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Technology, Employment, and Cleansing Effects: An Empirical Study of the G-7[*]

Hyeon-seung Huh[**] · Wongun Song[***]

This paper revisits the relationship between technology shocks and employment, which has caused considerable controversy since the appearance of Galí (1999). The organizing framework is cleansing effects, which posits recessions as the appropriate time for engaging in activities aimed at improving productivity. We examine the consistency of cleansing effects using G-7 data. Evidence reveals that the theoretical predictions from the cleansing effect are well supported across countries. Importantly, a positive technology shock increases employment, which is in contrast to the result of Galí. We also propose a simple test that can serve to distinguish between the cleansing and Galí models statistically. The test rejects the adequacy of Galí's specification in favor of the cleansing effect, with the possible exception of Japan.

JEL Classification: C32, E24, E32
Keywords: technology shocks, employment, Galí, cleansing effects, structural VAR

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[**] Author for Correspondence, School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul, 120-749, Republic of Korea, E-mail: hshuh@yonsei.ac.kr

[***] Economic Research Division, The Federation of Korean Industries, FKI Tower, 24 Yeoui-daero, Yeongdeungpo-gu, Seoul, 150-881, Republic of Korea, E-mail: wsong@fki.or.kr

1. INTRODUCTION

In an influential paper, Galí (1999) presents empirical evidence that technological improvements reduce employment for G-7 countries at least in the short run.[1)] He explains this based on a class of models that inherit price rigidities and imperfect competition in the Keynesian tradition. While a positive technology shock improves labor productivity, cost-minimizing firms reduce employment because the output price is fixed and thus the quantity demanded cannot change. In contrast, non-technology shocks, which Galí suggests can be interpreted as demand shocks, are shown to produce the typical pattern of positive co-movements among output, productivity, and employment. These results cast serious doubt on the usefulness of Real Business Cycle (RBC) theory, which assigns a central role to technology shocks in accounting for business cycle fluctuations. In the standard RBC model, a positive technology shock improves employment through an increase in the marginal product of labor and the consequent adjustments in the marginal rate of substitution between labor and leisure. Francis *et al*. (2003), Galí and Rabanal (2004), Francis and Ramey (2005), and Basu *et al*. (2006) also report a contractionary effect of technology shocks on employment. Francis and Ramsey note that if the results of Galí prove to be robust, they can be viewed as potential paradigm shifters, and renewed emphasis should be devoted to understanding the imperfections in the economy that allow demand shocks to produce the classic business cycle patterns.

A group of studies challenges this rejection of technology-driven RBC models. Examples include Sarte (1997), McGrattan (2004), Uhlig (2004),

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[1)] In his application, Galí used the total number of hours worked of all persons employed for the U.S. This is most likely a better measure of labor input than the total number of employed persons (head count) because the latter can hide changes in the average hours worked caused by the evolution of part-time work or the effects of variations in overtime. However, data on the total hours worked were not available for some of the G-7. To ensure comparability across countries, we use the total number of the employed as a measure of labor input and refer to both this variable and the total number of hours worked as employment without a distinction in the subsequent discussion. Galí also used the total number of the employed in all other G-7 countries.

Christiano *et al*. (2009), Chari *et al*. (2008), and Peersman and Straub (2009). They point out that the structural VAR models used to refute RBC-based explanations were either misspecified or not appropriately designed. Particularly, some of them question the empirical validity of the identifying assumption in Galí's VAR model, which constrains the long-run effect of demand shocks (non-technology shocks) on labor productivity to zero. Sarte states that demand shocks such as a permanent change in taxes may affect labor productivity permanently given a standard production function with constant returns to scale. Uhlig shows that shifts in the social attitudes to the workplace can also be a source of changes in long-run labor productivity.[2)] He adopts medium-run restrictions rather than conventional long- and short-run restrictions to identify underlying shocks. Christiano *et al*. report that the responses identified using short-run restrictions mimic the theoretical responses remarkably well, while those using long-run restrictions exhibit noticeable bias. Peersman and Straub identify structural shocks based on a set of sign restrictions that are consistent with general equilibrium models under both flexible and sticky prices/wages. All of these studies present empirical evidence that technological improvements lead to an increase in employment once alternative identification schemes are employed in place of the zero long-run effect of demand shocks on labor productivity.

Given the controversy concerning the relationship between technology and employment, the present paper approaches the issue from a different perspective. The underlying theoretical framework here is referred to as the cleansing effect, which revives the Schumpeterian view that the process of the creation and destruction of production units resulting from innovations is essential for understanding not only growth but also business cycles. Thus, the cleansing effect explicitly recognizes the interactions between cycles and growth. The RBC model also offers a unified treatment of growth and cycles by positing that technological shocks are the main determinant of both

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[2)] Many endogenous growth models also suggest that demand shocks may end up altering labor productivity in the long run as long as they produce temporary changes in the amounts of resources allocated to growth (Stadler, 1986; King *et al*., 1988).

phenomena. A key difference is that the cleansing effect emphasizes the demand pull hypothesis of innovation. In particular, recessions due to lower demand are viewed as providing a cleansing mechanism for reducing organizational inefficiency and resource misallocations. Caballero and Hammour (1994) argue that during recessions, less efficient firms become unprofitable and shut down, thus improving productivity overall in the economy. Moreover, the opportunity cost of undertaking productivity-enhancing activities is lower, so that recessions are the appropriate time to reorganize production, improve the match between workers and jobs, implement new technologies, invest in human capital, and initiate research and development (Hall, 1991; Davis and Haltiwanger, 1992; Saint-Paul, 1993; Aghion and Saint-Paul, 1998). Such efficiency effects are long-lasting.

We examine the relevancy of cleansing effects for G-7 countries. The empirical model is the same two-variable VAR of labor productivity and employment used in Galí. Both the cleansing and Galí models highlight the importance of demand shocks in accounting for business cycle fluctuations. However, the cleansing effect asserts that negative demand shocks leading to recessions have a positive effect on labor productivity in the long run as well as in the short run. One would not be able to adopt the identification restriction that demand shocks do not have a long-run effect on labor productivity. The model predictions are also different from Galí in that a negative demand shock decreases labor productivity in the short run. Consequently, we employ an alternative identification scheme which allows the effect of demand shocks on labor productivity to be determined by actual data. The key argument is how the effect on employment of technology shocks varies depending on the two models. This setup may also shed some light on the issue raised by several studies on the robustness of Galí's results to the zero long-run identification restriction. In the end, we are able to establish a testable relationship between the cleansing and Galí models. It is shown that in the former, demand shocks are causally prior to technology shocks, while the latter implies the opposite, i.e., that causality runs from technology shocks to demand shocks. Based on this structural difference, we statistically examine which model between the two is more consistent with the data.

The remainder of this paper is structured as follows. Section 2 defines a VAR model of labor productivity and employment to estimate cleansing effects, and its relationship to the Galí model is discussed. Empirical results for G-7 countries are provided in section 3, together with those from Galí for comparison. Section 4 conducts several robustness tests to gauge which model is more coherent with the actual data. Section 5 concludes the paper.

2. MODELS: GALÍ *VERSUS* CLEANSING EFFECTS

Following Galí (1999), consider a reduced-form VAR model of labor productivity (x_t) and employment (n_t):

$$\Delta x_t = \sum_{i=1}^{p} d_{xx,\,i} \Delta x_{t-i} + \sum_{i=1}^{p} d_{xn,\,i} \Delta n_{t-i} + e_t^x, \tag{1}$$

$$\Delta n_t = \sum_{i=1}^{p} d_{nx,\,i} \Delta x_{t-i} + \sum_{i=1}^{p} d_{nn,\,i} \Delta n_{t-i} + e_t^n, \tag{2}$$

where Δ is the first difference operator, and e_t^x and e_t^n denote reduced-from errors.[3] The structural VAR model is given as

$$\Delta x_t = \sum_{i=1}^{p} a_{xx,\,i} \Delta x_{t-i} + \sum_{i=0}^{p} a_{xn,\,i} \Delta n_{t-i} + \varepsilon_t^x, \tag{3}$$

$$\Delta n_t = \sum_{i=0}^{p} a_{nx,\,i} \Delta x_{t-i} + \sum_{i=1}^{p} a_{nn,\,i} \Delta n_{t-i} + \varepsilon_t^n, \tag{4}$$

[3] The constant term is suppressed for the sake of illustration.

where the two structural shocks, ε_t^x and ε_t^n, are technology and demand shocks, respectively. They are assumed to be mutually uncorrelated (i.e., $\text{Cov}(\varepsilon_t^x, \varepsilon_t^n) = 0$).

Galí introduced a long-run restriction of the type initially proposed by Blanchard and Quah (1989) to exactly identify the structural shocks of ε_t^x and ε_t^n in (3) an (4). Specifically, it is assumed that demand shocks do not have a long-run effect on labor productivity. This long-run identifying restriction can be imposed by rewriting (3) in an instrumental variable (IV) framework, for example, á la Shapiro and Watson (1988), as

$$\Delta x_t = \sum_{i=1}^{p} a_{xx,\,i} \Delta x_{t-i} + \theta \Delta n_t + \sum_{i=0}^{p-1} a^*_{xn,i}\, \Delta^2 n_{t-i} + \varepsilon_t^x, \tag{3.1}$$

where $\theta = \sum_{i=0}^{p} a_{xn,\,i}$ and $a^*_{xn,\,i} = \sum_{j=0}^{i} a_{xn,\,j}$. The zero long-run effect of demand shocks on labor productivity implies that $\theta = 0$. Under this restriction, (3.1) can be estimated consistently using an IV procedure.[4] An appropriate set of instruments is lags 1 through p of Δx_t and Δn_t. Equation (4) can be estimated using the same set of instruments plus $\hat{\varepsilon}_{t,\,G}^x$, the estimated residual from (3.1), where the subscript *G* denotes the Galí model. The residual $\hat{\varepsilon}_{t,\,G}^x$ is a valid instrument due to the orthogonality condition between structural shocks.

The long-run restriction above generates sufficient instruments for estimating all parameters of (3.1) including $\hat{\varepsilon}_{t,\,G}^x$. No other restriction is necessary, and (4) is subsequently estimated using $\hat{\varepsilon}_{t,\,G}^x$. Thus, an implicit assumption underlying the procedure is that a technology shock is causally prior to a demand shock, as Cover *et al*. (2006) and Enders and Hurn (2007) have also demonstrated. This feature allows one to obtain identical results by sequentially estimating (3.1) and (2), followed by an application of the Choleski decomposition.

The cleansing effect has different implications. Because recessions due

[4] Equation (3.1) will not be estimated by OLS due to the contemporaneous value of $\Delta^2 n_t$ in the right-hand variables.

to lower demand are viewed as an appropriate time for firms to engage in productivity activities, demand may play a role for technical change and the development of productivity. One implication is that demand shocks can exert a long-run effect on labor productivity. This differs from the Galí model, in which only technology shocks can do this. Equally important, the cleansing effect suggests the possibility that a demand shock may be causally prior to a technology shock. Basu *et al*. (2006) acknowledge this reverse causality of cleansing effects, noting that it challenges the basic assumption in Galí (as well as in the RBC). To account for the cleansing effect, we assume that a demand shock occurs prior to a technology shock in the identification of these two types of structural shocks. This identification restriction may be imposed by setting the contemporaneous effect of technology shocks on employment to zero; that is, $a_{nx,\,0} = 0$ in (4). Thus, the estimation of cleansing effects can be done as estimating (4) by OLS and then (3) using lags 1 through p of Δx_t and Δn_t plus $\hat{\varepsilon}^{n}_{t,\,C}$ as instruments, where $\hat{\varepsilon}^{n}_{t,\,C}$ is the residual series estimated from (4) in the cleansing model. Obviously, this is equivalent to applying the Choleski decomposition to the corresponding reduced-form VAR model of (2) and (1). Under this structure, the technology shock reflects its innovations net of the effects induced by the demand shock. Incidentally, Christiano *et al*. (2009) adopted the same identifying restriction of $a_{nx,\,0} = 0$ in a model of labor productivity and employment. Their simulation results indicate that this short-run restriction model mimics the true impulse responses accurately, whereas the long-run restriction model as in Galí exhibits noticeable bias.

There is another way to estimate cleansing effects which allows a direct comparison to the model of Galí. Once (4) is estimated under the assumption that $a_{nx,\,0} = 0,$ one can produce the same results by estimating (3.1) instead of (3) using the same instrumental variables. In the estimation of (3.1), the long-run effect of demand shocks on labor productivity, $\theta,$ is not restricted to zero but is allowed to be determined by the data. It is interesting to check whether demand shocks exert a long-run effect on labor productivity according to the cleansing effect. Of course, the estimate of θ

can be statistically indifferent from zero, giving empirical support to the identifying assumption in Galí. This point of distinction allows one to test statistically which model between the two is more consistent with the actual data. To see how, recall (3.1) and (4):

$$\Delta x_t = \sum_{i=1}^{p} a_{xx,\,i}\Delta x_{t-i} + \theta\Delta n_t + \sum_{i=0}^{p-1} a^{*}_{xn,\,i}\Delta^2 n_{t-i} + \varepsilon^x_t, \tag{3.1}$$

$$\Delta n_t = \sum_{i=0}^{p} a_{nx,\,i}\Delta x_{t-i} + \sum_{i=1}^{p} a_{nn,\,i}\Delta n_{t-i} + \varepsilon^n_t. \tag{4}$$

In the cleansing effect, (3.1) was estimated by the IV procedure using lags 1 through p of Δx_t and Δn_t plus $\hat{\varepsilon}^n_{t,\,C}$ as instruments. If the estimate of θ, $\tilde{\theta}$, is statistically significant, this means that demand shocks have a long-run effect on labor productivity, as prescribed in the cleansing model. Let $\tilde{\varepsilon}^x_t$ be the residual series from (3.1), and consider the estimation of (4) using the instrument set of lags 1 through p of Δx_t and Δn_t together with $\tilde{\varepsilon}^x_t$. Because there is no correlation between Δn_t and $\tilde{\varepsilon}^x_t$ by construction, the estimate of $a_{nx,\,0}$ becomes zero ($\tilde{a}_{nx,\,0} = 0$) and all other parameter estimates in (4) are identical to those in the cleansing model that were obtained under the identifying restriction of $a_{nx,\,0} = 0$. If $\tilde{\theta}$ is not statistically significant in (3.1), the Galí model is supported instead, as the long-run effect of demand shocks on labor productivity is zero. Indeed, the estimation of (4) using the instruments of lags 1 through p of Δx_t and Δn_t and $\tilde{\varepsilon}^x_t$ yields results identical to those of the Galí model, as estimated under the identifying restriction of $\theta = 0$. Taken altogether, whether $\tilde{\theta}$ is statistically zero or not can be used as a yardstick when determining which model between the two is more consistent with the actual data.[5)]

5) Huh (2011) derives a similar proposition for VEC models.

3. EMPIRICAL RESULTS

The analysis outlined above is applied to quarterly observations of labor productivity and employment in G-7 countries. The measure of employment (n_t) is the total number of employed persons expressed in logs, and the measure of real output (y_t) is the log of real GDP. The series for labor productivity (x_t) is constructed by subtracting employment from real output; that is, $x_t = (y_t - n_t)$. All data were seasonally adjusted and obtained from Global Insight. The sample period is 1981:Q1 to 2012:Q4. Prior to estimating the VAR models, tests for a unit root and cointegration of the data were conducted. The results indicated that labor productivity and employment were characterized as $I(1)$ processes and that there was no evidence of a cointegration relationship between these variables. Accordingly, labor productivity and employment enter the regressions of section 2 in their first differences. The lag length (p) is set at four for all countries on the basis of the Akaike information criterion.

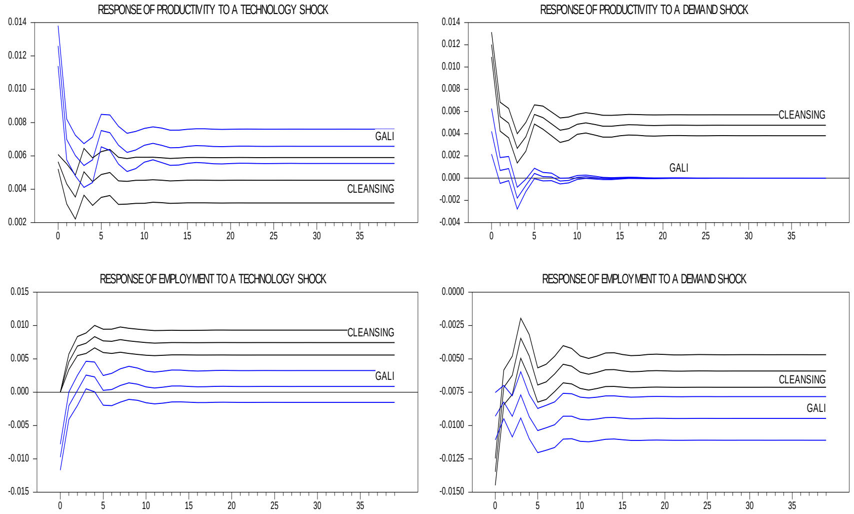
3.1. Impulse Responses

Figure 1 displays the responses of the variables in levels to technology and demand shocks, together with one-standard-error confidence bands generated using 500 bootstrap replications. Also depicted are the results from the model of Galí for comparison. Looking at the effects of a positive technology shock first, labor productivity increases across horizons. The responses are quite similar to those from the Galí model. However, employment responds differently depending on the model. The cleansing model shows that employment increases, and the effects are statistically significant in all G-7 countries.[6] In the Galí model, employment decreases

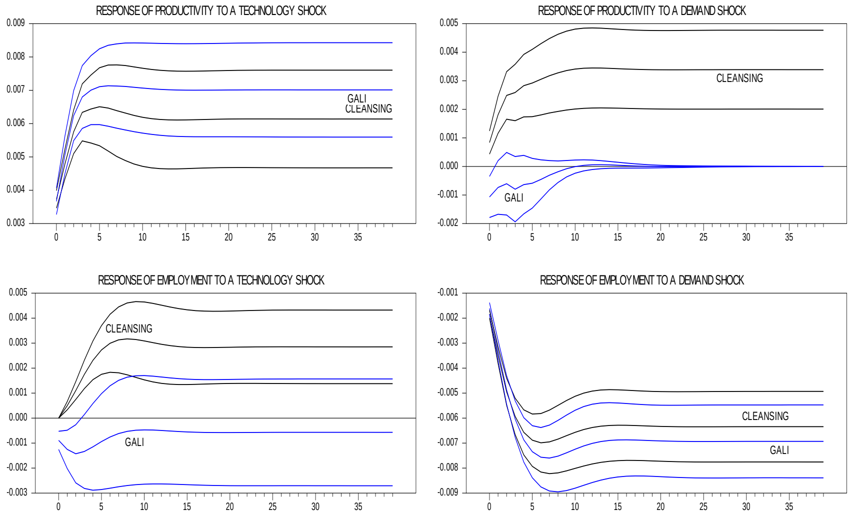
[6] The cleansing model is not specific about the employment effects of supply-side technological innovations. In principle, a positive technology shock would increase employment if it is labor-augmenting. On the other hand, employment can decrease, if the technology shock is capital-augmenting, and there is substitutability between labor and capital. For the latter case, Ju (2014) empirically finds only limited supporting evidence in the sample of 28 developed countries.

Figure 1 Responses of the Series in Levels

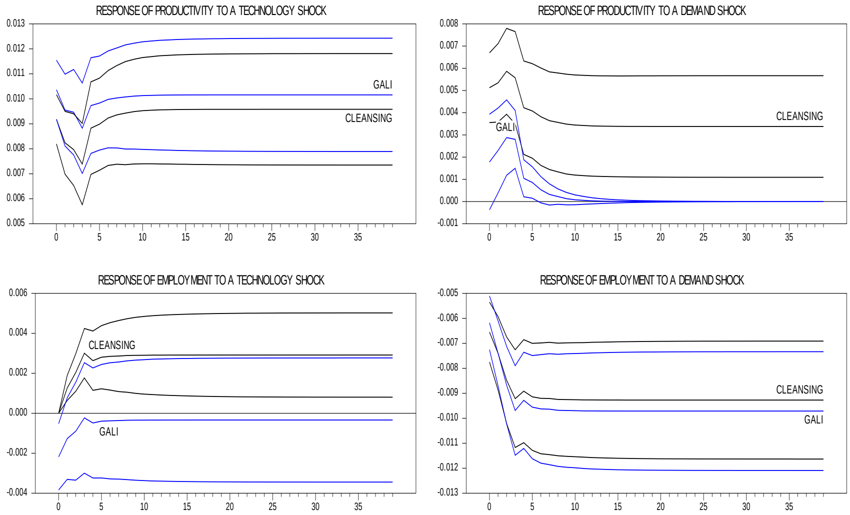
Canada



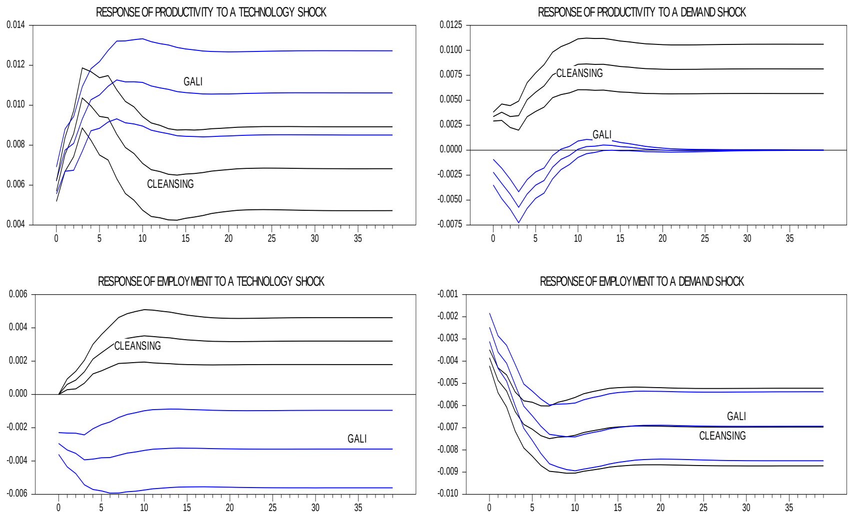
France



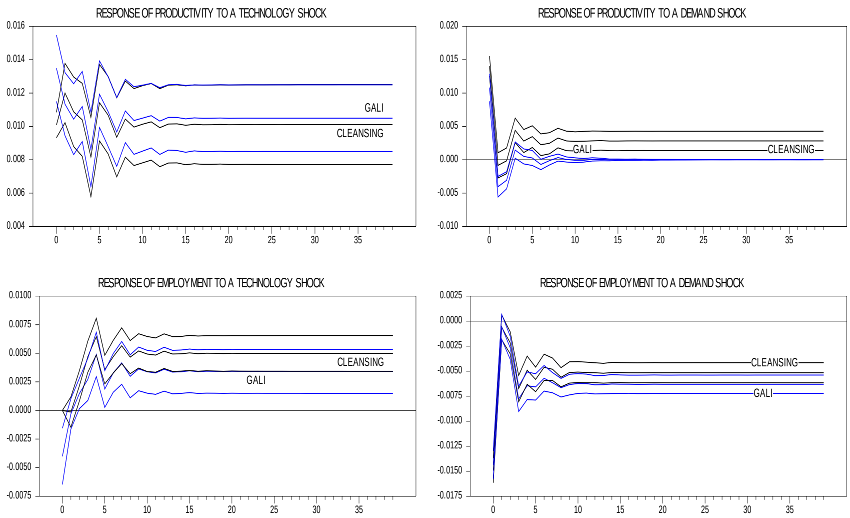
Germany



Italy



Japan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GALI
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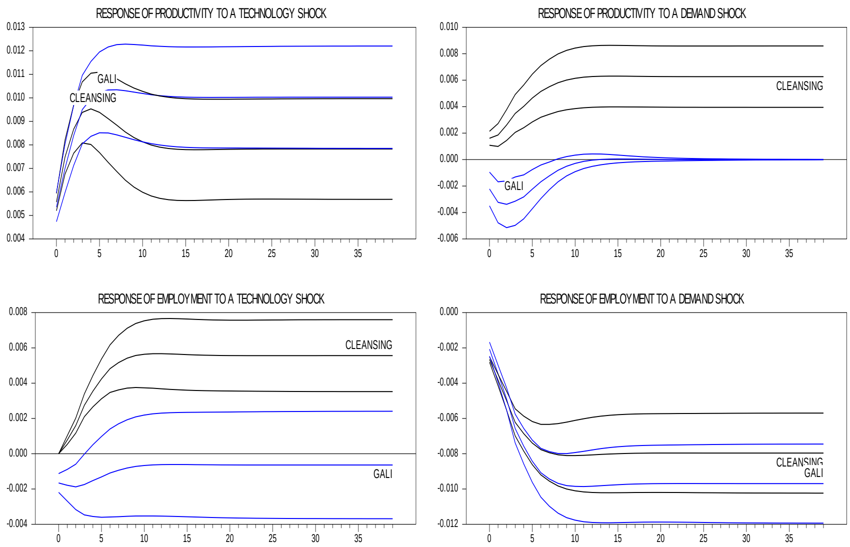
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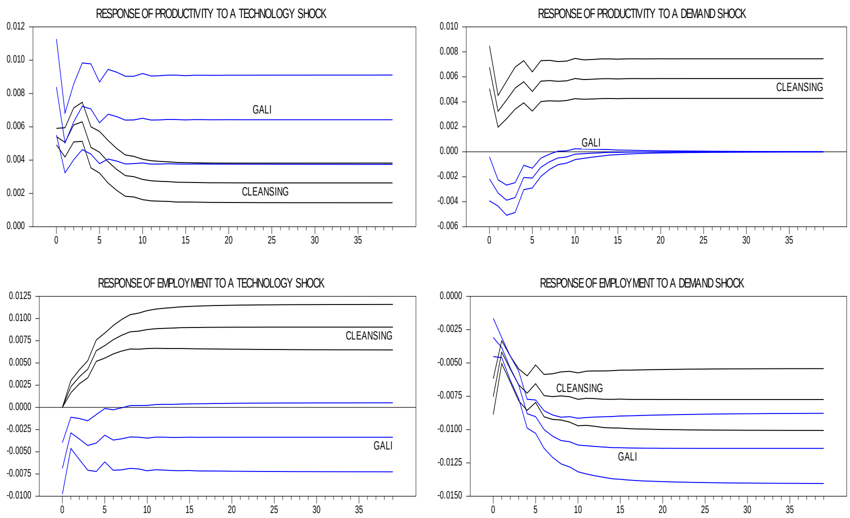

Note: The two lines around each response are the one-standard-error confidence bands which are generated using 500 bootstrap replications of the structural model.

at short horizons, and the effects become statistically insignificant at long horizons, except for the case of Italy. Galí used that short-run decrease in employment as evidence to refute technology-shock-driven RBC models. In the case of Japan, employment rapidly increases after an initial decrease.

Moving to the effects of a negative demand shock, the cleansing model exhibits that labor productivity increases and employment decreases across horizons for all G-7 countries.[7)] The responses are statistically significant in the long run as well as in the short run. This evidence indicates that the cleansing effect is borne out by data. In contrast, the Galí model produces mixed results for the responses of labor productivity. A negative demand shock decreases labor productivity in France, Italy, the U.K., and the U.S. at short horizons, as the model predicts. However, labor productivity increases for the remaining three countries (Canada, Germany, and Japan),

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7) Under the assumption of linearity, the responses are symmetric around zero.

which is in line with the cleansing model. The effects on labor productivity converge to zero in the long run as a consequence of the identifying assumption. In the case of employment, it decreases without an exception, and the responses do not appear to be much different from those in the cleansing model.

3.2. Variance Decompositions

Forecast error variance decompositions provide a way to assess the relative importance of structural shocks in accounting for variations in labor productivity and employment. Table 1 presents the forecast error variance decomposition results at various horizons for the cleansing and the Galí models. In the cleansing model, the demand shock explains a considerable portion of the variation in labor productivity across horizons. The evidence is particularly pronounced in Canada, Italy, and the U.S., in which the contributions of demand shocks are larger than those of technology shocks. For the remaining countries, demand shocks also contribute significantly to the long-run forecast error variance of labor productivity, while the effects are somewhat weak in Germany and Japan. By contrast, the Galí model shows that the technology shock explains most of the variation in labor productivity. The demand shock explains little for all G-7 countries, and its contribution eventually becomes zero given the identifying assumption.

Moving to the variance decompositions of employment, the cleansing model indicates that the two shocks are of nearly equal importance for Canada, Japan, and the U.S. The demand shock is the major determinant of employment in the other four countries across horizons. The results for the Galí model are not different in general, as demand shocks account for the majority of the variation in employment. The exceptions are Canada, Italy, and the U.S. at short horizons, where the contributions of technology shocks are larger than those of demand shocks. The technology shocks contribute only marginally to the variation in employment for the remaining four countries, with very few exceptions at the contemporaneous and one-quarter

Table 1 Decomposition of Forecast Error Variance

	Cleansing Model				Galí Model			
	Productivity		Employment		Productivity		Employment	
Qtrs.	Tech	Dem	Tech	Dem	Tech	Dem	Tech	Dem
Canada								
0	18.1*	81.9*	0.0	100.0	90.0*	10.0*	52.4*	47.6*
1	22.4*	77.6*	8.2*	91.8*	91.9*	8.1*	39.1*	60.9*
4	32.9*	67.1*	38.6*	61.4*	93.1*	6.9*	22.3*	77.7*
8	37.8*	62.2*	48.0*	52.0*	95.6*	4.4*	12.7*	87.3*
16	41.7*	58.3*	54.0*	46.0*	97.3*	2.7*	7.4*	92.6*
24	43.3*	56.7*	56.2*	43.8*	98.1*	1.9*	5.4	94.6*
36	44.7*	55.3*	57.9*	42.1*	98.7*	1.3*	4.0	96.0*
France								
0	95.2*	4.8*	0.0	100.0	92.2*	7.8	23.4*	76.6*
1	90.2*	9.8*	1.6*	98.4*	95.9*	4.1	14.9	85.1*
4	85.9*	14.1*	7.7*	92.3*	98.2*	1.8	5.8	94.2*
8	83.3*	16.7*	13.0*	87.0*	99.0*	1.0	2.7	97.3*
16	79.7*	20.3*	15.3*	84.7*	99.5*	0.5	1.6	98.4*
24	78.7*	21.3*	15.8*	84.2*	99.7*	0.3	1.3	98.7*
36	78.0*	22.0*	16.1*	83.9*	99.8*	0.2	1.1	98.9*
Germany								
0	76.2*	23.7*	0.0	100.0	97.1*	2.9	11.1	88.9*
1	73.5*	26.5*	1.6	98.4*	95.9*	4.1	6.4	93.6*
4	71.6*	28.4*	6.1	93.9*	94.7*	5.3	2.1	97.9*
8	77.9*	22.1*	7.5	92.5*	97.0*	3.0	1.1	98.9*
16	83.1*	16.9*	8.2	91.8*	98.4*	1.6	0.6	99.4*
24	85.0*	15.0*	8.5	91.5*	98.9*	1.1	0.4	99.6*
36	86.3*	13.7*	8.7	91.3*	99.2*	0.8	0.3	99.7*
Italy								
0	74.1*	25.9*	0.0	100.0	88.9*	11.1	58.7*	41.3*
1	77.6*	22.4*	1.0	99.0*	86.1*	13.9*	51.0*	49.0*
4	83.2*	16.8*	4.7	95.3*	80.3*	19.7*	39.1*	60.9*
8	71.6*	28.4*	10.6*	89.4*	88.1*	11.9*	28.5*	71.5*
16	55.4*	44.6*	14.9*	85.1*	94.0*	6.0*	22.4*	77.6*
24	50.8*	49.2*	15.8*	84.2*	95.9*	4.1*	21.0*	79.0*
36	47.7*	52.3*	16.3*	83.7*	97.2*	2.8*	20.1*	79.9*

				Japan				
0	34.0*	66.0*	0.0	100.0	60.8*	39.2*	7.2	92.8*
1	55.3*	44.7*	0.1	99.9*	69.9*	30.1*	7.3	92.7*
4	70.5*	29.5*	18.7*	81.3*	79.0*	21.0*	13.6*	86.4*
8	79.1*	20.9	27.8*	72.2*	88.2*	11.8*	16.0*	84.0*
16	84.8*	15.2*	36.6*	63.4*	93.1*	6.9*	18.9*	81.1*
24	87.1*	12.9*	40.1*	59.9*	95.1*	4.9*	20.1*	79.9*
36	88.8*	11.2*	42.3*	57.7*	96.6*	3.4*	20.9*	79.1*
				U.K.				
0	92.2*	7.8*	0.0	100.0	85.3*	14.7	39.1*	60.9*
1	93.5*	6.5*	2.7*	97.3*	83.5*	16.5	26.7*	73.3*
4	89.2*	10.8*	15.0*	85.0*	88.3*	11.7	9.5	90.5*
8	81.2*	18.8*	24.3*	75.7*	93.3*	6.7	3.9	96.1*
16	71.5*	28.5*	29.5*	70.5*	96.6*	3.4	1.8	98.2*
24	68.0*	32.0*	30.8*	69.2*	97.7*	2.3	1.3	98.3*
36	65.6*	34.4*	31.5*	68.5*	98.4*	1.6	1.0	99.0*
				U.S.				
0	39.0*	61.0*	0.0	100.0	93.7*	6.3	83.2*	16.8*
1	49.4*	50.6*	6.8*	93.2*	86.0*	14.0*	69.5*	30.5*
4	54.1*	45.9*	27.6*	72.4*	83.2*	16.8*	37.0*	63.0*
8	45.7*	54.3*	43.8*	56.2*	88.1*	11.9*	20.4*	79.6*
16	34.3*	65.7*	51.8*	48.2*	93.0*	7.0*	13.1	86.9*
24	29.2*	70.8*	54.0*	46.0*	95.1*	4.9*	11.2	88.8*
36	25.4*	74.6*	55.3*	44.7*	96.6*	3.4*	10.0	90.0*

Notes: 'Tech' and 'Dem' denote technology and demand shocks, respectively. * indicates significance, where one-standard-error confidence bands are generated using 500 bootstrap replications of the structural model.

horizons. The minor role of technology shocks should merit attention concerning the results in the Galí model. Galí's main argument was that technology shocks decrease employment at short horizons, as shown in figure 1 as well. Yet the short-run variation in employment is mainly accounted for by demand shocks in France, Germany, Japan, and the U.K. Because the technology shock explains little, the finding that this type of shock decreases employment can lose appeal empirically. A further investigation would be needed to ascertain whether Galí's argument is in fact strong enough to be accepted as a vehicle with which to refute the view that technology shocks improve employment, as in the cleansing and RBC models.[8)]

Interestingly, the cleansing effect can offer one possible explanation for the findings in France, Germany, Japan, and the U.K. If cleansing effects are present, the technology shock identified in the Galí model is in fact a mixture of a true positive technology shock and a negative demand shock. While both true positive technology shocks and negative demand shocks improve labor productivity, the former increase employment and the latter decrease it. If the effect of the demand shock dominates that of the true technology shock, employment ought to decrease, as shown in the Galí model.

4. ROBUSTNESS CHECK

Section 2 proposed a test for statistically assessing which one of the cleansing and Galí models is more consistent with actual data on the basis of equation (3.1). Table 2 presents the estimation results. For all countries apart from Japan, the *t*-test statistics rejects the null hypothesis of $\theta = 0$ at the 10% significance level. This implies that demand shocks have long-run effects on labor productivity, questioning the empirical relevancy of the identifying assumption in Galí. In contrast, the cleansing model is statistically supported, and the result is consistent with the impulse response analysis shown in figure 1. For the cleansing model, demand shocks were

[8)] In the paper, Galí did not report the results from a variance decomposition analysis, but we were able to reproduce them using his dataset covering the period up to 1994. It appears that the small contribution of technology shocks to the explanation of the variation in employment is more evident across G-7 countries. Italy and the U.K. were the only exceptions, where technology shocks respectively account for 47 and 43% of the forecast error variance of employment at the contemporaneous horizon. Even in these cases, the contribution of the technology shock disappears rapidly as the horizon increases, and demand shocks fill the gaps. For the remaining five countries, technology shocks contribute to less than 23% of the variation in employment at all horizons.

Table 2 Estimates of θ in Equation (3.1)

Canada	France	Germany	Italy	Japan	U.K.	U.S.
–0.432	–0.260	–0.315	–0.629	–0.430	–0.359	–0.433
(0.00)	(0.05)	(0.09)	(0.00)	(0.19)	(0.01)	(0.00)

Note: Figures in parentheses are the marginal significance levels (*p*-values) of the *t*-test statistics for the null hypothesis that θ is equal to zero.

shown to have long-run effects on labor productivity, where the effects were not restricted *a priori* and were allowed to be determined by the data. The Japanese case cannot reject the null hypothesis of $\theta = 0$ at standard significance levels. The demand shock does not have long-run effects on labor productivity, offering empirical support of the specifications in Galí. Yet the evidence is not very strong, with a marginal significance level of only 19%. Figure 1 also shows that the cleansing model produced responses quite similar to those of Galí. One possibility is that the two models may be difficult to distinguish empirically in the case of Japan.

Another manner in which the cleansing and Galí models can be compared is through their implications on real wages. Theoretically, the former suggests that negative demand shocks increase labor productivity, which leads to a rise in real wages. In the latter, labor productivity decreases and real wages fall accordingly. Which of these predictions is consistent with actual data can be used as a guide to assess the empirical relevancy of the two models. To do this, we consider the following equation for real wages (w_t):

$$\Delta w_t = \sum_{i=0}^{p} a_{wx,\,i} \Delta x_{t-i} + \sum_{i=0}^{p} a_{wn,\,i} \Delta n_{t-i} + \sum_{i=1}^{p} a_{ww,\,i} \Delta w_{t-i} + \varepsilon_t^w . \tag{5}$$

The new model consists of labor productivity, employment, and real wages. Here, both labor productivity and employment are assumed to be exogenous to real wages, so that the shock ε_t^w has no effect on these variables over all horizons. Under this stricture, the equations for labor productivity and employment are identical to (3) and (4) in section 2. Obviously, the exogeneity of labor productivity and employment is a strong assumption, but it allows us to keep all of the results of section 3 intact. We are then able to focus on the effects of structural shocks identified in the two-variable model on real wages.[9] Equation (5) can be estimated consistently using an IV procedure. An appropriate set of instruments is lags 1 through p of Δx_t, Δn_t, and Δw_t, together with the estimated residuals of $\hat{\varepsilon}_t^x$ and $\hat{\varepsilon}_t^n$ from (3) and (4), respectively.

Figure 2 presents the responses of real wages to the technology and demand shocks.[10] The cleansing and Galí models show that technology shocks push real wages up across countries. There does not appear to be a strong difference between the two models. However, the responses to demand shocks are distinguishable. Real wages rise in the cleansing model, as predicted. For the case of Germany, real wages show a decrease at mid- and long-term horizons, but the effects are not very strong and are not statistically significant (not shown). In contrast, the Galí model produces mixed results. While demand shocks lower real wages in France, Italy, and the U.S., real wages rise for Canada, Japan, and the U.K. in disagreement with the predictions of the model. Germany also shows that real wages rise before deceasing at mid- and long-term horizons.[11] Overall, the cleansing model can account for features in the real wage data well. This does not seem to be the case for the Galí model, as there are several exceptions that need to be addressed.[12]

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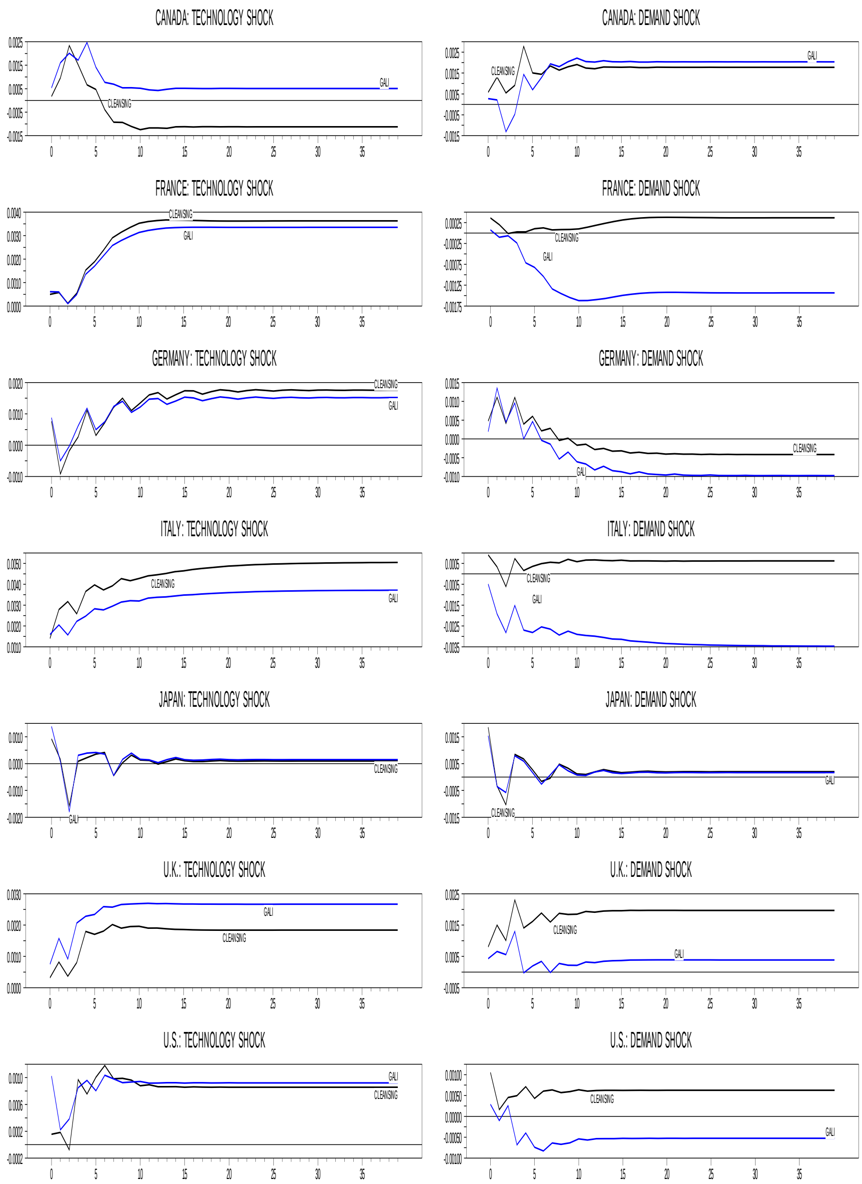
9) Without this exogeneity restriction, we need to redo the analysis in section 3 using the three-variable model. This would complicate a direct comparison with the original model of Galí and also take up a lot of additional space.

10) Data on real wages are obtained from Global Insight.

11) The responses in Japan are not very different from those of the cleansing model. In Figure 1, it is also shown that both the cleansing and the Galí models produce similar responses to technology and demand shocks. These findings provide evidence with regard to the test results in table 2 that the two models may not be statistically distinguishable in the case of Japan.

12) To check for robustness, we also experimented with an alternative model that includes p lags of Δw_t in the equations of labor productivity and employment. Under this specification, ε_t^w is allowed to affect labor productivity and employment at all horizons other than the contemporaneous one. The results did not change much, and the main findings remained unaltered. This data is available from the authors upon request.

Figure 2 Responses of Real Wages in Levels



5. CONCLUSION

Galí (1999) has sparked considerable debate concerning the relationship between technology and employment. His result that technological progress decreases employment constitutes not only a strong objection to the technology-driven RBC model but also poses a perplexing challenge to many policymakers who pursue the creation of jobs through productivity-enhancing innovations. Many studies have followed, scrutinizing the robustness of the results in Galí, especially from RBC proponents. This paper adds to the literature by looking at the subject from a different theoretical perspective. The organizing framework is cleansing effects, emphasizing the demand pull side of technological progress. In particular, recessions due to lower demand are viewed as the right time to reduce organizational inefficiency and resource misallocations. Productivity improves, and such efficiency gains are long-lasting.

We empirically examine how well the cleansing effect is consistent with actual data for G-7 countries, and the results are compared to those from the Galí model. It appears that the cleansing model fits the data well for all G-7 countries. As the model predicts, a negative demand shock increases labor productivity and hence, real wages rise, whereas employment decreases. A positive technology shock improves labor productivity and raises real wages. Importantly, employment increases across horizons, consistent with the common belief and with technology-driven RBC models. This is in sharp contrast to the Galí model, in which employment is shown to decrease at least in the short run. However, several issues arise with regard to the results of Galí. For example, a technology shock contributes only marginally to explaining the variability in employment in four out of the seven countries. For those countries, it is not clear whether the decrease in employment is actually binding empirically. That a negative demand shock has raised real wages in some countries is also difficult to reconcile with the model predictions. While there can be other reasons, one may be associated with the identifying assumption in Galí, which constrains the long-run effect of demand shocks on labor productivity to zero. Our testing results reject the relevancy of this assumption with actual data for the G-7, with the possible exception of Japan. Where the identifying assumptions are inconsistent with the data, their imposition may result in a misrepresentation of the true dynamic structure. Indeed, the Galí model produces several empirical exceptions, and they need to be resolved for this model to gain stronger support.

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