On the Sources of the Great Moderation[*]

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Abstract

The remarkable decline in macroeconomic volatility experienced by the U.S. economy since the mid-80s (the so-called Great Moderation) has been accompanied by large changes in the patterns of comovements among output, hours and labor productivity. Those changes are reflected in both conditional and unconditional second moments as well as in the impulse responses to identified shocks. That evidence points to structural change, as opposed to just good luck, as an explanation for the Great Moderation. We use a simple macro model to suggest some of the immediate sources which are likely to be behind the observed changes.

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1 Introduction

A large (and growing) body of empirical research in macroeconomics has provided evidence of a substantial decline in the volatility of most U.S. time series over the postwar period. That phenomenon, which has also been experienced by other industrialized economies, has come to be known as "the Great Moderation."[1]

Table 1 serves us as a reminder of the magnitude of the volatility decline associated with the Great Moderation. It shows the standard deviation for two indicators of economic activity, (log) GDP and (log) non-farm business output, before and after 1984, a date which is generally viewed as a starting point of the period of enhanced stability in the U.S. economy. We use quarterly data covering the period 1948:I-2005:IV. Both variables are normalized by the size of the working age population. We report evidence for both the first-differenced and band-pass filtered transformations of each variable.[2] As shown in the Table, and for the two variables and transformations considered, the standard deviation for the post-84 period is less than half that corresponding to the pre-84 period. Tests of equality of the variance across subperiods reject that null hypothesis in all cases with a minuscule p-value.

While there is widespread consensus among macroeconomists on the existence and rough timing of the Great Moderation, its interpretation is still

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[1]Early papers on the Great Moderation include those of Kim and Nelson (1999), McConell and Pérez-Quirós (2000), and Blanchard and Simon (2001). A survey of the literature, as well as a discussion of alternative interpretations, can be found in Stock and Watson (2002). Stock and Watson (2005) and Cecchetti, Flores-Lagunes and Krause (2006) present and discuss some international evidence.

[2]We use the approximate band-pass filter of Baxter and King (1999). Following widespread practice, we identify the cyclical component of fluctuations as that corresponding to an interval between 2 and 32 quarters.

subject to much disagreement. The various hypotheses put forward in the literature can be thought of as falling under two broad categories.

The first view, often referred to as the "good luck" hypothesis, suggests that the greater macroeconomic stability of the past twenty years is largely the result of smaller shocks impinging on the economy, with structural changes having played at most a secondary role.[3] The second view attributes instead the bulk of the reduction in aggregate volatility to changes in the economy's structure and/or in the way policy has been conducted.[4]

In the present paper we provide some evidence on the relative merits of those two broad competing hypotheses. Our evidence is based on the observed comovements among output, hours and productivity, the identification of the sources of those comovements, and the study of their changes over time. The focus on these three variables is motivated by their central role in existing theories of the business cycle and the frequent use of their comovements in efforts to sort out among competing theories.[5]

We find it useful to distinguish between two versions of the "good luck" hypothesis. We define the "strong" version of that hypothesis as one that implies a (roughly) proportional decline in the variance of *all* shocks, regardless of their nature. By contrast, the "weak" version attributes the decline in aggregate volatility to a reduction in the variance of *a small subset* of the

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[3]See, e.g., Justiniano and Primiceri (2006) and Arias, Hansen and Ohanian (2006) for examples of authors making a case for the good luck hypothesis.

[4]Such explanations include better monetary policy (e.g. Clarida, Galí and Gertler (2000)), improvements in inventory management (e.g. Kahn, McConnell and Perez-Quirós (2002)), and financial innovation and better risk sharing (e.g. Dynan, Elmendorf and Sichel (2006)).

[5]Christiano and Eichenbaum (1992), Hansen and Wright (1992), and Galí (1999) are examples of work in that tradition.

relevant shocks.[6]

The basic idea underlying our approach is straightforward. If the good luck hypothesis is correct in its strong version, the overall scaling down in the size of fluctuations reported in the literature should coexist with an unchanged correlation structure. On the other hand, under the weak version of that hypothesis we would expect the structure of correlations (and, possibly, relative volatilities as well) to be altered as a result of the change in the relative importance of different shocks. In either case, however, the structure of correlations *conditional* on each type of shock (as well as the associated impulse responses) should remain unchanged. Finally, under the hypothesis of structural change, we would expect to observe some variation over time in at least some of the conditional correlations among variables. That variation should in turn be reflecting changes in the economy's dynamic response to one or more types of shocks, as a result of underlying structural change.

Our estimates of conditional second moments, and their changes over time, are based on a structural vector autoregression (SVAR) for (log) labor productivity and (log) hours. Following Galí (1999) we interpret variations in those variables–as well as in (log) output, which is given by their sum–as the result of two types of shocks impinging on the economy: technology and non-technology shocks. Technology shocks are assumed to be the source of the unit root in labor productivity; accordingly, they are identified as the only shocks which may have a permanent effect on that variable. Following Primiceri (2005), our estimated SVAR allows for time-varying coefficients,

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[6]Of course, under a view of the business cycle in which the latter is largely driven by a single shock–a view held by proponents of early RBC models–the distinction between the two versions of the good luck hypothesis is meaningless.

which makes it possible to uncover changes over time in the responses of different variables to each type of shock, as well as the contribution of the different shocks to the decline in volatility. Furthermore, as emphasized in Gambetti (2006), the use of time-varying coefficients overcomes the potential bias that results from the presence of significant low frequency comovements between productivity growth and hours in postwar U.S. data, a problem first diagnosed by Fernald (2005).[7]

Our main findings can be summarized as follows:

- As emphasized by other authors, the volatility of output, hours and labor productivity declined dramatically around the mid-80s and has remained low ever since. We show, however, that such a decline has not been proportional: the volatility of hours and labor productivity has risen considerably *relative* to the volatility of output.

- Several correlations among the variables considered display remarkable changes. In particular, the correlation of hours with labor productivity has experienced a remarkable decline, shifting from values close to zero in the pre-84 period to large negative values after 1984. The decline in that correlation, as stressed in Stiroh (2006), explains (in an accounting sense) a substantial fraction of the decline in output volatility. Similarly, the correlation of output with labor productivity and has declined significantly (from positive values to values close to zero).[8]

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[7]Fernald (2005) makes a forceful case for the important role played by the positive low frequency comovement between labor productivity growth and (log) hours per capita in accounting for the conflicting evidence in Galí (1999) and Christiano, Eichenbaum and Vigfusson (2003).

[8]Barnichon (2006), in work conducted independently, stresses the change in the corre-

- The Great Moderation can be largely explained by a sharp fall in the contribution of non-technology shocks to the variance of output. That decline is partly explained by (i) a smaller conditional volatility of hours, and (ii) a vanishing procyclical response of labor productivity to non-technology shocks.

- The contribution of technology shocks to output volatility appears to have increased somewhat over time, in both relative and absolute terms. That increase is associated with a smaller negative response of hours to productivity improvements, with the consequent larger effect on output.

- Using a stylized macro model, we can show that a significant fraction of the observed changes in comovements and impulse responses can be explained by two developments: (i) a change in the interest rate rule, giving a larger weight to inflation stabilization (relative to output stabilization) and (ii) an apparent end of short run increasing returns to labor (SRIRL).[9]

The paper is organized as follows. Section 2 reports estimates of the standard deviations and correlations of output, hours and labor productivity and their changes over time. Section 3 introduces the time-varying VAR approach used to estimate changes over time in conditional second moments and impulse responses, and presents the associated evidence. Section 4 presents

lation between unemployment and labor productivity, as well as the decline in the procyclicality of the latter variable.

[9]Barnichon (2006) comes to similar conclusions, using a search model with nominal rigidities.

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the main empirical findings. Section 5 analyzes a stylized macro model and identifies the changes in parameters that could potentially account for some of our findings. Section 6 concludes.

2 Labor Markets and the Great Moderation

2.1 Changes in Volatility

Table 2 summarizes the evidence on volatility changes in output, hours and labor productivity by showing their respective standard deviations for the pre-84 and post-84 periods, as well as the ratio between the two. On the right hand panel we also report the corresponding standard deviation relative to output, and the ratio of relative standard deviations between the two sub-periods. We use quarterly data covering the sample period 1948:I-2005:IV. All variables refer to the non-farm business (NFB) sector. Again, we report estimates for both first-differenced and BP-filtered data, after taking logarithms.

Turning to the main findings, we see that independently of the transformation used, and in a way analogous to output, both hours and labor productivity have experienced a large (and highly significant) reduction in their volatility in the post-84 period. Yet, it is worth pointing out that their volatility decline–as measured by the ratio of standard deviations, shown on the right hand panel–is not as large as that experienced by output. That change in relative standard deviations is our first piece of evidence pointing to the presence of changes beyond those that would result from a mere scaling down of volatility.

2.2 Changes in Comovements

Next we turn to examination of the comovements among labor market variables and their changes over time. For each pair of variables considered, Table 3 reports their estimated correlation in the pre-84 period and the post-84 period, as well as the difference between the two. As above, evidence is reported for two different transformations of the data, first-differenced and BP-filtered data.

The estimated changes in comovements are large and highly significant. In particular, the cyclical behavior of labor productivity, measured by its comovement with either output or hours, has experienced a considerable change. Thus, the correlation of labor productivity with output has declined considerably across the two periods. In particular, productivity appears to have lost its condition of a highly procyclical variable, a property that was one of the empirical cornerstones of the technology-driven view of the business cycle endorsed by RBC theory. In fact, when we use the BP-filter, labor productivity becomes an (essentially) acyclical variable in the post-84 period.

When we take hours as a reference cyclical indicator, we see that behavior of labor productivity switches from being largely acyclical to being countercyclical, with the change in correlations being highly significant independently of the transformation used. As emphasized by Stiroh (2006), the decline in the correlation between labor productivity and hours can explain, from an accounting point of view, a substantial fraction of the decline in output volatility.

We view that variation in the pattern of correlations and relative standard

deviations across sample periods as evidence against the strong version of the good luck hypothesis, and reflecting instead changes in either the composition of shocks or in the structure and transmission mechanisms operating in the U.S. economy. Some of those changes may hold the key to the causes of the Great Moderation, and are the focus of our analysis in the next section.

3   A VAR Model with Time-Varying Coefficients and Stochastic Volatility

The present section describes our baseline empirical model, which consists of a VAR with time-varying coefficients as in Primiceri (2005), with structural shocks identified following Galí (1999).

Let y_t and n_t denote, respectively, (log) output and (log) hours, both in per capita terms. We define $x_t \equiv [\Delta(y_t - n_t), n_t]$, and assume that the joint process for (log) labor productivity and (log) hours admits a time-varying VAR representation given by

$$x_t = A_{0,t} + A_{1,t}\ x_{t-1} + A_{2,t}\ x_{t-2} + ... + A_{p,t}\ x_{t-p} + u_t \tag{1}$$

where $A_{0,t}$ is a vector of time-varying intercepts, and $A_{i,t}$, $i = 1, ..., p$, are matrices of time-varying coefficients. We assume that all the roots of the VAR polynomial lie outside the unit circle for all t; i.e. the process is "locally stationary." The sequence of innovations $\{u_t\}$ follows a Gaussian white noise process with zero mean and time-varying covariance matrix Σ_t, and uncorrelated with all lags of x_t. Letting $A_t = [A_{0,t}, A_{1,t}..., A_{p,t}]$, we define $\theta_t = vec(A_t')$ where $vec(\cdot)$ is the column stacking operator. Conditional on the roots of the associated VAR polynomial being outside the unit circle for

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all t, we assume θ_t evolves over time according to the process

$$\theta_t = \theta_{t-1} + \omega_t \tag{2}$$

where ω_t is a Gaussian white noise process with zero mean and constant covariance Ω, and independent of u_t at all leads and lags.

We model the time variation for Σ_t as follows. Let $F_t D_t$ be the Cholesky factor of Σ_t, where F_t is lower triangular with ones in the diagonal and D_t a diagonal matrix containing the standard deviations of u_t. Let $\gamma_t = vec(F_t^{-1})$ and $\sigma_t = vec(D_t)$.[10] We assume

$$\begin{aligned} \gamma_t &= \gamma_{t-1} + \zeta_t \\ \log \sigma_t &= \log \sigma_{t-1} + \xi_t \end{aligned}$$

where ζ_t and ξ_t are Gaussian white noise processes with zero mean and (constant) covariance matrices Ψ and Ξ, respectively. Finally, we assume that ξ_t, ζ_t, and ω_t are all mutually independent.

We assume that the vector of VAR innovations u_t is a (time-varying) linear transformation of the vector of underlying "structural" shocks $\varepsilon_t \equiv [\varepsilon_t^a, \varepsilon_t^d]'$, satisfying $E\{\varepsilon_t \varepsilon_t'\} = I$ for all t, where ε_t^a represents a technology shock and ε_t^d is a non-technology shock (which we often refer to for convenience as a "demand "shock). Thus we assume $u_t = K_t \, \varepsilon_t$ for all t for some non-singular matrix K_t satisfying $K_t K_t' = \Sigma_t$. Note that, given our normalization, changes in the contribution of different structural shocks to the volatility of innovations in output, hours or productivity will be captured by changes in K_t.

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[10] Strictly speaking the vector γ and σ only contain the non zero elements of G_t and D_t.

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Our identification of structural shocks follows Galí (1999), by assuming that only technology shocks may affect labor productivity in the long-run. As we will see next, that assumption imposes some restrictions that allow us to recover matrix K_t from our estimated reduced form model (1).

Before we proceed it is convenient to rewrite (1) in companion form:

$$\mathbf{x}_t = \boldsymbol{\mu}_t + \mathbf{A}_t \ \mathbf{x}_{t-1} + \mathbf{u}_t$$

where $\mathbf{x}_t \equiv [x'_t, x'_{t-1}, ..., x'_{t-p+1}]'$, $\mathbf{u}_t \equiv [u'_t, 0, ..., 0]'$, $\boldsymbol{\mu}_t \equiv [A'_{0,t}, 0, ..., 0]'$ and $\mathbf{A}_t$ is the corresponding companion matrix. We use a *local approximation* of the implied response at $t + k$ of labor productivity growth and (log) hours to a realization of the innovation vector in period t. Formally, that local response is given by

$$\frac{\partial x_{t+k}}{\partial u'_t} = \mathcal{E}_{2,2} \ \mathbf{A}_t^k \equiv B_{t,k}$$

for $k = 1, 2, ..$where $\mathcal{E}_{2,2}(M)$ is a function which selects the first 2 rows and 2 columns of any matrix M, and where $B_{t,0} \equiv I$. Thus, the $k-$period horizon impulse responses of labor productivity growth and hours to structural shocks hitting the economy at time t are given by

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\begin{aligned}
\frac{\partial x_{t+k}}{\partial \varepsilon'_t} &= \frac{\partial x_{t+k}}{\partial u'_t} \frac{\partial u_t}{\partial \varepsilon'_t} \\
&= B_{t,k} \ K_t \equiv C_{t,k}
\end{aligned}
$$

for $k = 0, 1, 2, ..$Notice that in contrast with the fixed-coefficient model, the impulse response of a variable to a shock at any given horizon varies over time.

Let $\widetilde{B}_{t,k} \equiv \sum_{j=0}^{k} B_{t,j}$ and $\widetilde{C}_{t,k} \equiv \sum_{j=0}^{k} C_{t,j}$. That absence of a long run effect of the non-technology shocks on the level of labor productivity implies

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that the matrix of long-run cumulative multipliers $\widetilde{C}_{t,\infty} \equiv \widetilde{B}_{t,\infty} K_t$ is lower triangular. This, combined with the fact that $K_t K_t' = \Sigma_t$, yields

$$\widetilde{C}_{t,\infty}\widetilde{C}_{t,\infty}' = \widetilde{B}_{t,\infty}' \Sigma_t \ \widetilde{B}_{t,\infty}'$$

which in turn allows us to determine (up to column sign) $\widetilde{C}_{t,\infty}$ as the Cholesky factor of $\widetilde{B}_{t,\infty}'\Sigma_t\widetilde{B}_{t,\infty}'$. Given $\widetilde{C}_{t,\infty}$, the structural impulse responses of shocks occurring at time t can be obtained using

$$\frac{\partial x_{t+k}}{\partial \varepsilon_t'} = B_{t,k} \ \widetilde{B}_{t,\infty}^{-1} \ \widetilde{C}_{t,\infty}$$

for $k = 0, 1, 2, ...$which is a function only of parameters describing the reduced form time-varying VAR (1). We refer the reader to Appendix 1 for a detailed description of the method used to estimate that model, which follows Primiceri (2005).

Our analysis below focuses on the second moments (conditional and unconditional) of the growth rates of output (Δy_t), labor productivity ($\Delta(y_t - n_t) \equiv \Delta q_t$), and hours ($\Delta n_t$). Our model allows us to write each of those variables as a time-varying distributed lag of the two structural disturbances. Thus, letting $x_{i,t}$ represent one of those variables we have

$$x_{i,t} = \mu_t^i + \sum_{k=0}^{\infty} C_{t,k}^{ia} \ \varepsilon_{t-k}^a + \sum_{k=0}^{\infty} C_{t,k}^{id} \ \varepsilon_{t-k}^d$$

Given estimates of the coefficients of such distributed lags, we can construct time-varying measures of unconditional and conditional second moments of the three variables under consideration. Thus, for instance, the unconditional variance at time t of variable $x_{i,t}$ is given by

$$var(x_{i,t}) = \sum_{k=0}^{\infty}(C_{t,k}^{ia})^2 + \sum_{k=0}^{\infty}(C_{t,k}^{id})^2$$

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where the two terms on the right hand side represent the contribution of each of the shocks to that variance (or, equivalently, the variances conditional on each of the shocks).

Similarly, the covariance at time t between $x_{i,t}$ and $x_{j,t}$ is given by

$$cov(x_{i,t}, x_{j,t}) = \sum_{k=0}^{\infty} C_{t,k}^{ia} C_{t,k}^{ja} + \sum_{k=0}^{\infty} C_{t,k}^{id} C_{t,k}^{jd}$$

with each of the terms on the right hand side representing the covariances at time t conditional on technology and non-technology shocks, respectively.

In the next section we report estimates of a number of time-varying second moments in order to shed some light on the sources of the Great Moderation.

4 Sources of the Great Moderation

4.1 Unconditional Moments

Next we report some unconditional second moments implied by our estimated time-varying VAR. Figure 2 plots the evolution of the (unconditional) standard deviation of output growth over time. The overall pattern is consistent with the findings in the literature and, in particular, with the estimates reported in Section 2: the volatility of output experiences a remarkable decline between 1980 and 1986, stabilizing at a low level after that date. Before that transition the estimated volatility is far from constant, experiencing instead a substantial increase since the early 70s.[11]

Figure 3 shows the time-varying decomposition of the variance of output growth into its three components, in accordance to the identity

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[11] A similar observation is made in Blanchard and Simon (2001)

$$var(\Delta y_t) = var(\Delta n_t) + var(\Delta y_t - \Delta n_t) + 2 \ cov(\Delta n_t, \Delta y_t - \Delta n_t) \qquad (3)$$

While the three components seem to have contributed significantly to the decline in the variance of output growth, it is clear that the timing of that contribution is not uniform. In particular, the volatility of labor productivity goes down only gradually over time, whereas that of hours as well as the comovement of labor productivity and hours experience a dramatic decline between 1980 and 1986, thus explaining (in an accounting sense) the start of the Great Moderation.

In order to confirm that the decline in the covariance component in Figure 3 is not due exclusively to the lower volatility of hours and productivity, Figure 4 displays the estimates of the time-varying correlation between those variables. Notice that the correlation experiences a large decline (and a sign switch) at about the same time as the volatility of output implodes. That observation confirms, using a different approach (based on an estimated time-varying VAR), our findings of Section 2, as well as those in Stiroh (2006). For the purposes of the present paper, we also view those findings as *prima facie* evidence against the strong version of the good luck hypothesis for, as argued in the introduction, the latter would predict a scaling down of fluctuations in all variables without a corresponding change in their correlations.

Next we try to dig deeper and assess the extent to which the change in the labor productivity-hours correlations reflects a composition effect (resulting from variations in the relative importance of different types of shocks) or whether, instead, there has been a genuine change in the economy's response to each kind of shock. In order to address that question we turn to the

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analysis of the estimated conditional moments.

4.2 Conditional Volatilities: What Shocks are Responsible for the Great Moderation?

Figure 5 plots estimates of the (time-varying) standard deviation of output growth *conditional* on technology and non-technology shocks, implied by our estimated SVAR. The pattern that emerges in Figure 5 is unambiguous: the Great Moderation can be accounted for by the decline in the contribution of non-technology shocks to the variance of output. The timing of the decline, between 1980 and 1985, matches well that of the unconditional standard deviation of output, as shown in Figure 2.

By contrast, and perhaps surprisingly, technology shocks appear to have a increasing contribution to the variance of output growth, as captured by the slightly upward trend in the corresponding conditional standard deviation displayed in Figure 5. It is interesting to note that, starting from a dominant role of non-technology shocks in the early 60s, the different trends in the conditional volatilities mentioned above have implied a gradual convergence in the contribution of both shocks, with their weights being essentially the same at the end of the sample.

The evidence described above is at odds with the hypothesis of a declining contribution of technology shocks to output variability put forward in Arias, Hansen and Ohanian (2006; AHO henceforth), and which is claimed by the latter authors to fully account for the decline in the cyclical volatility of output. To be more specific, those authors show that the standard deviation of measured total factor productivity (TFP) has declined by a factor of about

1/2 between the pre-84 and post-84 periods. As shown by AHO, when two alternative calibrations of the technology process consistent with that observation are considered, an RBC model predicts a decline in the volatilities of output and its components similar to those observed in the data. The empirical evidence presented here shows no sign of a decline in the contribution of technology shocks to output volatility, and hence calls into question the conclusions of AHO's analysis.

4.3 The Role of Non-Technology Shocks in the Great Moderation

As discussed above, our approach points to non-technology shocks as the main source of the decline in output growth volatility after the mid-80s. Figure 6 digs a bit deeper by showing the decomposition of the variance of output growth associated with non-technology shocks. Most interestingly, we see that the bulk of the decline in the conditional volatility of output appears to result largely from (i) a decline in the conditional variance of hours (after a persistent surge during the 70s) and (ii) a large and prolonged decline in the covariance between labor productivity and hours.

Where do these changes come from? Figures 7-9 show the evolution over time in the impulse responses of output, hours and labor productivity to a non-technology shock. More specifically, the left panel of each figure shows the impulse response corresponding to the first quarter of each calendar year, while the right panel displays the average of those impulse responses over the entire pre-84 and post-84 subperiod.

Note that the pattern of the response of output (Figure 7) and hours (Fig-

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ure 8), characterized by a hump-shape, is very similar, both across variables and across subsamples. The decline in the size of the response is apparent in both cases, though considerably larger in the case of output. Most interestingly, Figures 8 and 9 combined allow us to identify the "immediate" source of the large decline in the comovement of labor productivity and hours conditional on non-technology shocks: while in the early sample period both variables respond strongly and in the same direction to a positive non-technology shock, in the more recent period the response of labor productivity is far more muted and indeed switches sign, turning negative after one period.

We thus have uncovered what appears to be evidence of a structural change that is relevant for our interpretation of the Great Moderation. In the pre-84 period, and in response to non-technology shocks, we find evidence of "short-run increasing returns to labor" (SRIRL).[12] Surprisingly, that phenomenon seems to have vanished in the post-84 period. That change alone accounts for much of the decline in output volatility, given the (conditional) volatility of hours. The decline in the latter, though not as dramatic, accounts for the bulk of the remaining drop in output volatility.

4.4 The Role of Technology Shocks in the Great Moderation

As discussed earlier, the time-varying conditional volatility estimates of Figure 2 suggest that the contribution of technology to the variance of output growth has experienced a slight increase over time. Figure 10 seeks to uncover

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[12]Albeit with different methods, the phenomenon of SRIRL had been emphasized by numerous authors. See, e.g., Gordon (1990).

the immediate sources of that increase. The evidence seems little ambiguous: the increase in the variance of output growth conditional on technology shocks is a consequence of the rise in the associated conditional covariance between labor productivity and hours, from a large negative value in the 60s to a value close to zero in the more recent period. The gradual vanishing of that negative conditional covariance more than offsets the mild decline in the conditional variance of hours or labor productivity.

A look at the impulse responses to a technology shock and their evolution over time, shown in Figures 11-13, holds the key to understanding the slight increase in output volatility. In response to a positive technology shock (i.e. one that increases labor productivity permanently), hours show a persistent decline, a finding consistent with the evidence in Galí (1999), Basu, Fernald and Kimball (2005), and Francis and Ramey (2005), with that response on impact accounting for the estimated negative correlation between hours and labor productivity. Yet, as Figure 12 makes clear, the size of the response of hours has gone down over time in absolute value, thus explaining the vanishing negative conditional comovement between labor productivity and hours as well as the rise over time in the size of the output response to the technology shock–and thus in the latter's conditional variance.

The previous finding accords with the evidence, reported in Galí, López-Salido, and Vallés (2003), of large and significant contractionary effects of aggregate technological improvements on employment in the pre-Volcker period, in contrast with the small and largely insignificant short term effects over the Volcker-Greenspan period. Galí, López-Salido, and Vallés (2003) argue that such evidence can be potentially explained by a change in the

monetary policy rule, from a rule that tends to stabilize output in the face of technology shocks (as is the case with a monetary targeting rule) to one that focuses on stabilizing inflation.

4.5 Evidence from Historical Decompositions

Tables 4 and 5 allow us to examine the sources of the changes in volatilities from a different perspective. They shows the (conditional) standard deviations and cross-correlations of the estimated technology and non-technology components of output, hours and labor productivity, for both the pre-84 and post-84 sample periods. In contrast with the evidence shown in Figures 5, 6 and 10, the statistics reported in Tables 4 and 5 depend both on the estimated moving average coefficients (the $C_{t,k}^{ij}$'s of section 3) *and* the specific realizations of the structural shocks. As we did for the original data, we report statistics for both the first-differenced and BP-filtered transformations of each of those components and test for the significance of the estimated changes across the two subsamples.

The evidence reported in Tables 4 and 5 points to the following key changes, all of them significant at the 5 percent level, uncovered by our analysis. First, non-technology shocks appear to be the main source of the decline in the volatility of output and labor productivity. Second, the drop in the volatility of hours seems to be largely associated with technology shocks. Finally, we see that non-technology shocks are largely responsible for the significant decline in the correlation between labor productivity and hours on the one hand, and labor productivity and output on the other.[13]

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[13]Note that the latter decline is (partly) offset by the small (but significant, in the BP-filtered case) increase in the correlation between labor productivity and output resulting

We interpret the previous findings as a additional evidence in support of the idea that some fundamental structural changes in the U.S. economy lie behind the decline in macroeconomic instability of the past two decades. We want to emphasize, however, that our findings leave room for a reduction in the size of shocks or a change in their relative composition to have played a role in the Great Moderation, though our empirical approach does not allow us to quantify the size of their respective contribution. Uncovering the latter would require the specification and estimation of a full-fledged structural model, which is beyond the scope of the present paper. Nevertheless, in Section 5 below we illustrate, in the context of a stylized new Keynesian model, how a relatively small change in the size of two parameters can go a long way in accounting for a large fraction of the observed volatility decline.

4.6 The Role of Investment-Specific Technology Shocks

In this section we extend our empirical analysis along the lines of Fisher (2006), in order to disentangle the role played by neutral technology shocks (henceforth, N-shocks) and investment-specific technology shocks (I-shocks) in the Great Moderation. This extension is of particular interest in light of the findings in Justiniano and Primiceri (2006) based on time-varying estimates of a DSGE model, and which point to the smaller size of I-shocks as the main explanation for the decline in output growth volatility.

Following Fisher (2006), we identify I-shocks as the only source of the unit root in the relative price of investment, i.e. we restrict N-shocks and non-technology shocks not to have a long run effect on that variable. On the other

from technology shocks.

hand, we allow both N-shocks and I-shocks to have a long run effect on labor productivity. We construct a series for the (log) real price of investment as in Justiniano and Primiceri (2006), as the weighted average of the (log) deflators of nondurables and services consumption minus the weighted average of the (log) deflators for investment and durable consumption, with the weights given by the relative (nominal) shares of each spending category.

Figure 14 plots estimates of the (time-varying) standard deviation of output growth conditional on the three types of shocks. Note that N-shocks have a relatively small and stable contribution to the volatility of output throughout the sample period. As in our bivariate model, this is the result of two opposite effects (not shown): a gradual reduction in the volatility of both hours and labor productivity and an (also gradual) increase in their conditional correlation. Secondly, both I-shocks and non-technology shocks play an important role in the Great Moderation. Interestingly, however, the patterns of their contribution differ substantially. Roughly speaking, while non-technology shocks account for the downward trend, investment specific technology shocks appear to be responsible for the hump observed during the second half of the 1970s. As shown in Figure 15, the latter phenomenon is associated to a large extent with a temporary increase in the 1970s in the volatility of hours worked resulting from I-shocks, with the conditional volatility of labor productivity and the productivity-hours correlation playing a smaller role.

Our augmented model thus points to an important role of I-shocks as a source of both the extraordinary increase in volatility of the 1970s and the subsequent decline in the mid-1980s. It is in that sense that we uncover a role

for I-shocks as an explanation for the Great Moderation. By contrast, and as shown in Figure 14, non-technology shocks display a prolonged gradual decline in their contribution to the volatility of output growth. That pattern is driven to a large extent by the associated decline in the conditional volatility of hours and the conditional correlation between hours and productivity (not shown, but with patterns similar to those in Figure 6).

5   What Structural Changes?   Elements for an Explanation

In the present section we use a simple New Keynesian model to explore the kind of structural changes that are needed to account for the evidence uncovered in the previous section. The nature of the model and the exercise imply that our findings should be viewed as suggestive, a full-fledged estimation of a richer and more realistic structural model falling beyond the scope of the present paper.

The log-linearized equations describing the equilibrium of the model are the following:

$$y_t = E_t\{y_{t+1}\} - (i_t - E_t\{\pi_{t+1}\}) + d_t \tag{4}$$

$$\pi_t = \beta \ E_t\{\pi_{t+1}\} + \kappa \ (y_t - a_t) \tag{5}$$

$$i_t = \phi_\pi \ \pi_t + \phi_y \ \Delta y_t \tag{6}$$

$$y_t = a_t + \gamma \ n_t \tag{7}$$

where y_t is (log) output, n_t denotes (log) hours, i_t is the short-term nominal rate, π_t is inflation, d_t is an exogenous demand shock, and a_t is an exogenous technology shock. Equation (4) results from combining the household's Euler

equation (under the assumption of utility separable and logarithmic in consumption) with the market clearing condition $y_t = c_t$ for all t. Equation (5) is a New Keynesian Phillips curve, with a_t corresponding to the natural level of output. Note that the demand disturbance d_t does not affect the natural level of output, as in the case of a shock to the discount rate. Equation (6) is a Taylor-type interest rate rule. Equation (7) represents a reduced form aggregate production relationship, allowing for short-run increasing returns to labor (SRIRL) when $\gamma > 1$, possibly as a result of labor hoarding and variable effort.[14]

The two driving forces evolve over time according to the stochastic processes

$$\Delta a_t = \rho_a \ \Delta a_{t-1} + \varepsilon_t^a$$

$$d_t = \rho_d \ d_{t-1} + \varepsilon_t^d$$

We analyze the behavior of the above model economy under two regimes, characterized by a different calibration of parameters ϕ_π, ϕ_y and γ are assumed to take different values across the two regimes. For simplicity, we refer to to the two configurations as "pre-84 calibration" and "post-84 calibration." In the pre-84 calibration we have

$$\gamma = 1.1 \ ; \ \phi_\pi = 1.01 \ ; \ \phi_y = 0.25$$

Under this calibration the economy displays some mild SRIRL, possibly due to labor adjustment costs. Though we do not model the latter explicitly, they are likely to lead to large variations in effort in the same direction as

---

[14]See Sbordone (1996), Galí (1999), and Barnichon (2006) for examples of structural models generating such SRIRL as a result of variable effort.

variations in observable hours, generating the assumed SRIRL in equilibrium. On the other hand, monetary policy responds to inflation just enough to guarantee that the Taylor principle be met.

The post-84 calibration is defined by

$$\gamma = 0.9 \; ; \; \phi_\pi = 2.0 \; ; \; \phi_y = 0.1$$

Thus, under this calibration the economy is no longer assumed to display SRIRL, which we interpret as capturing a reduction in the labor adjustment costs (or more precisely, the costs of adjusting hours), which makes endogenous variations in unobserved effort less important.[15] In addition, the monetary authority is assumed to put more weight on inflation stabilization relative to output stabilization, in a way consistent with the evidence for the U.S. economy.[16]

The remaining parameters are assumed to take identical values across regimes. They are

$$\beta = 0.99 \; ; \; \kappa = 0.34 \; ; \; \rho_a = 0.1 \; ; \; \rho_d = 0.5 \; ; \; \sigma_a = 0.04 \; ; \; \sigma_d = 0.14$$

The values assumed for β and κ correspond to a standard calibration of the New Keynesian model. Our choices of autoregressive coefficients ρ_a and ρ_d is meant to capture the patterns of the estimated impulse responses. Finally, we calibrate σ_a and σ_d so that under the pre-84 calibration we match the unconditional volatility of output growth (1.57) as well as the ratio of

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[15] The models of Galí (1999) and Barnichon (2006) would interpret the change in γ as the result of a change in the elasticity of marginal disutility of effort vs. that of hours.

[16] See, e.g. Clarida, Galí, and Gertler (2000). Barnicho (2006), in independent work, also explores the implications of analogous structural changes in the context of a search and matching model with nominal rigidities.

conditional volatilities of the same variable (= 1.14/0.52), both corresponding to the pre-84 sample period.

For each calibration we compute the second moments (standard deviations and cross-correlations) of output, hours and labor productivity generated by the equilibrium of the above model. We report the resulting statistics in Tables 6 and 7. We can now pose the following question: To what extent the (relatively small) changes in the three structural parameters assumed above can account for the variation in the estimated second moments between the pre-84 and post-84 periods, without having to resort to any changes in the properties of the exogenous driving forces?

The findings in Table 6 and 7 suggest that the change in the interest rate rule coefficients, in combination with the disappearance of SRIRL, are capable of accounting for slightly more than half the decline in output volatility, and about *3/4* of the decline in the volatility of hours (though not of labor productivity). In addition, the calibrated model can explain more than half the decline in the output-hours and hours-productivity correlations (though only a small fraction of the decline in the output-productivity correlation).[17]

Figures 14 through 17 display the impulse responses of output, hours and labor productivity to technology and non-technology shocks, under the two regimes considered. The changes in the impulse responses predicted by the model match, in most cases and at least in a qualitative sense, the estimated changes in the same impulse responses presented and discussed in the previous section.

The simplicity of our model notwithstanding, we interpret the findings of

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[17]Barnichon (2006) comes to similar qualitative conclusions.

the previous exercise as suggesting that two "plausible" structural changes provide a potential explanation for a substantial fraction of the changes in second moments. The remaining decline could very well be explained by a reduction in the size of the shocks themselves, which for simplicity we have kept unchanged in the exercise above.

6 Concluding remarks

The remarkable decline in macroeconomic volatility experienced by the U.S. economy since the mid-80s (the so-called Great Moderation) has not just involved a mere scaling down of the size of fluctuations. In particular, it has been associated with large changes in the patterns of comovements among output, hours and labor productivity. Those changes are reflected in both conditional and unconditional second moments as well as in the impulse responses to identified shocks. That evidence points to structural change, as opposed to just good luck, as an explanation for the Great Moderation. The shrinking contribution of non-technology shocks to output volatility appears to be a central feature of the postwar U.S. economy, and thus a key factor behind the Great Moderation. In particular, those shocks seem largely responsible for the decline in the correlation between hours and labor productivity, which is as one of the immediate factors behind the decline in output volatility. That finding is robust to the allowance for two types of technology shocks, neutral and investment-specific, though in that case the latter (i.e. I-shocks), account for the sharp increase in output volatility in the 70s, and the subsequent dramatic fall of the mid 80s, whereas the contribution of non-technology declines more gradually.

Using a highly stylized macro model we have shown that a significant fraction of the observed changes in comovements and impulse responses to identified shocks can be explained by two developments: (i) a change in the interest rate rule, giving a larger weight to inflation stabilization (relative to output stabilization) and (ii) an apparent end of short run increasing returns to labor (SRIRL).

Appendix

This appendix describes our approach for estimating the time-varying SVAR, which in turn follows closely Primiceri (2005).

A. Priors

Let z^T be a sequence of z's up to time T and let ϕ denote the vector containing all hyperparameters of the model (Ψ, Ξ, Ω). We assume that the conditional prior density of θ^T is given by:

$$p(\theta^T | \gamma^T, \sigma^T, \phi) \propto I(\theta^T) \; f(\theta^T | \gamma^T, \sigma^T, \phi)$$

where $I(\theta^T) = \prod_{t=0}^{T} I(\theta_t)$,

$$f(\theta^T | \gamma^T, \sigma^T, \phi) = f(\theta_0) \prod_{t=1}^{T} f(\theta_t | \theta_{t-1}, \gamma^T, \sigma^T, \phi)$$

and $f(\theta_t | \theta_{t-1}, \gamma^T, \sigma^T, \phi)$ is representable with (2). The function $I(\theta_t)$ assumes value 1 if all the roots of the VAR polynomial associated to θ_t are larger than one in modulus and 0 otherwise. To calibrate the prior densities of the other coefficients we estimate a time invariant VAR. Following Benati and Mumtaz (2006) we make the following assumptions.

$$
\begin{aligned}
p(\theta_0) &\propto I(\theta_0) N\left(\hat{\theta}_{OLS}, 4\hat{V}(\hat{\theta}_{OLS})\right) \\
p(\log \sigma_0) &= N\left(\log \hat{\sigma}_{OLS}, 10 \times I\right) \\
p(\gamma_0) &= N\left(\hat{\gamma}_{OLS}, \hat{V}(\hat{\gamma}_{OLS})\right) \\
p(\Omega) &= IW\left(\bar{\Omega}^{-1}, T_0\right) \\
p(\Psi) &= IW(\bar{\Psi}^{-1}, 2) \\
p(\Xi_{i,i}) &= IG\left(\frac{0.0001}{2}, \frac{1}{2}\right)
\end{aligned}
$$

where $\hat{\theta}_{OLS}$ is the OLS estimate of the VAR coefficients and $\hat{V}(\hat{\theta}_{OLS})$ is the estimate of their covariance matrix, $\hat{\sigma}_{OLS}$ is a vector containing the squared elements of the diagonal matrix $\hat{D}$ and $\hat{\gamma}_{OLS}$ is the element 2,1 of the lower triangular matrix $\hat{F}$, where $\hat{F}\hat{D} = \hat{\Sigma}_{OLS}$, $\hat{V}(\hat{\gamma}_{OLS}) = 10 * |\hat{\gamma}_{OLS}|$, and $\bar{\Omega} = 0.0025 \times V(\hat{\theta}_{OLS})$, T_0 is the number of observations in the initial sample, $\bar{\Psi} = 0.001 * |\hat{\gamma}_{OLS}|$.

B. Estimation

To draw realizations from the posterior density we use an MCMC algorithm which works in an iterative way. Each repetition basically is done in four steps and consists in drawing a subset of coefficients conditional to particular realization of the remaining coefficients and then use such a realization in the conditional densities of the remaining coefficients. Under regularity conditions and after a burn-in period, iterations on these four steps produce draws from the joint density.

- Step 1: $p(\theta^T | x^T, \gamma^T, \sigma^T, \phi)$

Conditional on $x^T, \gamma^T, \sigma^T, \phi$, the unrestricted posterior of the states is normal. The conditional mean and variance of the terminal state θ_T is computed using standard Kalman filter recursions. For all the other states up to $t-1$ the following backward recursions are employed

$$
\begin{aligned}
\theta_{t|t+1} &= \theta_{t|t} + P_{t|t} P_{t|t+1}^{-1} (\theta_{t+1} - \theta_{t|t}) \\
P_{t|t+1} &= P_{t|t} - P_{t|t} P_{t+1|t}^{-1} P_{t|t}
\end{aligned}
\tag{8}
$$

where $\theta_{t|t+1} \equiv E(\theta_t | \theta_{t+1}, x^T, \gamma^T, \sigma^T, \phi)$ and $P_{t|t+1} \equiv Var(\theta_t | \theta_{t+1}, x^T, \gamma^T, \sigma^T, \phi)$.

- Step 2: $p(\gamma^T | x^T, \theta^T, \sigma^T, \phi)$

This is done following the same procedure described in Primiceri (2005). Basically in this second step the same algorithm applied in step 1 is repeated using as the set of observational equations the transformation $F_t^{-1}(x_t - A_{0,t} + A_{1,t} \ x_{t-1} + ... + A_{p,t} \ x_{t-p}) = F_t^{-1}u_t$.

• Step 3: $p(\sigma^T|x^T, \theta^T, \gamma^T, \phi)$

This is done using the univariate algorithm by Jacquier, Polson and Rossi (2004) used in Cogley and Sargent (2005) (see Appendix B.2.5).

• Step 4: $p(\phi|x^T, \theta^T, \gamma^T, \sigma)$

Conditional on $x^T, \theta^T, \gamma^T, \sigma$ all the remaining hyperparameters, under conjugate priors, can be sampled from IW and IG distributions.

We perform 15000 repetitions. CUMSUM graphs are used to check for convergence and we found that the chain had converged, roughly, after 5000 draws. The densities for the parameters are typically well behaved. We keep one every 10 of the remaining 10000 draws to break the autocorrelations of the draws. Finally we discard all the draws generating explosive paths in order to ensure converge of the impulse response functions and make long run restrictions implementable.

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Table 1. The Great Moderation

| | *Standard Deviation* | | | |
	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$	p-value
First-Difference				
GDP	1.21	0.54	0.44	<0.01
Nonfarm Business Output	1.57	0.68	0.43	<0.01
BP-Filter				
GDP	2.01	0.93	0.46	<0.01
Nonfarm Business Output	2.61	1.21	0.46	<0.01

Note: All variables transformed by taking the natural logarithm and applying the transformation indicated in the table (first difference or band-pass filter). P-values correspond to a test of equality of variances across the two subsamples based on the asymptotic standard errors of variance estimates computed using an 8-lag window.(see, Priestley (1991), p. 327).

Table 2. Changes in Volatility

	Standard Deviation				Relative Standard Deviation		
	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$	p-value	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$
First-Difference							
Output	1.57	0.68	0.43	0.00	1.00	1.00	1.00
Hours	1.05	0.65	0.61	0.00	0.66	0.95	1.41
Productivity	1.00	0.61	0.62	0.00	0.63	0.89	1.44
BP-Filter							
Output	2.61	1.21	0.46	0.00	1.00	1.00	1.00
Hours	2.07	1.33	0.64	0.04	0.79	1.10	1.39
Productivity	1.26	0.71	0.56	0.00	0.48	0.58	1.21

Note: P-values correspond to a test of equality of variances across the two subsamples based on the asymptotic standard errors of variance estimates computed using an 8-lag window.(see, Priestley (1991), p. 327)

Table 3. Changes in Cross-Correlations

First-Difference	pre-84	post-84	change
Output, Hours	0.78	0.57	-0.20^{**}
			(0.08)
Hours, Productivity	0.18	-0.41	-0.59^{**}
			(0.10)
Output, Productivity	0.75	0.50	-0.24^{**}
			(0.11)
BP-Filter	pre-84	post-84	change
Output, Hours	0.87	0.84	-0.03
			(NA)
Hours, Productivity	0.16	-0.42	-0.59^{**}
			(0.14)
Output, Productivity	0.62	0.12	-0.49^{**}
			(0.16)

Note: Test of equality of correlations across the two subsamples based on the asymptotic standard errors of estimated correlations computed using an 8-lag window.(see, e.g., Box and Jenkins (1976), p. 376). One asterisk denotes significance at the 10 percent level. Two asterisks indicate significance at the 5 percent level.

Table 4. Changes in Conditional Volatility

	Non-Technology Shocks				Technology Shocks			
	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$	p-value	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$	p-value
First-Difference								
Output	1.14	0.62	0.54	0.00	0.52	0.54	1.05	0.70
Hours	0.79	0.65	0.82	0.26	0.34	0.21	0.61	0.00
Productivity	0.46	0.20	0.37	0.00	0.72	0.67	0.88	0.52
BP-Filter								
Output	1.93	1.19	0.62	0.07	0.65	0.65	1.01	0.95
Hours	1.59	1.35	0.85	0.51	0.47	0.30	0.65	0.05
Productivity	0.49	0.33	0.67	0.06	0.89	0.81	0.91	0.59

Note: P-values correspond to a test of equality of variances across the two subsamples based on the asymptotic standard errors of variance estimates computed using an 8-lag window.(see, Priestley (1991), p. 327)

Table 5. Changes in Conditional Correlations

	Non-Technology Shocks			Technology Shocks		
	pre-84	post-84	change	pre-84	post-84	change
First-Difference						
Output, Hours	0.94	0.94	-0.00 (*NA*)	-0.39	-0.48	-0.09 (0.10)
Hours, Productivity	0.63	-0.30	-0.93^{**} (0.08)	-0.75	-0.70	0.04 (0.07)
Output, Productivity	0.84	-0.01	-0.85^{**} (0.16)	0.90	0.96	0.05 (0.08)
BP-Filter						
Output, Hours	0.97	0.97	-0.01 (*NA*)	-0.26	-0.34	-0.06 (0.19)
Hours, Productivity	0.60	-0.59	-1.19^{**} (0.12)	-0.71	-0.65	0.06 (0.11)
Output, Productivity	0.75	-0.39	-1.14^{**} (0.15)	0.86	0.93	0.07^{**} (0.03)

Note: Test of equality of correlations across the two subsamples based on the asymptotic standard errors of estimated correlations computed using an 8-lag window.(see, e.g., Box and Jenkins (1976), p. 376). One asterisk denotes significance at the 10 percent level. Two asterisks indicate significance at the 5 percent level.

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Table 6. Changes in Volatility: Data vs. Calibrated Model

	Data			Calibrated Model		
	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$	Pre-84	Post-84	$\frac{\text{Post-84}}{\text{Pre-84}}$
First-Differences						
Output	1.57	0.68	0.43	1.57	1.10	0.70
Hours	1.05	0.65	0.61	1.30	0.93	0.71
Productivity	1.00	0.61	0.62	0.71	0.71	1.0

Table 7. Changes in Cross-Correlations: Data vs. Calibrated Model

	Data			Calibrated Model		
	Pre-84	Post-84	change	Pre-84	Post-84	change
First-Differences						
Output, Hours	0.78	0.57	-0.20	0.89	0.76	-0.13
Hours, Productivity	0.18	-0.41	-0.59	0.13	-0.13	-0.26
Output, Productivity	0.75	0.50	-0.24	0.56	0.53	-0.03

Figure 1

U.S. GDP Growth
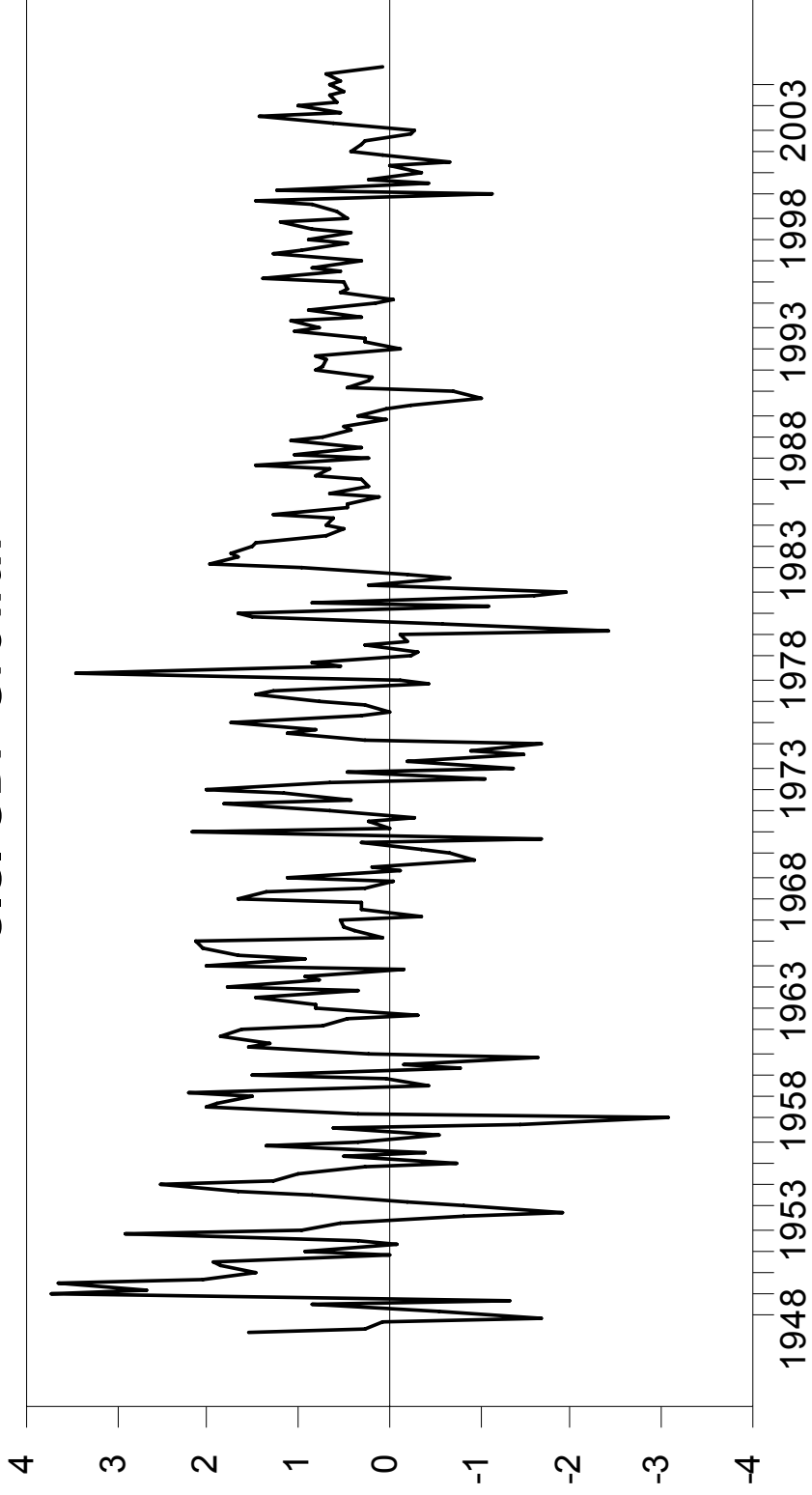
Figure 2
Standard Deviation of Output Growth
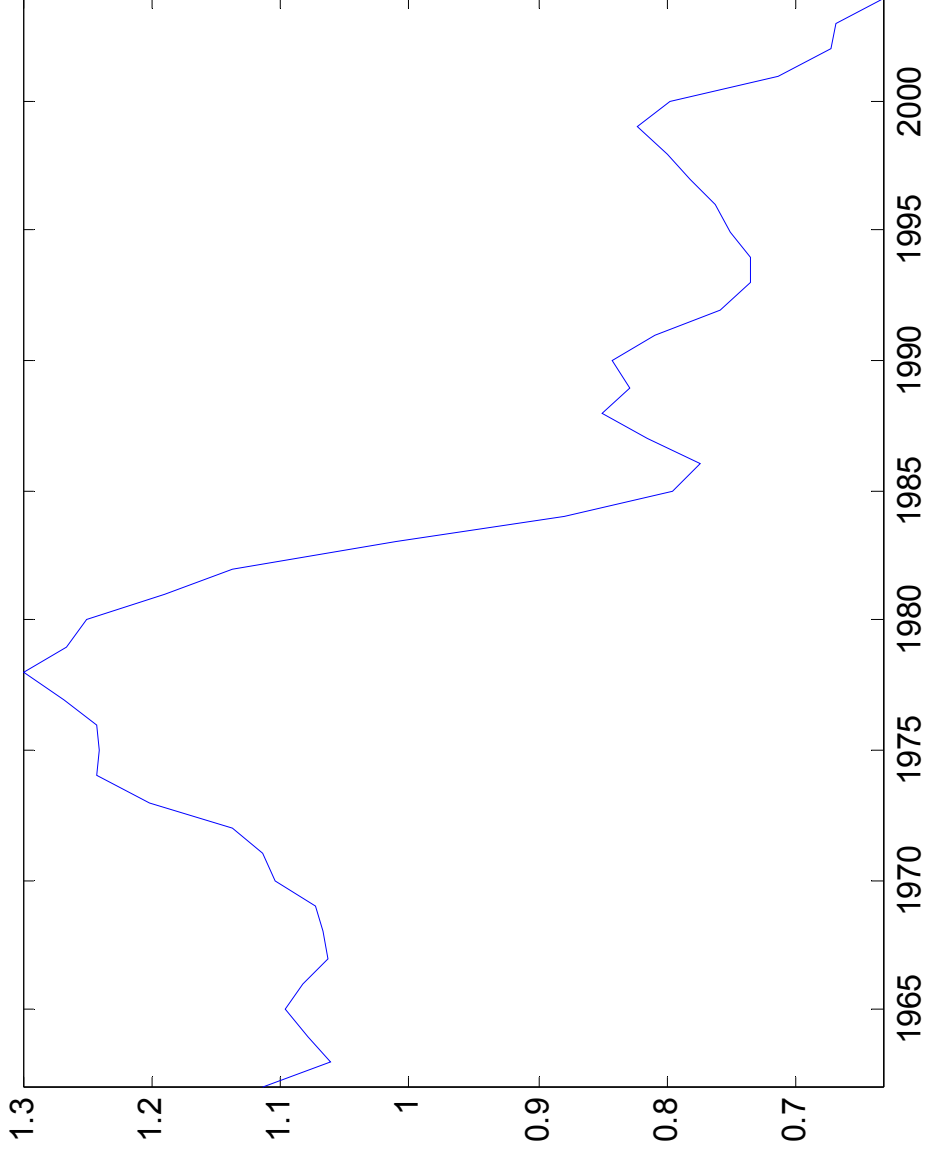
Figure 3
Decomposition of GDP Growth Variance
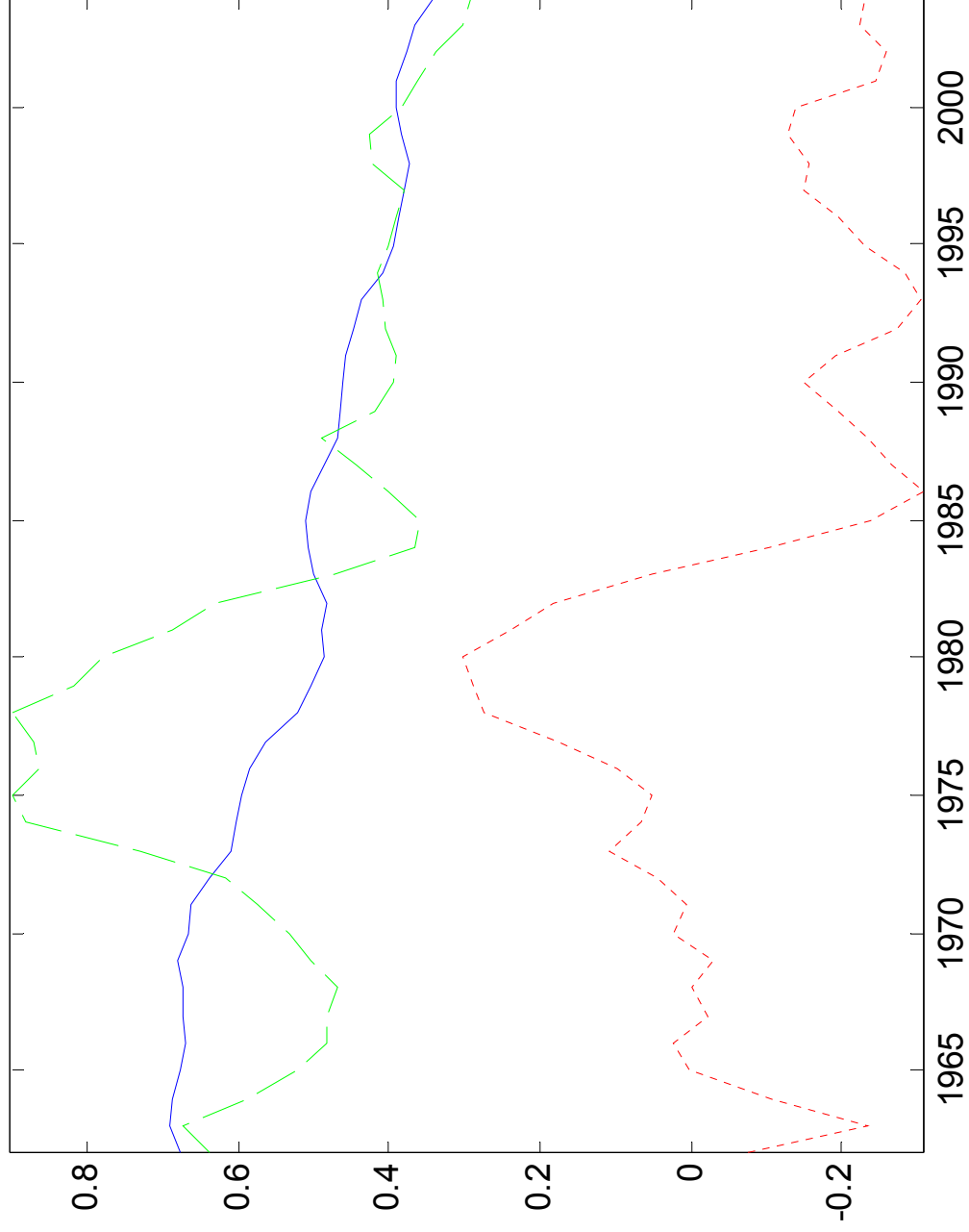
Note: var[Δ(y-n)]: blue solid ; var[Δn]: green dashed ; 2*cov[Δ(y-n),Δn]: red dotted

Figure 4
Correlation of Hours and Labor Productivity Growth
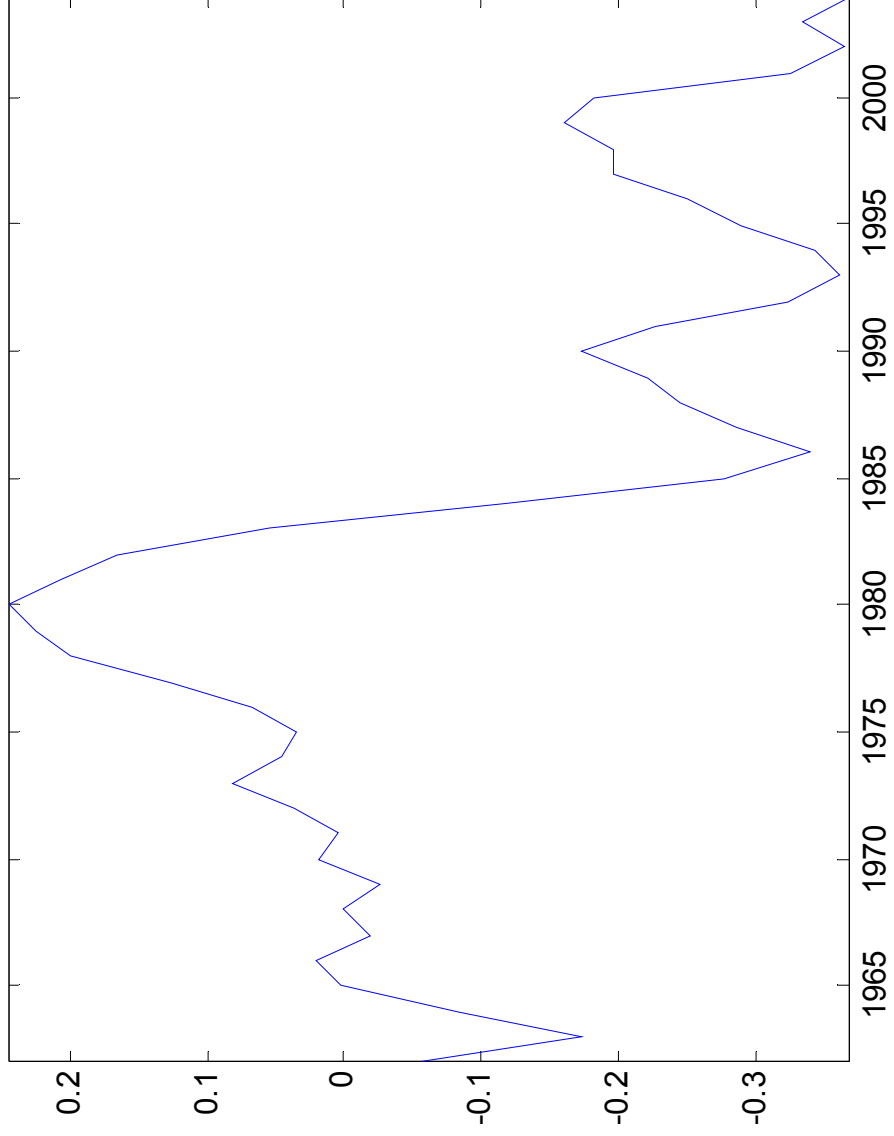
Figure 5

Technology and Non-Technology Components
of Output Growth Volatility
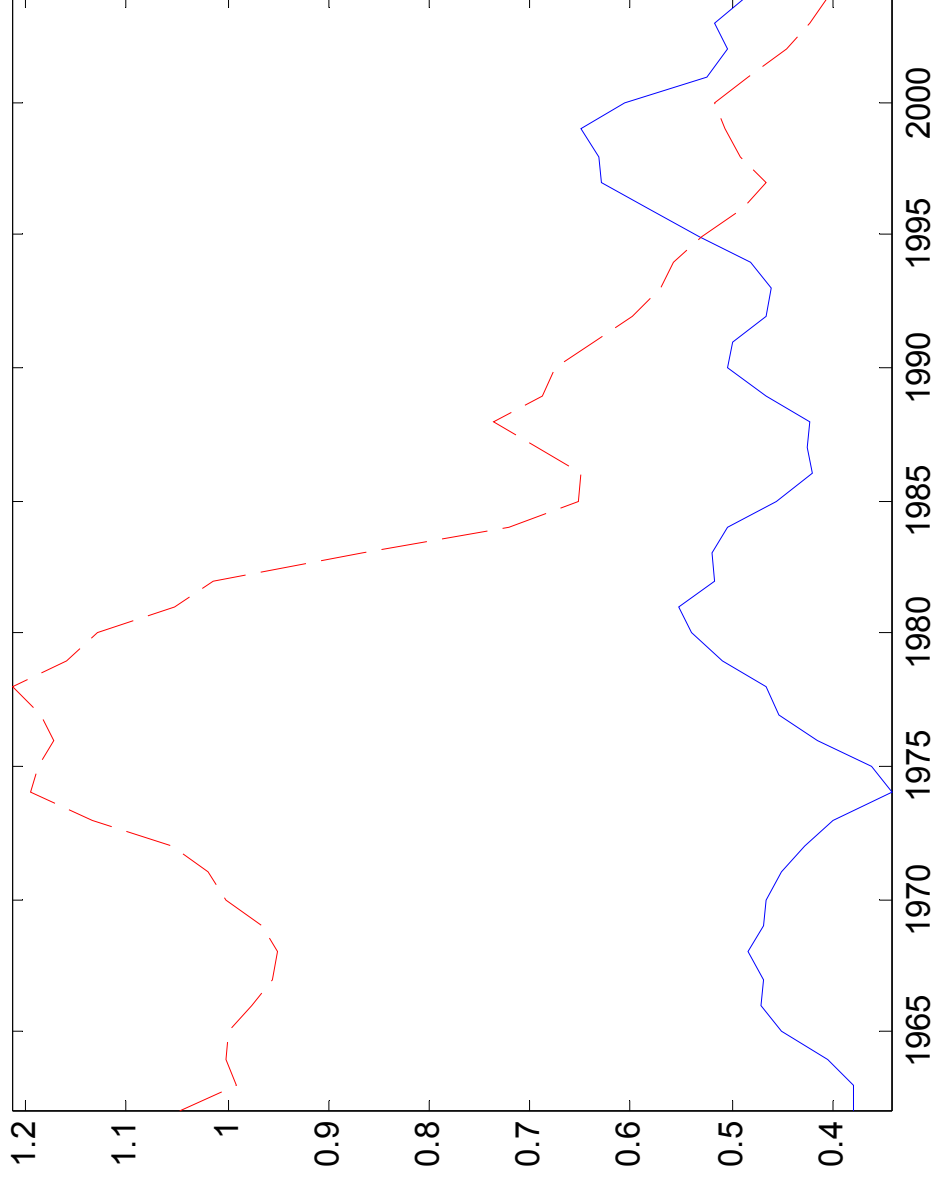
Note: technology: blue solid ; non-technology: red dashed

Figure 6
Non-Technology Shocks:
Conditional Variance Decomposition
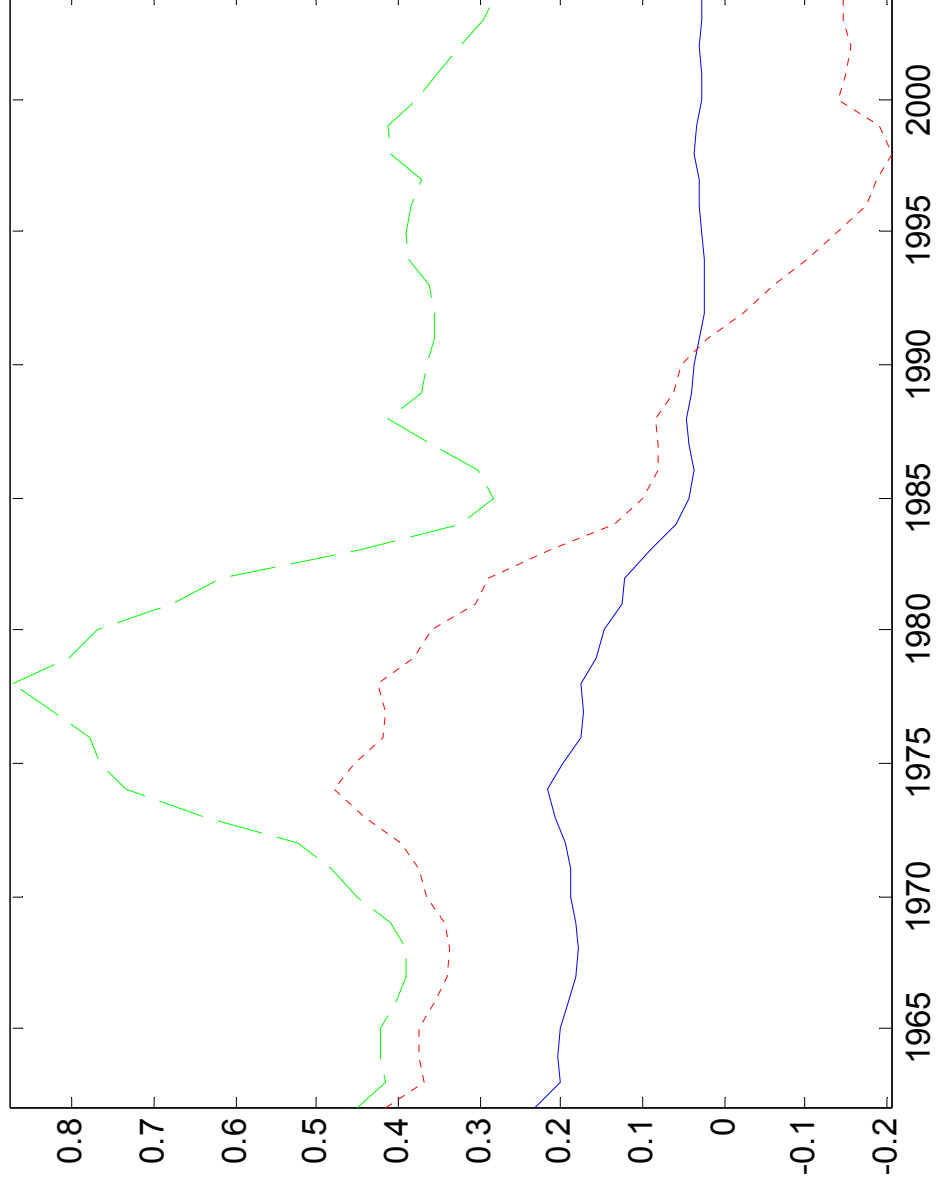
Note: var[Δ(y-n)]: blue solid ; var[Δn]: green dashed ; 2*cov[Δ(y-n),Δn]: red dotted

Figure 7
Non-Technology Shocks: Output Response

Rolling Impulse Responses

Average Impulse Responses
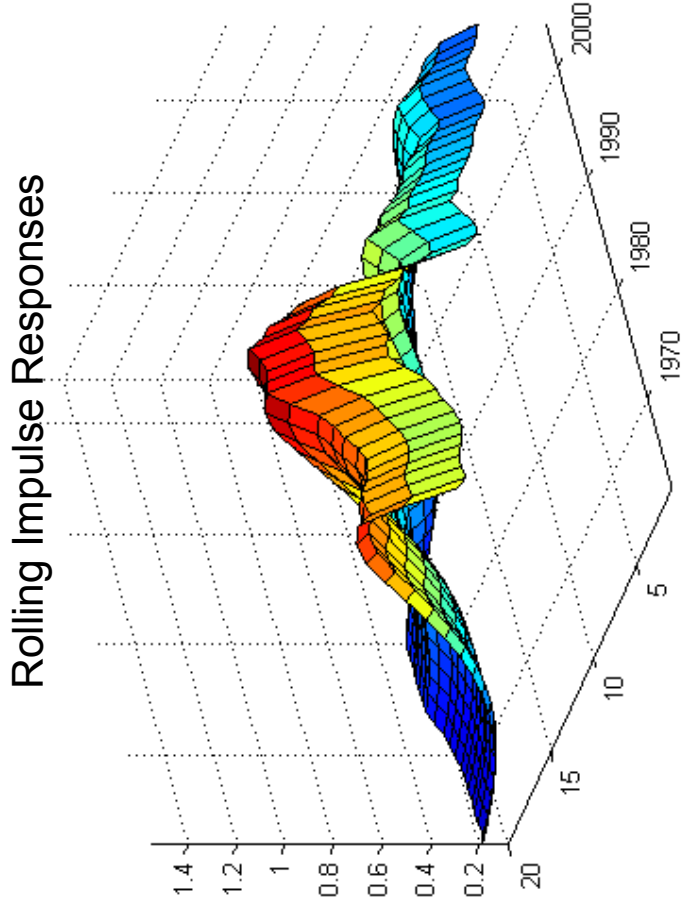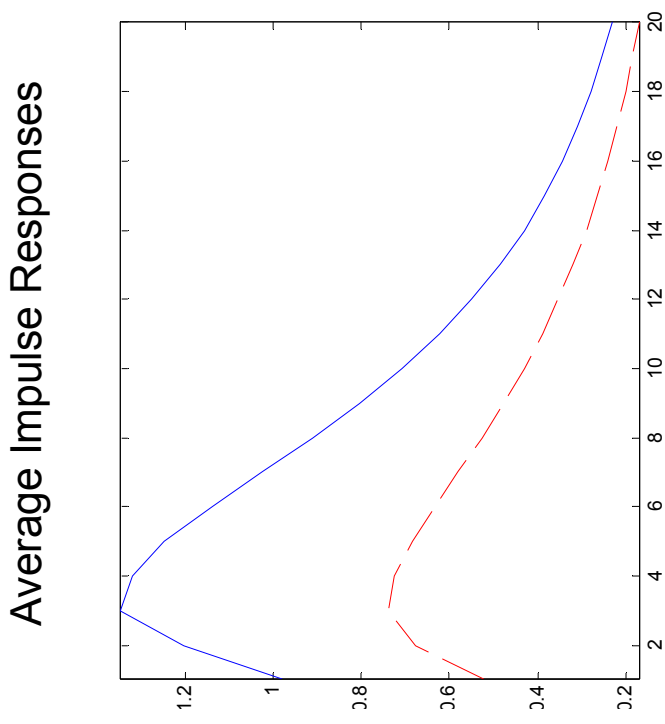
Note: pre-84: blue solid ; post-84: red dashed

Figure 8
Non-Technology Shocks: Hours Response

Average Impulse Responses

Rolling Impulse Responses
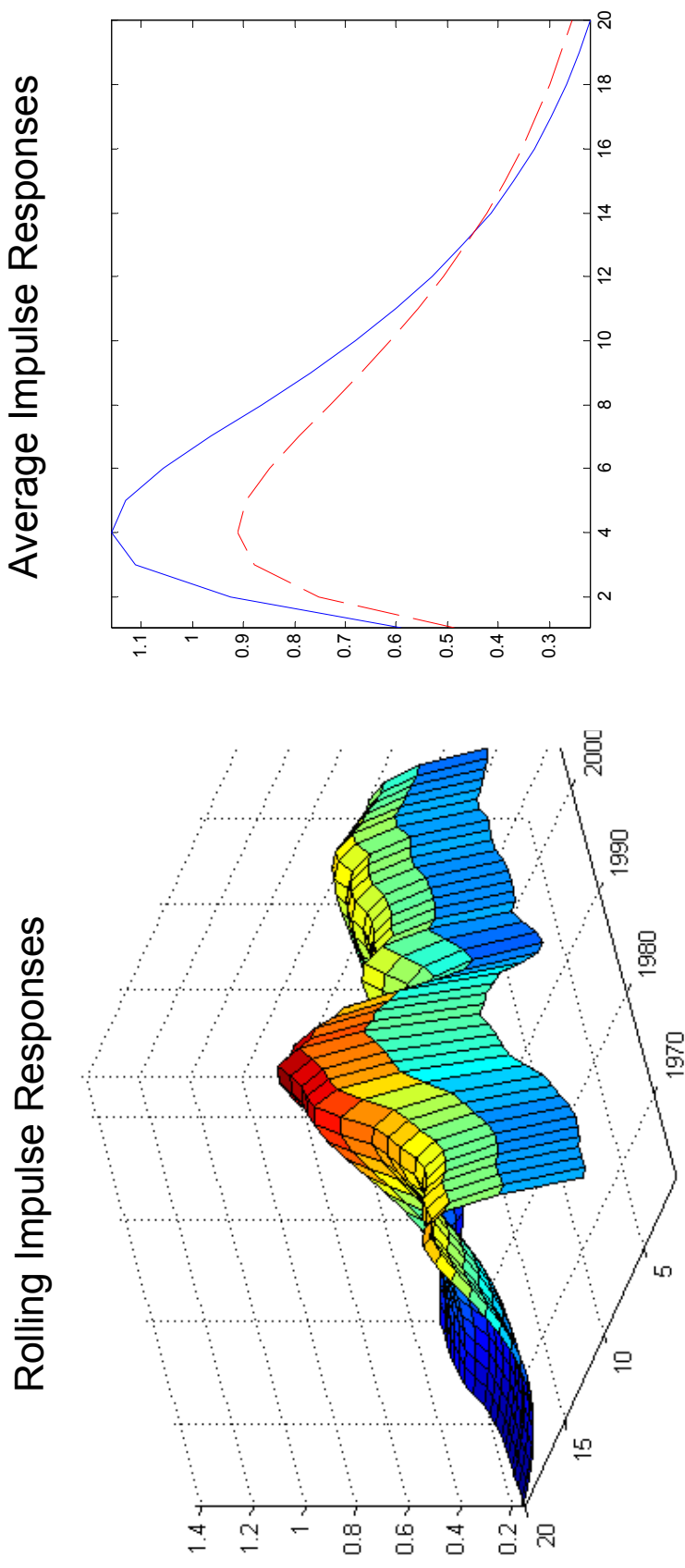
Note: pre-84: blue solid ; post-84: red dashed

Figure 9

Non-Technology Shocks: Labor Productivity Response

Rolling Impulse Responses

Average Impulse Responses
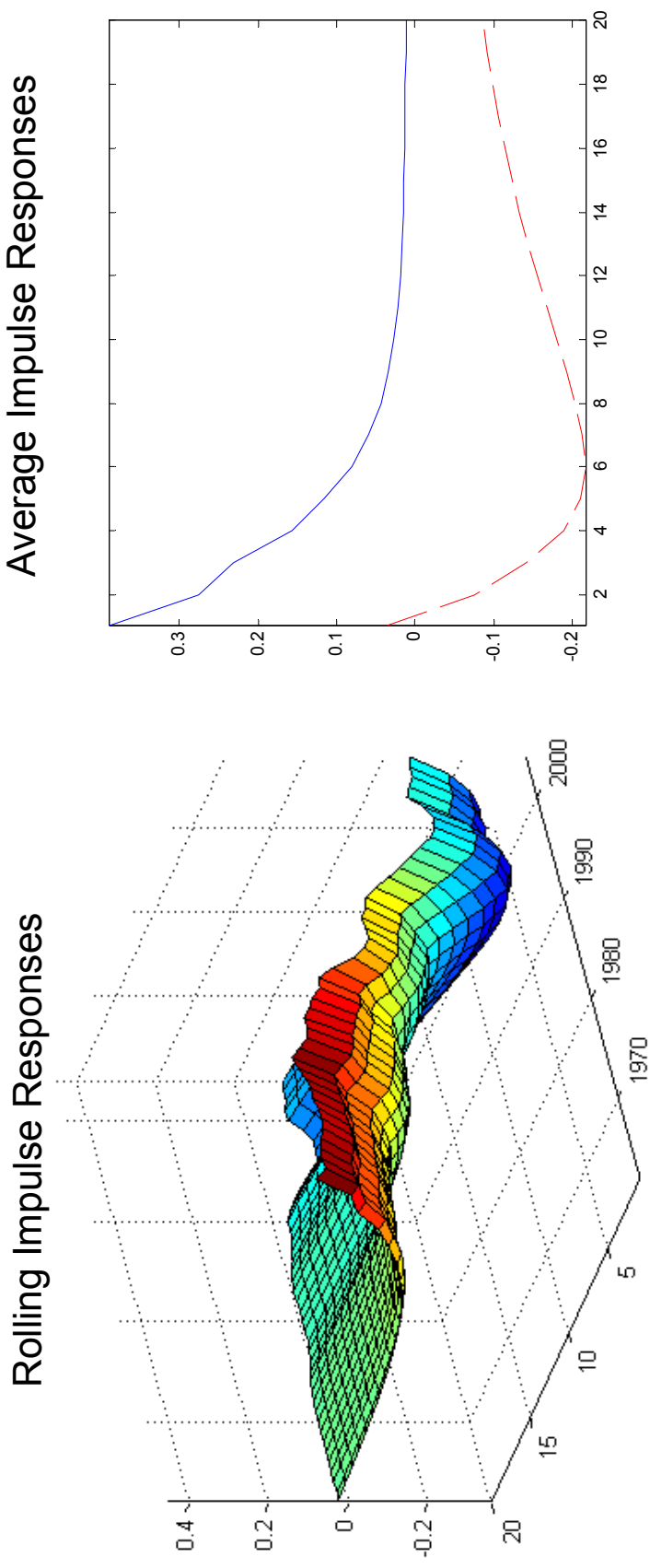
Note: pre-84: blue solid ; post-84: red dashed

Figure 10

Technology Shocks: Conditional Variance Decomposition
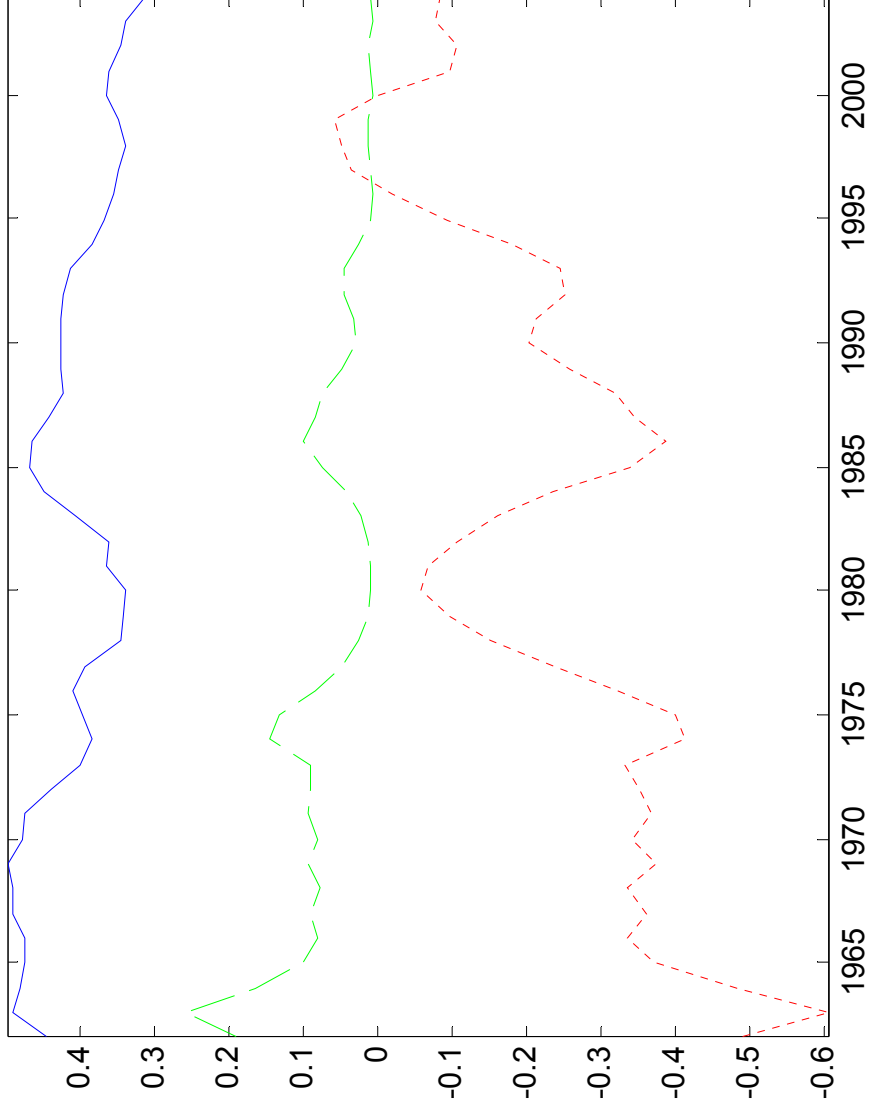
Note: var[Δ(y-n)]: blue solid ; var[Δn]: green dashed ; 2*cov[Δ(y-n),Δn]: red dotted

Figure 11
Technology Shocks: Output Response

Rolling Impulse Responses

Average Impulse Responses
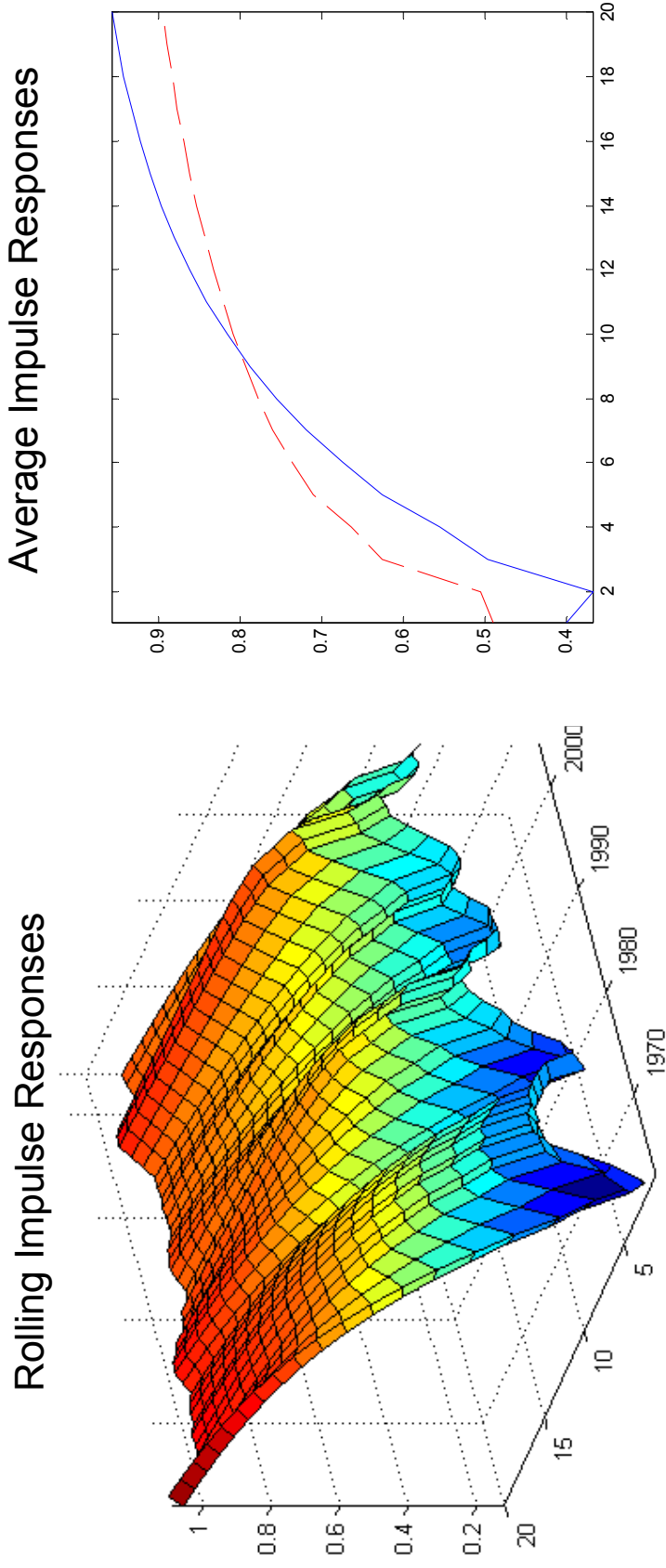
Note: pre-84: blue solid ; post-84: red dashed

Figure 12

Technology Shocks: Hours Response

Rolling Impulse Responses

Average Impulse Responses
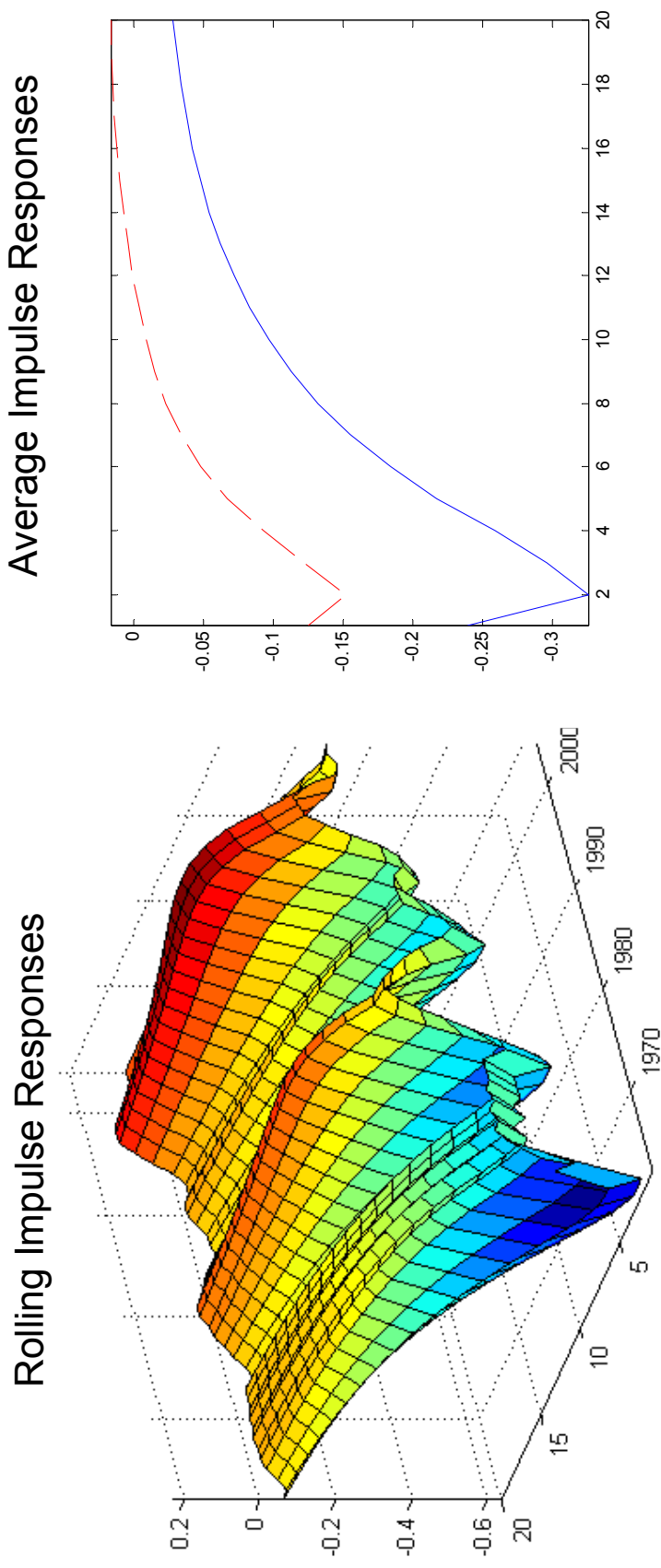
Note: pre-84: blue solid ; post-84: red dashed

Figure 13
Technology Shocks: Labor Productivity Response

Rolling Impulse Responses

Average Impulse Responses
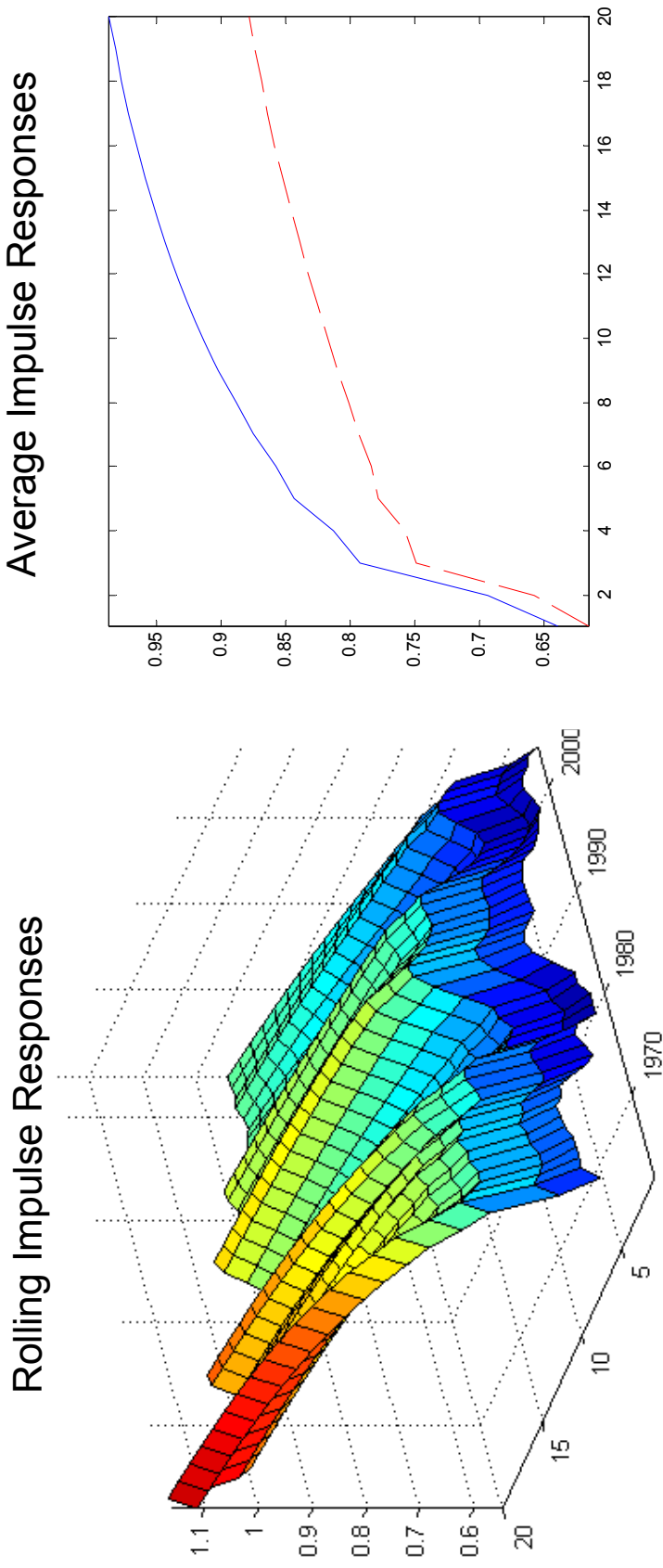
Note: pre-84: blue solid ; post-84: red dashed

Figure 14

Augmented Model: Decomposition of Output Growth Volatility
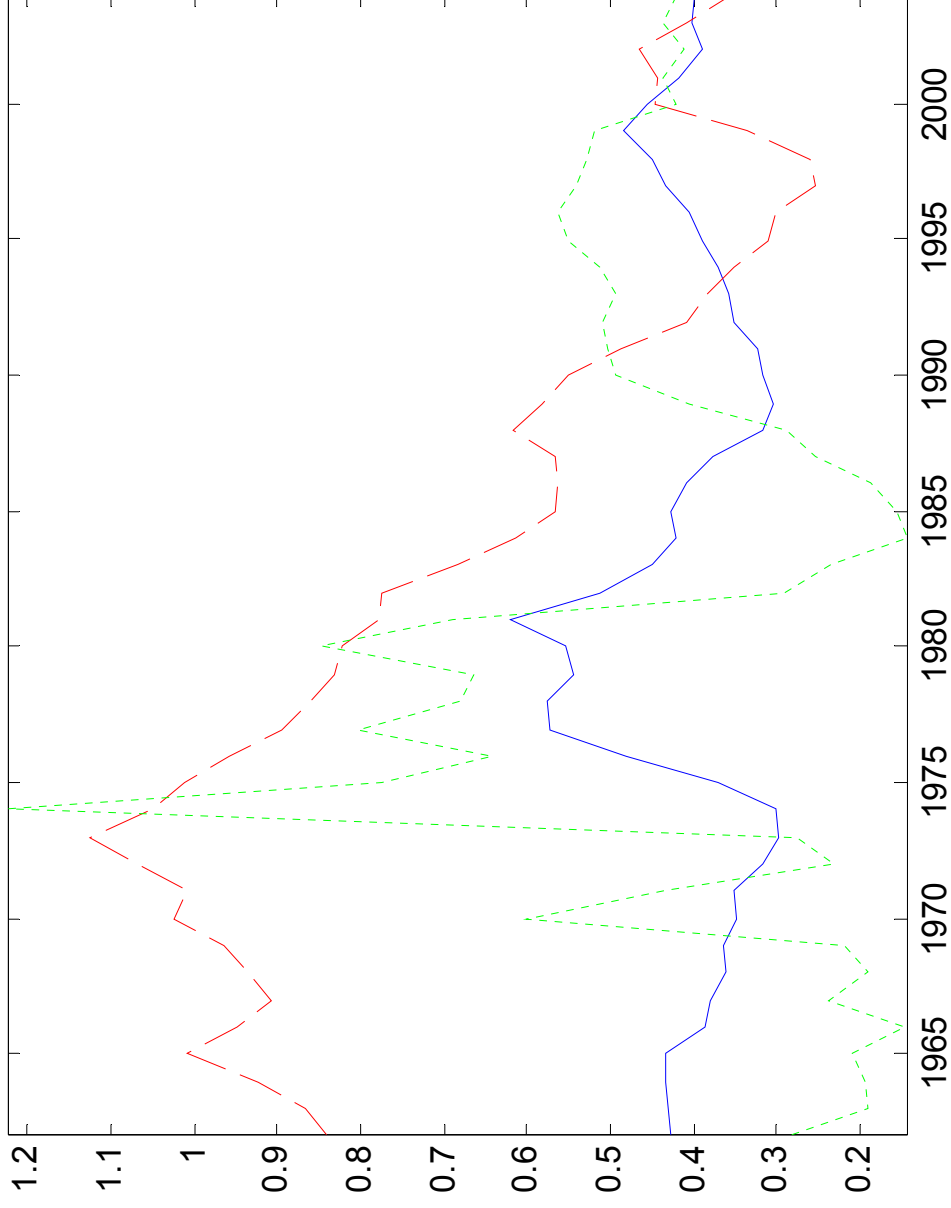
Note: N-shocks: blue solid ; I-shocks: green dotted ; Non-technology: red dashed

Figure 15

I-Shocks: Conditional Variance Decomposition
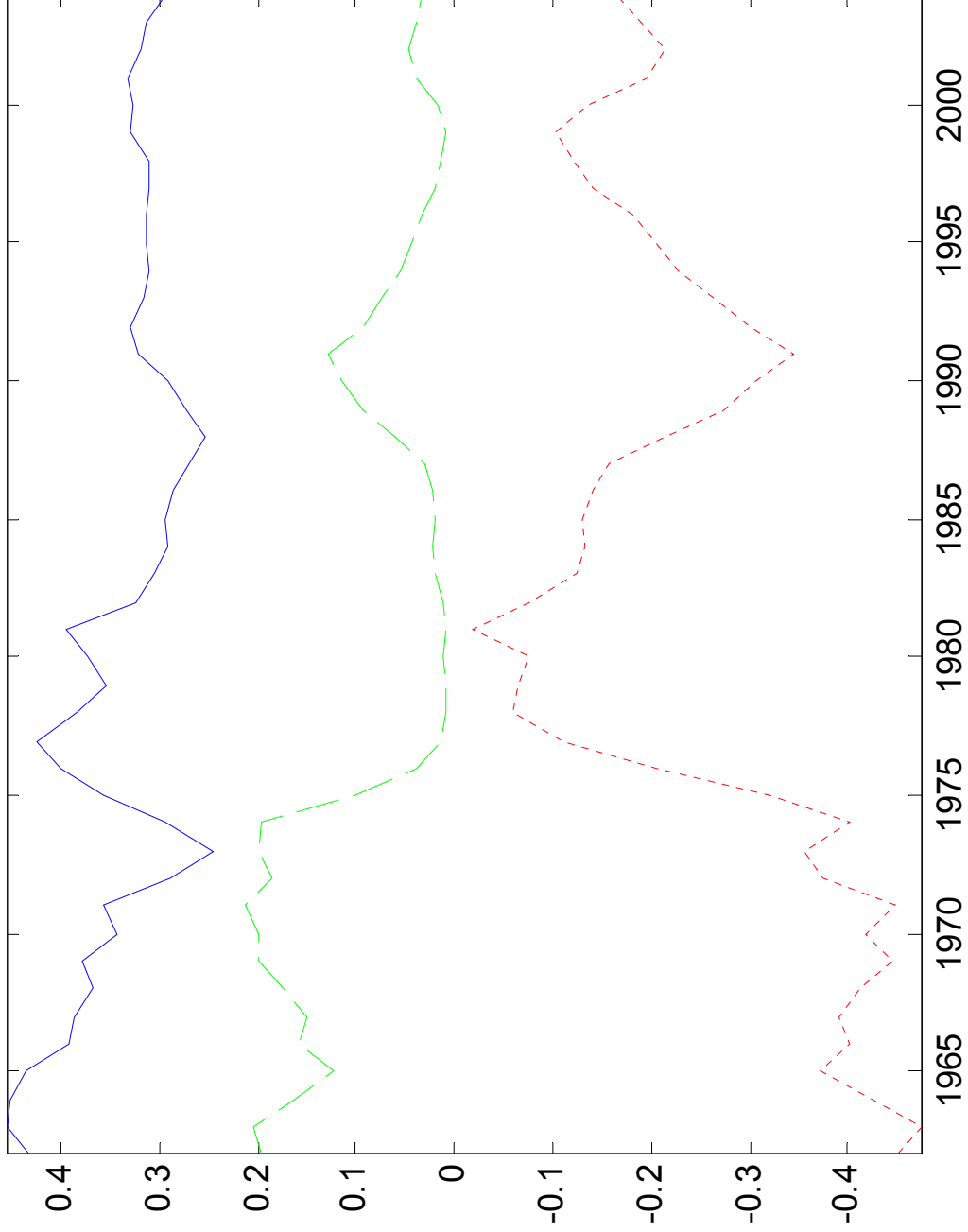
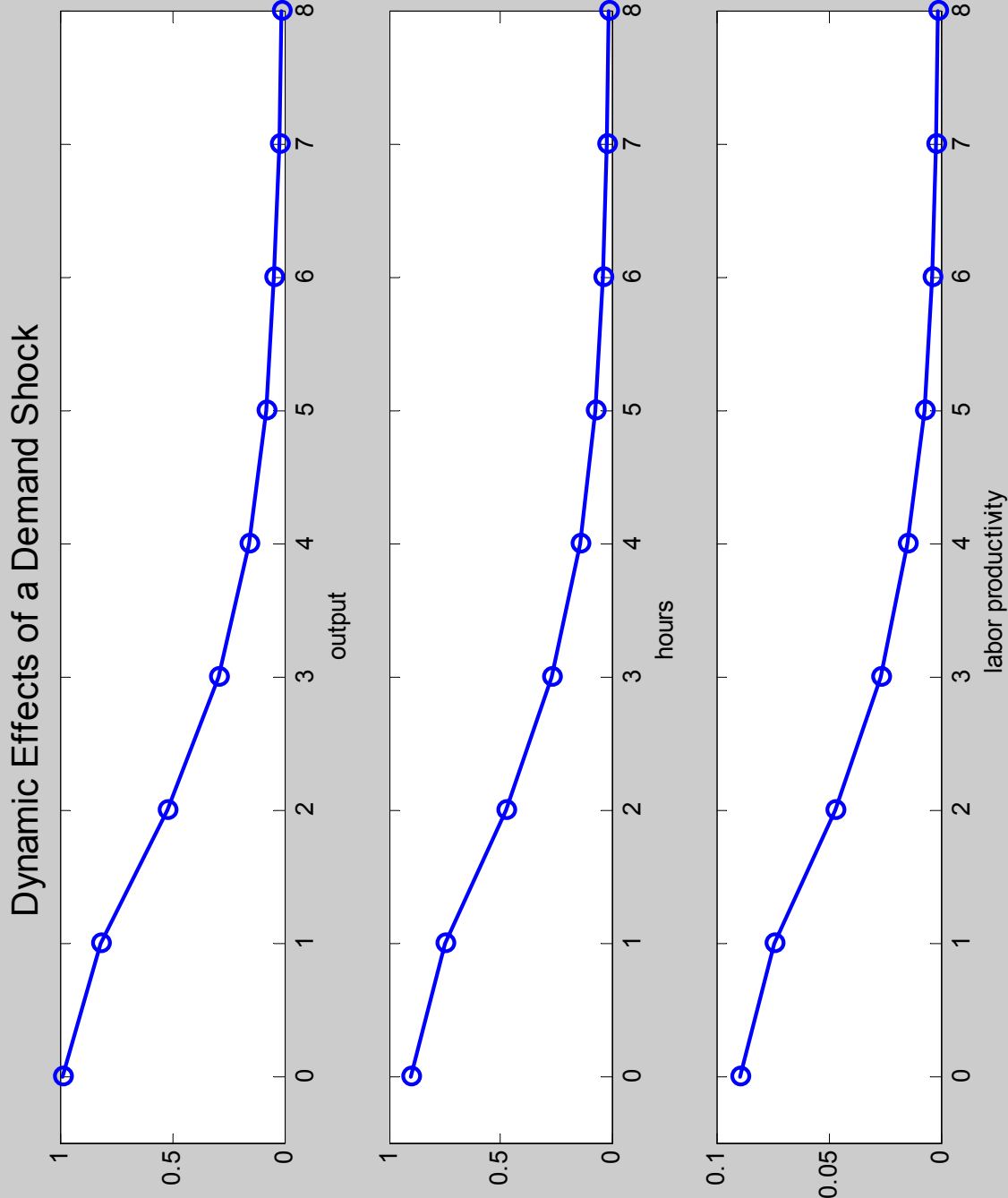Note: var[Δ(y-n)]: blue solid ; var[Δn]: green dashed ; 2*cov[Δ(y-n),Δn]: red dotted

Figure 16
Pre-84 Calibration: Technology Shock
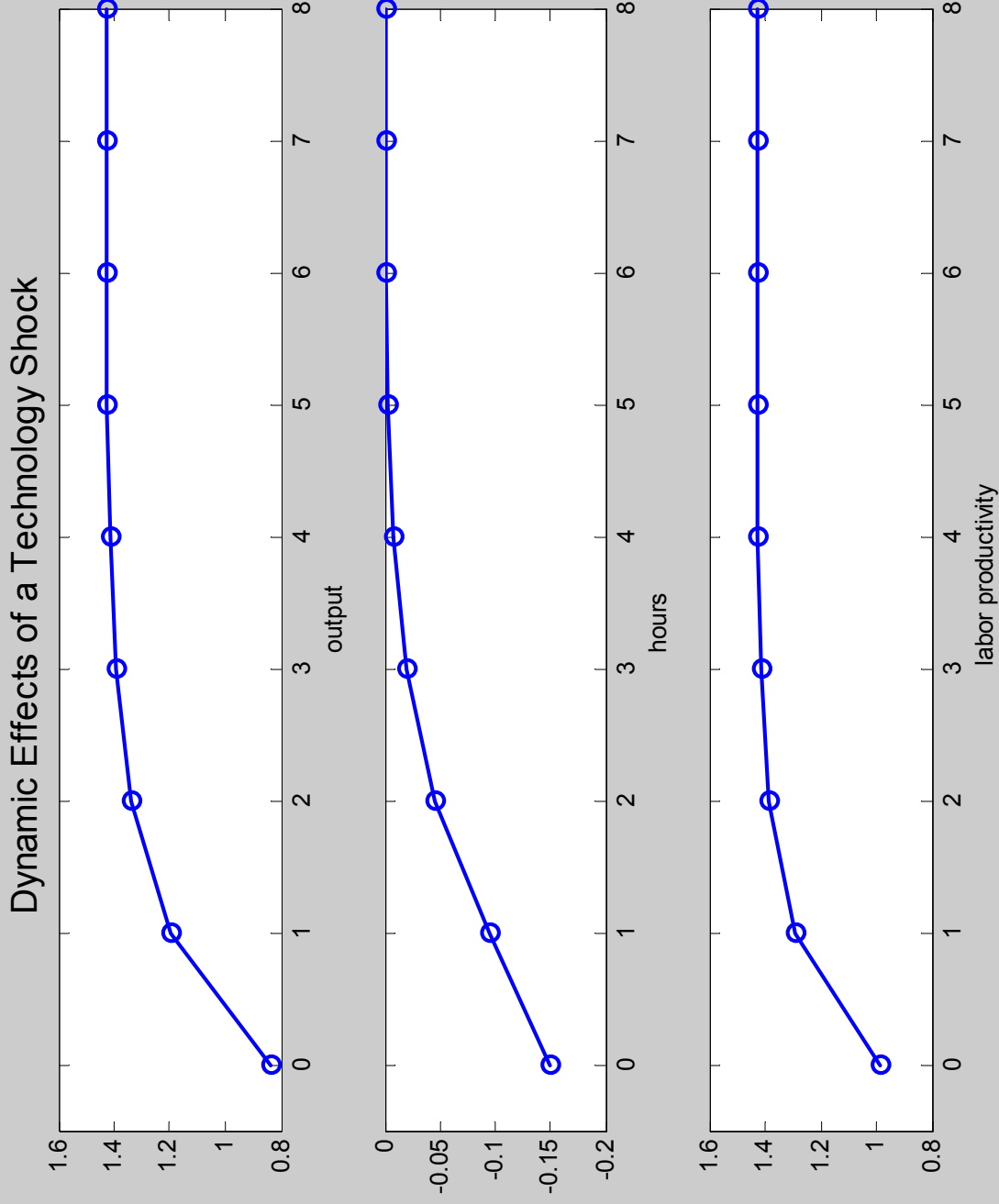
Figure 17

Pre-84 Calibration: Demand Shock

Figure 18
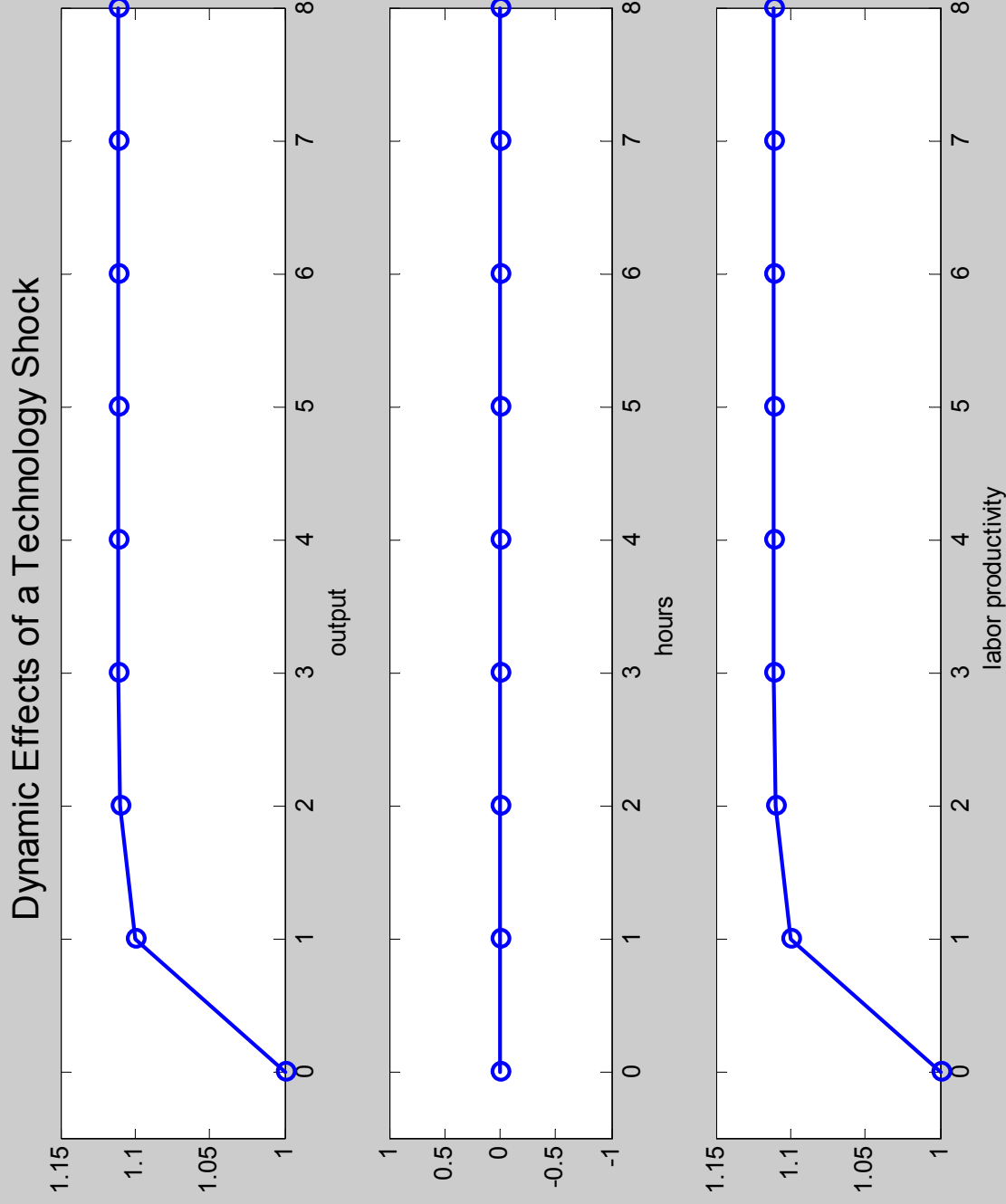Post-84 Calibration: Technology Shock

Dynamic Effects of a Technology Shock

Figure 19

Post-84 Calibration: Demand Shock

Dynamic Effects of a Demand Shock