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Abstract

This paper investigates the validity of technology shocks as a driving force of U.S. business cycle fluctuations. Using three well-known structural vector autoregression (SVAR) models, we analyze how structural shocks are associated with the variations of output and hours worked at business cycle frequencies. Empirical results reveal that technology shocks remain an important source of cyclical movements in output. Furthermore, a positive technology shock does not lead to a decline in hours worked in contrast to previous studies. Our SVAR-based evidence does not support discarding a technology shock-driven business cycle theory.

Keywords: Structural vector autoregression, Technology shocks, Demand shocks, Real business cycles

JEL Classification: C32, E32

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I Introduction

Do we have sufficient empirical evidence to warrant discarding technology shocks as the main driver of economic fluctuations? The RBC hypothesis posits that technology or productivity shocks are the dominant source of fluctuations, propagated through intertemporal substitutions by optimizing households and firms in response to the shocks. The hypothesis implies that government stabilization policies could be counter-productive. In contrast, the New Keynesian models emphasize the role of demand shocks propagated due to the presence of price stickiness and imperfect competition, justifying active demand management through short-run stabilization programs. Thus, empirical investigation of the main source of business cycle fluctuations is important not only as a guide for developing a useful positive theory but also because policy implications can vary substantially depending on which interpretation is correct.

Following the emergence of the New Keynesian research program, there has been considerable debate as to whether the RBC predictions are borne out by data. Many empirical studies have relied on structural vector autoregression (SVAR) approaches to evaluate the empirical validity of the RBC hypothesis. Notably, Galí (1999), Galí and Rabanal (2004), and Francis and Ramey (2005) all reported that positive technology shocks lead to a decline in hours worked, casting serious doubt on the usefulness of RBC theory as a quantitative theory of economic fluctuations. Typically, these studies adopted long-run restrictions to identify shocks with the interpretation of "technology shocks" and compared the congruence between the impulse responses of an estimated SVAR model and those of an RBC model.

However, McGrattan (2004), Christiano *et al*. (2003), and Chari *et al*. (2008) all challenged this rejection of technology-shock driven RBC models. Specifically, they argued that the SVAR models used to refute RBC-based explanations were either misspecified or not appropriately designed to evaluate the calibrated general equilibrium business cycle theory. In a similar vein, Wang and Wen (2011) argued that conditional impulse responses generated by SVAR models cannot serve as grounds to reject the technology shock-driven RBC hypothesis because the dimension of such a highly stylized model is different from that of an empirical characterization of data.

In this paper, we utilize several well-established SVAR models and present a set of further results that provide alternative perspectives into the empirical source of fluctuations. Our work is not an attempt to engage in the methodological debate over the best practice to empirically evaluate the RBC theory or, more generally, calibrated macroeconomic models. In spirit, it is rather in line with Cochrane (1994a), Galí (1999), and others, that rely on the VAR models for determining which empirical shocks actually drive economic fluctuations. Yet, there is an interesting point of departure. Unlike previous studies, we focus on business cycle frequencies and estimate the contribution of technology *vs* demand (and other) shocks by imposing a minimal number of identifying assumptions. The SVAR models under investigation are Galí (1999), Shapiro and Watson (1988), and King *et al*. (1991).[1] These SVAR models were selected because they are among the best understood and the most popular models in empirical business cycle research. The key analytical tool in this paper is the decomposition of permanent and transitory components, similar to that of Beveridge and Nelson (1981). By construction, the permanent component determines the long-run movements of the variables, while the transitory component captures the short-run dynamics. To take this decomposition into economic perspectives, consider a case of technology shocks as an example. In response to a positive technology shock, the economy moves to a permanently higher steady-state capital stock, lifting up the permanent component of output. However, the capital stock does not immediately jump into the new higher level because that would entail too large a reduction of current consumption. Rather there is a transition period during which capital is built up, and adjustment costs and lags are other factors that prolong

[1] In an earlier version, we also considered the bivariate SVAR model studied by Cochrane (1994b) but later dropped it as its essence can be captured by the more general SVAR model developed by King *et al*. (1991).

the transition process. The short-run dynamics in the variables are essentially movements along the adjustment path as the capital stock rises to a new steady-state level. Through this channel, the technology shock accounts for the transitory components of the variables.[2]

Both permanent and transitory components can be constructed after estimating structural models in conjunction with identifying restrictions. This allows us to analyze how the underlying shocks of models are associated with the transitory component of output, which captures fluctuations at business cycle frequencies. Based on the conditional correlations of shocks with cyclical output, we examine how different structural shocks have contributed to postwar U.S. business cycle fluctuations. We also provide detailed findings on two important issues. First, we shed light on whether the importance of technology shocks is sensitive to whether hours worked is specified to be difference-stationary or trend-stationary, as RBC proponents such as Christiano *et al*. (2004) have argued. The second issue concerns the empirical findings that a positive technology shock leads to a decline in hours, which Galí and others have used as evidence against the RBC theory. Overall, this study provides further and alternative perspectives using the evidence that is clearly at odds with the earlier findings of Galí and others.

The remainder of this paper is organized as follows. Section II outlines the three SVAR models explored in the paper, and Section III presents our empirical strategy for measuring the relative contribution of structural shocks in accounting for the business cycle fluctuations of the variables. The results are given in Section IV. Section V offers further discussion of the results, with particular emphasis on robustness, and revisits the issue raised by Galí concerning the relationship between technology shocks and hours worked. Section VI summarizes the key results of the paper and concludes the paper.

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[2] By the same reasoning, some studies posit the permanent component of output as a measure of potential output and the transitory component as output gap in the SVAR models, for example, King *et al*. (1991), Dupasquier *et al*. (1999), and Demiroglu and Salomon (2002).

II Three SVAR models

Galí (1999) offered a refutation of the RBC theory's predictions, arguing that technology shocks have a limited ability to explain postwar U.S. business cycles. His empirical investigation adopted two models: (i) a bivariate SVAR model comprising labor productivity (x) (defined as output less hours worked) and hours worked (n), i.e., with the vector $\left[x_t,\ n_t\right]'$, and (ii) a five-variable SVAR model with the vector of variables $\left[x_t,\ n_t,\ m_t-p_t,\ R_t-\Delta p_t,\ \Delta p_t\right]'$, where, in addition to labor productivity and hours worked, real money balances (nominal money, m, less the price level, p), real interest rates (nominal interest rates, R, minus the rate of inflation, Δp), and the inflation rate (Δp) enter the system.[4] In the current paper, we consider only the latter model, as the bivariate model does not make a distinction between non-technology supply shocks and demand shocks. The five-variable SVAR model assumes that there are five structural shocks: technology shocks (v_{1t}), labor supply shocks (v_{2t}), and three demand-side shocks (v_{3t}, v_{4t}, and v_{5t}).

For identification of the underlying shocks, it is assumed that labor productivity and hours are not affected by the three demand shocks, v_{3t}, v_{4t}, and v_{5t}, in the long run. This distinguishes the technology and labor supply shocks from the demand shocks. The two supply shocks are identified individually on the assumption that the labor supply shock has no long-run effect on labor productivity. The three demand shocks are not disentangled individually, and their combined effects are used. The structural vector moving average (VMA) representation with the long-run identifying restrictions in use can be written as

$$\begin{bmatrix} \Delta x_t \\ \Delta n_t \\ \Delta m_t-\Delta p_t \\ R_t-\Delta p_t \\ \Delta^2 p_t \end{bmatrix} = \delta + C(L)\begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \\ v_{5t} \end{bmatrix} \text{ and } C(1)=\begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}$$

[4] Note that the lowercase variables denote that the variables are logged, e.g., $y = \log Y$.

where Δ is the first difference operator, δ is a constant vector, L is the lag operator, $C(L)=\sum_{i=0}^{\infty} C_i L^i$ is a lag polynomial matrix, $C(1)=\sum_{i=0}^{\infty} C_i$ measures the long-run effects on the levels of the series of the structural shocks, and the * indicate the parameters to be estimated. As output is obtained through the relationship that $y_t = x_t + n_t$, it is affected by the two supply shocks at all horizons, while none of the demand shocks has long-run effects.

Shapiro and Watson (henceforth SW, 1988) present a five-variable SVAR model comprising the variables $[o_t,\ n_t,\ y_t,\ \Delta p_t,\ R_t - \Delta p_t]'$, where o_t is the price of oil. In the model, the oil price is assumed to be exogenous to all of the other variables, so that its reduced-form residuals become the oil price shocks. This allows us to reduce the original specification to the four-variable model of $[n_t,\ y_t,\ \Delta p_t,\ R_t - \Delta p_t]'$ with the oil price entering the equations as an exogenous regressor. There are assumed to be four structural shocks governing the economy: labor supply shocks (v_{1t}), technology shocks (v_{2t}), and two demand shocks (v_{3t} and v_{4t}). The labor supply shock is identified on the assumption that it is the only shock that has a long-run effect on hours. None of the other three shocks will exhibit any long-run effect on hours. The technology shock is identified using the long-run output neutrality so that the two demand shocks do not have long-run effects on output. Again, the demand shocks are not identified individually, and their combined effects are considered instead. The SW model can be written in the form of a structural VMA as

$$\begin{bmatrix} \Delta n_t \\ \Delta y_t \\ \Delta^2 p_t \\ R_t - \Delta p_t \end{bmatrix} = \delta + C(L)\begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix} \text{ and } C(1) = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \end{bmatrix}.$$

King *et al.* (henceforth KWSW, 1991) analyze a vector error correction model (VECM) comprising the six-variable $[y_t,\ \Delta p_t,\ c_t,\ i_t,\ m_t - p_t,\ R_t]'$, where consumption ($c_t$) and investment ($i_t$) are also included. They suggest that there are three co-integrating relations present in the system. Two of these are the great ratios: that is, ($c_t - y_t$) and ($i_t - y_t$) are stationary (after the adjustment for real interest rate effects), while the remaining relation is a long-run money demand relation among real money ($m_t - p_t$), output (y_t), and the nominal interest rate (R_t). On the basis of three cointegrating relations, there are assumed to be three structural shocks whose effects are permanent, and they are identified as balanced-growth (productivity) shocks (v_{1t}), inflation shocks (v_{2t}), and real interest rate shocks (v_{3t}). The remaining three shocks (v_{4t}, v_{5t}, and v_{6t}) have only transitory effects on the variables, and are not given specific economic interpretations.[6]

The productivity (technology) shock is identified under the assumption that neither the inflation shock nor the real interest rate shock has a long-run effect on output.[7] The shocks to inflation and the real interest rate are individually identified by assuming that the real interest rate shock does not have a long-run effect on inflation. These three restrictions are sufficient for exact identification of the permanent shocks in the model, as the remaining three shocks, v_{4t}, v_{5t}, and v_{6t}, exhibit only transitory effects. The KPSW model may be expressed in the form of a structural VMA as

$$\begin{bmatrix} \Delta y_t \\ \Delta^2 p_t \\ \Delta c_t \\ \Delta i_t \\ \Delta m_t - \Delta p_t \\ \Delta R_t \end{bmatrix} = \delta + C(L) \begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \\ v_{5t} \\ v_{6t} \end{bmatrix} \text{ and } C(1) = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \end{bmatrix}$$

Unlike the Galí and SW models, KPSW allow for investment dynamics to be expressed within the system. Cogley and Nason (1995) showed that investment dynamics play a central role through adjustment lags or costs in accounting for the propagation

[6] See also Gonzalo and Ng (2001) and Pagan and Pesaran (2008) for the implications of cointegration in the structural identification of the VECM model.
[7] We use the terms productivity and technology interchangeably unless stated otherwise.

mechanism. McGrattan (2004) eloquently argued that technology shocks typically influence the business cycle through investment, rather than hours. Her point casts doubt on the premise of sticky-price models of the business cycle because models, including the one studied by Galí, dispense with the role of investment in propagating technology shocks. Fama (1992) also presented evidence that the hump-shaped response of output is largely due to the multiplier effect of variations in investment. A recent work by Fisher (2006) further strengthened the case for the importance of investment and the role of investment-specific technology shocks.

III Measuring the contribution of structural shocks at business cycle frequencies

Let Z be a (k×1) vector of variables consisting of k_1 non-stationary variables and k_2 stationary variables, i.e., $Z_t = \left[\Delta X_{1t}', X_{2t}'\right]'$. The structural VMA representation can be compactly expressed as

$$Z_t = \Gamma(L)v_t \tag{1}$$

where v_t represents a vector of structural shocks, and the lag polynomial matrix $\Gamma(L)$ tracks the response of Z to the structural shocks. For expositional convenience, assume that output in differenced form, Δy, is the first variable in the vector Z. This allows the following decomposition, in a manner analogous to Beveridge and Nelson (1981):

$$\Delta y_t = \Gamma_y(L)v_t = \Gamma_{yp}(L)v_t^p + \Gamma_{yc}(L)v_t^c \tag{2}$$

where v_t^p is a vector of shocks that have permanent effects on output, e.g., technology shocks, and v_t^c is a vector of shocks that exert only transitory effects, e.g., IS and LM shocks. Equation (2) can be further decomposed as

$$\Delta y_t = \left[\Gamma_{yp}(1) + \Gamma_{yp}^*(L)\right]v_t^p + \Gamma_{yc}(L)v_t^c = \Gamma_{yp}(1)v_t^p + \Gamma_{yp}^*(L)v_t^p + \Gamma_{yc}(L)v_t^c \tag{3}$$

where $\Gamma^*_{yp}(L) = \left[\Gamma_{yp}(L) - \Gamma_{yp}(1)\right]$, $\Gamma_{yp}(1)$ captures the effects of v_t^p on the long-term trend of output, and $\Gamma^*_{yp}(L)$ measures the effects of v_t^p on the short-run dynamics of output. For instance, technology shocks affect long-term output, which is reflected in $\Gamma_{yp}(1)$, and also cause business cycles through changes in capital investment and adjustment costs or lags in labor input, that is captured by $\Gamma^*_{yp}(L)$. Equation (3) can be transformed in levels as

$$y_t = y_t^p + y_t^c = \Gamma_{yp}(1)\sum_{t=0}^{t} v_t^p + \Gamma^*_{yp}(L)\sum_{t=0}^{t} v_t^p + \Gamma_{yc}(L)\sum_{t=0}^{t} v_t^c \tag{4}$$

In (4), the cyclical component of output corresponds to $y_t^c = \Gamma^*_{yp}(L)\sum_{t=0}^{t} v_t^p + \Gamma_{yc}(L)\sum_{t=0}^{t} v_t^c$. As it comprises the components separately driven by permanent shocks and transitory demand shocks, we are able to examine which shock is mainly responsible for fluctuations in output at business cycle frequencies. This may provide a better way of defining determinants underlying business cycles than the typical tool of impulse responses and variance decompositions. The impulse response and variance decomposition analyses are constructed based on $\Gamma_{yp}(L)$, which captures the composite of the effects on the short-run dynamics $\Gamma^*_{yp}(L)$ and the effects on the long-term trend $\Gamma_{yp}(1)$ at business cycle frequencies.

Using the decomposition outlined above, we calculate the conditional correlations of different shocks with the cyclical component of output. To take a five-variable model as an example, let $\rho_{v,1}$ be the correlation coefficient between cyclical output y_t^c and the first shock in the model, e.g., technology shock v_{1t}. Then, the coefficient $\rho_{v,2345}$ captures the correlation of y_t^c with all other shocks combined, indexed 2 to 5 combined, e.g., the composite non-technology shocks. The conditional correlation quantifies the extent to which each structural shock is associated with output fluctuations at business cycle frequencies. In addition, by squaring the correlation coefficients, we can analyze the contribution of the shocks to accounting for the variance of y_t^c. To see this, rewrite y_t^c in (4) as

$$y_t^c = a_{01}v_{1t} + a_{02}v_{2t} + a_{03}v_{3t} + a_{04}v_{4t} + a_{05}v_{5t} + \\ a_{11}v_{1t-1} + a_{12}v_{2t-1} + a_{13}v_{3t-1} + a_{14}v_{4t-1} + a_{15}v_{5t-1} + \cdots\cdots\cdots$$

Then, the conditional correlation of y_t^c with the i^{th} shock v_{it} can be obtained as

$$\rho_{v,i} = Corr(y_t^c, v_{it}) = \sqrt{a_{0i}^2\sigma_i^2} \,/\, \sqrt{\sum_{i=1}^{5} a_{0i}^2\sigma_i^2}$$

where σ_i^2 is the variance of the shock v_{it}. Squaring the coefficient of the correlation yields

$$\rho^2{}_{v,i} = \left[Corr(y_t^c, v_{i,t})\right]^2 = a_{0i}^2\sigma_i^2 \,/\, \sum_{i=1}^{5} a_{0i}^2\sigma_i^2$$

The denominator represents the variance of y_t^c explained by all shocks in time t, and the numerator measures the contribution of the i^{th} shock v_{it}.

IV Empirical results

(i) Impulse responses and historical decompositions

The Galí, SW, and KPSW models in Section II are estimated using the same data series, lag lengths, and starting dates as those used in the original contributions.[9] This paper, however, extends the sample period for all models to end in 2008:Q4.[10] We first present the results from impulse responses and historical decompositions. For the former, we examine how a variable responds to the structural shocks and check whether these responses are consistent with the theory. For the latter, we assess the ability of structural shocks to explain the stochastic movement in a variable over time. At the outset, it should be remembered that demand shocks in the Galí and SW models, and transitory shocks in the KPSW model, were

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[9] The number of lags is 4, 6, and 8, and the starting date is 1959:Q1, 1951:Q1, and 1954:Q1 for the Galí, SW, and KPSW models, respectively.

[10] This effectively excludes the full effect of the recent financial crisis as an outlier.

not individually identified (see Section II). As such, the responses of the variables to these shocks are not reported in the impulse response analysis, while the historical decomposition analysis reports their combined contribution to tracking the stochastic movements of the variables. We also note that hours worked is assumed to be a difference-stationary process. In the next section, we will examine how the results differ when hours worked is assumed to be a trend-stationary process.

Figure 1.1 depicts the responses of labor productivity, output, and hours in levels to the two supply-side shocks identified in the Galí model, that is, technology (TN) and labor supply (LS) shocks. Also shown around each response is the one standard error confidence interval generated by 1,000 bootstrap replications. All of the responses are not different from those presented by Galí. A positive technology shock raises labor productivity and output permanently, while hours show a significant decline at short-run horizons. As Galí forcefully argues, this finding is apparently evidence against the RBC theory, which predicts pro-cyclical labor hours in response to technology shocks. A positive labor supply shock increases hours and output permanently, and the effect on labor productivity converges to zero by the identifying assumption. Figure 2.1 shows the historical decompositions of the key variables. Technology shocks explain most of the variation in labor productivity, while the variation of hours is mostly accounted for by labor supply shocks. Interestingly, the result shows that the labor supply shock is also the main determinant of the movements in output. None of the technology or demand shocks plays any significant role. We will discuss these results subsequently in detail.

Figure 1.2 shows the responses of the variables to technology and labor supply shocks estimated from the SW model. Overall, output and hours respond in a very similar manner to the Galí model. The level of hours falls in response to a positive technology shock before converging to zero by the identifying restriction. Positive shocks to labor supply and technology increase output permanently. The historical decomposition yields similar results, as displayed in Figure 2.2. The labor supply shock is the main factor in explaining the stochastic movements in hours and output, while technology and demand shocks contribute little to the movements in output.

For the KPSW model, Figure 1.3 shows the responses of three real variables – output, consumption, and investment – to the three permanent shocks: shocks to technology (TN), inflation (IF), and the real interest rate (RR). A positive technology shock raises output, consumption and investment permanently, as expected *a priori*. The inflation shock has little impact on the variables except at some short-run horizons. In response to a positive real interest rate shock, the three variables show strong initial increases. These impulse responses are difficult to interpret, as KPSW also acknowledged.[11] Figure 2.3 shows the results from historical decompositions. Technology shocks account for most of the variations in output and consumption. The other two permanent shocks, as well as transitory shocks, seem not to contribute as much. In the case of investment, the technology shock is still a major determinant, but the combined transitory shocks also capture a sizable portion of the movements, particularly for the second half of the sample period.[12]

(ii) Cyclical output and shocks

The crux of this paper is an examination of the sources of fluctuations at business cycle frequencies. While the results in the preceding section provide useful insights, they are not complete for an often neglected reason – the impulse response function is designed to capture the combined effects of shocks on both long-term trends and short-run dynamics. To business cycle researchers, a particular concern in the Galí and SW models would be that output fluctuations were mostly accounted for by labor supply shocks. Technology and demand

[11] Fisher *et al.* (2000) suggest that a real spending shock, in place of the real interest rate shock, provides a better economic interpretation of the KPSW findings. Under this alternative interpretation, the strong initial increases in the variables in response to the shock are consistent with the predictions of conventional economic theory.

[12] We also computed the forecast error variance decompositions of the variables. The implications are similar to those from the historical decompositions across three models. For space conservation, we do not report these results from the variance decomposition analysis, but they are available upon request.

shocks contributed little, which is hard to reconcile with the RBC or even with the Keynesian perspective. When focusing on business cycle fluctuations, as in the current study, it may be more prudent to look at the relationships between underlying shocks and cyclical output rather than the output variable *per se*. As RBC models are typically analyzed in terms of the steady state deviations in response to a shock, decomposing output into permanent, defining the steady state, and transitory components is legitimate, justifying the empirical strategy detailed in Section III. Assuming the transitory component as a measure of cyclical output, we examine how and to what extent cyclical output is associated with the shocks in the model.

Table 1 reports the conditional correlations of cyclical output with respect to the structural shocks. Starting from the Galí model in the top panel, the correlation coefficient between cyclical output and technology shocks is 0.69. Squaring it yields that technology shocks account for about 48 percent of the variance in cyclical output. Demand shocks are almost as highly correlated with cyclical output ($\rho_{v,345} = 0.68$) as technology shocks. In contrast, the correlation coefficient between the labor supply shock and cyclical output is low, at 0.33; only 10 percent of variance in cyclical output is explained by the labor supply shock. To elaborate on these results, Figure 3.1 reports the historical decomposition of cyclical output, and the shaded areas represent periods between peaks and troughs in the U.S. business cycles, dated by the National Bureau of Economic Research (NBER). Indeed, both technology and demand shocks capture the movements in cyclical output equally well, while labor supply shocks perform poorly. The results are quite different from those of the impulse response and variance decomposition analysis in the preceding section. The technology and demand shocks now emerge as the main determinant of output movements at business cycle frequencies, while the contribution of the labor supply shock is substantially reduced once the low-frequency component of output is removed. Figure 4 displays the cross correlations of cyclical output with the shocks at leads up to eight quarters. The correlations at leads can assess the predictive properties of the shocks over the business cycle. From the top panel, the technology shock is found to lead cyclical output more strongly than demand shocks across the leads, while the labor supply shock fails to lead cyclical output.

The middle panel reports the conditional correlations between cyclical output and the structural shocks estimated from the SW model. For technology shocks, the correlation coefficient is 0.58, while the coefficient for the combined demand shocks is much higher, at 0.83. Similar to the Galí SVAR, the association between output and labor supply shocks becomes significantly weaker and statistically insignificant over the business cycle. Although the level of correlation between technology shocks and cyclical output is lower than in the Galí SVAR, technology shocks still account for about 34 percent of the variance in cyclical output, with the remainder being explained by the demand and labor supply shocks together. The historical decomposition in Figure 3.2 confirms these findings. Demand shocks closely follow the movements in cyclical output over the sample period, while labor supply shocks contribute very little. The technology shock still retains a considerable ability to explain cyclical output, although not as well as demand shocks. Again, these results are quite different from those of the historical decomposition for output, in which demand and technology shocks played a negligible role. Looking at the middle panel of Figure 4 demand shocks better predict cyclical output than the technology shock, although the difference is diminished at long leads. The labor supply shock does not exhibit any discernible ability to lead cyclical output across all leads. Overall, the Shapiro and Watson SVARs produce qualitatively similar results to those from the Galí SVAR. In both models, technology and demand shocks are the main drivers of cyclical output, while the labor supply shock becomes insignificant.

Finally moving to the results for the KPSW model in the bottom panel, the technology shock is the most significant force, with a correlation coefficient of 0.61. The correlation of cyclical output with the two demand shocks combined (shocks to inflation and the real interest rate) is 0.48, while the correlation with the three (unidentified) transitory shocks is 0.56. Although results depend somewhat on how transitory shocks are actually identified, they are more likely to originate from the demand side rather than the supply side. This allows us to combine these transitory shocks with the two permanent demand shocks and interpret them as non-technology shocks that mainly reflect changes in demand. As a consequence, the non-technology shock is more highly correlated with cyclical output ($\rho_{v,23456} = 0.77$) than the technology shock. Figure 3.3 shows the decomposition of cyclical output attributable to the structural shocks. The technology and transitory shocks appear to track the movements in cyclical output equally well. When the demand and transitory shocks are combined, the resulting non-technology shock shows a better fit with cyclical output throughout the entire sample period. The bottom panel of Figure 4 adds an interesting observation concerning the ability of the shocks to predict cyclical output in the KPSW model. The non-technology shock outperforms the technology shock for up to three quarters of leads, while the reverse is true thereafter. As the forecasting horizon increases beyond three quarters, the technology shock exhibits better predictive abilities for cyclical output.

V Issues surrounding hours worked

In the New Keynesian-RBC debate over the importance of technology shocks, there are two important issues concerning the empirical characterization of hours worked. The first issue is the sensitivity of the results to the assumption of whether hours worked is difference-stationary or trend-stationary. The second issue, related to the first one, is whether a positive technology shock does, in fact, lead to a decline in hours worked, as argued by Galí (1999). This section addresses each of these issues with respect to our results from the Galí and SW models.

(i) Stationary vs non-stationary hours worked

Theoretically speaking, hours worked is a bounded series, and conventional RBC models predict that in the presence of technology shocks, the substitution and income effects cancel each other out, with no clear impact on the steady-state level of hours. In finite samples, however, it is debatable whether such theoretical constraints are borne out by the data. Some RBC proponents, such as Christiano *et al*. (2004), argue that the findings of Galí (1999) depend critically on whether the level of hours is assumed to be stationary. This was also noted earlier by Shapiro and Watson (1988), as they observed that the output effects of technology and labor supply shocks may vary depending on whether hours worked is assumed to be difference-stationary or trend-stationary.

In the preceding section, the Galí and SW models adopted the assumption of difference-stationary hours. Figures 5.1 and 5.2 show the impulse responses and historical decompositions estimated from the Galí and SW models when hours worked is assumed to be a trend-stationary process. For both models, the impulse responses remain largely unchanged, with two obvious exceptions. First, the effects of the labor supply shock on the variables are transitory; secondly, all responses of hours converge to zero in the long run. Both of these findings reflect the assumption that hours worked is trend-stationary. Again, a positive technology shock leads to a decline in hours, analogous to the finding under the assumption of difference-stationary hours. However, the historical decomposition produces quite a different picture; across the models, the technology shock is now the main source of movements in output, and the contribution of the labor supply shock shrinks considerably, particularly since the mid-1970s. Similar changes are also observed for explaining the variability of hours. The technology shock emerges as the main determinant, while the labor supply shock contributes far less than before.

To further illustrate, we re-compute the conditional correlations of the structural shocks with cyclical output under the assumption that hours worked is a trend-stationary process. The results are reported in Table 2. Several changes are worth discussion. Examining the Galí model first, the technology shock is the most highly correlated with cyclical output, as documented by the correlation coefficient of 0.87. The correlation between demand shocks and cyclical output is only about 0.2, which is quite low compared with the correlation coefficient of 0.68 when hours worked was assumed to be a difference-stationary process. Even when all non-technology shocks are combined, the correlation coefficient is just 0.33, which is far less than the correlation between the technology shock and cyclical output.

The SW model produces the same implications. The correlation of cyclical output with the technology shock rises considerably to 0.84, while the corresponding figure for demand shocks is more than halved to 0.37 in comparison to the result when hours was assumed to be difference-stationary. The historical decomposition of cyclical output reported in Figure 5.3 consolidates the results. The technology shock accounts for most of the movements in cyclical output, while both labor supply and demand shocks contribute little. Figure 5.4 shows that the predictive power of technology shocks is also strengthened under the assumption of stationary hours. For both the Galí and SW models, the technology shock leads cyclical output far better than the labor supply and demand shocks across all leads, showing particularly strong effects at short leads. Even over longer leads, such as eight quarters, the coefficient remains higher than 0.5. For the SW model, demand shocks exhibit some predictability at short leads but only marginally, while the labor supply shock fails to lead cyclical output.

To sum up, the RBC hypothesis is more preferred in the case that hours worked is assumed to be a trend-stationary process. The evidence is more pronounced when we decompose the variables into permanent and transitory components and focus only on the latter components, which reflect movements at business cycle frequencies. When hours worked is assumed to be difference-stationary, technology and demand shocks are almost equally important in accounting for cyclical output. Under the trend-stationary assumption, the technology shock becomes the major determinant of cyclical output, outperforming all other shocks, including demand shocks. The results are robust for both Galí and SW models, despite the fact that these models have different structures and identifying assumptions.[13] Whether hours worked is a difference-stationary or trend-stationary process appears to really matter, as the previous studies have suggested. While more comprehensive research is warranted, it could be difficult to draw an empirical distinction concerning the time-series properties of hours, given the well-known low power problem of unit root tests coupled with the typical sample size of macroeconomic data. Because this issue is beyond the scope of the current paper, we leave it for future research and move on to another related issue.

(ii) Technology shocks and hours worked

Galí (1999) argued that technology shocks lead to a decline in hours worked whether hours worked is difference-stationary or trend-stationary, using this as evidence against the RBC hypothesis. In the impulse response analysis, we find results similar to those of Galí, as displayed in Figures 1.1, 1.2, and 5.1. The figures also indicate that the decline in hours is present only in the short-run horizon, after which the responses of hours to a positive technology shock are statistically insignificant (Figure 1.1) or converge to zero (Figures 1.2 and 5.1) by the identifying assumptions. As stated earlier, the impulse response analysis reflects the composite effects on both long-term movements and short-term dynamics. To isolate the short-term from the long-term movements, the decomposition outlined in Section III was applied to hours worked. In this way, we seek to determine whether Galí's argument would still hold once confined to movements at business cycle frequencies.

[13] For example, the Galí model assumes that technology shocks can affect all of the variables in the long run, but labor supply shocks are not allowed to have a long-run effect on labor productivity. The converse is assumed in the SW model: labor supply shocks can have a long-run impact on all of the variables, while technology shocks cannot have permanent effects on labor supply.

Figure 5.5 displays the conditional correlations between technology shocks and cyclical hours over up to eight quarters of leads. The technology shock appears to be positively correlated with cyclical hours contemporaneously across the Galí and SW models. This is robust whether hours worked is assumed to be a difference-stationary or trend-stationary process. The correlations range between 0.59 and 0.88 and are particularly strong under the trend-stationarity assumption. It is also notable that the Galí and SW models produce coefficients of a very similar magnitude, validating the robustness of the results. Furthermore, the technology shock is found to lead cyclical hours considerably, displaying positive and statistically significant correlations at most of the leads. Thus, our evidence does not support Galí's finding that a positive technology shock leads to a decline in hours, when examined over business cycle frequencies. Rather, our finding that a technology shock has a strongly positive association with cyclical variation in hours is quite well explained by the RBC models.[14]

VI Conclusion

This paper examined the empirical sources of business cycle fluctuations in the postwar U.S. economy using three popular SVAR models: Galí (1999), Shapiro and Watson (1988), and King, Plosser, Stock, and Watson (1991). In adopting these models, a minimum set of theoretical restrictions were imposed *a priori* to avoid favoring a particular theory, especially between New Keynesian and RBC paradigms. The current study went significantly further than the original SVAR contributions by making extensive use of the statistical properties of the data and results. In particular, the variables were decomposed into permanent and transitory components; using the latter, we investigated the relationships between underlying structural shocks and movements of the variables at business cycle frequencies. This strategy

[14] In RBC models, a positive shock to technology leads to a rise in hours worked through an increase in the marginal product of labor and the consequent adjustments in the marginal rate of substitution.

appeared to pay economically interesting dividends. Technology and demand shocks were both shown to be the most important sources of variation in cyclical output. This finding is different from that suggested by the conventional impulse response and historical decomposition analysis.

This paper also examined two important issues still being debated in the literature: whether the assumption of stationarity of hours worked matters and whether a positive technology shock leads to a decline in hours, as claimed by Galí (1999). As to the first issue, our results showed considerable changes under the trend-stationary assumption. Of particular interest is that a technology shock was the most important determinant of cyclical output, while all other shocks, including demand shocks, contributed only marginally. This study yields an equally interesting result with regard to the second issue. While we, like other authors, found a decline in hours in response to a positive technology shock, a very different picture emerged when focusing on the movements at business cycle frequencies. The technology shock was positively correlated with the contemporaneous and future values of cyclical hours, invalidating Galí's claim. The effects were more pronounced when hours was assumed to be trend-stationary. Our evidence is robust across the models under consideration. Taking all of these results together, it is concluded that technology shocks should not be discarded as an important driver of business cycle fluctuations, nor should the RBC be thrown out simply because of its emphasis on technology shocks.[15]

[15] Cochrane (1994b) remarks that we may "forever remain ignorant of the fundamental causes of economic fluctuations."

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Table 1: Correlations of Shocks with Cyclical Output, *Difference-stationary Hours*

Galí SVAR			
Technology shock ($\rho_{v,1}$)	Labor supply shock ($\rho_{v,2}$)	Demand shocks combined ($\rho_{v,345}$)	Non-technology shocks ($\rho_{v,2345}$)
0.69 (0.31)	0.33 (0.32)	0.68 (0.26)	0.78 (0.23)
Shapiro and Watson SVAR			
Technology shock ($\rho_{v,2}$)	Labor supply shock ($\rho_{v,1}$)	Demand shocks combined ($\rho_{v,34}$)	Non-technology shocks ($\rho_{v,234}$)
0.58 (0.29)	0.15 (0.30)	0.83 (0.25)	0.86 (0.13)
KPSW SVAR			
Technology shock ($\rho_{v,1}$)	Demand shocks combined ($\rho_{v,23}$)	Transitory shocks combined ($\rho_{v,456}$)	Non-technology shocks ($\rho_{v,23456}$)
0.61 (0.28)	0.48 (0.25)	0.56 (0.19)	0.77 (0.17)

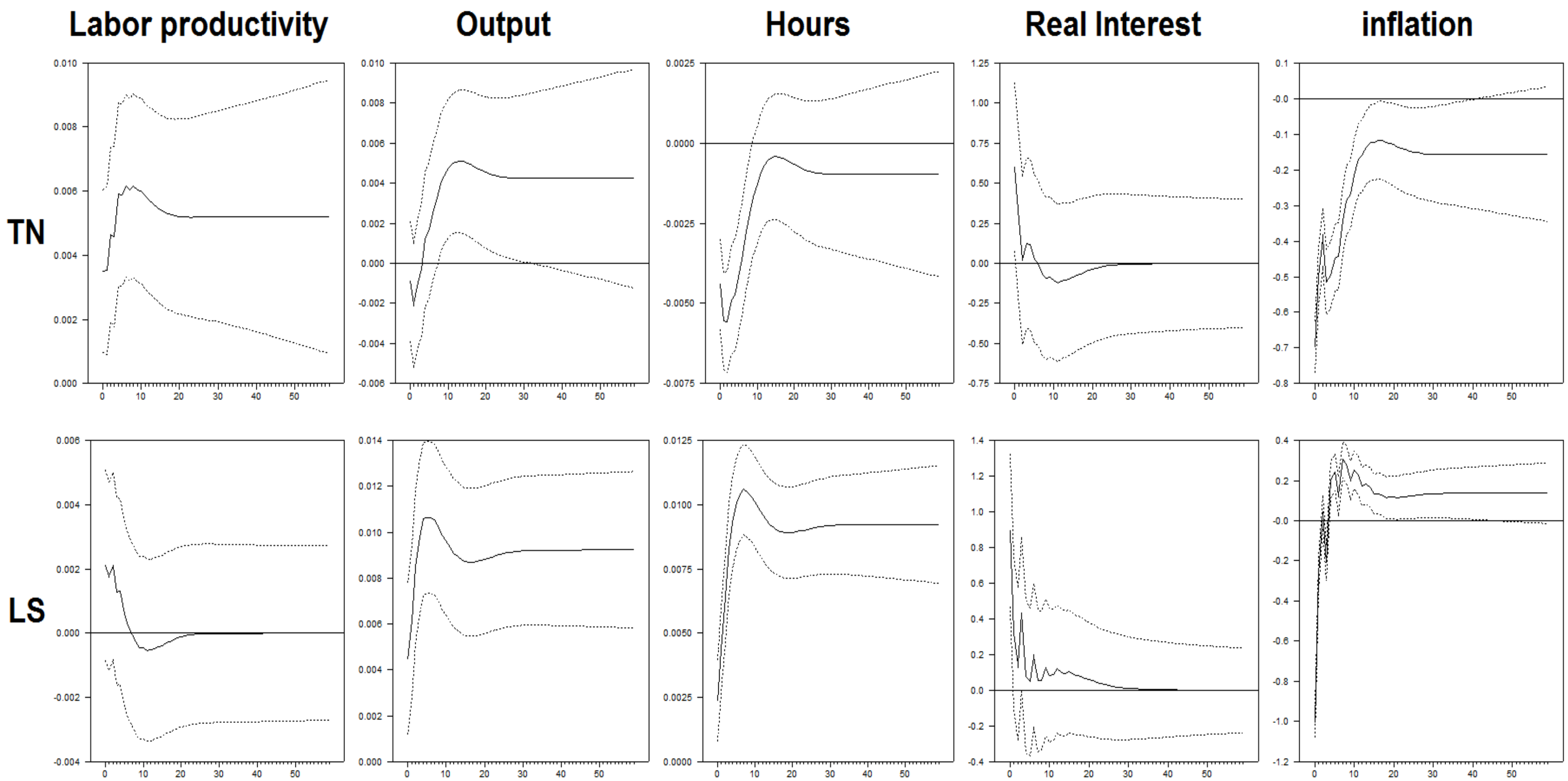
Note: Figures in parentheses are one-standard errors of the estimates generated by 1,000 bootstrap replications.

Table 2: Correlations of Shocks with Cyclical Output, *Trend-stationary Hours*

Galí SVAR			
Technology shock ($\rho_{v,1}$)	Labor supply shock ($\rho_{v,2}$)	Demand shocks combined ($\rho_{v,345}$)	Non-technology shocks ($\rho_{v,2345}$)
0.87 (0.16)	0.27 (0.19)	0.20 (0.14)	0.33 (0.19)
Shapiro and Watson SVAR			
Technology shock ($\rho_{v,2}$)	Labor supply shock ($\rho_{v,1}$)	Demand shocks combined ($\rho_{v,34}$)	Non-technology shocks ($\rho_{v,234}$)
0.84 (0.17)	-0.01 (0.22)	0.37 (0.20)	0.15 (0.21)

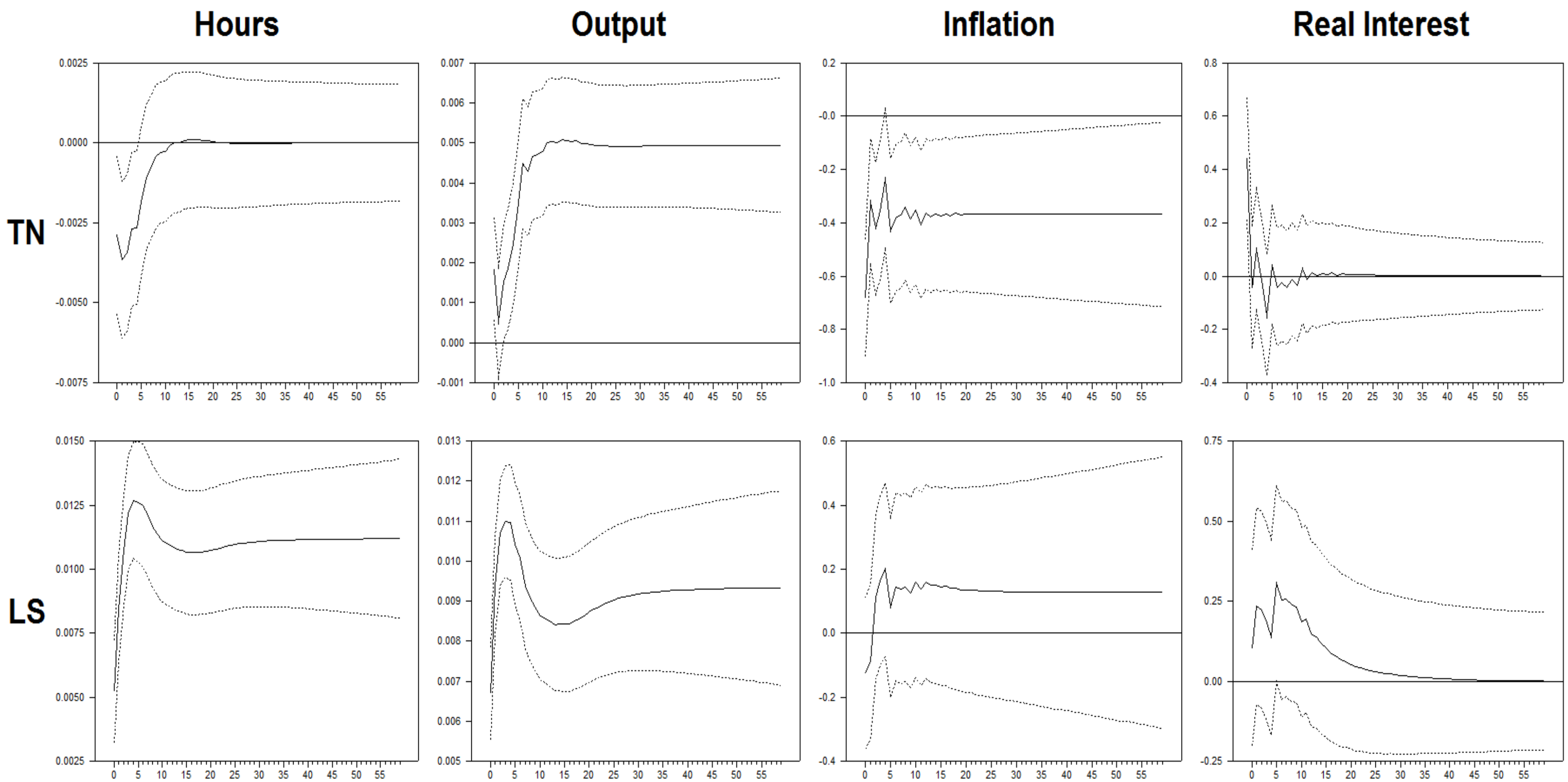
Note: Figures in parentheses are one-standard errors of the estimates generated by 1,000 bootstrap replications.

Figure 1.1: Impulse Responses from Galí SVAR



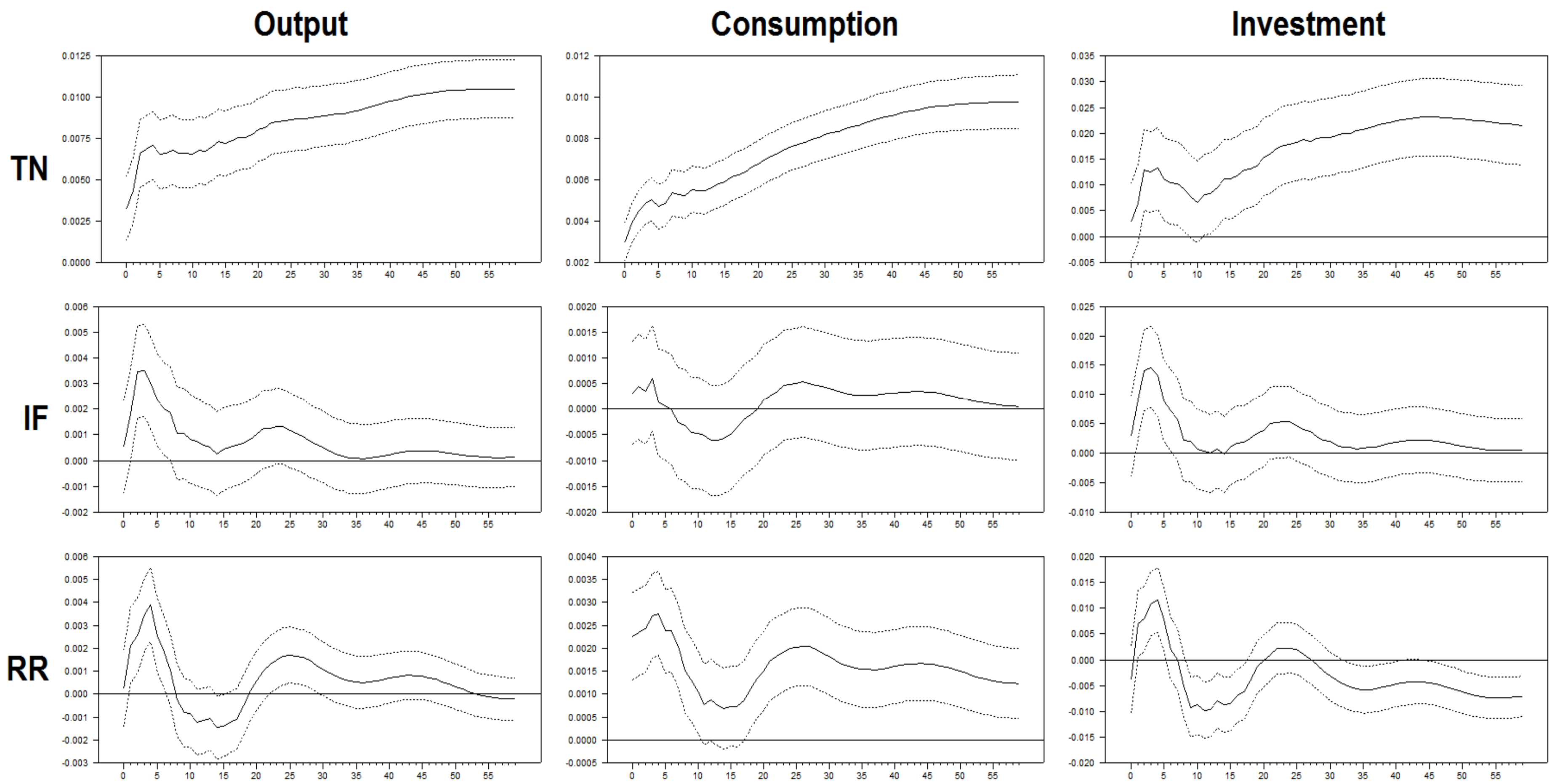
Notes: TN and LS denote technology and labor supply shocks, respectively. Shown around each response in dotted lines is the one standard error confidence interval generated by 1,000 bootstrap replications.

Figure 1.2: Impulse Responses from Shapiro and Watson SVAR



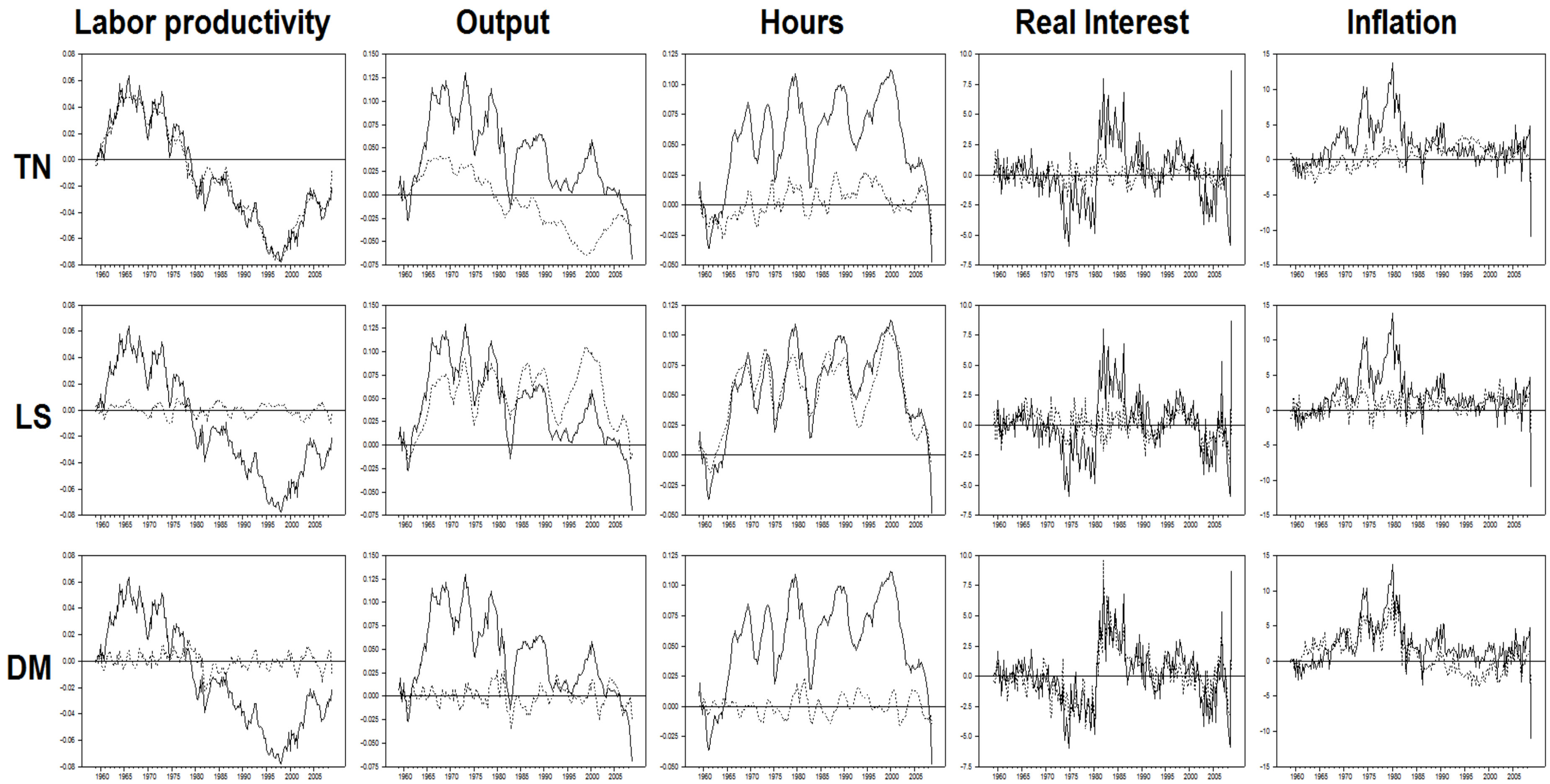
Notes: TN and LS denote technology and labor supply shocks, respectively. Shown around each response in dotted lines is the one standard error confidence interval generated by 1,000 bootstrap replications.

Figure 1.3: Impulse Responses from KPSW SVAR



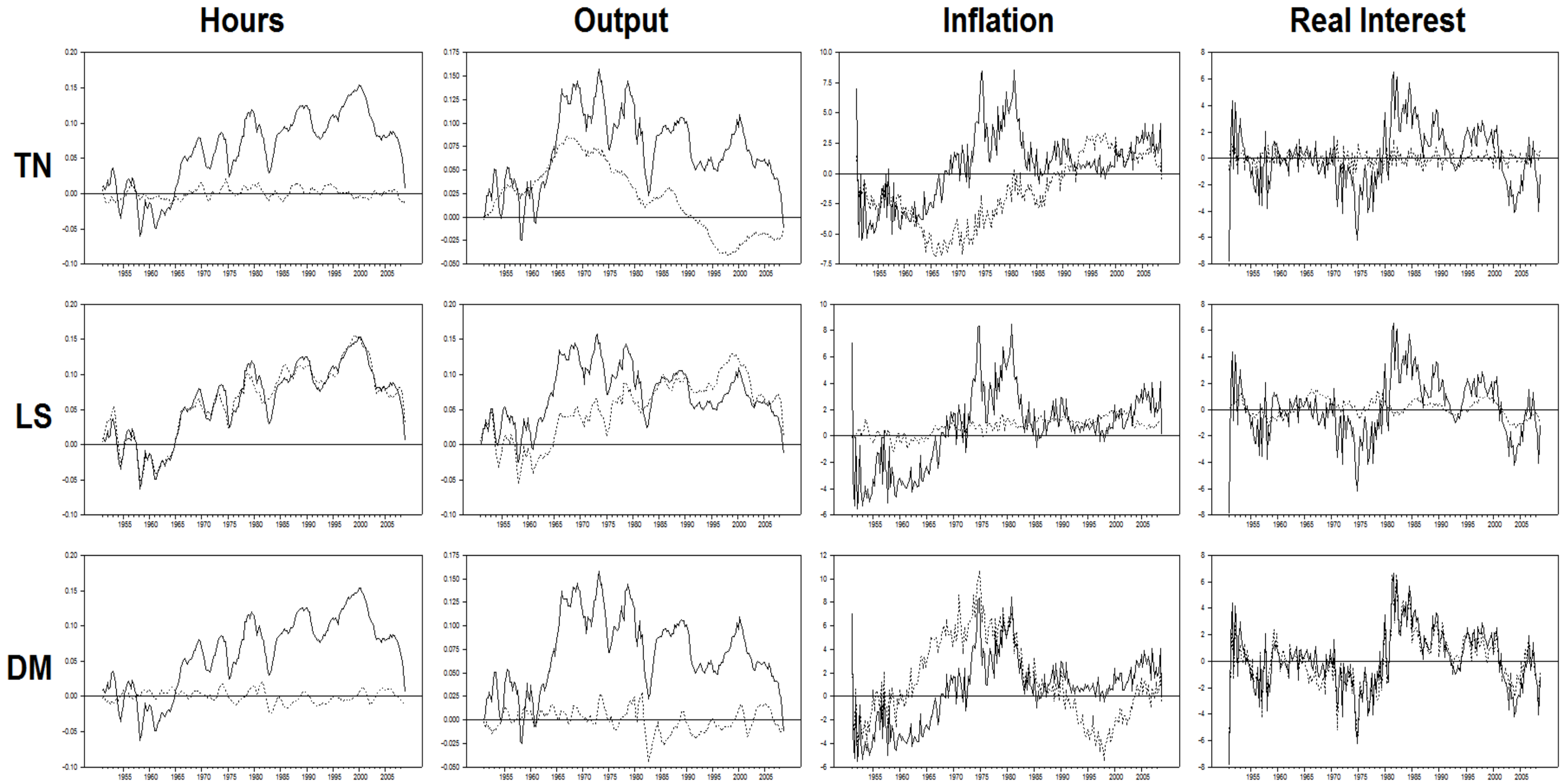
Notes: TN, IF, and RR denote shocks to technology, inflation, and real interest rate, respectively. Shown around each response in dotted lines is the one standard error confidence interval generated by 1,000 bootstrap replications.

Figure 2.1: Historical Decompositions from Galí SVAR



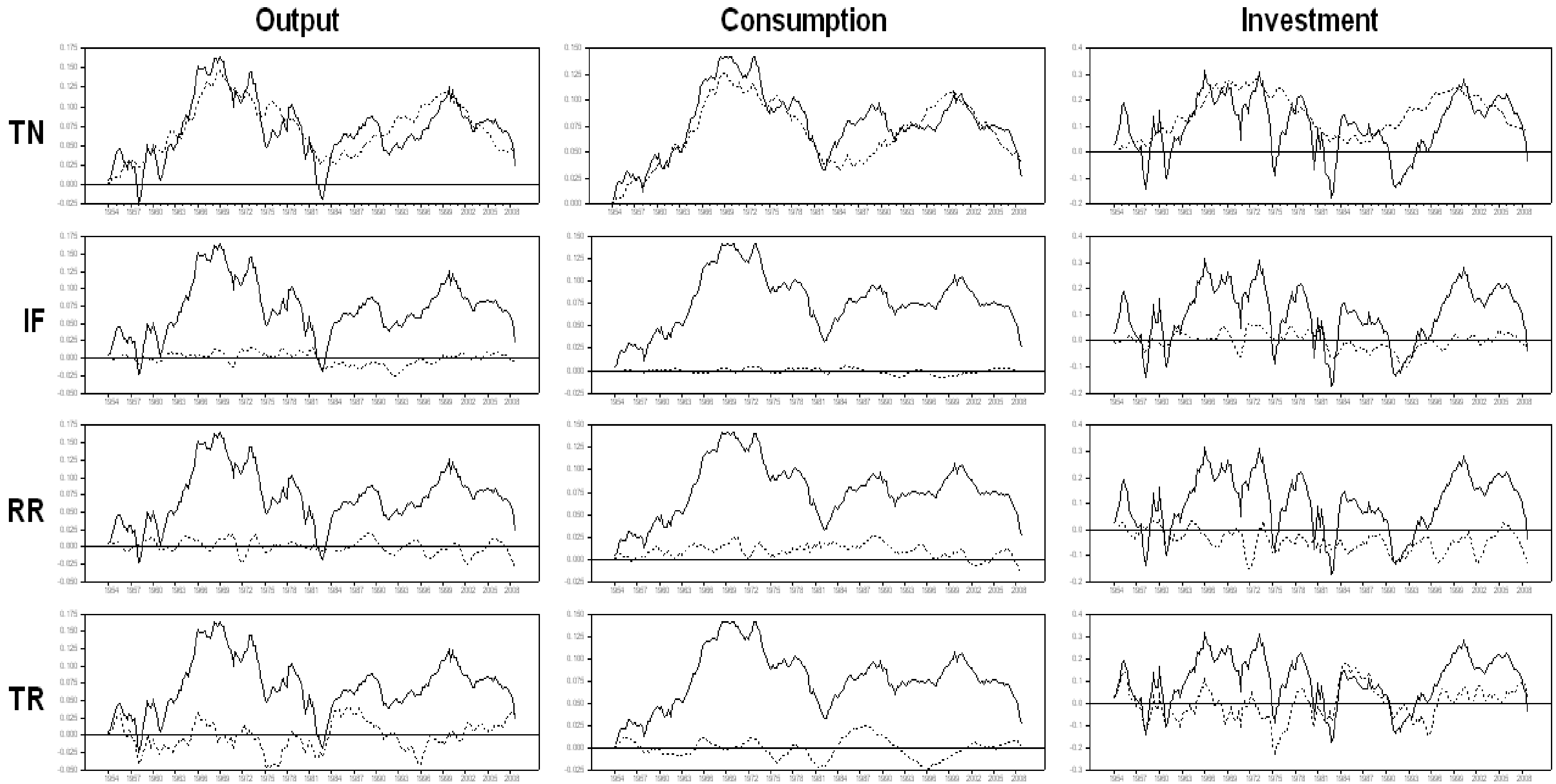
Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, LS, and DM denote shocks to technology, labor supply, and demand, respectively.

Figure 2.2: Historical Decompositions from Shapiro and Watson SVAR



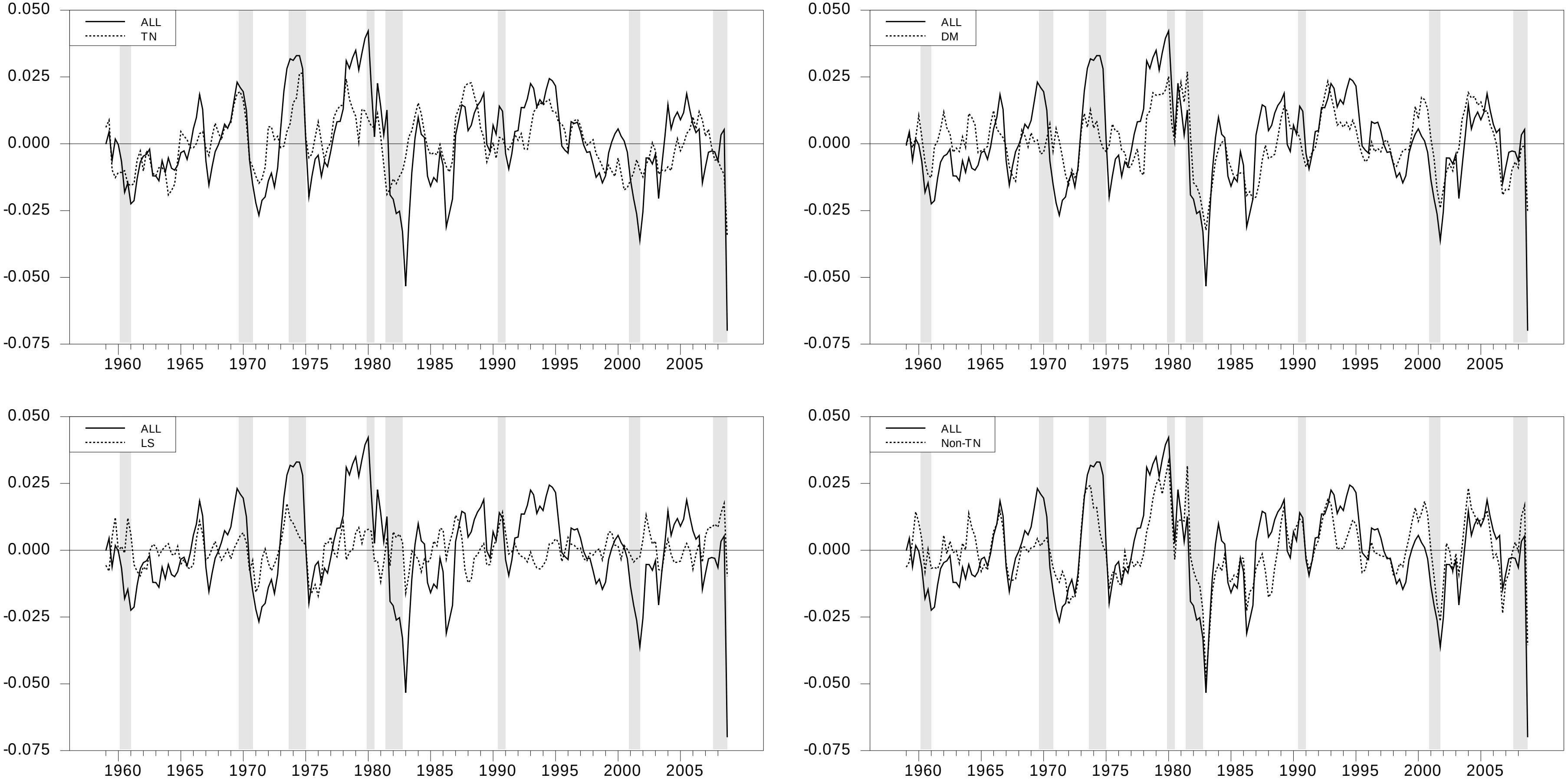
Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, LS, and DM denote shocks to technology, labor supply, and demand, respectively.

Figure 2.3: Historical Decompositions from KPSW SVAR



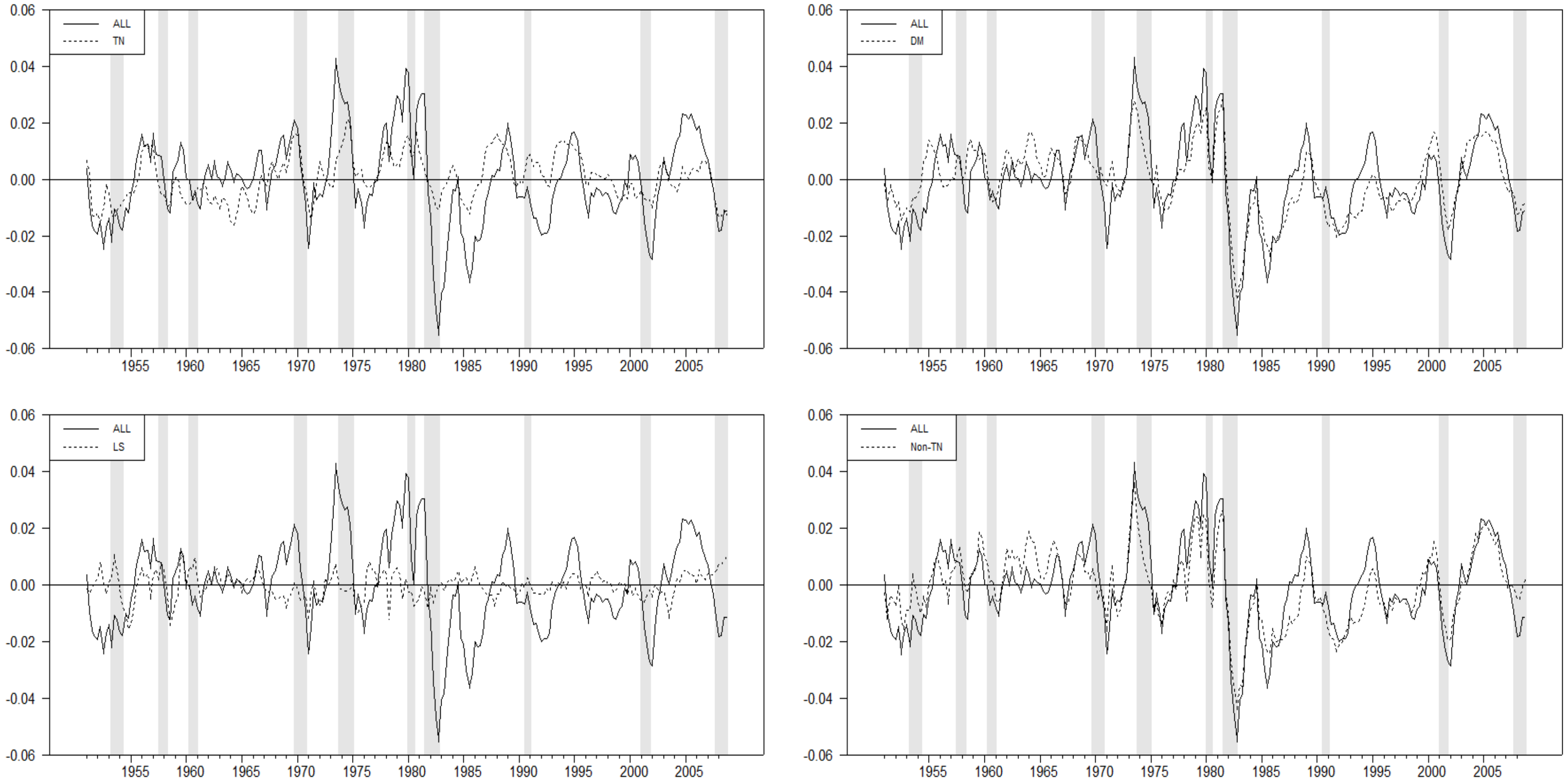
Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, IF, RR, and TR denote technology shock, inflation shock, real interest rate shock, and transitory shocks, respectively.

Figure 3.1: Cyclical Output and Shocks from Galí SVAR



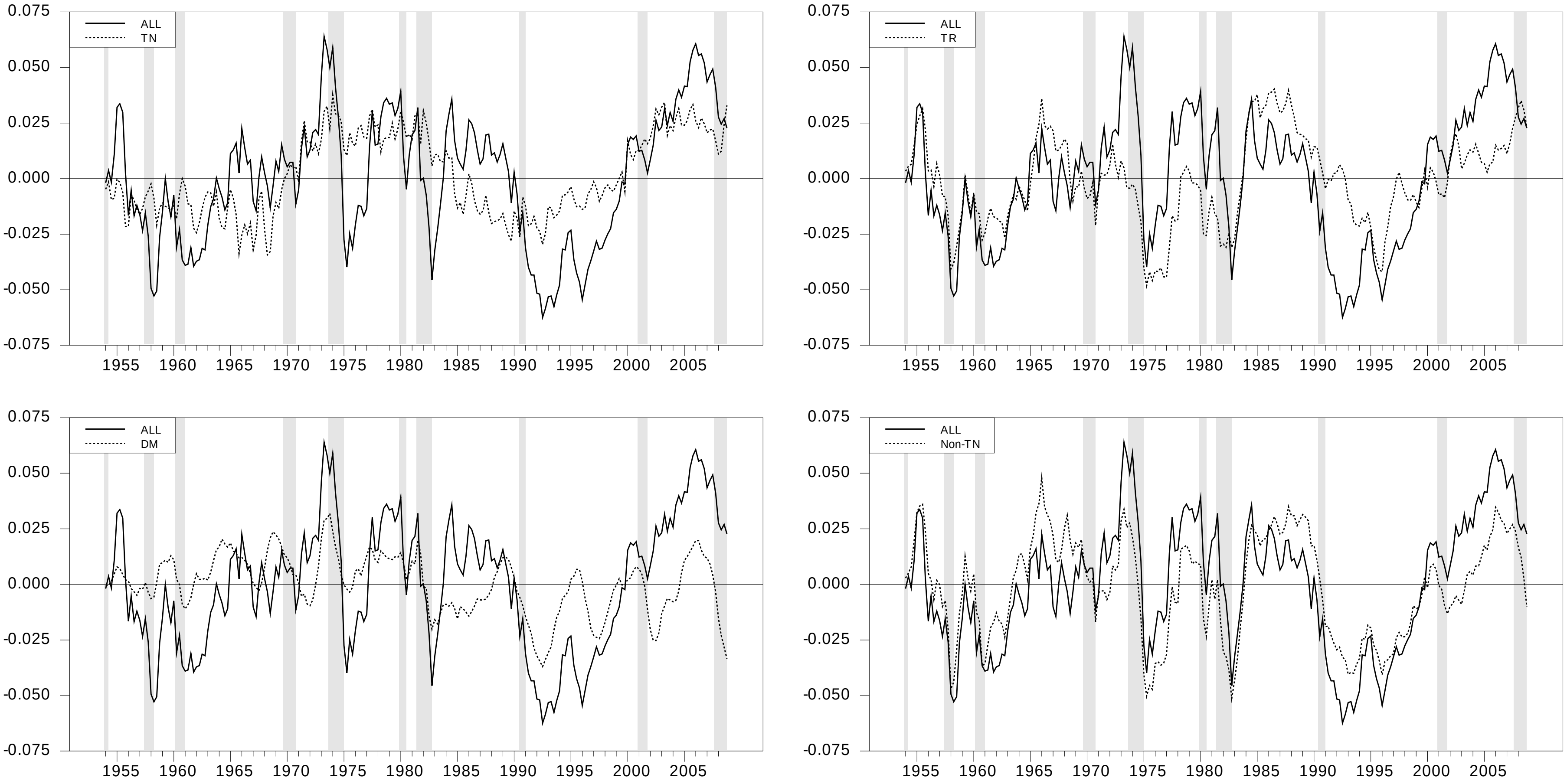
Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).

Figure 3.2: Cyclical Output and Shocks from Shapiro and Watson SVAR



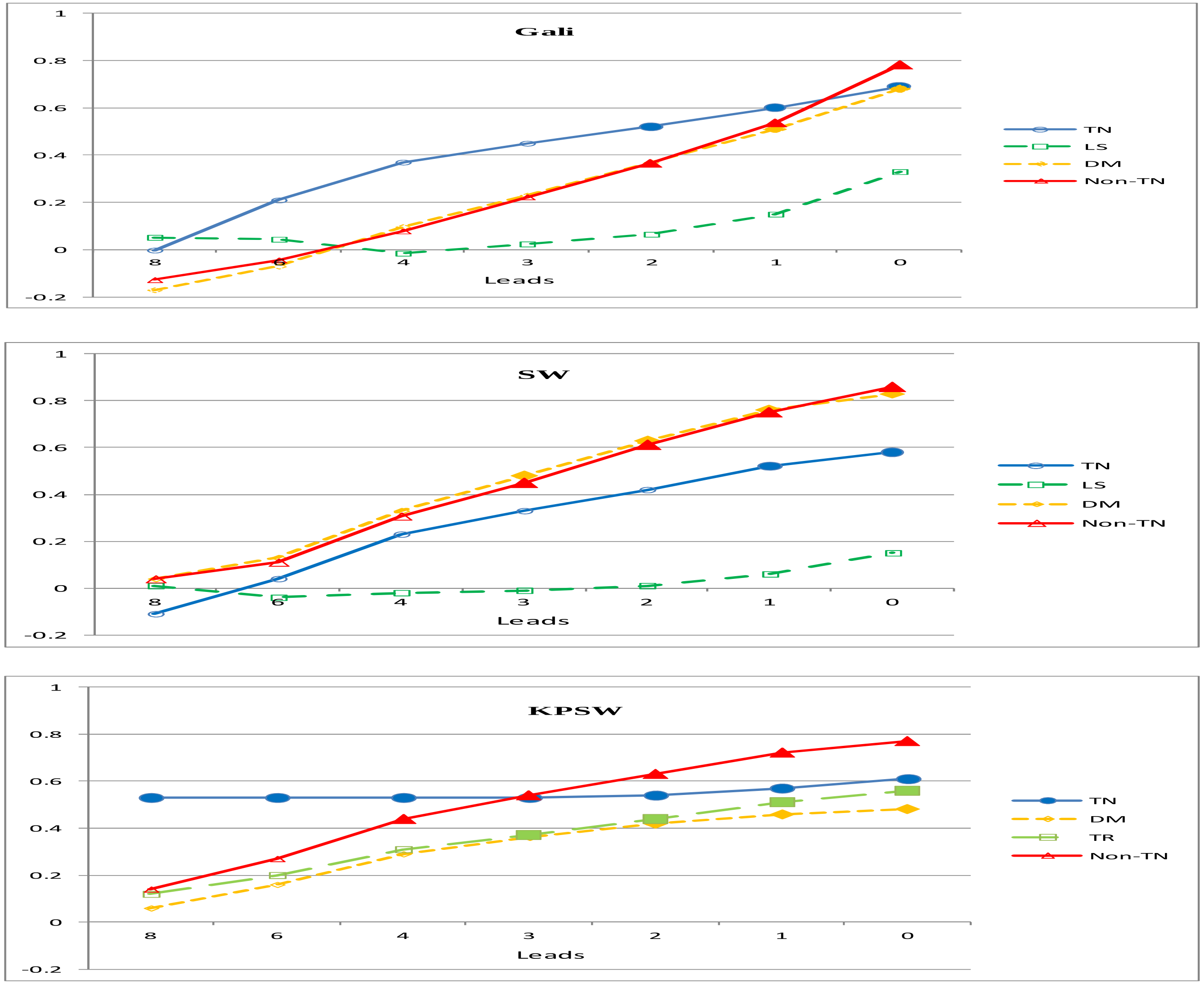
Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).

Figure 3.3: Cyclical Output and Shocks from KPSW SVAR



Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).

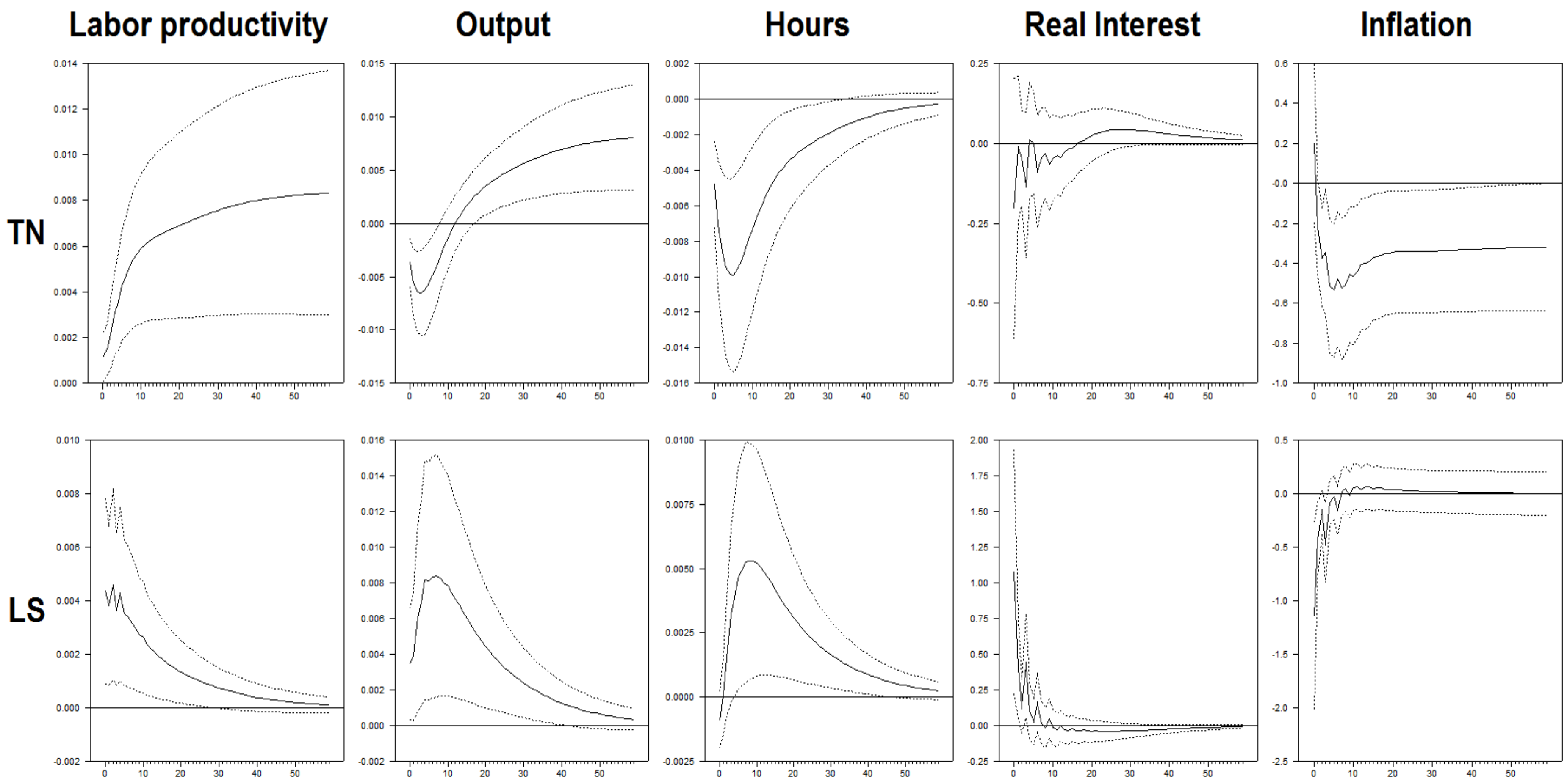
Figure 4: Predictive Properties of Shocks



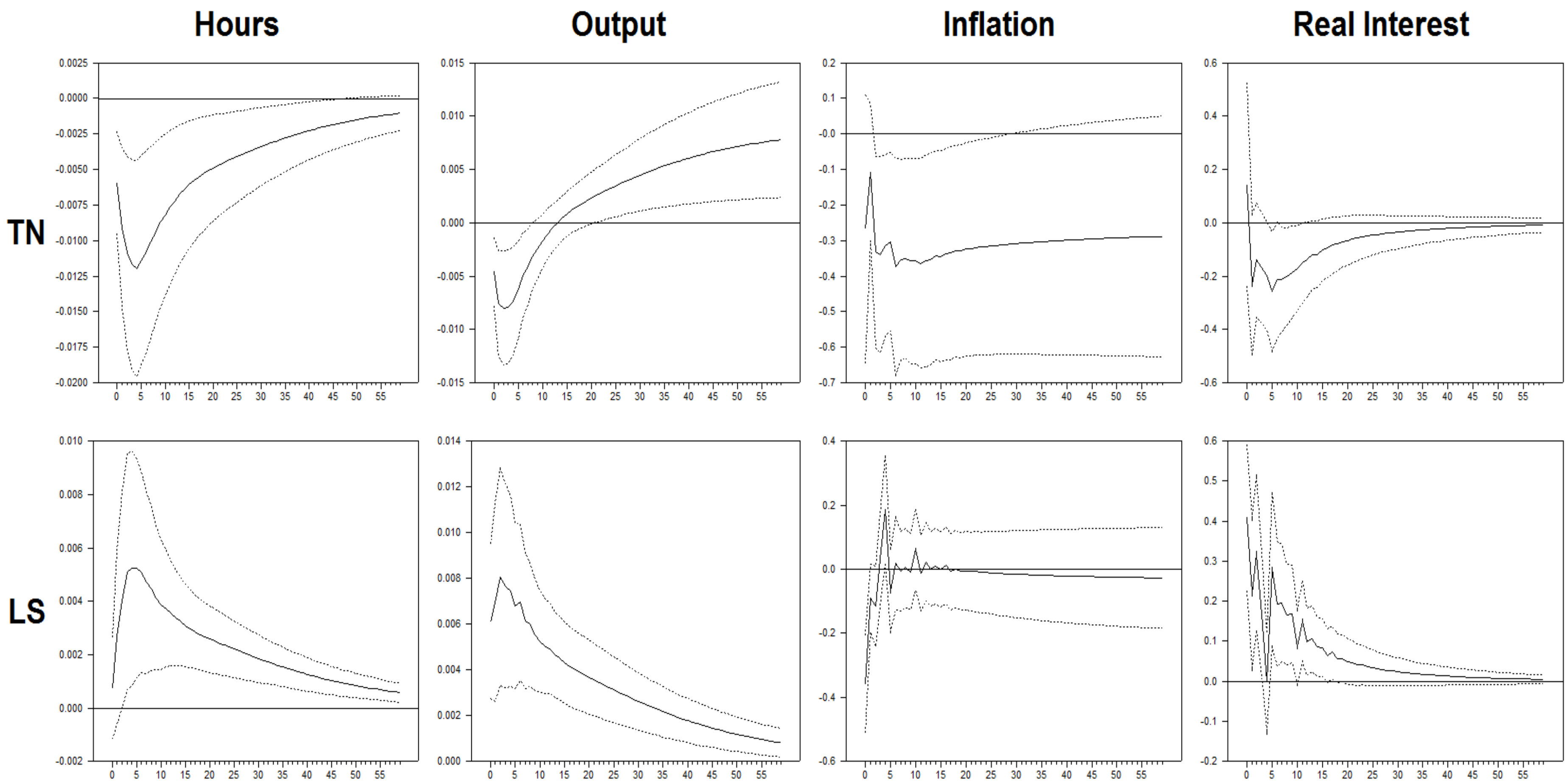
Note: The solid pronounced markers indicate statistically significant point estimates at the 10 percent level.

Figure 5.1: Impulse Responses with Trend-stationary Hours

(a) Galí SVAR



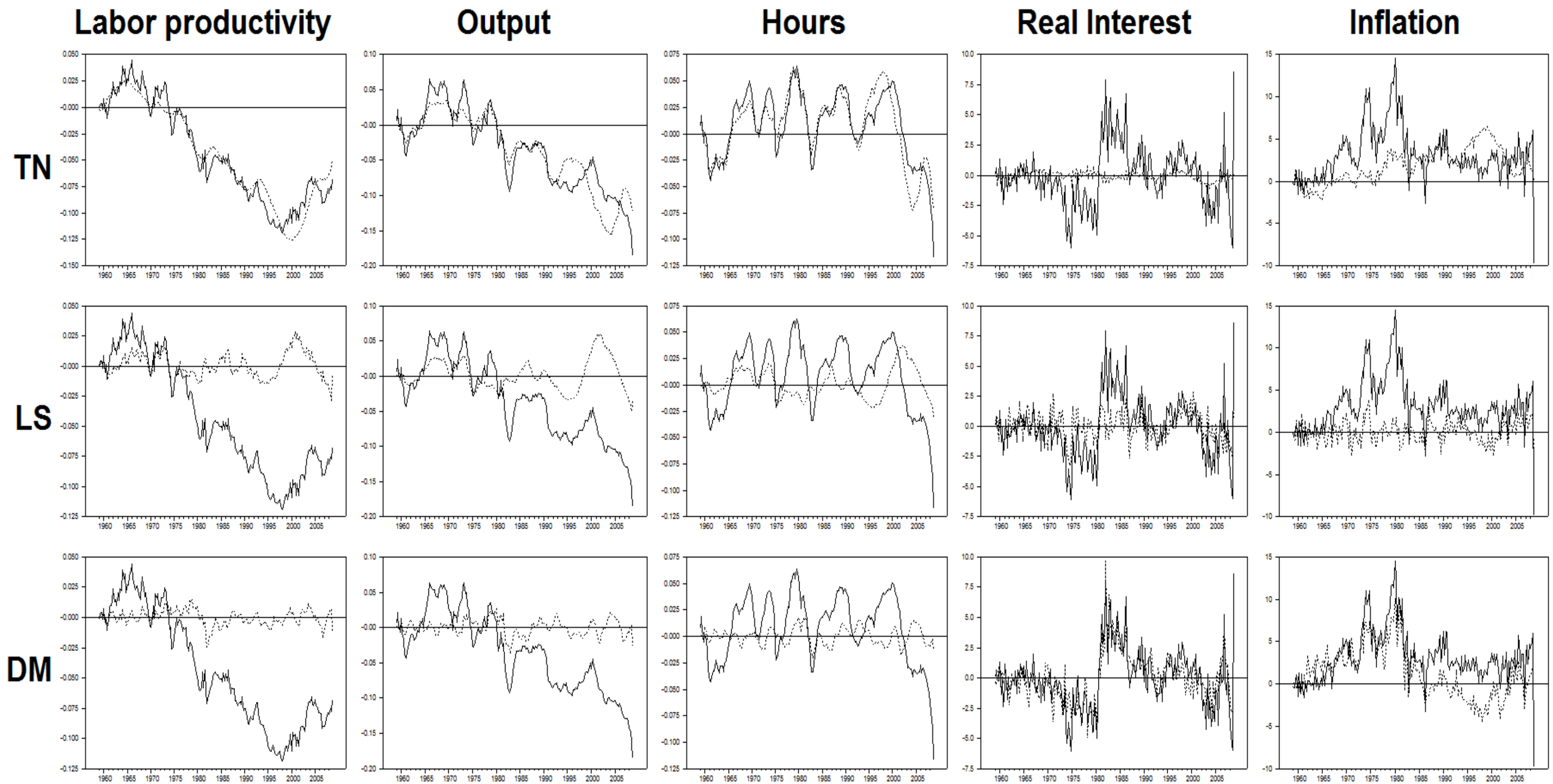
(b) Shapiro and Watson SVAR



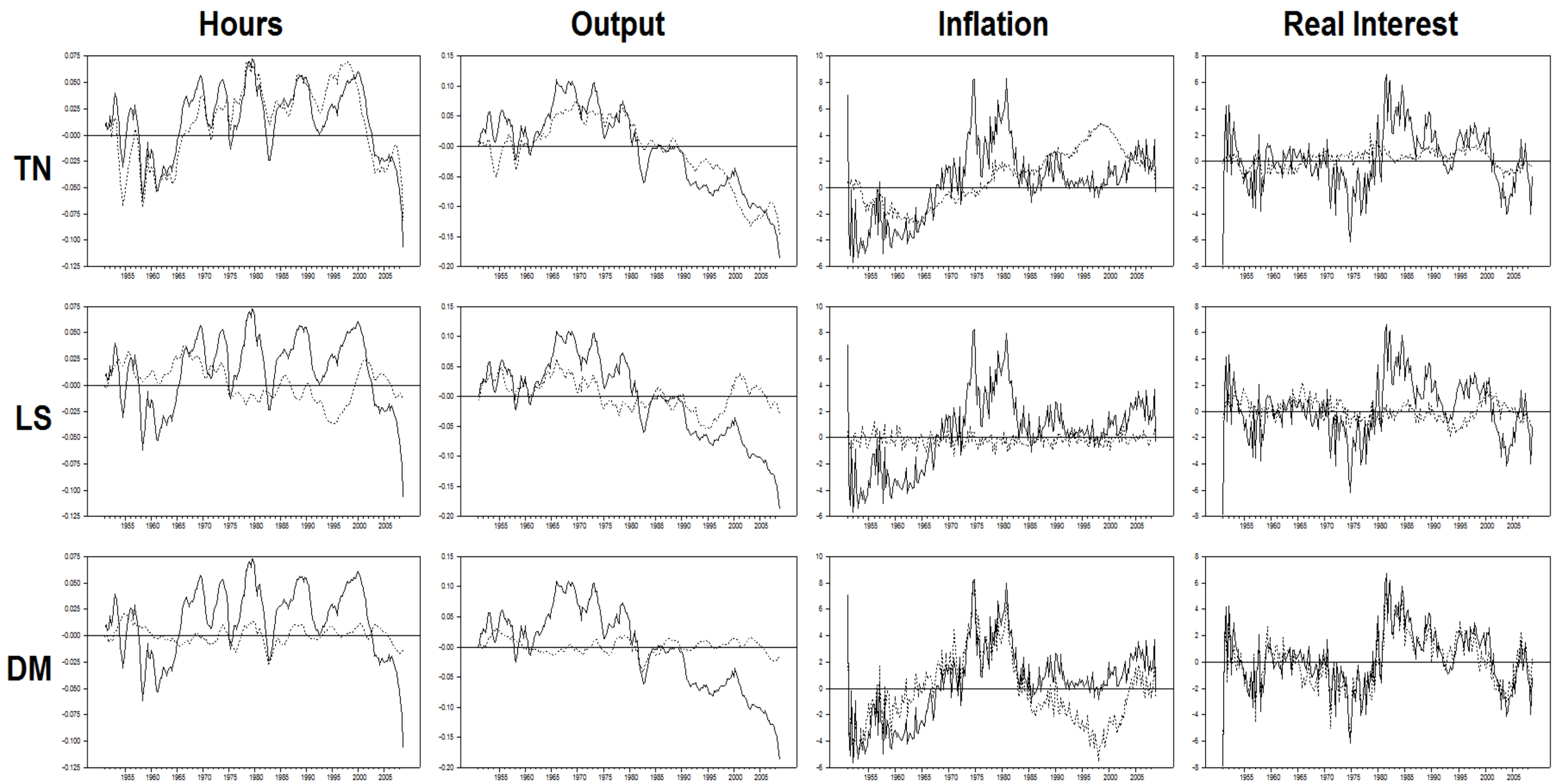
Notes: TN and LS denote technology and labor supply shocks, respectively. Shown around each response in dotted lines is the one standard error confidence interval generated by 1,000 bootstrap replications.

Figure 5.2: Historical Decomposition of Output and Hours with Trend-stationary Hours

(a) Galí SVAR



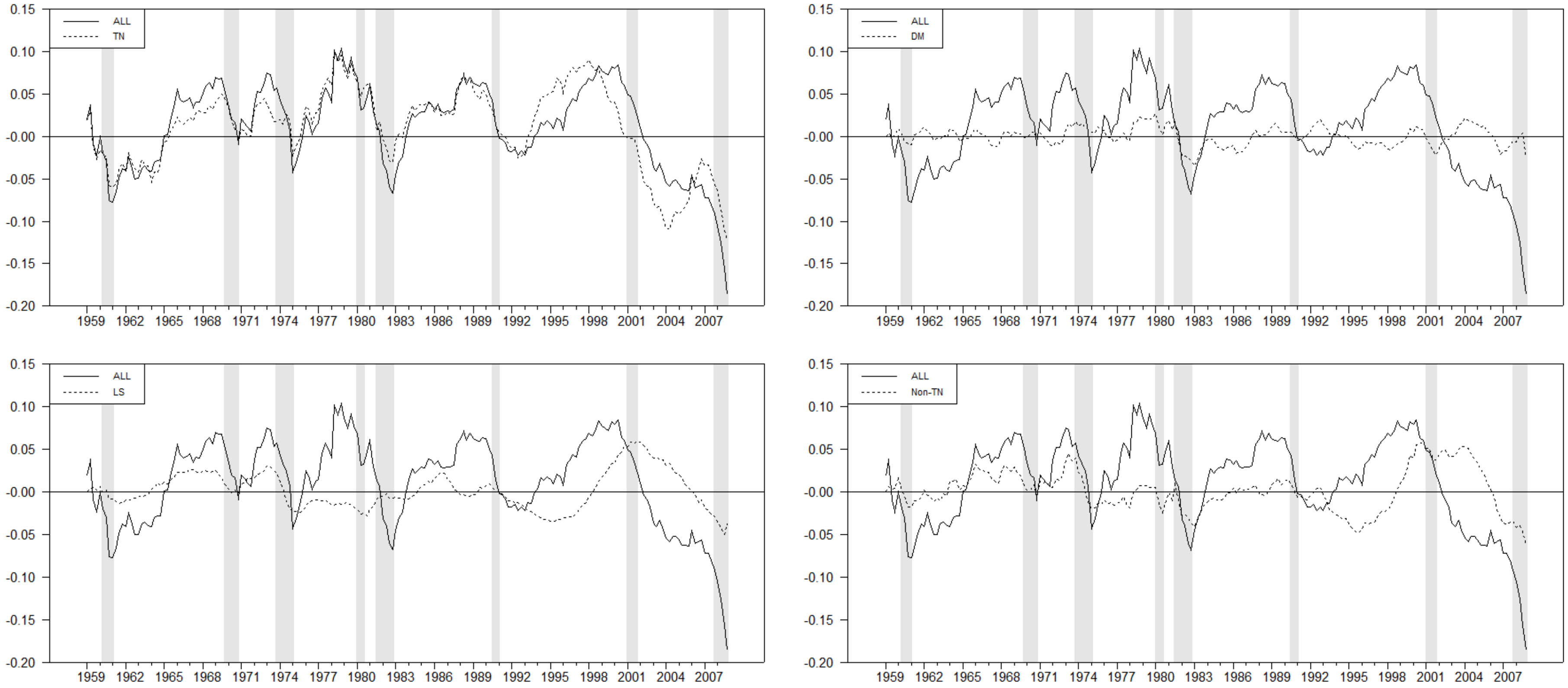
(b) Shapiro and Watson SVAR



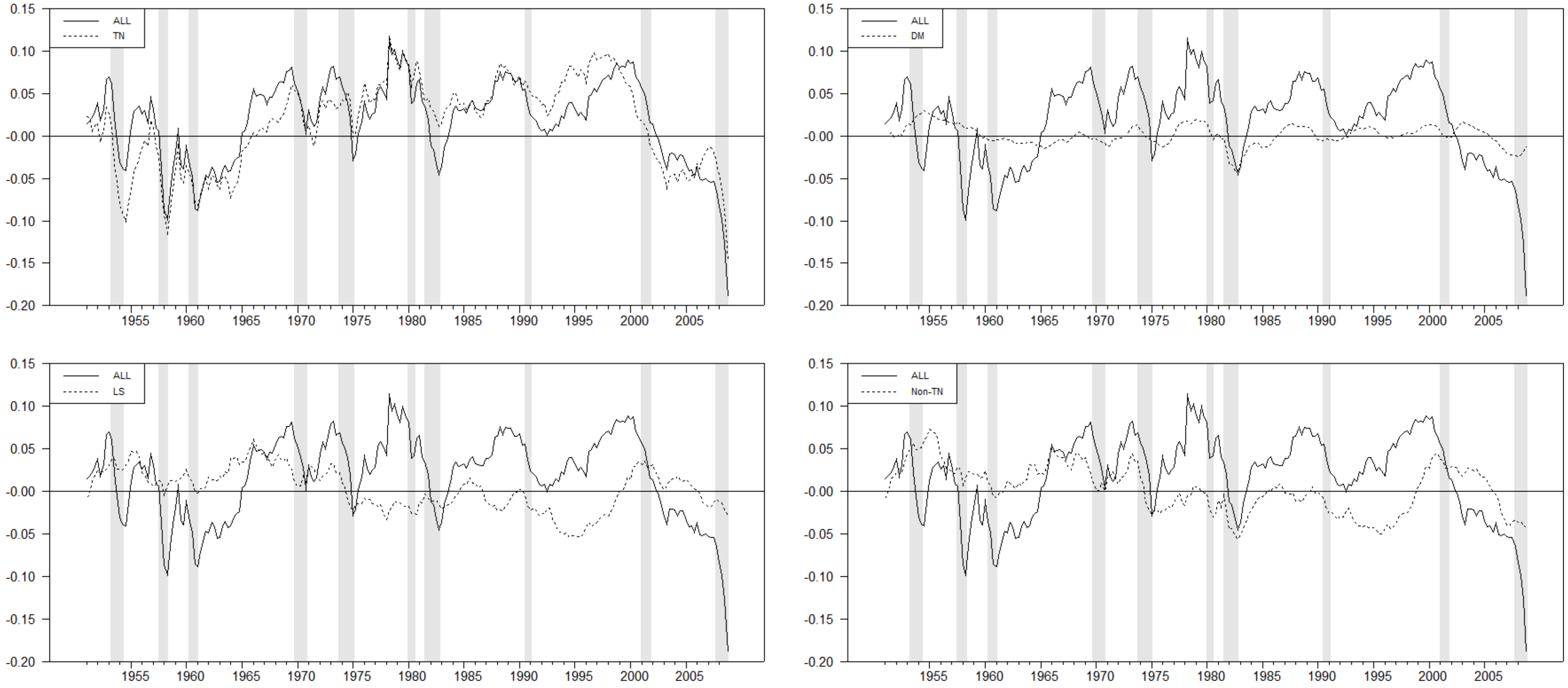
Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, LS, and DM denote shocks to technology, labor supply, and demand, respectively.

Figure 5.3: Shocks over the Business Cycle with Trend-stationary Hours

(a) Galí SVAR

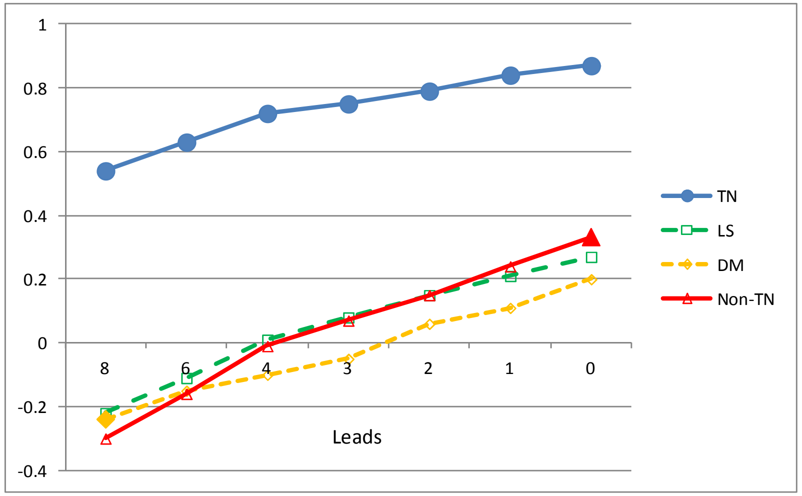


(b) Shapiro and Watson SVAR

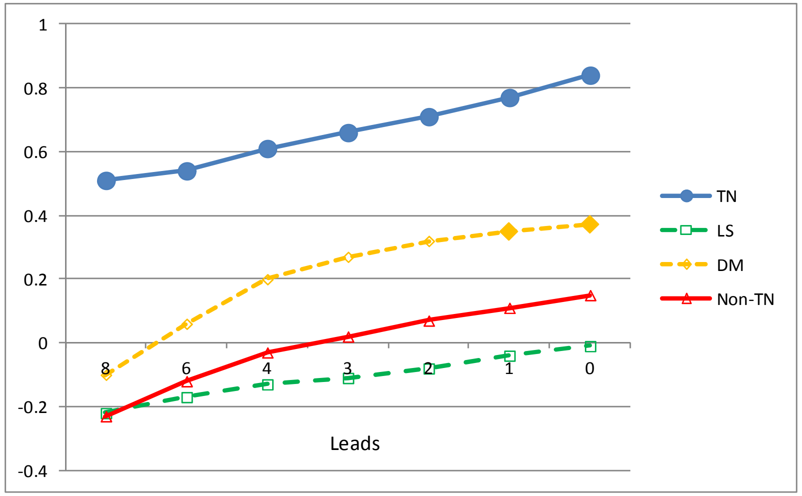


Notes: In each graph, the solid line is the stochastic movement of cyclical output while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).

Figure 5.4: Predictive Properties of Shocks with Trend-stationary Hours



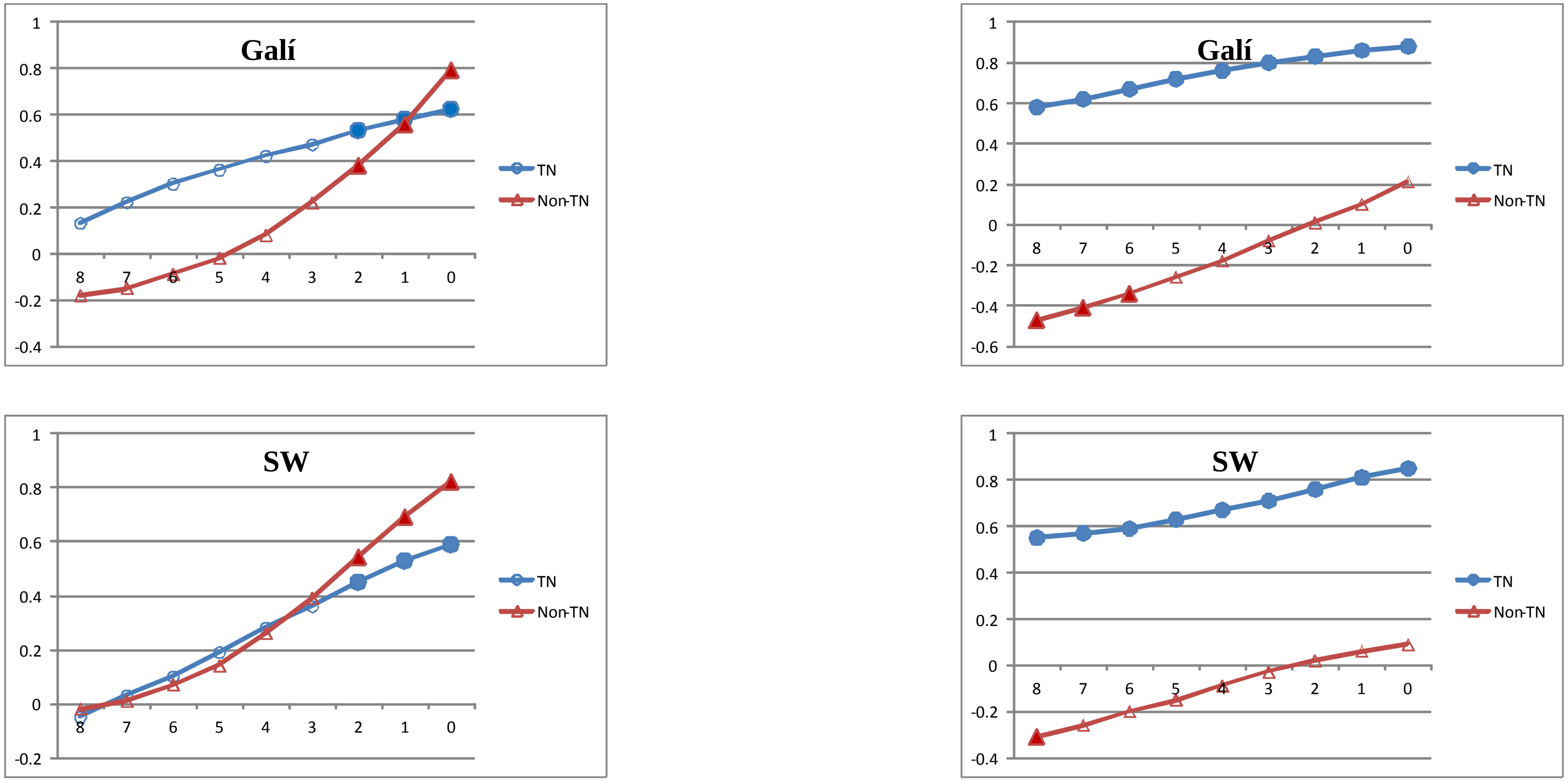
(a) Galí SVAR



(b) Shapiro and Watson SVAR

Note: The solid pronounced markers indicate statistically significant estimates at the 10 percent level.

Figure 5.5: Cross Correlations between Technology Shocks and Hours Worked



(a) Galí SVAR

(b) Shapiro and Watson SVAR

Note: The solid pronounced markers indicate statistically significance at the 10% level.