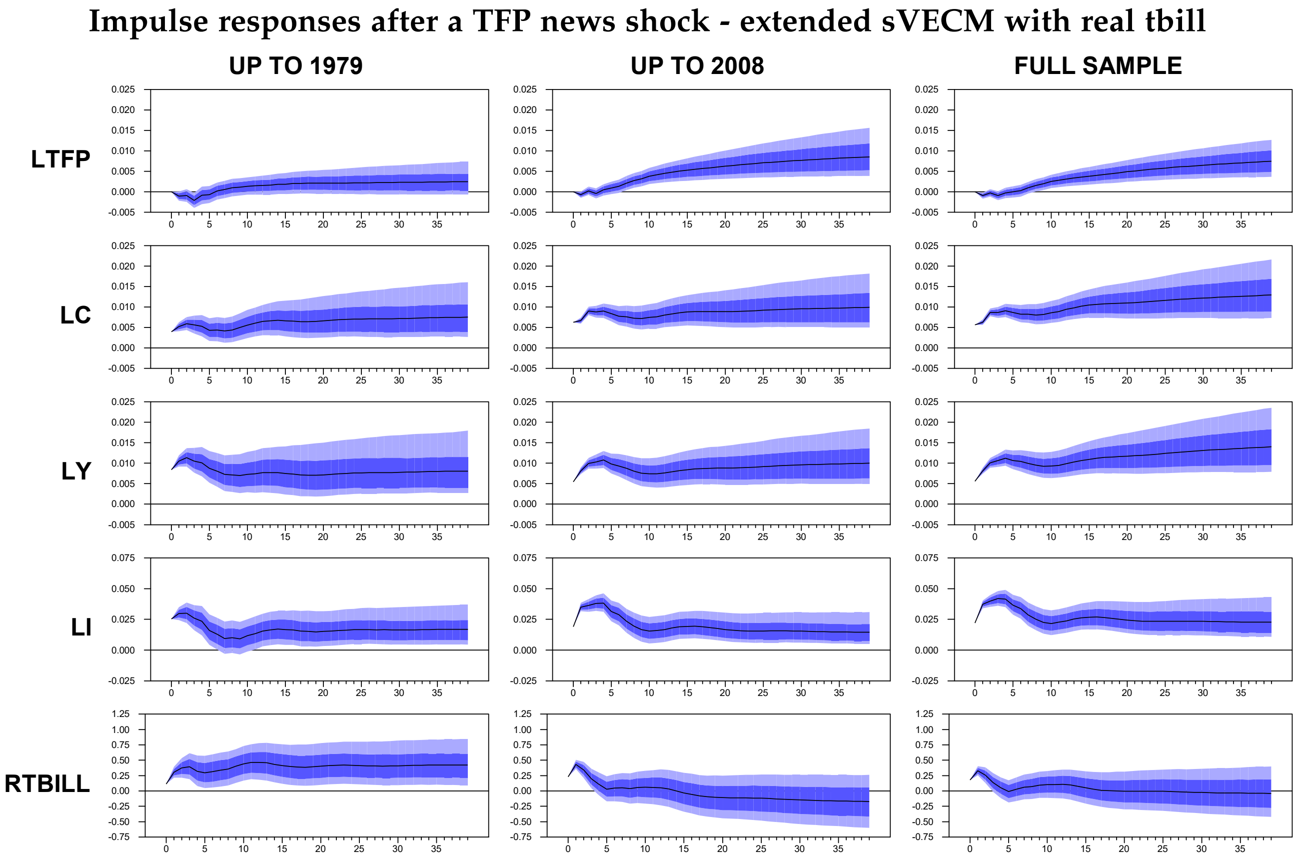

Figure 6: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and real treasury bill (RTBILL), including 2 cointegrating relationships. In the rows we represent the variables and in the columns are the three different sample periods: 1948-1979q1, 1948-2008q3, 1948-2017q3. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

shock is not significant in both cases. Instead, the response to a positive non-technology permanent shock is contractionary and looks more persistent from the 80's.

The role of financial deregulation for the propagation of technology news shocks.

Based on the response of the real rate in the short run after a technology news shock, we cannot find differences across different sample periods. However, we find that the monetary policy response is more persistent before the 80's after a technology news shock. Thus, it is difficult to argue that the monetary policy response can explain the weaker transmission of the news shock before the 80's. In the next paragraphs we show that the financial transmission channel was substantially weaker before the 80's and that might have contributed, in connection with the monetary policy response, to the relative unimportance of these shocks. To demonstrate our argument we extend the core system by including the corporate Baa spread variable. For the identification of the fifth shock we use the identifying assumptions used for inflation. These assumptions allow us to identify a financial shock that can potentially affect permanently all the variables in the system. The assumptions that a financial shock affects the macroeconomic variables with a delay is used also in Gilchrist and Zakrajšek (2012) and Walentin (2014).

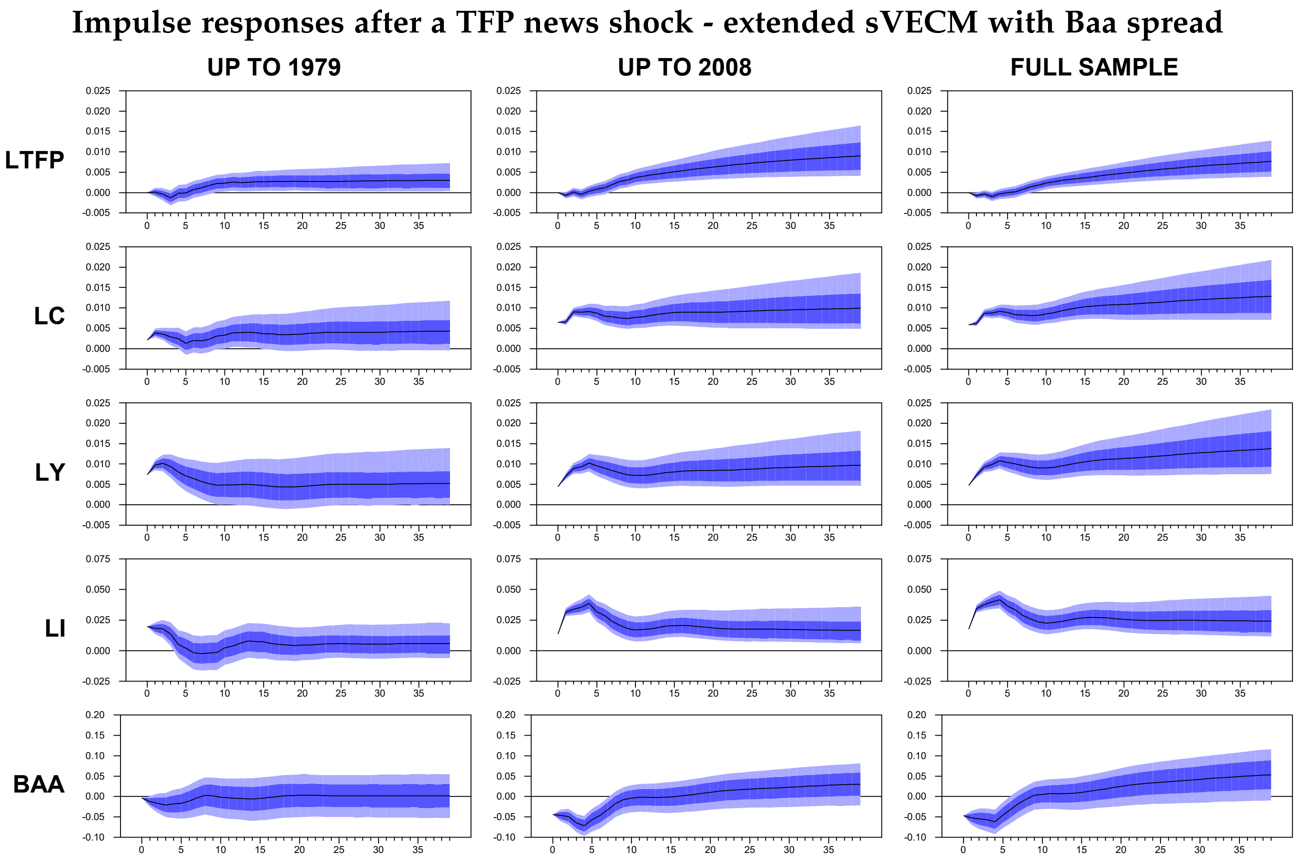

Figure 7: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and Baa corporate spread (BAA), including 2 cointegrating relationships and 6 lags. In the rows we represent the variables and in the columns are the three different sample periods: 1948-1979q1, 1948-2008q3, 1948-2017q3. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

In Figure 7 we show that after a positive news shock the Baa corporate spread does not respond in a significant way in the short sample. Instead, for the extended sample periods the response of the corporate Baa spread on impact is negative and stays significantly negative for around 8 quarters. The negative response of the corporate spread indicates an improvement of the financing conditions. That would have allowed the technology news shocks to propagate better so as to have a larger effect on the real variables. It is worth pointing out that the response of the Baa spread turns to be insignificant at the point of the realization of technology news. Indeed, this is also the quarter when the real rate turns to be insignificant. All the important actions needed for the propagation of news shock happen before its realization. When we look at the dynamic response of the Baa spread after the permanent non-technology shock, we do not see differences across the two samples (Figure B.6 and B.7 in Appendix B). That can explain why we have not found any differences in the responses to this shock in the core four variable system across different sub samples. Summing up, we argue that the technology news shock is the driving force of the business cycle mostly from the 80's, due to its stronger propagation through the financial markets.

Gambetti et al. (2018) studies the transmission of the news shock in two different subsamples. They find that the news shock causes an increase in interest rates and corporate spread before the 80's and a fall afterwards. Hence, a common finding between their paper and ours is that after a positive news shock financial conditions were more favorable from the 80's. However, we find a similar short-run increase in the real rate, independently of the sample period, while inflation decreases before and increases afterwards. Our proposed explanation for the different role of the news shock is the improved financial intermediation after the regulatory reforms of the 80's, instead of the different response of monetary policy that Gambetti et al. (2018) find.

5.3 The response of hours worked after technology shocks

The literature on news shock is divided regarding the response of hours worked after a news shock. Based on the original work by Beaudry and Portier (2006), hours worked should increase after a news shock, as found also in Beaudry and Lucke (2010). Another body of the literature on news shocks (Barsky and Sims (2011), Forni et al. (2014), Kurmann and Sims (2017)) finds that hours fall significantly on impact, thus pointing to the conclusion that the news shock can not be the main driver of the business cycle. We include hours worked as a fifth variable in the core system as done before. The fifth shock is not allowed to affect the TFP and real macroeconomic quantities in the short run, but can do it in the long run. Figure 8 shows that hours worked increase significantly on impact and remain positive after a positive news shock, independent of the the sample period. This positive response is in accordance with our message that the major business cycle shock is a shock to expectations about future technology and it behaves like a demand shock.

In the first column of Figure B.8 we see that the response of hours worked after a surprise technology shock is negative on impact and turns positive after few quarters, although insignificantly. There is a large literature (see Ramey (2016)) that discusses what is actually the "right" response of hours worked after a technology shock. In fact, the response depends often on whether hours worked is assumed to be stationary or not, which is also the topic of the debate. Lindé (2009) concludes that hours worked fall after a technology shock if the series enters the VAR system in first difference and increase if the series enters in levels. Canova et al. (2010) show that hours worked fall after a technology shock, when

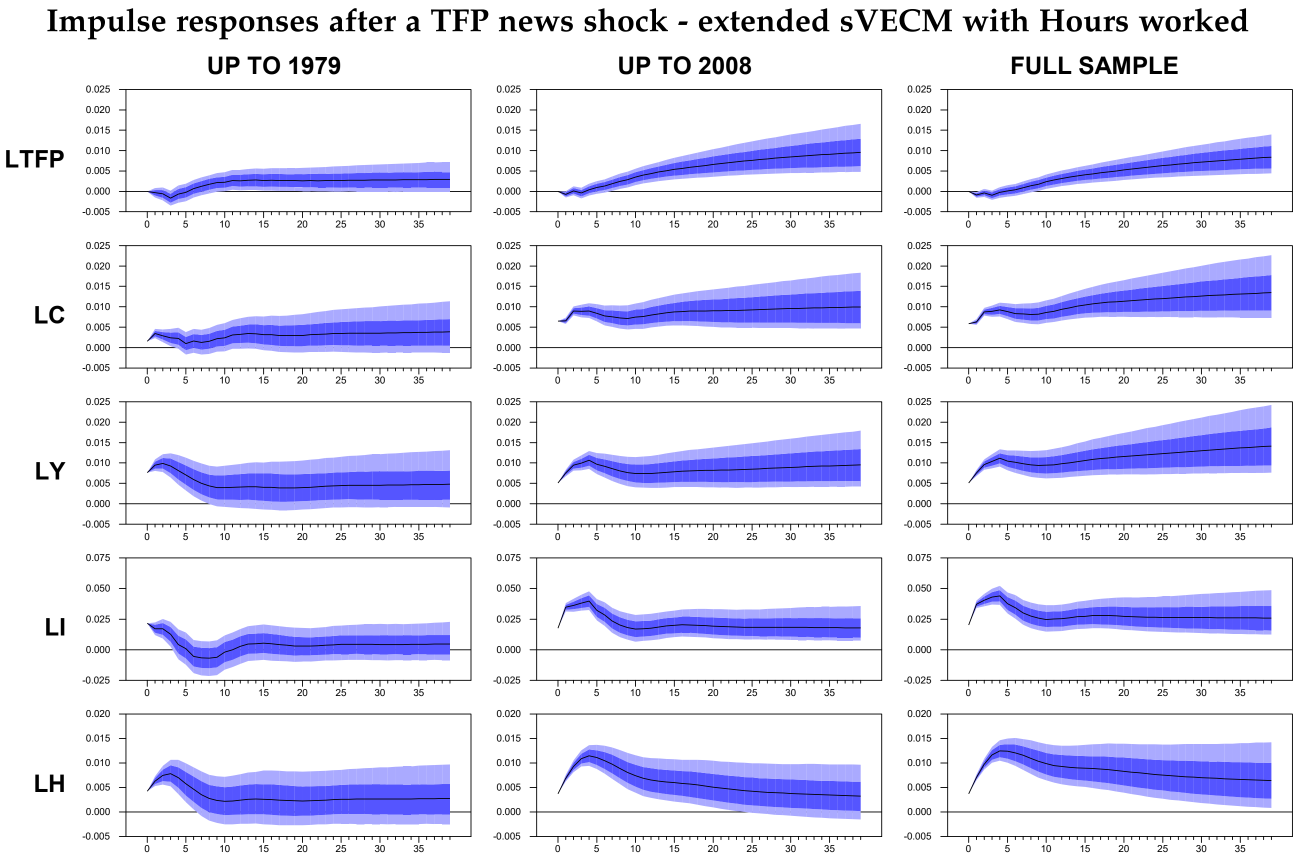

Figure 8: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and hours worked (LH), including 2 cointegrating relationships and 6 lags. In the rows we represent the variables and in the columns are the three different sample periods: 1948-1979q1, 1948-2008q3, 1948-2017q3. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

the long cycles in the series are well accounted for. We confirm Francis et al. (2014)'s result with a different identification strategy, based on the maximization of the FEVD at a long but finite horizon. Hence, our result is in line with the recent literature on technology shocks and shows that we have correctly identified this shock. Finally, the response of hours worked after the second most important source of business cycle variations, the non-technology non-inflationary shock, is positive on impact and has a persistent positive effect, similarly to the response after a news shock. Combining this results with the inflation response, the technology news shock behaves like a demand shock.

6 Additional results

In this section we report the results of additional analysis that gives more insight and serves as robustness of our findings. First, we introduce the so-called sentiment and uncertainty shocks. Second, we allow for the identification of a TFP measurement error shock, to capture possible measurement problems related to the adjusted TFP series. Third, we test for non-fundamentalness, that means testing for the likelihood that our core model contains enough information to let us recover the structural shocks. Overall, our results are robust to the inclusion of the additional shocks and do not present serious non-fundamentalness issues. Fourth, we show the choice of the sample period for the analysis may explain the lack of consensus on the role of the news shock in the literature. Finally, we discuss more in detail the possible nature of the permanent non-technology shock we have identified.

6.1 News, confidence and financial uncertainty

In the last years the research has focused on different types of shocks as drivers of the business cycle, that are uncorrelated to current fundamentals. One such case is the sentiment shock. Sentiment shocks represent changes in expectations about future developments that actually never materialize. Angeletos and La'O (2013) and Angeletos et al. (2018) are two prominent examples of models where sentiment shocks have a leading role of the business cycle, generating waves of optimism and pessimism unrelated to fundamentals. Barsky and Sims (2012) argue that news shocks are more important than noise or sunspot shocks. Fève and Guay (2018) have identified news and sentiment shocks in a VAR model, where the news shocks turn out to be the most important shocks.

A second type of shock unrelated to fundamentals is the uncertainty shock. This shock captures the exogenous change in the volatility of forecast errors of macroeconomic or financial aggregates.[23] Increases in uncertainty shocks are found to be contractionary for the economy in Jurado et al. (2015).

In order to assess the robustness of our results, we allow for the introduction of sentiment and uncertainty shocks, one at a time. We extend our core model to include a measure of confidence, like the one used in Fève and Guay (2018), or a measure of financial uncertainty to recover sentiment and uncertainty shocks. Notice that the series of confidence and uncertainty are only available from 1960, hence we compare the results with our core model estimated from 1960.

We introduce the aforementioned variables as done before with inflation, spread and the real rate. The variables enter the VEC system, but not the cointegrating vector. To identify the sentiment shock and the uncertainty shock we use the same restrictions used in the previous 5-variable systems. Both shocks are assumed to be orthogonal to TFP and the macroeconomic variables on impact. The restrictions are in line with Fève and Guay (2018) and Jurado et al. (2015). In fact, we find that the sentiment shock is the main driver

[23] We consider this type of uncertainty shocks because we use the data by Jurado et al. (2015), but other interpretations of uncertainty exist.

of confidence (80% of FEVD after 40 quarters), while the uncertainty shock is the main driver of financial uncertainty (45% of FEVD after 40 quarters).

Impulse responses after a TFP news shock -
Comparison between core sVECM and extend sVECM's with confidence and uncertainty.

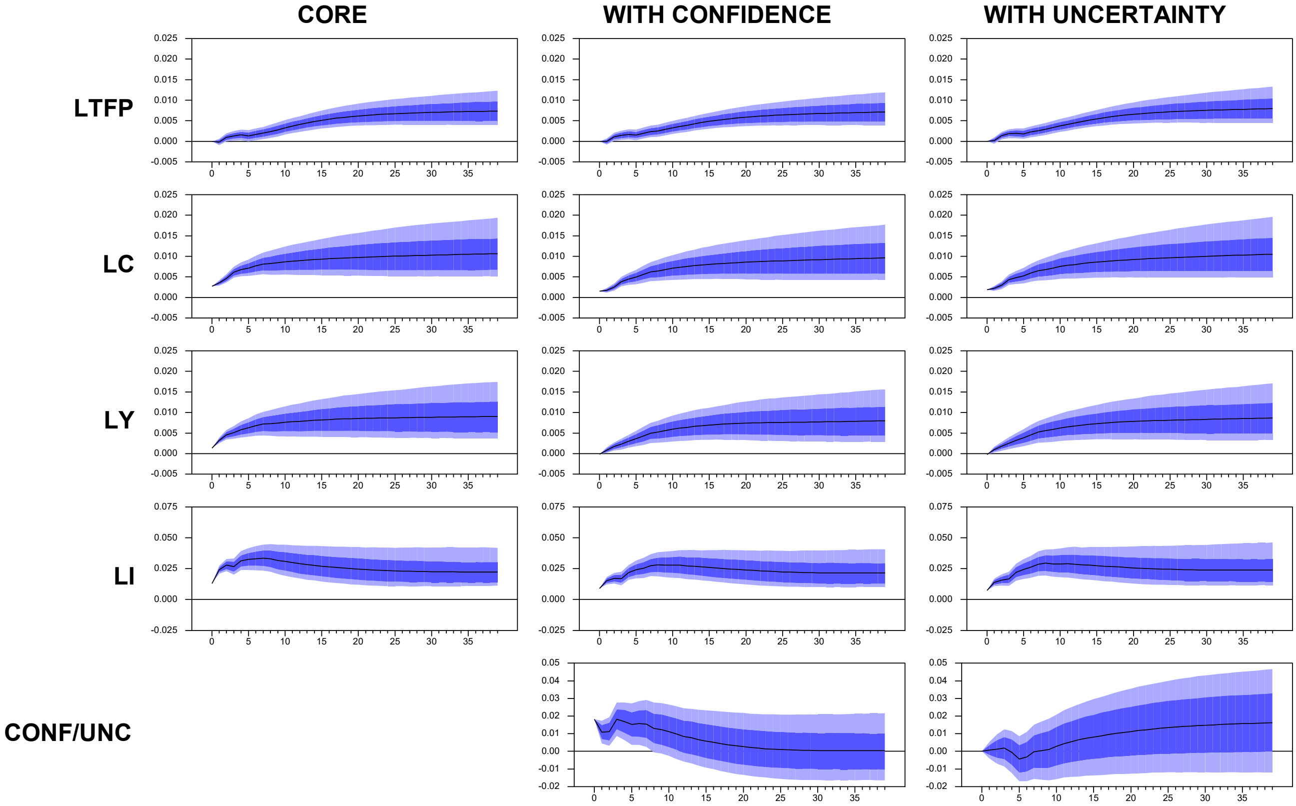

Figure 9: Impulse response functions after a technology news shock for three different structural VEC models for the period 1960q3-2017q3. Core (column 1): 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and hours worked (LH), including 2 cointegrating relationships and 6 lags. Core sVECM extended with confidence (column 2). Core sVECM extended with uncertainty (column 3). Rows represent the variables. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Figure 9 reports the comparison of the response to the news shock for the core system, the model with confidence and the model with uncertainty.[24] We notice that confidence rises in the short run after a news shock, as found in Barsky and Sims (2011), Beaudry and Portier (2014) and Fève and Guay (2018). A positive shock to sentiment brings about a boom in the economy. On the other hand, uncertainty is not affected by the news shock in the short run, but increases in the long run, although not significantly. The effect of the news shock on the macroeconomic variables does not seem to change in the extended model. At the same time, the share of forecast error variance decomposition explained

[24] Figure B.10 and B.11 in Appendix B show the responses of all variables to all shocks identified in the systems with confidence and uncertainty.

by the news shock is marginally affected. While the news shock explains around 40% of FEVD of output at the 10-year horizon in the core model for the period 1960-2017, the share decreases to 30% in the model with confidence and 33% in the model with uncertainty. The share of non-technology permanent shocks goes from around 50% to 42% in the extended models. The sentiment shocks explains 22% of the FEVD of output at the 10-year horizon, while the uncertainty shock has a share of 16%. Overall, the introduction of the sentiment shock and uncertainty shocks has a moderate impact on the behaviour and the importance of the news shocks. Hence, our results are robust to the inclusion of those shocks.

6.2 News and TFP measurement error shocks

The key variable for the identification of technology shocks is the measure of TFP. The most widely accepted measure of adjusted TFP is the one proposed by Fernald (2014), although problems with the adjustment of the series for capital utilization have emerged recently. In this section we analyse how sensitive are our results to the possibility that adjusted TFP is not well measured.

Sims (2016), Cascaldi-Garcia (2017b) and Kurmann and Otrok (2017) show how different vintages of the measure of TFP by Fernald (2014) affect the identification of technology news shocks. In particular, the important change seems to be the correction of the measurement of adjusted TFP undertaken in March 2014 by Fernald. Bouakez and Kemoe (2017) and Kurmann and Sims (2017) have proposed modifications to the identification strategy of technology news shocks by Barsky and Sims (2011), that makes the results robust to measurement errors. Bouakez and Kemoe (2017) introduce an additional technology shock, to account for TFP measurement errors, while Kurmann and Sims (2017) modify the assumption that TFP is orthogonal to technology news shocks on impact.

We consider the following identification for the four-variable VEC model. We allow the fourth shock to affect TFP on impact but not in the long run. Moreover, due to the two cointegrating relationships, this shock is implicitely assumed not to affect all the macroeconomic variables in the long run.

$$B = \begin{bmatrix} * & 0 & 0 & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \tag{9}$$

$$\Xi B = \begin{bmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & 0 & 0 \end{bmatrix} \tag{10}$$

In this way we have three technology shocks: the first one can affect TFP in the short run and the long run; the second one can affect TFP only in the long run; the third (that is the fourth in the system) can affect TFP only in the short run. Hence, now the last two shocks are both temporary and we have ruled out the possibility of a permanent non-technology shock.

Figure 10 reports the impulse responses of the model. The news shock still affects TFP in the long run, as much as the surprise technology shock, although the response of TFP to the technology news shock now turns negative for the first quarters. The news shock is still the main driver of the business cycle, generating comovement among consumption, output and investment and accounting for most of their forecast error variance decomposition. Hence, our results are robust to the presence of TFP measurement errors in the series of adjusted TFP.

6.3 Testing for non fundamentalness in the core sVECM

The work by Beaudry and Portier (2006) is based on a small-scale VEC model, with 2 and up to 4 variables. Due to the small size of the model, Forni et al. (2014) have raised the issue of non-fundamentalness (see also Beaudry and Portier (2014) for a review on the topic), arguing that the news shock cannot be recovered in a small-scale system. The problem of non-fundamentalness is related to the case when the econometrician has less information than the agents in the economy and thus cannot recover the structural shocks. This is more likely when the econometrician tries to estimate technology news shocks, because the economic agents may have more information about the future fundamentals. To overcome this problem, the identification of the news shock needs to rely on a variable that contains expectations about the future. We have used consumption and we have shown that it is indeed useful to recover the news shock. Here we will show that our VEC model does not suffer from serious non-fundamentalness issues.

We conduct the test of non-fundamentalness suggested by Forni et al. (2014) and further enriched by Beaudry et al. (2016). The test consists on regressing the shock of interest on the lags of some factors constructed from a large set of macroeconomic variables. If the shocks are orthogonal to the factors, the shock identified is fundamental. Moreover, Beaudry et

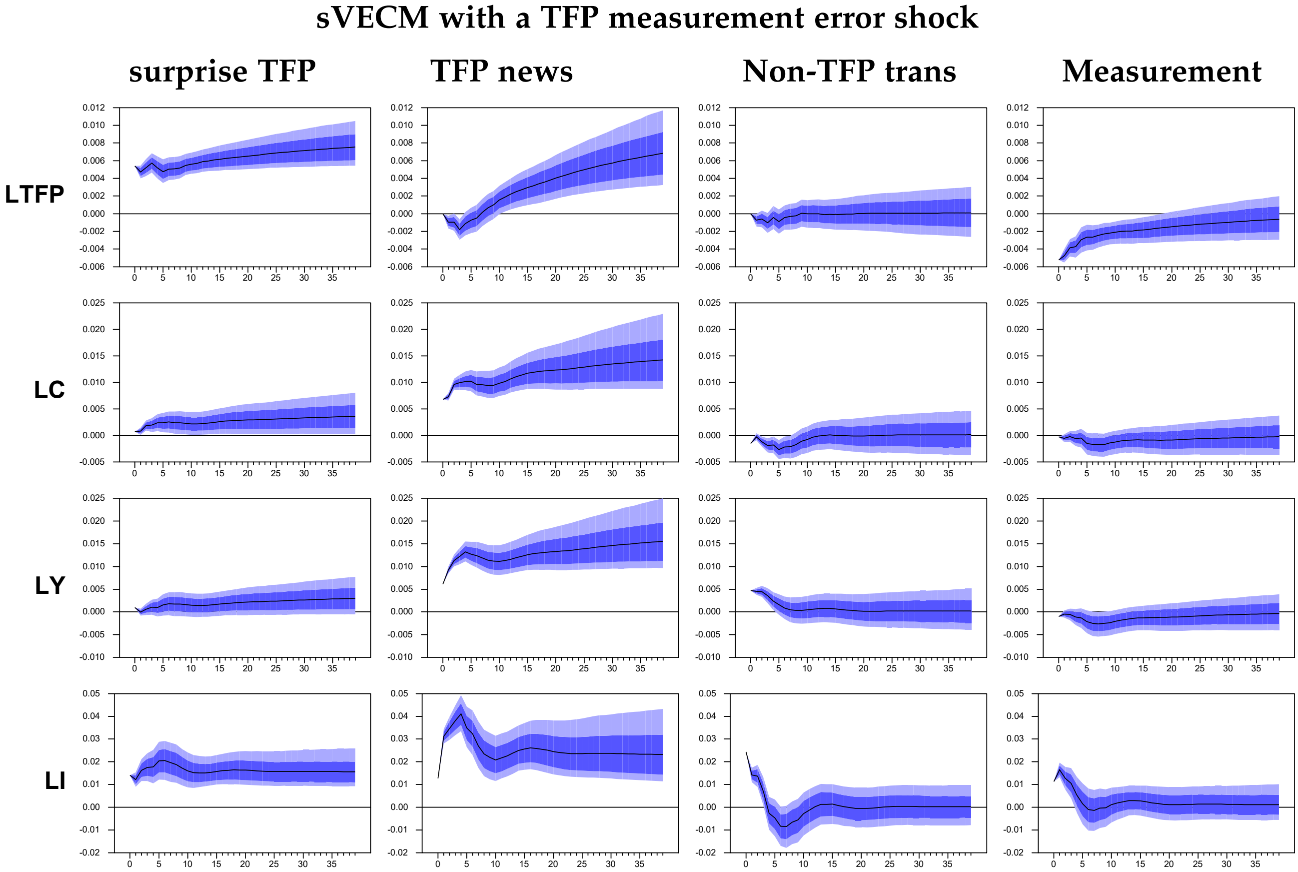

Figure 10: Impulse response functions for the 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY) and investment (LI), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the four shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP transitory, Column 4: TFP measurement error. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

al. (2016) show that the R-squared of the regression contains information about how serious is the problem of non-fundamentalness. Applying the test to the shocks identified by Beaudry and Portier (2006), Beaudry et al. (2016) find that the tests reject the hypothesis of orthogonality for 1 and 4 lags of the factors, but the values of R-suqared are low, ranging from 0.03 to 0.21. Following Fève and Guay (2018), we use the eight Ludvigson-Ng macroeconomic factors, based on Ludvigson and Ng (2009)[25]. Since the factors are available only from 1960, we estimate our VEC model for the same period for consistency reasons, although, as discuss below, a longer sample period is important for the long-run relationship we estimate. We consider our core four-variable VEC model and the model augmented with inflation. Regressing the identified news shocks on the lags of the factors, we find that we reject the hypothesis of orthogonality (based on the F-test) at 5% level for the first lag of the factors. On the other hand, we cannot reject the hypothesis of orthogonality

[25]The data are available for download at https://www.sydneyludvigson.com/data-and-appendixes/.

at 5% level for more lags. Moreover, the R-squared of the regression with the first lag is 0.095. Similar results, albeit with smaller R-squared (0.084) are obtained for the news shock identified with the 5-variable VEC model. Hence, the problem of nonfundamentalness is not a significant issue in our model.

6.4 Reconciling different views about the news shock: On the sample period choice

The literature on news shocks has not managed to agree on whether the news shock is the main driver of the business cycle (see Beaudry and Portier (2014) and Ramey (2016) for discussion). The problem can be summarized as follows. The part of the literature on news shocks that follows Beaudry and Portier (2006)'s paradigm argues that technology news shocks are the driving force of the business cycle, because they induce positive comovement among the real macroeconomic quantities and hours worked. Another strand of the literature, mostly based on Barsky and Sims (2011)'s approach, finds that news shocks cannot be the driver of the business cycle because they do not generate positive comovement in the main macroeconomic variables.[26] We show that the choice of the sample period might have played an important role for the differences between the two seemingly contradictory findings. Once we estimate our model for the sample period most used in the second strand of the literature, we obtain a different role for the news shock. Following Barsky and Sims (2011), most of the following literature start the analysis in the first quarter of 1960. We estimate the core model for the period 1960:01-2007:04.

In Figure 11 we notice that the response of the macroeconomic variables after a technology news shock is not as strong as before. In fact, even the output response is close to zero. Moreover, TFP responds positively to the technology news shock directly after the first quarter, as in Barsky and Sims (2011) and not in line with the theory of a delayed diffusion process. Looking at the forecast error variance decomposition, the technology news shocks is not the most important driver of the business cycle. However, to obtain such a result we have excluded the period before the 60's, that is a period of generally low growth, and the period during and after the Great Recession, that is again a period of low growth. Such sample selection implies that we are overestimating the potential growth rate of the U.S. economy with our VEC model. The implications from this can be seen in the historical decomposition of the level of output (Figure 12). If one believes that 1960-2007 is the "right" sample period, one has to accept that for almost the whole 80's the U.S. economy was operating far below its potential output. At the same time, the potential TFP

[26] Additionally, Ramey (2016) shows that the news shocks identified with different approaches are basically uncorrelated with each other.

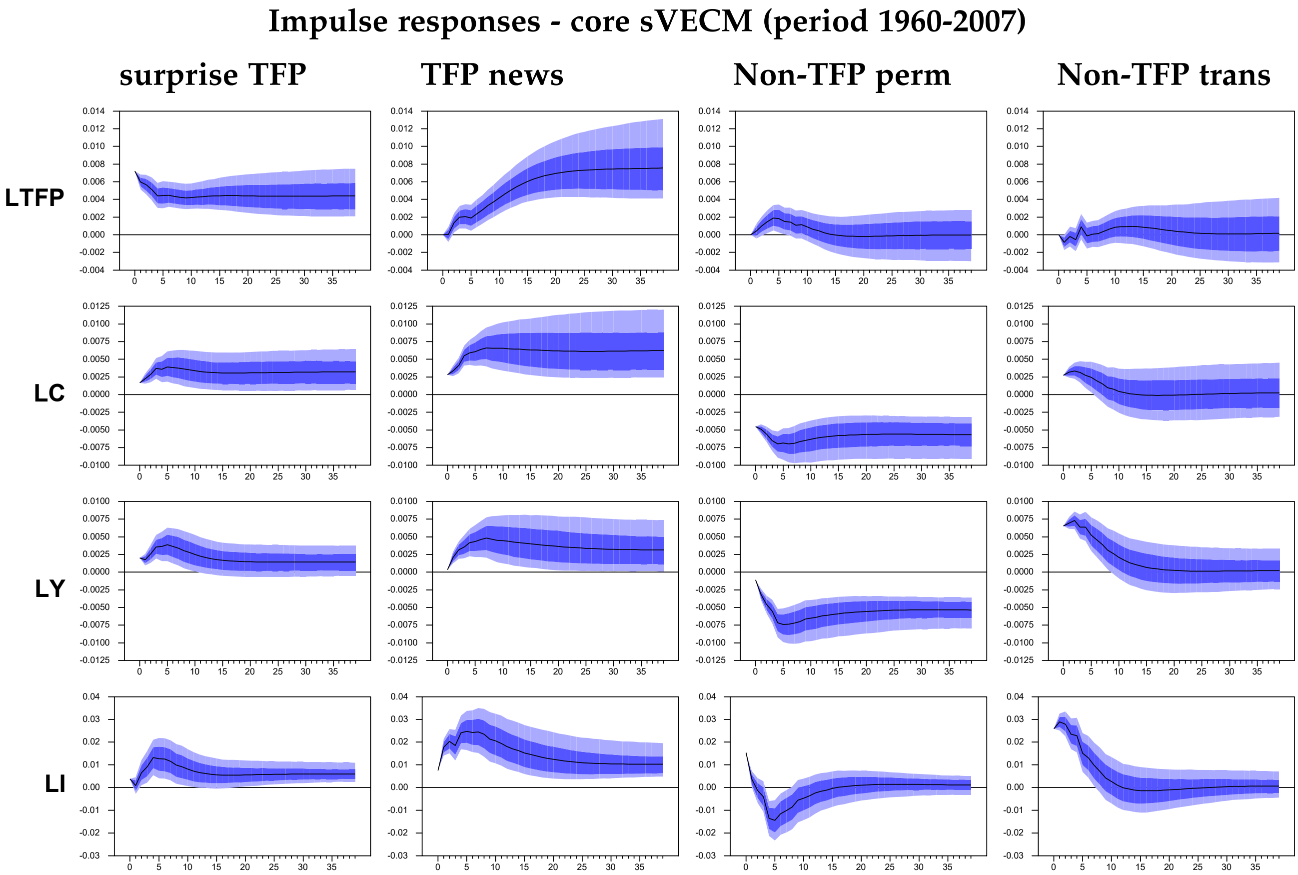

Figure 11: Impulse response functions for the 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY) and investment (LI), including 2 cointegrating relationships and 6 lags. Sample period is 1960-2007. The graph displays the variables responses (rows) to the four shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

growth does not change so much going from the shorter to the full sample. This upward bias in GDP growth potential compared to TFP growth potential affects mostly the shock that links future technology changes with macroeconomic quantities. Hence, the shorter sample gives more importance to a non-technology force of the business cycle. That might explain why other studies find other shocks as driving forces. From our point of view, the longer sample period allows to better estimate the long-run relationship among the core variables.

Our result is not surprising and it actually complements the findings in Cascaldi-Garcia (2017a). Based on Barsky and Sims (2011)'s identification of news shocks, he finds that the response of the macroeconomic variables after a technology news shock is sensitive to the sample period chosen. He shows that the impact response of hours worked even switches sign. Based on our identification, the impact response of hours worked and other variables does not switch sign, but it is weaker than in the full sample. However, as we have argued,

Historical decomposition: Output - Barsky and Sims (2011) sample period

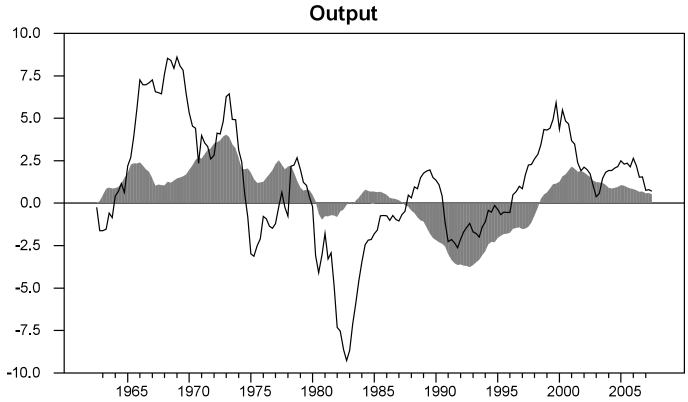

Figure 12: Historical decomposition of output from the 4-variable VEC model with TFP, consumption, output and investment, including 2 cointegrating relationships and 6 lags. Sample period is 1960-2007. The black line represents the variation from the baseline projection and the grey area is the contribution of the news shock.

one should trust more the results coming from the longer sample rather than the shorter one, especially for cointegrated systems.

6.5 Can the permanent non-technology shock be a labor supply shock?

In table 4 we have shown that the vast majority of business cycle variation for output for the post World War II period can be accounted for by the technology news shock. However, a small but non negligible share of the unexplained variation in output is accounted for by the non-technology shock that has a permanent effect on output. In this section we shed light on the nature of this shock.

The third shock of our core model is identified as a non-technology shock because it cannot affect technology neither in the short run, nor in the long run. However, it is distinguished from the fourth shock because it can affect output, consumption and investment at any horizon. Indeed, we have found that a positive non-technology permanent shock affects positively output in the long run (Figure 1), has a non-significant impact on inflation (Figure 3), but it decreases the GDP deflator growth (Figure B.1). Moreover, it increases the real Tbill rate (Figure B.4) and hours worked (Figure B.8).

The permanent non-technology shock is not the main driver of the business cycle in the full sample period, but it seems to have been as important as the surprise technology shock and the technology news shock before the 80's (Figure B.2). Up to the 80's, this shock explains almost all the variability of hours worked in the long run (Figure B.9). We conjecture that our identified non-technology permanent shock looks like the labor supply shock in Shapiro and Watson (1988). They identify the labor supply shock as the only shock that can affect both output and hours in the long run, while the surprise technology shock can affect only output in the long run. They find that the labor supply shock is the main driver of the business cycle for the period 1951-1987. Unlike Shapiro and Watson (1988), we have identified the labor supply shock without imposing restrictions on hours worked, but instead imposing restrictions on technology (TFP). Hence, we have identified it indirectly and found similar results in a similar sample period. The results in the extended sample, though, show that the labor supply shock has lost importance for the business cycle.

7 Conclusion

This paper argues that the main source of business cycle fluctuations is a technology news shock that acts like a demand shock. Anticipated shifts in technology generate strong positive correlation between output, consumption and investment, and a weak positive correlation between these quantities and inflation. The technology news shock has become the most important driver of the business cycle from the 80's, coinciding with the era of financial deregulation. This shock was as important as the unanticipated technology shock and a non-technology permanent shock before the 80's. We attribute the relative increased importance of the technology news to the improved propagation through the financial sector. The response of corporate spread to the technology news shock is null before the 80's and negative afterwards, implying easing of financing conditions. Our preferred explanation is that the financial deregulation of the 80's improved the financial transmission of the technology news shock. At the same time, the monetary policy response was contractionary, no matter the sample period. The response of the real rate to the technology news shock from the 80's, though, is less persistent than before the 80's and with respect to the response to other non-technology shocks.

For our analysis we have utilized vector error correction models, identifying two technology and two non-technology shocks with zero short and long-run restrictions for our baseline model. The identifying assumptions for the technology news shock are based on the prominent work by Beaudry and Portier (2006), but we modify and enrich it in important dimensions. We use the measure of consumption instead of stock prices to identify news shocks. Moreover, we extend their model to have enough information as to overcome non-fundamentalness problems and identify other shocks that can compete with technology shocks.

Our identified technology news shock is in line with the benchmark New Keynesian model, because it induces an increase in economic activity and an increase, albeit weak, in inflation. However, to reproduce the rich dynamic responses of the variables, one may need to incorporate additional features in the baseline model. Moreover, the identified role of the financial propagation of the shock provides support for DSGE models with financial amplification channels, like the one estimated in Görtz and Tsoukalas (2017).

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Appendix A Cointegrating vectors

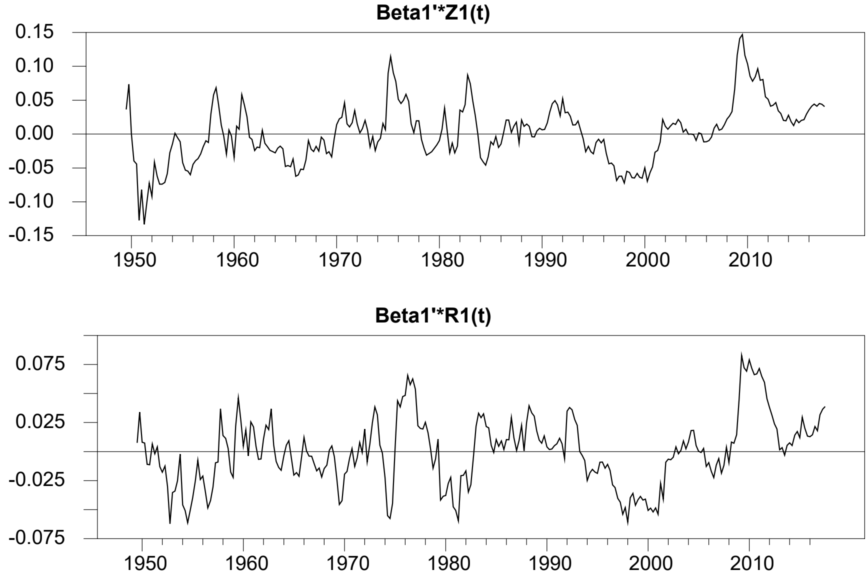

Figure A.1: Graphs of the first cointegrating vector for the model with TFP, output, consumption and investment series, with linear trend inside the cointegrating vector and 6 lags. The graph above reports the equilibrium error as a function of short-run dynamics and deterministic terms. The graph below reports the equilibrium error corrected for the short-run effects.

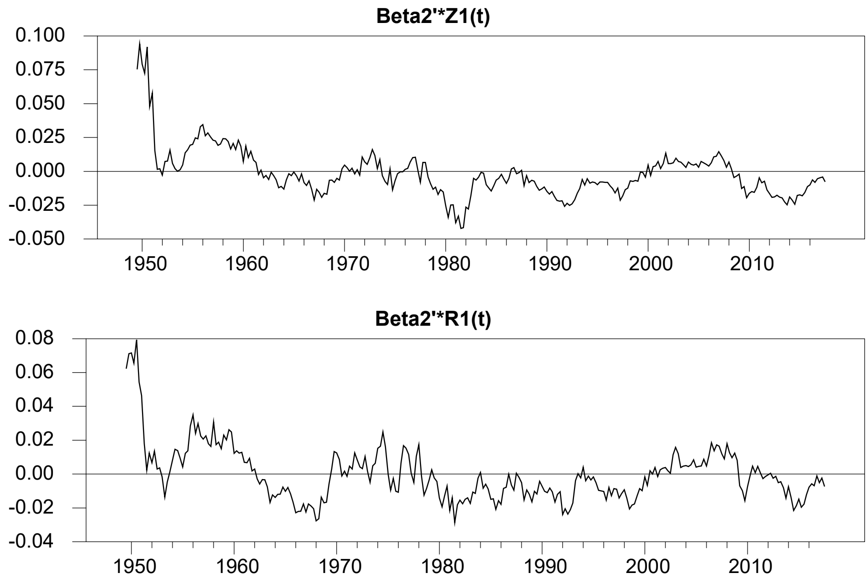

Figure A.2: Graphs of the second cointegrating vector for the model with TFP, output, consumption and investment series, with linear trend inside the cointegrating vector and 6 lags. The graph above reports the equilibrium error as a function of short-run dynamics and deterministic terms. The graph below reports the equilibrium error corrected for the short-run effects.

Appendix B Impulse Responses for the 5 variable VECM's

GDP deflator

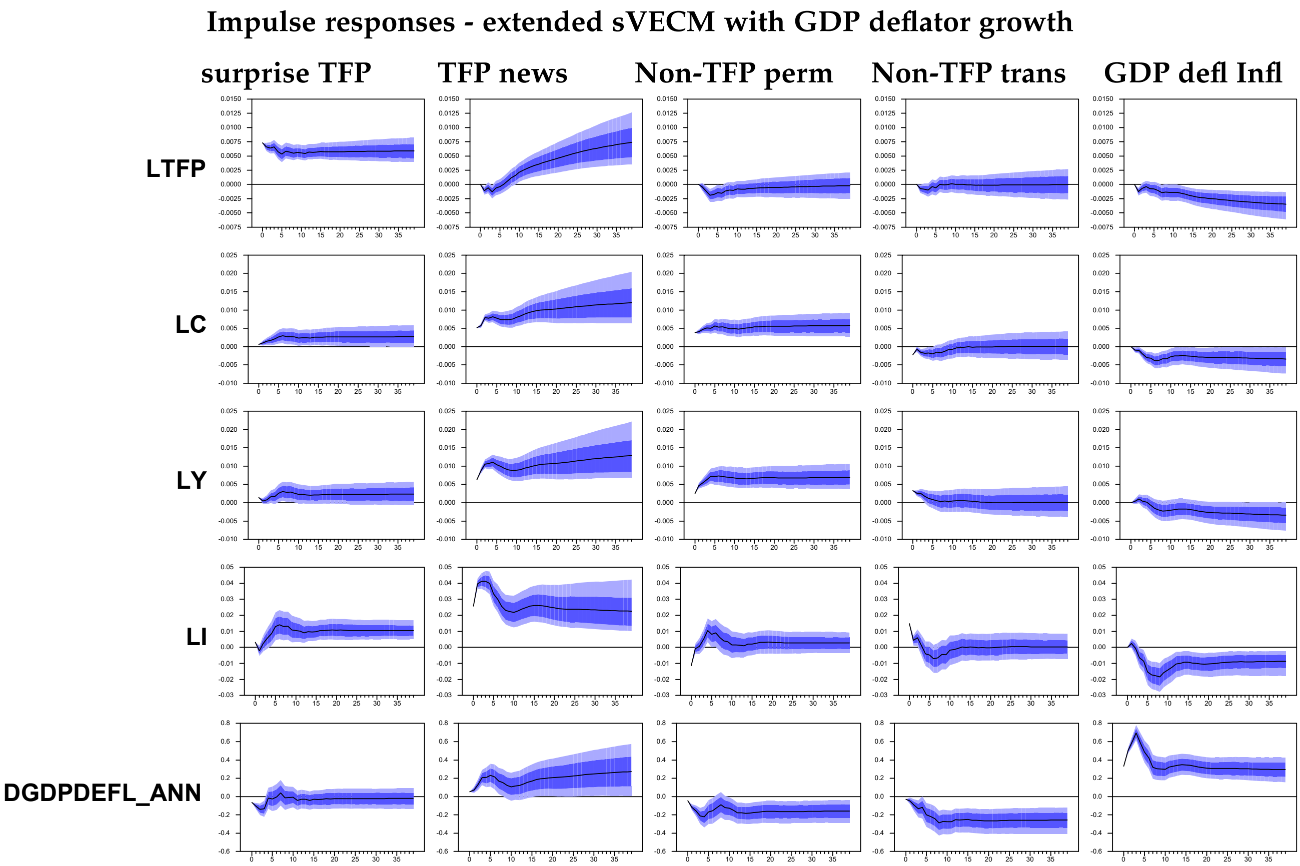

Figure B.1: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and GDP deflator growth(DGDPDEFL_ ANN), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: GDP defl Infl. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

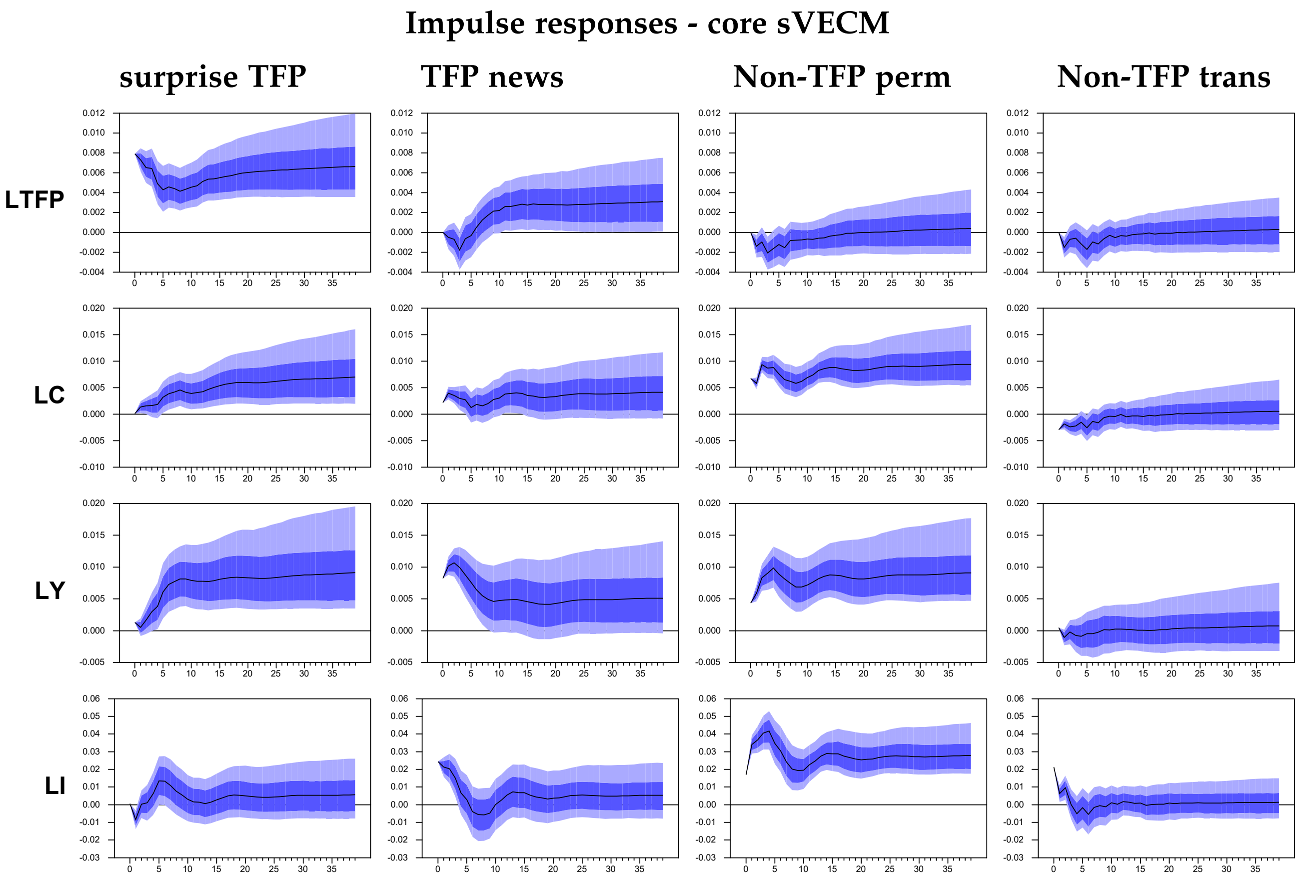

Figure B.2: Impulse response functions for the 4-variable VEC model with TFP (LTFP), consumption (LC), output (LY) and investment (LI), including 2 cointegrating relationships and 6 lags. Sample period is 1948:01-1979:01. The graph displays the variables responses (rows) to the four shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

CPI inflation

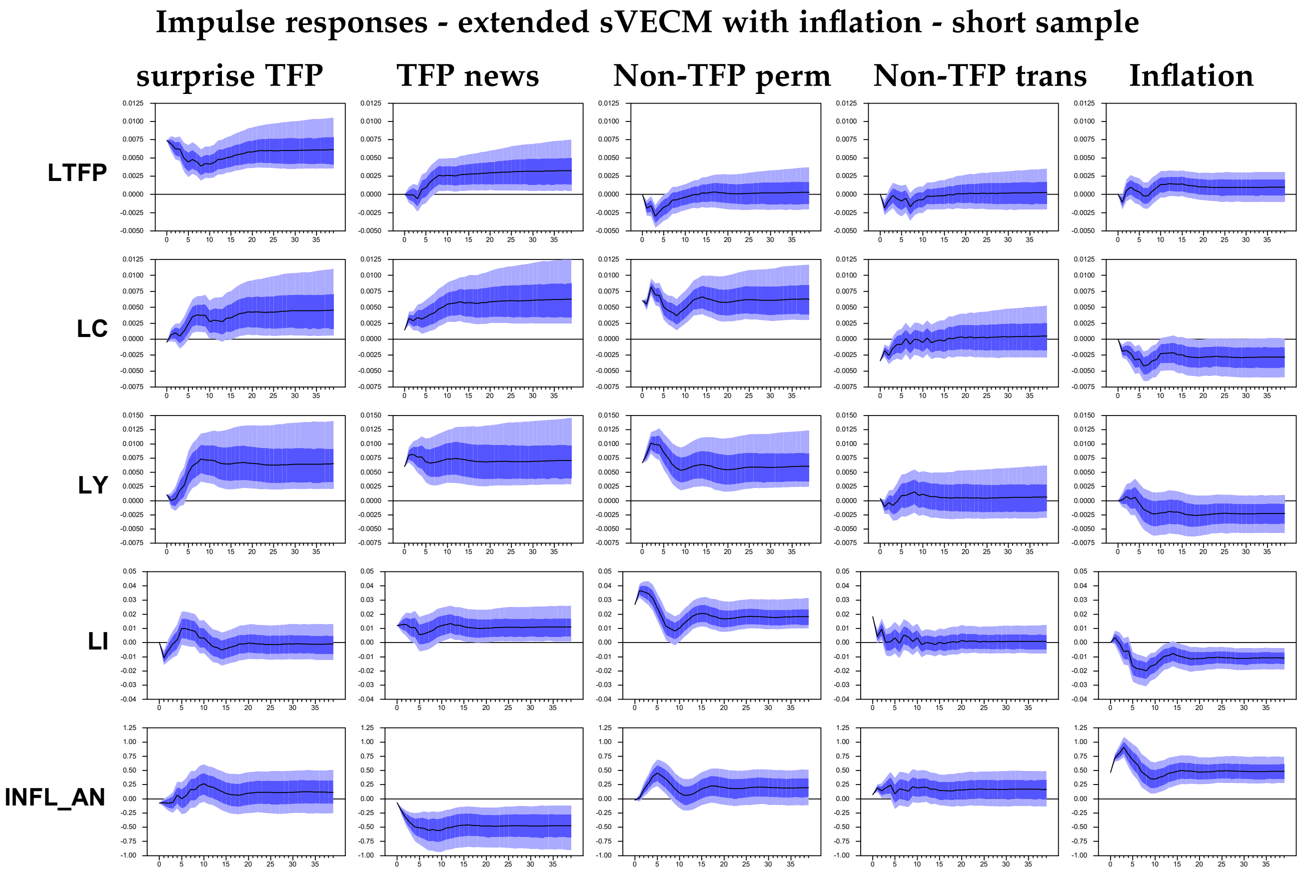

Figure B.3: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and annualized inflation(INFL_ AN), including 2 cointegrating relationships and 6 lags. Sample period is 1948-1979:01. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Inflation. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Real Treasury bill yield

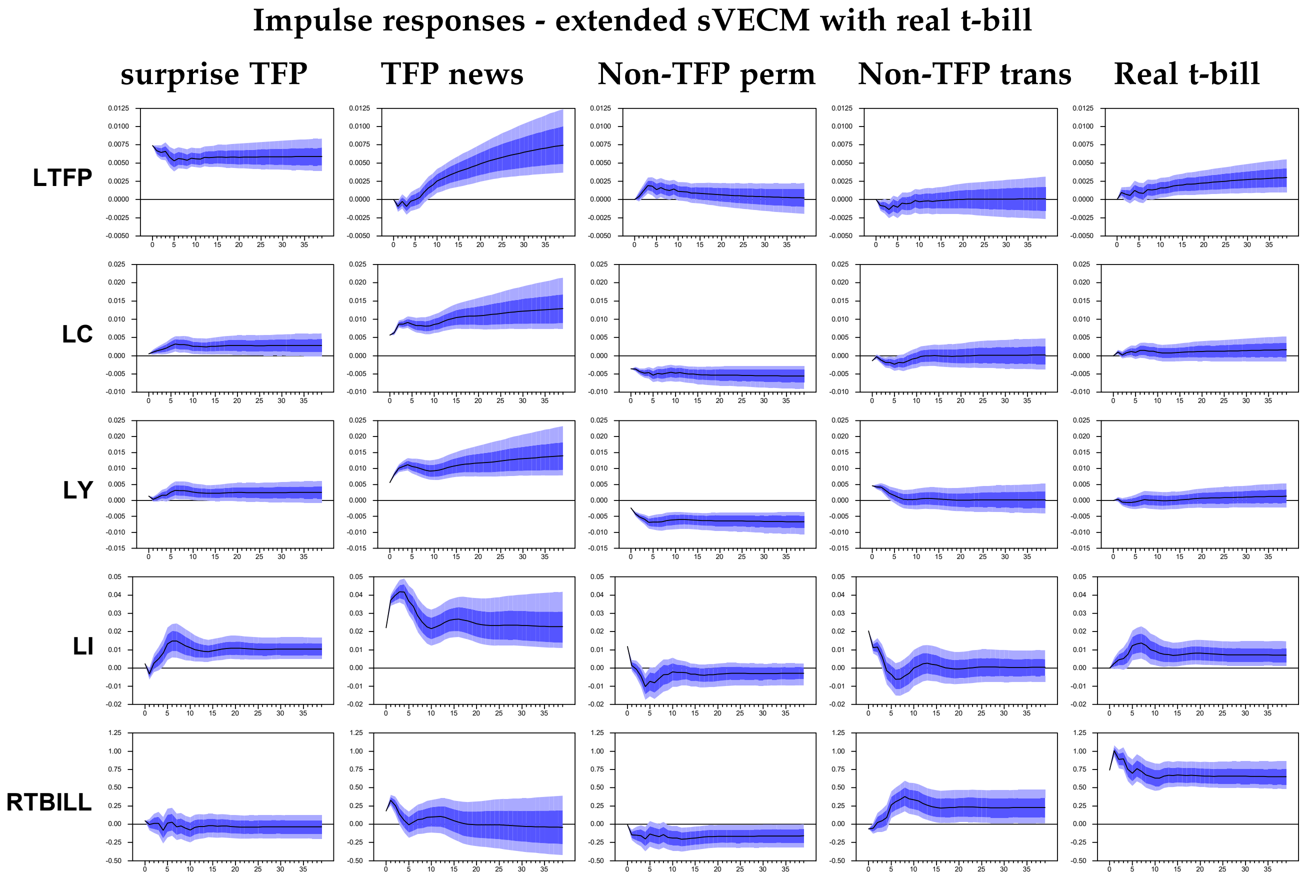

Figure B.4: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and real treasury bill yield (RTBILL), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Real t-bill. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Real Treasury bill yield

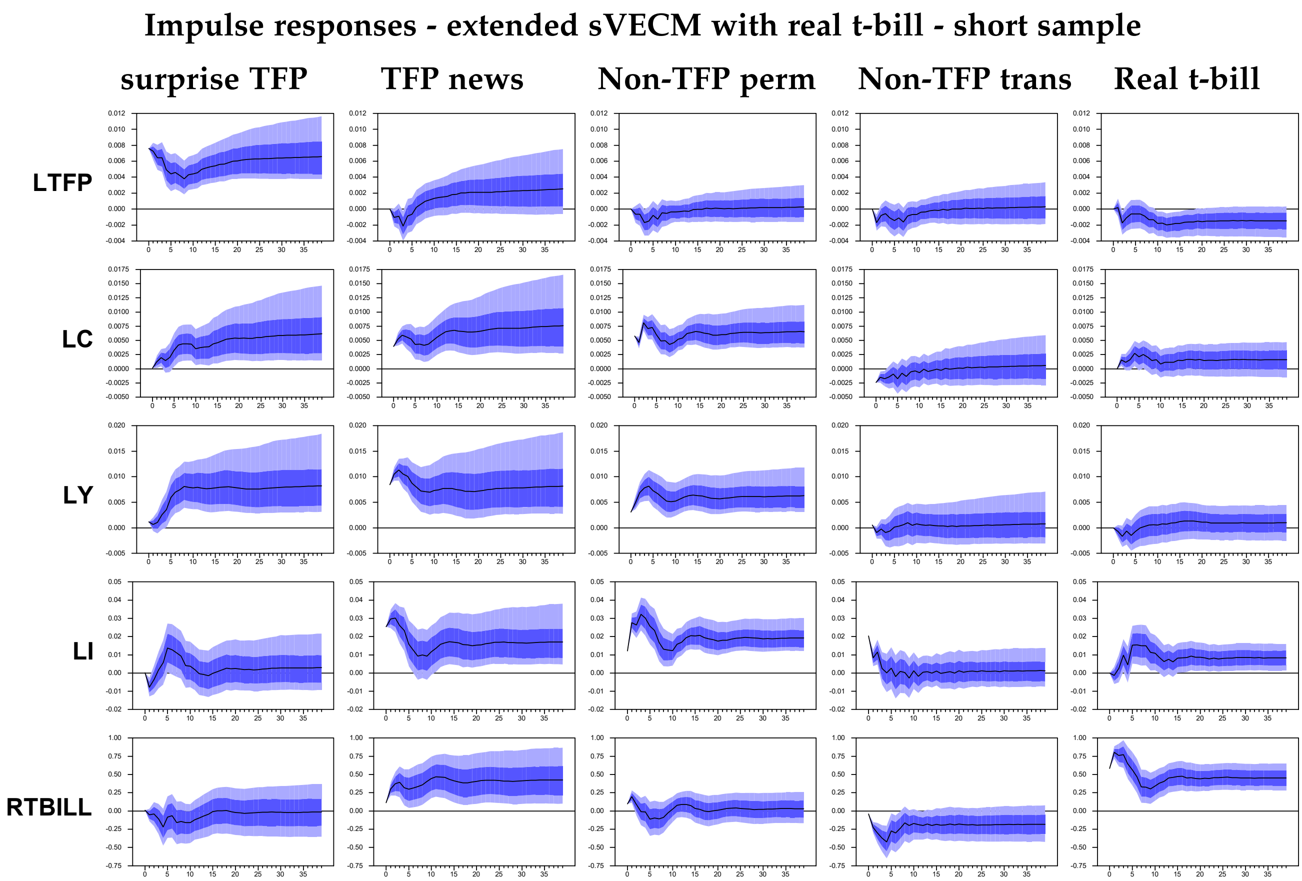

Figure B.5: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and real treasury bill yield (RTBILL), including 2 cointegrating relationships and 6 lags. Sample period is 1948-1979:1. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Real t-bill. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Baa corporate spread

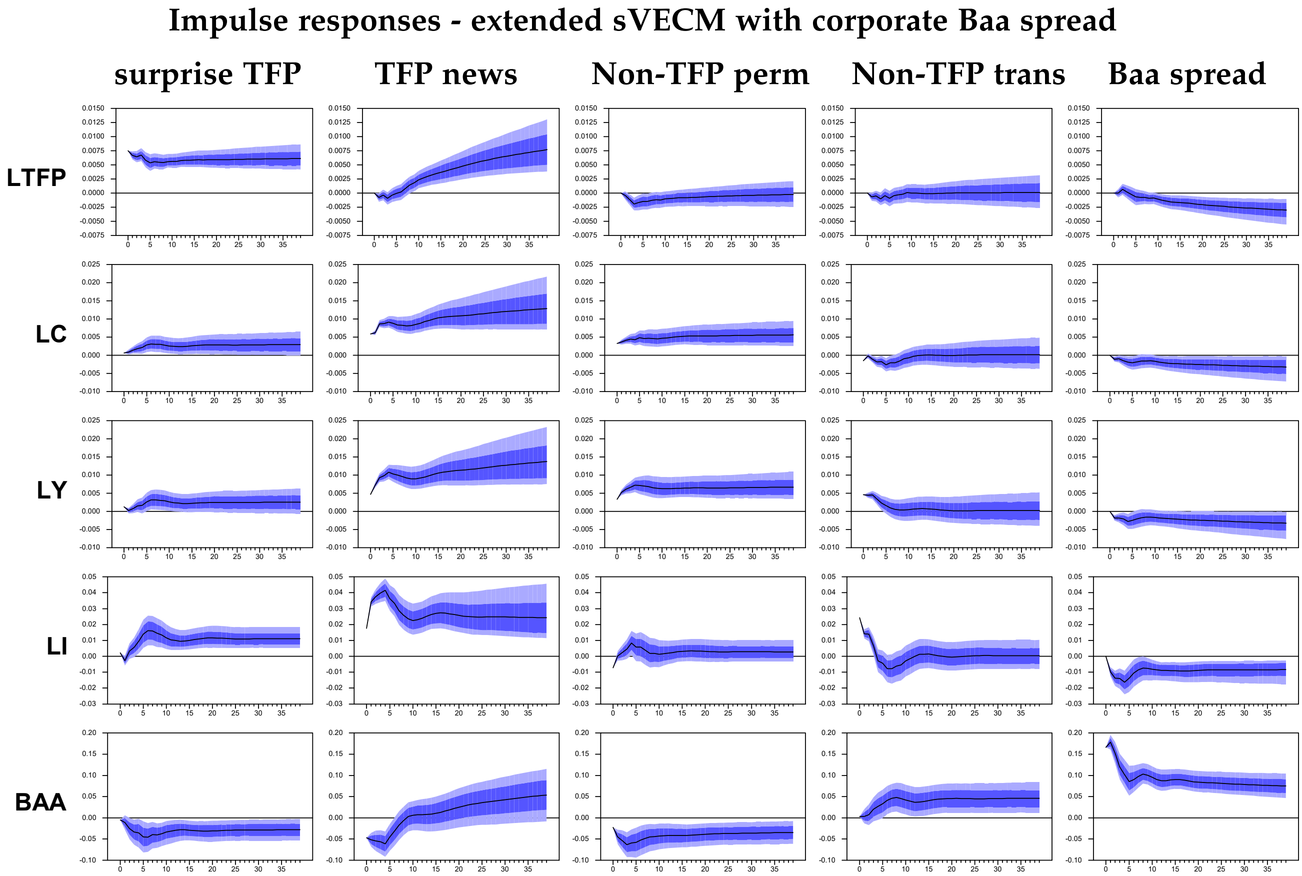

Figure B.6: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and corporate Baa spread (BAA), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Baa spread. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Baa corporate spread

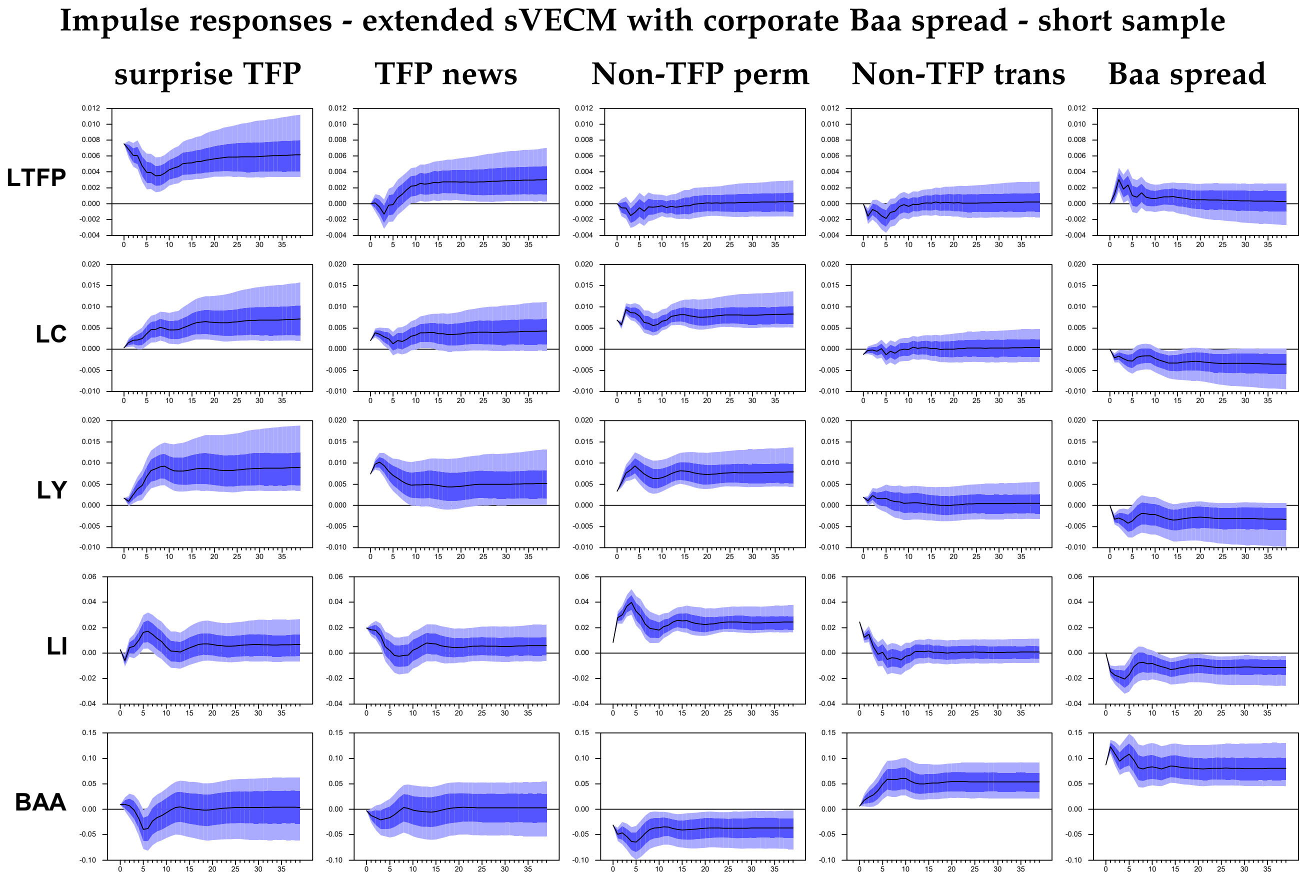

Figure B.7: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and corporate Baa spread (BAA), including 2 cointegrating relationships and 6 lags. Sample period is 1948-1979:01. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Baa spread. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Hours worked

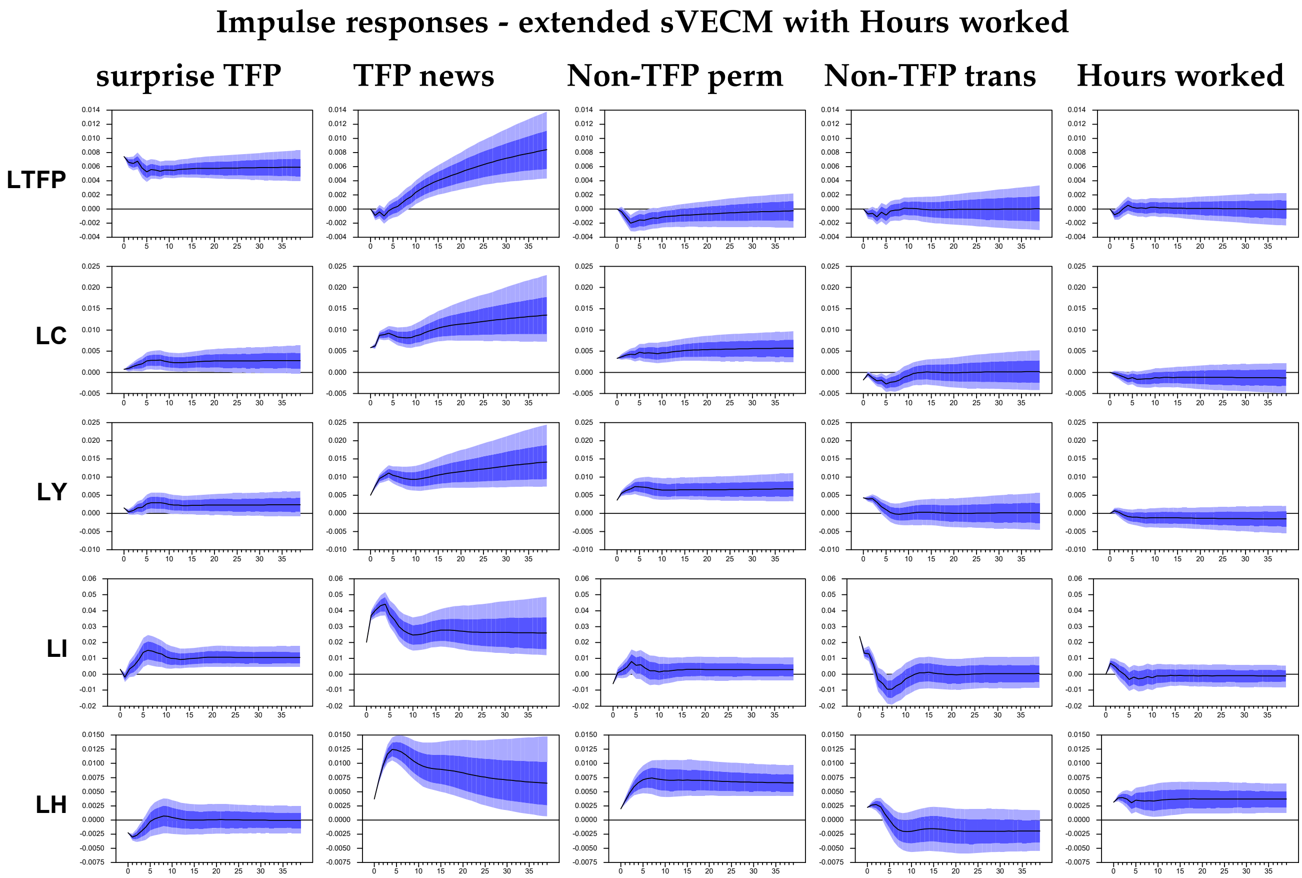

Figure B.8: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and Hours worked(LH), including 2 cointegrating relationships and 6 lags. Sample period is 1948-2017. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Hours worked. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Hours worked

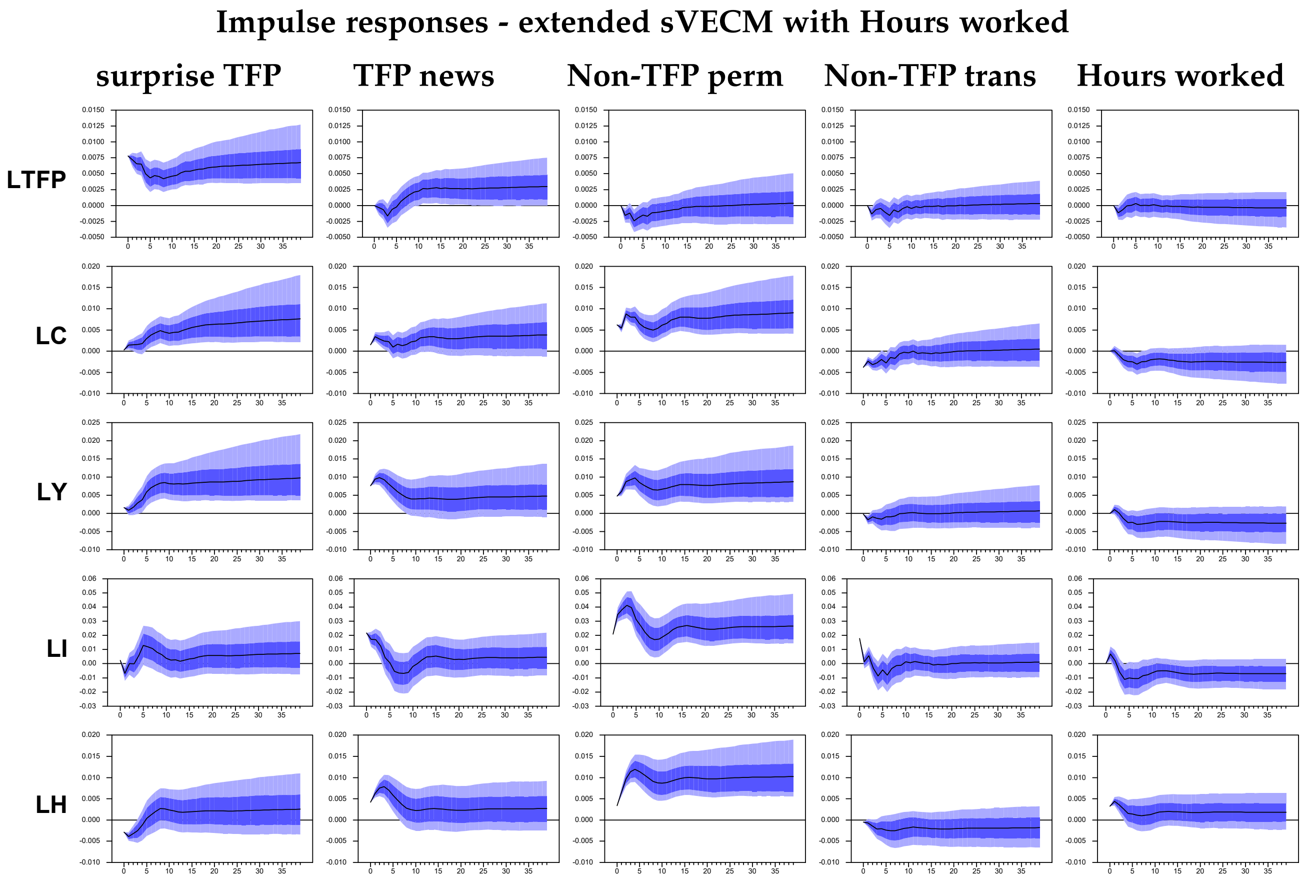

Figure B.9: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and Hours worked(LH), including 2 cointegrating relationships and 6 lags. Sample period is 1948:01-1979:01. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Hours worked. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Confidence

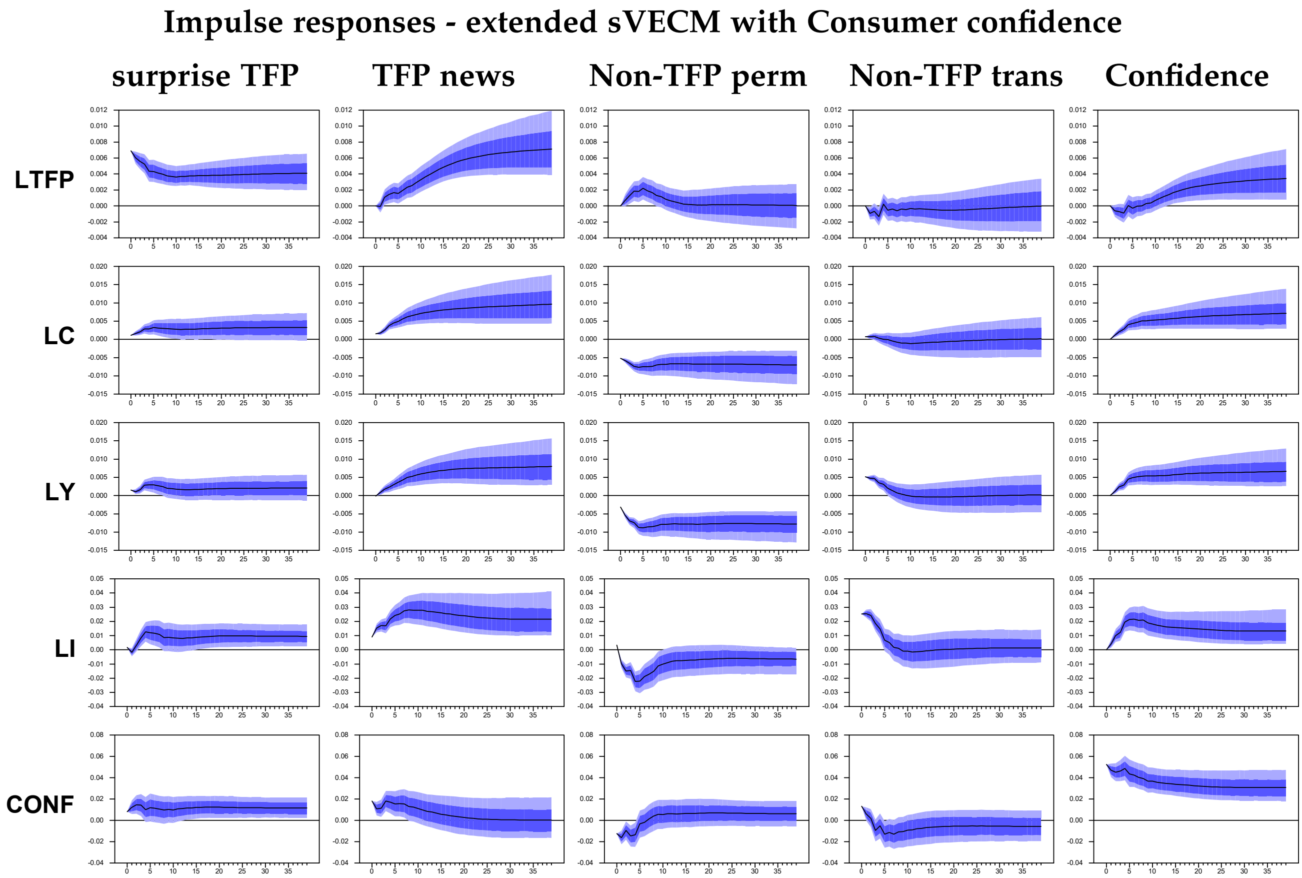

Figure B.10: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and Consumer confidence (CONF), including 2 cointegrating relationships and 6 lags. Sample period is 1960:3-2017:3. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: Confidence. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

Uncertainty

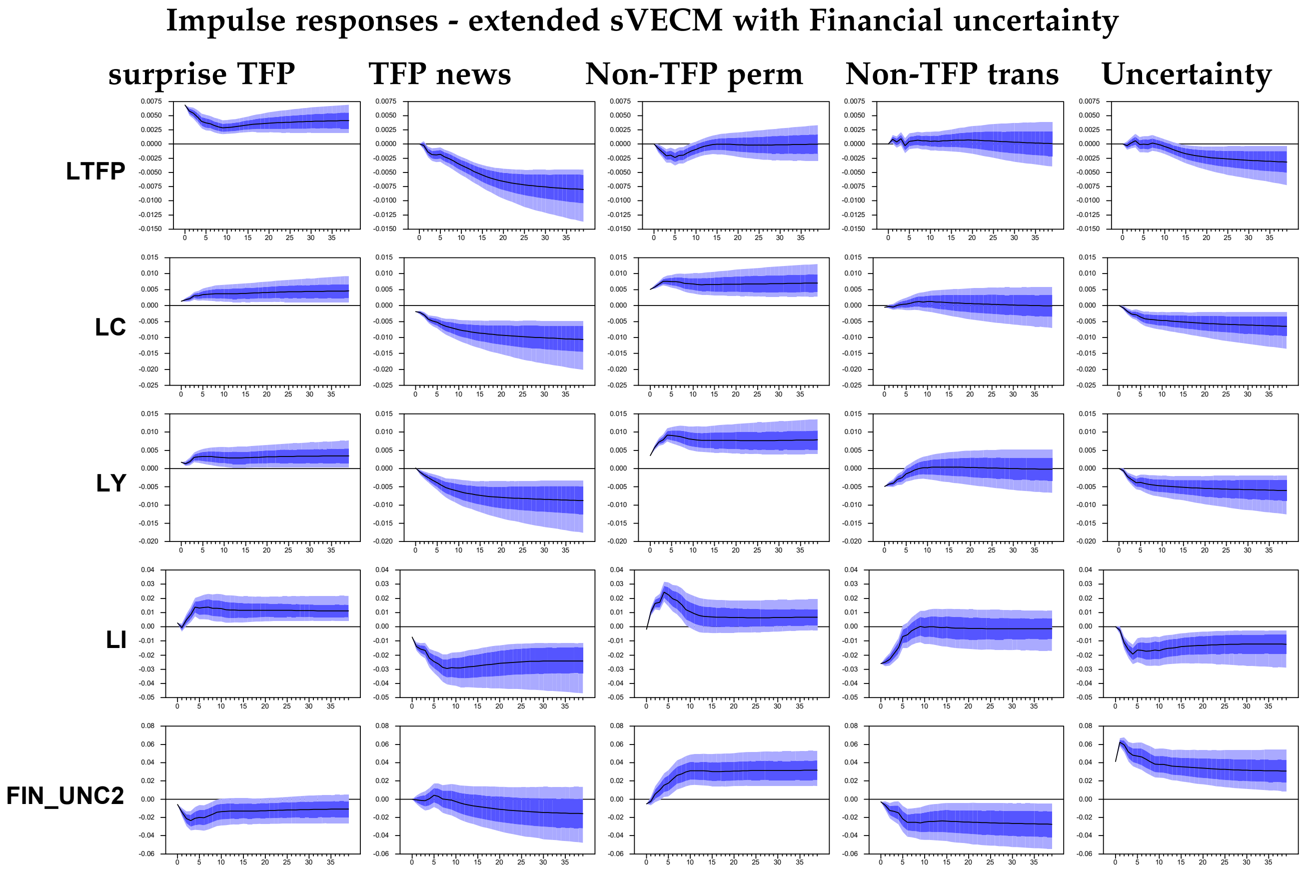

Figure B.11: Impulse response functions for the 5-variable VEC model with TFP (LTFP), consumption (LC), output (LY), investment (LI) and financial uncertainty (FIN_ UNC2), including 2 cointegrating relationships and 6 lags. Sample period is 1960:3-2017:3. The graph displays the variables responses (rows) to the five shocks: Column 1: surprise TFP, Column 2: TFP news, Column 3: non-TFP permanent, Column 4: non-TFP transitory, Column 5: financial uncertainty. We obtain the Bayesian simulated distribution of IRF by Monte Carlo integration with 5000 replications. The black solid line represent the median response. We plot the distribution of IRF at 16% to 84% interval (dark blue) and at 5% to 95% interval (light blue)

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