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5 June 2018

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June 5, 2018

Abstract

Much of macroeconomic theorizing rests on assumptions that define the short-run output adjustment of a mass-production economy. The demand effect of investment on output, assumed much faster than its supply effect, works through employment expanding *pari passu* with changes in capacity utilization while productivity remains constant. Using linear Structural VAR and Time-Varying Parameter Structural VAR models, we document important changes in the short-run output adjustment in the USA. The link between changes in employment, capacity utilization and investment has weakened, while productivity became more responsive following demand shifts caused by investment since the early 1990s.

JEL Classification: B50, E10, E32.

Keywords: changes in short-run output adjustment, capacity utilization, employment, mass-production economy, post-Fordism.

1. Introduction

The paper discusses if some of macroeconomists' theoretical priors still retain their relevance today, presenting evidence that suggests they no longer might. The rise of mass production economy in the manufacturing industry at the turn of the previous century had shaped many of the building blocks of macroeconomic theorizing. However, not only manufacturing has shrunk relative to other sectors in terms of its share of output (and in absolute terms in terms of employment), but also its organization of production in advanced countries such as the USA has long been transformed, altering the link between employment and output. When it comes to the modality of this link, *fixed productivity* and *variable capacity utilization/employment* are, according to Edward J. Nell's succinct formulation, the defining characteristics of mass production (Aglietta, 1979; Nell, 1992; Piore and Sable, 1984), which differ from the so-called craft system with its *fixed capacity utilization/employment* and *variable productivity*. Ever since Piore and Sable's (1984) seminal work, it is commonly recognized that the rise of information technologies may have revived the work pattern of a craft economy, and a large literature discusses the effect this had on the rise of *flexible specialization* and employment (post-Fordism, for short).[1]

The present paper focuses on the implications of the latter for the short-run output adjustment in the US economy. Using linear Structural Vector Autoregressive models and Time-Varying Parameter Structural Vector Autoregressive models, we present evidence that the link macroeconomists take for granted between changes in employment, capacity utilization and investment has become weaker since the early 1990s; while productivity appears to have become more responsive to demand shifts caused by investment. The results point out that the output

[1]See, among others, Jessop (1995, 2005) and Amin (1995) for a useful reader on post-Fordism. Closer to our paper is discussions of Nell's *transformational growth* in connection with business cycle dynamics –see, Nell & Phillips (1995) and Ertürk (2004) for a formalization.

adjustment characteristic of the mass production system has lost some of its importance while that depicting the craft production system has become more relevant.

Our contribution is also related to two strands of literature. First, the recent literature on "jobless recoveries" (Burger & Schwartz, 2018; Chen & Cui, 2017; DeNicco & Laincz, 2018; Panovska, 2017) has pointed out that the past three recoveries in the USA have been markedly different from most postwar recoveries prior to 1990. In each successive episode, not only employment continued to decline even as output began to revive but also permanent job losses over temporary layoffs were higher. Although there is consensus in the literature regarding the change in the dynamics of employment, there is no general consensus on the cause of jobless recoveries. Several explanations for this change in the relationship between labor market variables and output have been proposed in the theoretical literature, such as shifts across sectors and occupations, employment overhang, changes in the persistence and amplitude in the output cycle, and changes in the nature of the labor market, where demand shocks are absorbed on the intensive margin (hours worked) or by using more flexible labor inputs.

Second, the observed weakening relationship between employment and output has also raised questions about the stability of Okun's Law. During the three most recent US recessions and the Great Recession, the unemployment rate became much more sensitive to output growth and output gap fluctuations than employment (Owyang and Sekhposyan, 2012; Elsby et al., 2010). Different explanations have focused on aggressive job cutting by firms in part because of deunionization and the diminished bargaining power of workers (Berger, 2012; Gordon, 2010), changing industry composition (Basu & Foley, 2013), and labor reallocation (Garin et al., 2013). Yet another view emphasized shifts in productivity growth (Daly & Hobjin, 2010) and the effect of technological change on job polarization (Jaimovich & Siu, 2012; Siu and Jaimovich, 2015).

Although not inconsistent with any of these, our paper focuses more narrowly on whether (or to what extent) the changing organization of work has blurred the distinction between fixed and variable costs, lowering the importance of short-run output adjustments based on capacity utilization variations and raising the one based on productivity fluctuations.

The following discussion is organized in three sections. Section 2 gives a conceptual overview of craft and mass production systems and discusses the effect that the rise of mass production had on the traditional conceptualization of output adjustment. Section 3 shows that the empirical evidence supporting the conventional view of output adjustment based on the link between employment, capacity utilization and investment has significantly weakened; while the short-run responsiveness of productivity to investment has increased. The paper ends with a brief conclusion presented in Section 4.

2. Craft and mass production systems

In a craft economy production is to order, and current costs are largely fixed. Work tends to be specialized and requires teamwork. Being indispensable, each crew member needs to be present for production to take place, which makes start-up and shut-down costs significant. The product is customized (and thus non-standard) and few (if any) economies of scale exist. The system is highly versatile in the face of shifts in demand and relative prices, and works well in the production of non-standard, customized goods. However, craftsmen need a long time to acquire the prerequisite level of skills, and thus can be a bottleneck in production. The dependence on teamwork is also a constraint on output, with rising adjustment and coordination costs and diminishing returns that quickly set in when the scale of production is increased (Nell, 1992).

Historically, these drawbacks gave an impetus to the switch to producing standardized goods which were cheaper, although often inferior, substitutes for custom crafted goods. The cost advantage was achieved by scale economies made possible by breaking down each complex task performed by skilled workers to a series of routine tasks that could be performed by low skill workers (Sokoloff, 1984). This also paved the way for the eventual introduction of machinery since a mechanical arm could replace an organic one more easily if it performed a simple, routinized task (Sherwood, 1985; MacKenzie, 1983). The new labor process inflexibly paired low skills with routine tasks, replacing the fluid pairing of complex skills with variable tasks under the craft economy. As a pre-designed sequence of routinized sub-tasks could become the unifying thread of production, skilled craftsmen ceased to be indispensable. The resulting decrease in requisite skill level in production made workers easily replaceable and the transformation of the labor process eventually culminated in the rise of *mass production* and the modern *assembly line.*[2]

Unlike in a craft economy, economies of scale conferred competitive advantage on large firms in mass production. The competitive pressures to better exploit it raised the minimum scale of fixed investment over time, which meant increasingly long gestation periods before new plants and equipment could begin operation. This in turn produced an inflexible structure of production that became the soft belly of the system as the stable economic conditions that defined the "Golden Age" began to unravel. The economic uncertainties of the 1970s –price volatility and increasingly unpredictable fluctuations in consumer demand– raised the risk of large scale fixed investments. As markets became more contingent and consumer demand more uncertain, the premium on flexibility increased, undermining mass production. *Economies scope* became increasingly more

[2]Nevertheless, craft system was never completely superseded since mass production also had the effect of raising the demand for a new breed of craftsmen such as engineers, designers and managers. The standardized goods that were produced by low skill workers required product-specific, specialized machinery, which could not be mass produced themselves.

important as competitive advantage accrued to those who could adjust their product mix swiftly under rapidly changing conditions. Eventually, globalization carried off much of the old mass production industries to developing countries leaving the “rustbelt” in its wake, while the diffusion of information technologies had a radical effect on the labor process throughout the economy. Even though little remains of the old mass production economy today, our idea of how short-run output adjustment works still dates back from the time of its rise.

The importance of scale economies under mass production implied no natural size of operations for firms and gave rise to oligopolistic markets. With firms building plants with reserve capacity to administer prices, output, employment, and capacity utilization tended to vary *pari passu* in response to changes in demand as labor productivity remained constant. Output moved with demand as any change in autonomous spending gave rise to induced spending in the same direction, while long gestation periods meant that the supply effect of fixed investment could safely be ignored in the short run. Arguably, it was these patterns that tightly linked output adjustment to changes in employment that moved with capacity utilization, responding to the demand shifts from fixed investment.

Consider the equation that sets output equal to the product of labor productivity (π) times the quantity of labor employed (N). Since by definition $\pi = Y/N$, then

$$Y = \pi N \quad \ldots \ldots \ldots \quad (1)$$

It follows that the rate of change of output, $\mathrm{d}Y$, is equal to:

$$\mathrm{d}Y = \pi \mathrm{d}N + N \mathrm{d}\pi \quad \ldots \ldots \ldots \quad (2)$$

In the craft economy, output adjustment is based on variations in productivity where employment remains mainly constant, which suggests that $\mathrm{d}N = 0$. Therefore:

$$\mathrm{d}Y = N\mathrm{d}\pi \quad \dots\dots\dots \quad (3)$$

By contrast, in a mass production economy, output adjustment is based on variations in employment where productivity remains fixed. In other words, $\mathrm{d}\pi = 0$, which gives:

$$\mathrm{d}Y = \pi\mathrm{d}N \quad \dots\dots\dots \quad (4)$$

Capacity utilization (v) plays an important role in this alternative specification. Again, by definition, we have:

$$Y = \frac{Y}{Y^*} = vY^* \quad \dots\dots\dots \quad (5)$$

where Y^* is potential output. The change in output is now equal to:

$$\mathrm{d}Y = v\mathrm{d}Y^* + Y^*\mathrm{d}v \quad \dots\dots\dots \quad (6)$$

In mass production economy, the relatively long gestation period of fixed investments conceptually defines the "short period" as the period long enough when the supply effect of investment on capital stock –and thus on potential output– can be ignored, so that $\mathrm{d}Y^* = 0$ and

$$\mathrm{d}Y = Y^*\mathrm{d}v \quad \dots\dots\dots \quad (7)$$

Yet a third relation for changes in output is given by the Keynesian multiplier, tying it to shifts in investment:

$$\mathrm{d}Y = \frac{1}{s}\mathrm{d}I \quad \dots\dots\dots \quad (8)$$

where s is the propensity to save/invest, and $\mathrm{d}I$ is the rate of change of saving/investment.

Putting all three together gives the conventional idea of short-run output adjustment that characterizes the mass production system, where employment moves with changes in capacity utilization that respond to autonomous shifts in aggregate demand. Therefore, combining equations (4), (7) and (8) we have:

$$\pi \mathrm{d}N = Y^{*}\mathrm{d}v = \frac{1}{s}\mathrm{d}I$$

$$\mathrm{d}N = \frac{Y^{*}}{\pi}\mathrm{d}v = \frac{1}{s}\mathrm{d}I \quad \dots\dots\dots \quad (9)$$

The underlying assumption in this conception is that both labor productivity and potential output are invariant in the short run with respect to changes in investment. But, it is plausible that neither assumption is as relevant today as it once was. At least in some sectors such as the manufacturing industry, the prevalence of large fixed investments with long gestations periods might have markedly decreased with the declining importance of economies scale.

If *nimble* firms that flexibly specialize in niche production are nearly as prevalent as commonly argued in the *post-Fordism* literature, one would reasonably expect smaller scale investments with shorter gestation periods on average and thus a shortening of the period long enough when capacity can be safely assumed constant. Moreover, with much of technological change embedded in new investment (as is especially the case with *information technologies*) the effects on labor productivity can be discernible relatively quickly. Thus, the short run demand effect of fixed investment might increasingly blend with its supply effect on capacity output and productivity within the short period.[3] This suggests an alternative form of output adjustment where variable productivity rather than capacity utilization variations become important in a way that

[3]Although this cannot be pursued here, in related work we observe significant divergence across different sectors in terms of their modality of output adjustment since the 1990s.

resembles the characteristic of a craft economy. Using equations (3), (6) and (8), this alternative type of adjustment can be expressed as[4]:

$$\mathrm{d}\pi = \frac{v}{N}\mathrm{d}Y^* = \frac{1}{s}\mathrm{d}I \quad \dots\dots\dots \quad (10)$$

The evidence we present for the aggregate economy in the next section shows that the links between investment and capacity utilization and between capacity utilization and employment appear to have significantly weakened, and that the short run link between investment and productivity has become stronger.

3. Empirical evidence

We estimate linear Structural Vector Autoregressive (SVAR) models and Time-Varying Parameter SVAR (TVP-SVAR) models over different subperiods in order to study the changing effects of investment on capacity utilization; capacity utilization on employment; and investment on productivity. We focus on the interactions between the variables by presenting the Impulse-response Functions (IRFs) derived from the identification strategies described in Section 3.2.

3.1 Data

Our data ranges from 1967Q1 until 2017Q4. The quarterly series were extracted from the National Income and Product Accounts (NIPA) produced by the Bureau of Economic Analysis (BEA); the Federal Reserve Database (Fed); the Federal Reserve Bank of St. Louis Economic Database (FRED); and the Bureau of Labor Statistics (BLS).[5]

[4]Note that equation (10) uses the assumption that $\mathrm{d}v = 0$ from equation (6) to represent the characteristics of a craft economy.

[5]We also estimated the models without considering the end of sample instability generated by the Great Recession and subsequent recovery. The results for the period 1967Q1-2007Q3 show even stronger responses of the relevant

The investment rate (i_t) corresponds to the ratio of Private Fixed Investment to GDP (both extracted from Table 1.1.5. Gross Domestic Product, NIPA). The capacity utilization rate (v_t) corresponds to the Fed's total industry capacity utilization rate (extracted from Table G.17. Industrial Production and Capacity Utilization).[6] The employment rate corresponds to the civilian employment rate (n_t), defined as defined as $100 - u_t$, where u_t corresponds to the percent civilian unemployment rate (extracted from the FRED database, UNRATE series).[7] Finally, productivity (π_t) refers to the natural log of output per worker employed of the US business sector (extracted from the BLS database).[8]

Figure 1 below plots the v_t and i_t series; and Figure 2 shows the n_t and v_t series. With respect to the former, it is possible to observe that before the recessions of the early 1980s both the v_t and i_t series tended to move together, but the relationship seems to have weakened since then. The same holds true for the relationship between n_t and v_t: before the crisis of the early 1990s, the n_t and v_t series tended to drop simultaneously during recessions and to increase during expansions and were almost perfectly synchronized; however, the correlation between these variables has become less pronounced since then.

relationships studied. Thus, although the Great Recession seems to have slightly modified the relevant correlations, the overall patterns do not revert to early sample estimates. These results are available on request.

[6]We deem that the measure of v_t published by the Fed captures more adequately the concept of capacity utilization that we are interested in since it refers to the percentage of resources used by corporations and factories to produce goods in manufacturing, mining, and electric and gas utilities for all facilities located in the USA (excluding those in U.S. territories). As a robustness check, however, we also report the results obtained using a measure of v_t constructed using the Hamilton (2018) filter. These results are presented in Section 3.4.

[7]We also used the n_t for prime-age workers (ages 25-54, extracted from the FRED database, LREM25TTUSM156S series). The results obtained corroborate the main findings and are available on request.

[8]Strictly speaking, the constructed indicator of productivity corresponds to a measure of output per job since we divided the business sector's output indicator (PRS84006043 series) by the business sector's employment indicator (PRS84006013 series) provided by the BLS. We tried to measure productivity as output per worker (instead of output per hour) to avoid the possible effects on hours worked. Nevertheless, the results obtained using the business sector's output per hour as a measure of productivity also corroborate the main findings (once again, these results are available on request).

[INSERT FIGURE 1 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

3.2 SVAR models

The short-run output adjustment associated with the mass production system (MPS) can be studied by presenting the dynamic interactions between i_t, v_t, and n_t. On the other hand, the short-run output adjustment that depicts the craft production system (CPS) can be studied by presenting the interactions between i_t, v_t, and π_t. We compare the IRFs obtained from both models over different subperiods.

First, we carried out different unit root tests to study the order of integration of the series, finding that the i_t, v_t, and n_t are stationary processes, that is, $I(0)$; and that π_t is a non-stationary series integrated of order 1, that is, $I(1)$.[9] Hence, in order to estimate Vector Autoregressive (VAR) models in which the variables have the same order of integration we included i_t, v_t, and n_t for the MPS; and i_t, v_t, and $\Delta\pi_t$ for the CPS (where Δ denotes the first differences).[10]

The estimated VAR models adopted the following general form:

$$\mathrm{y}_t = \mathrm{C}_0 + \sum_{i-1}^{p} \mathrm{C}_i \mathrm{y}_{t-i} + u_t \quad \dots\dots\dots \quad (11)$$

$$\mathrm{Ay}_t = \mathrm{A}_0 + \sum_{i-1}^{p} \mathrm{A}_i \mathrm{y}_{t-i} + \mathrm{B}\varepsilon_t \quad \dots\dots\dots \quad (12)$$

where equation (11) represents the reduced-form VAR and equation (12) shows the SVAR model; and u_t and ε_t are white-noise vector processes with $u_t{\sim}N(0,I)$ and $\varepsilon_t{\sim}N(0,\Sigma)$, respectively. The vector y_t contains either i_t, v_t and n_t to characterize the short-run output adjustment associated

[9]A full description of the results obtained from the different unit root tests is available on request.
[10]Specifically, we considered $\Delta\pi_t = 100 * (\pi_t - \pi_{t-1})$.

with the MPS or i_t, v_t and $\Delta\pi_t$ to characterize the short-run output adjustment of the CPS. This leads to the well-known identification problem for both cases: recovering the SVAR models in equation (12) from the estimated reduced-form models shown in equation (11).

For simplicity, let us consider only the variables included in the MPS model. From (11) and (12) it is possible to observe that $u_t = \mathrm{A}^{-1}\mathrm{B}\varepsilon_t$, or $\mathrm{A}u_t = \mathrm{B}\varepsilon_t$. Expanding, we have:

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} u_{i_t} \\ u_{v_t} \\ u_{n_t} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_{i_t} \\ \varepsilon_{v_t} \\ \varepsilon_{n_t} \end{pmatrix} \quad \dots\dots\dots \quad (13)$$

We used a simple Cholesky decomposition to solve the identification problem. Specifically, we assume that $a_{12} = a_{13} = a_{23} = 0$; $b_{11} = b_{22} = b_{33} = 1$; and $b_{12} = b_{13} = b_{21} = b_{23} = b_{31} = b_{32} = 0$. Therefore, equation (13) becomes:

$$\begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} u_{i_t} \\ u_{v_t} \\ u_{n_t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{i_t} \\ \varepsilon_{v_t} \\ \varepsilon_{n_t} \end{pmatrix} \quad \dots\dots\dots \quad (14)$$

These restrictions imply that the investment rate does not react to capacity utilization or the employment rate within the period; capacity utilization reacts to investment but not to employment within the period; and the employment rate reacts to both investment and capacity utilization contemporaneously. In other words, we assume that the investment rate is, relatively, the "most exogenous" variable in the system.[11]

[11]We believe that this identification strategy is the best way to capture the causal dynamics of the variables. However, as a robustness check, we also used an alternative ordering of the variables to identify the system (specifically, we assumed the following ordering: $v_t \to n_t \to i_t$, which assumes that v_t is the most exogenous variable in the system) and the Generalized IRFs developed by Pesaran and Shin (1992), which do not require the orthogonalization of shocks and are invariant to the ordering of the variables in the VAR. The results obtained remained qualitatively the same and are available on request.

Likewise, we also employed a similar identification strategy for the variables included in the CPS model:

$$\begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} u_{i_t} \\ u_{v_t} \\ u_{\Delta\pi_t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{i_t} \\ \varepsilon_{v_t} \\ \varepsilon_{\Delta\pi_t} \end{pmatrix} \quad \dots\dots\dots \quad (15)$$

The restrictions imposed in (15) imply that the investment rate does not react to capacity utilization or productivity contemporaneously; capacity utilization reacts to investment but not to productivity within the period; and that productivity reacts to both investment and capacity utilization within the period.

To summarize, the key difference between equations (14) and (15) is the inclusion of $\Delta\pi_t$ instead of n_t, which allows us to distinguish between the short-run adjustment characteristic of the CPS and MPS, respectively. With respect to the MPS, our main interest consists in evaluating if the responses of v_t to i_t shocks and of n_t to v_t shocks have decreased over time. Regarding the CPS, we are interested in testing if the response of v_t to i_t shocks has decreased over time and if the response of $\Delta\pi_t$ to i_t shocks has increased over time.

3.3 Results

The SVAR models that depict the MPS and the CPS were estimated over two different subsamples, 1967Q1-1992Q3 and 1992Q4-2017Q4. We selected these two periods because each one of them contains approximately 50% of the observations of the whole sample. More importantly, we corroborated the appropriateness of this sample splitting approach using a Likelihood Ratio test, thus testing for the presence of a structural break in the VAR models.

Following Lütkepohl (2006), the Likelihood Ratio statistic (λ_{LR}) can be constructed as follows: $\lambda_{\mathrm{LR}} = 2 * (\lambda_{\mathrm{U}} - \lambda_{\mathrm{R}})$, where λ_{U} is the log-likelihood obtained from the unrestricted VAR (sum of the log-likelihoods estimated from the VAR models considering two different periods, 1967Q1-1992Q3 and 1992Q4-2014Q4) and λ_{R} is the log-likelihood obtained from the restricted VAR (obtained from the VAR model considering only one period, 1967Q1-2014Q4). Under the null hypothesis that the dataset can be represented by a single VAR (that is, there is no structural change)[12], the λ_{LR} has an asymptotic χ^2-distribution with degrees of freedom (m) equal to the number of linearly independent restrictions.[13] If $\lambda_{\mathrm{LR}} > \chi^2(m)$ then the null hypothesis is rejected.

Table 1 below summarizes the results. It is possible to observe that the null hypothesis of no structural change is rejected at the 5% level for the VAR models that depict both the MPS and the CPS. Hence, there is evidence of a structural break in the VAR models, and it is appropriate to divide the sample into two subperiods.

[INSERT TABLE 1 ABOUT HERE]

Figures 3 and 4 below present the most relevant IRFs for both periods. The former presents the results for the MPS, and the latter presents the ones obtained from the CPS.[14]

[INSERT FIGURE 3 ABOUT HERE]

[INSERT FIGURE 4 ABOUT HERE]

With respect to short-run output adjustment characteristic of the MPS, it is possible to observe that the response of v_t to i_t shocks is considerable lower in the second period. In the same vein, the response of n_t to v_t shocks is also lower during the period 1992Q4-2017Q4 than during the period 1967Q1-1992Q3.

[12]In brief, this approach tests the null hypothesis that all coefficients are time-invariant against the alternative that the white-noise covariance matrix is time invariant while the rest of the coefficients vary across subsamples (see Lütkepohl, 2006).
[13]Therefore, $m = (s-1)k(kp+1)$, where s is the number of subperiods considered, and k and p are the number of variables and the number of lags included in the restricted VAR, respectively.
[14]A complete report showing the different responses of all variables to all shocks in the respective systems is available on request.

On the other hand, from the short-run output adjustment associated with the CPS it is possible to observe that the response of v_t to i_t shocks is also lower in the second period and the response of π_t to i_t shocks is both statistically significant and larger during the period 1992Q4-2017Q4 compared to the period 1967Q1-1992Q3.

In order to summarize the main findings, Figure 5 compares only the mean responses (without confidence intervals) of the variables for both periods.

[INSERT FIGURE 5 ABOUT HERE]

The main results can be summarized as follows. From the MPS we can conclude that: 1) a 1 percentage point shock to i_t increased v_t by approximately 0.49 percentage points during the period 1967Q1-1992Q3 and by approximately 0.25 percentage points during the period 1992Q4-2017Q4; and 2) a 1 percentage point shock to v_t increased n_t by approximately 0.18 percentage points during the period 1967Q1-1992Q3 and by approximately 0.09 percentage points during the period 1992Q4-2017Q4.

On the other hand, the results for the CPS show that a 1 percentage point shock to i_t increased v_t by approximately 0.55 percentage points during the period 1967Q1-1992Q3 and by approximately 0.21 percentage points during the period 1992Q4-2017Q4. More importantly, the contemporaneous response of $\Delta\pi_t$ to a 1 percentage point shock to i_t is statistically non-significant in the first period; however, during the period 1992Q4-2017Q4 the response of $\Delta\pi_t$ to i_t becomes statistically significant: a 1 percentage point shock to i_t increased productivity growth by approximately 0.15 percentage points.

As an alternative to estimating linear VAR models over two different subsamples, we also performed the estimation of TVP-SVAR models developed by Primiceri (2005) and Del Negro and Primiceri (2015). One of the main advantages of this methodology is that it represents a multivariate time series technique with both time-varying parameters and time-varying covariance matrix of the additive innovations. This is done by allowing the model parameters and the entire variance covariance matrix of the shocks to evolve smoothly over time. The drifting coefficients allows us to capture possible non-linearities or time-variation in the lag structure of the model; whereas the multivariate stochastic volatility is meant to capture possible heteroskedasticity of the shocks and non-linearities in the simultaneous relations among the variables of the model.[15]

Figure 6 summarizes the most important IRFs for both the MPS and CPS models.[16] The TVP-SVAR models generate IRFs at every single data point, so reporting the full set becomes a challenge. The dates chosen for the comparison were 1977Q3 (1978Q3) for the MPS (for the CPS) and 2004Q4, which approximately correspond to middle dates between the first and last NBER trough and peak dates included: 1975Q1-1980Q1 and 2001Q4-2007Q4.[17]

[INSERT FIGURE 6 ABOUT HERE]

It is possible to observe that the results obtained from the TVP-SVARs corroborate the ones obtained from the linear SVARs. With respect to the MPS, the response of v_t to a 1 percentage point increase in i_t was 0.31 percentage points in 1977Q3 and 0.25 percentage points in 2004Q4; and the response of n_t to a 1 percentage point increase in v_t was 0.11 in 1977Q3 and 0.10 in 2004Q4. Regarding the CPS, a 1 percentage point increase in i_t increased v_t by around 0.30

[15]Appendix A contains a description of the most important technical aspects of TVP-SVAR models.

[16]For simplicity, Figure 5 only reports a summary of the IRFs. A more complete set of results is presented in Appendix B. Figures B.1 and B.2 report the stochastic volatility parameters and the IRFs together with their respective confidence intervals for the MPS; and Figures B.3 and B.4 show the results for the CPS. It is worth noting that the stochastic volatility coefficients estimated for both models show a clear downward trend, which corroborates one of the findings of the literature on the Great Moderation (that is, a reduction in the volatility of business cycle fluctuations).

[17]Note that the first 10 years of observations are "not available" because these are used for the initialization of the prior (see Appendix A). Note also that, with respect to the CPS, less observations are available because of the use of the first-differences of the log of productivity. Therefore, we selected the one-year later date, 1978Q3, instead of 1977Q3. It is also worth mentioning that experiments with different dates for the MPS and CPS over the periods 1975Q1-1980Q1 and 2001Q4-2007Q4 give very similar conclusions.

percentage points and had no significant effect on $\Delta\pi_t$ in 1978Q3; whereas it increased v_t by around 0.19 percentage points and had a statistically significant effect on $\Delta\pi_t$ of approximately 0.06 percentage points in 2004Q4 (after one quarter).

Hence, it is possible to say that the responses of v_t to i_t and of n_t to v_t have decreased since the early 1990s and that the response of $\Delta\pi_t$ to i_t has increased since then. In other words, the short-run output adjustment characteristic of the MPS has become less important and the one characteristic of the CPS has become more relevant.

3.4 Robustness of results

As an alternative to the Fed's v_t, we also used a measure of v_t constructed as $100 * (y_t - y_t^*)$, where y_t corresponds to the natural log of Real GDP (extracted from the FRED database, GDPC1 series) and y_t^* corresponds to the natural log of the trend component of y_t obtained using the method proposed by Hamilton (2018). Hamilton (2018) has recently criticized the use of the Hodrick and Prescott (1997) and has developed an alternative methodology that consists in using simple forecasts of the series to remove the cyclical component.[18] Therefore, the y_t^* series corresponds to a smoothed estimate of y_t generated using the fitted values from a regression of the latter on 4 lagged values of y_t back-shifted by two years (that is, 8 observations in quarterly data) and a constant: $y_t = \beta_0 + \beta_1 y_{t-8} + \beta_2 y_{t-9} + \beta_3 y_{t-10} + \beta_3 y_{t-11} + e_t$, where e_t denotes the residuals of this regression.

[18]The use of the Hodrick-Prescott filter has been criticized by Hamilton (2018) because: 1) it produces series with spurious dynamic relations that have no basis in the underlying data-generating process; 2) filtered values at the end of the sample are very different from those in the middle and are also characterized by spurious dynamics; and 3) a statistical formalization of the problem typically produces values for the smoothing parameter vastly at odds with common practice.

Figure 7 below plots the two different measures of v_t, and we also compare them with a measure of utilization generated considering y_t^* as the trend component obtained from the Hodrick and Prescott filter (1997).[19] Although the three measures of v_t present similar movements over the business cycle, only the Fed's measure of v_t and the one generated using Hamilton's method present a statistically significant downward trend.[20] Given the drawbacks associated with the Hodrick-Prescott filter, we only report the results obtained using Hamilton's method.[21]

[INSERT FIGURE 7 ABOUT HERE]

Figure 8 summarizes the most important results obtained from the linear SVAR models for the periods 1967Q1-1992Q3 and 1992Q4-2017Q4; and Figure 9 presents the IRFs obtained from the TVP-SVARs.[22] It is possible to observe that both the SVAR and TVP-SVAR models show that the response of v_t to i_t is lower in the second period compared to the first period. This result takes place both in the MPS and CPS models. The contemporaneous response of n_t to v_t is lower in the second period when the MPS is considered, although its response is statistically significantly higher during two more quarters according to the linear SVAR models. Finally, with respect to the CPS model, the response of $\Delta\pi_t$ to a 1 percentage point increase in i_t is statistically significant in the second period during approximately two quarters (one quarter) when the SVAR (when the

---

[19]The y_t^* series obtained using Hamilton's method and the Hodrick-Prescott filter (in which the smoothing parameter was selected to be 1600 since we have quarterly data) were generated for the period 1948Q1-2017Q4, but we only considered the period 1967Q1-2017Q4 to compare them with the Fed's measure of v_t.

[20]This is corroborated by different unit root tests, which show that the Fed's v_t and the one constructed using Hamilton's method are trend stationary series, and the v_t derived from the use of the Hodrick-Prescott filter is simply a stationary series. (Results are available on request).

[21]The results obtained using the Hodrick-Prescott filter are also available on request. In brief, the main results are also corroborated when we used this filtering technique, the only exception being the response of productivity to investment shocks.

[22]We only present the mean responses of the relevant variables and refer to the significance of the estimates without presenting the respective confidence intervals. A full report that also includes the latter is available on request.

TVP-SVAR) model was used; and it was found to be statistically non-significant during the first period.

[INSERT FIGURE 8 ABOUT HERE]

[INSERT FIGURE 9 ABOUT HERE]

Hence, although less drastic, the results obtained using this alternative measure of v_t corroborate the ones derived from the use of the Fed's measure of v_t. The short-run adjustment characteristic of the MPS has lost some of its importance since the early 1990s, and the output adjustment characteristic of the CPS has gained importance since then.

4 Conclusions

The traditional idea of short period output adjustment rests on the assumption that the demand effect of investment is almost immediate while its supply effect comes much later. In an economy not constrained by full employment or capacity, output response to demand stimuli during this short period is thought to derive from employment that expands *pari passu* with changes in capacity utilization while productivity remains constant. These ideas, which remain foundational for much contemporary macroeconomic theorizing, characteristically define a mass production economy.

In this paper, we hypothesized that the eclipse of mass production in advanced economies such as the USA is what lies at the bottom of the widely observed weakened link between employment and output since the early 1990s. Asking whether the link between changes in employment, capacity utilization and investment has changed over time, we empirically investigated the effect of mass production system's decline on short run output adjustment. Using linear Structural Vector Autoregressive models and Time-Varying Parameter Structural Vector

Autoregressive models, we found that capacity utilization variations have become progressively less sensitive while productivity became more responsive to demand shifts caused by investment since the early 1990s. These results point out an important change in the short-run output adjustment for the US economy, thus suggesting that the one associated with a mass production economy has weakened and the one characteristic of a craft production system has become more relevant.

Our findings might be capturing not only economy wide behavioural changes, but also compositional effects caused by increased sectoral differences, which we have not examined in this paper. We hope that our paper will inspire other researchers to study if and how short-run output adjustment might have diverged across different sectors of the economy.

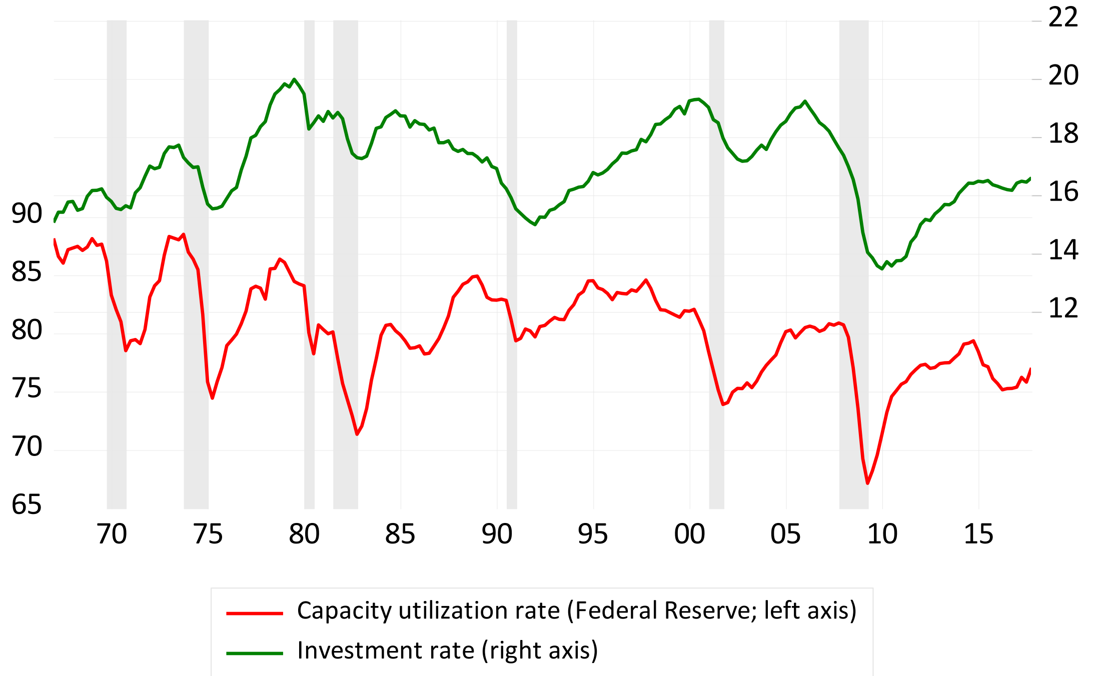


Figure 1. USA, 1967Q1-2017Q4. Capacity utilization and investment rates. (Shaded areas indicate NBER recession dates.)

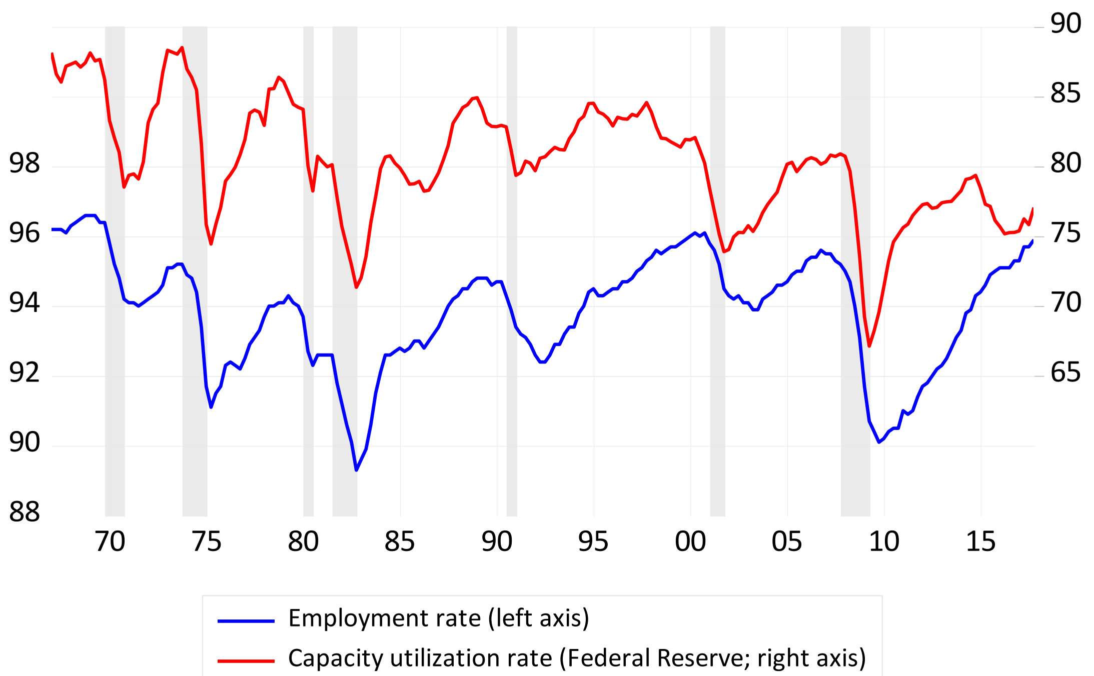
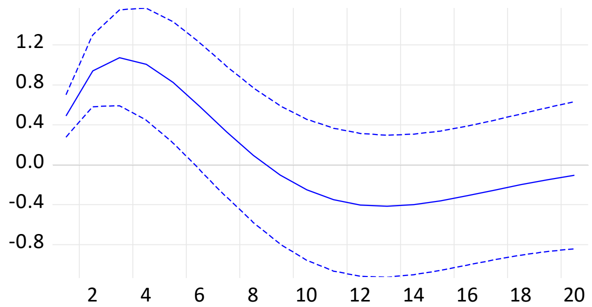


Figure 2. USA, 1967Q1-2017Q4. Employment and capacity utilization rates. (Shaded areas indicate NBER recession dates.)

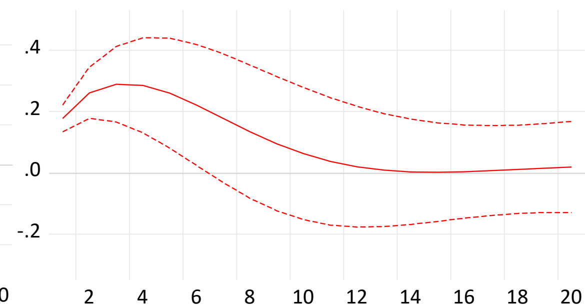
Table 1. Likelihood ratio tests for structural breaks in the VAR models[a]						
	λ_{s_1}[b]	λ_{s_2}[b]	λ_{U}[b]	λ_{R}[b]	λ_{LR}[b]	$\chi^2(m)$[b]
VAR models for the mass production system (including i_t, n_t and v_t)	-109.83	23.58	-86.25	-131.43	90.36	54.57
VAR models for the craft production system (including i_t, n_t and $\Delta\pi_t$)	-239.41	-102.75	-342.16	-405.24	126.15	54.57

Notes: [a]The optimal lag length for the VAR models was selected according to the Schwarz information criterion. However, most of these models presented serial correlation problems at the 5% level, so it was necessary to increase the number of lags. The restricted VARs both for the mass and craft production systems included 4 lags. The unrestricted VAR for the mass production system included 2 and 4 lags in the first and second periods, respectively. The unrestricted VAR for the craft production system included 3 and 6 lags in the first and second periods, respectively. [b]λ_{s_1}: Log-likelihood for the first period, 1967Q1-1992Q3; λ_{s_2}: Log-likelihood for the second period, 1992Q4-2017Q4; $\lambda_{\mathrm{U}} = \lambda_{s_1} + \lambda_{s_2}$: Log-likelihood for the unrestricted VAR; λ_{R}: Log-likelihood of the restricted VAR; $\lambda_{\mathrm{LR}} = 2 * (\lambda_{\mathrm{U}} - \lambda_{\mathrm{R}})$: Likelihood ratio statistic; $\chi^2(m)$: Critical value of the χ^2 distribution at the 5% level with $m = (s-1)k(kp+1) = 39$ degrees of freedom, where $s = 2$, $k = 3$ and $p = 4$ denote the number of subperiods considered, and the number of variables and lags in the restricted VAR, respectively.



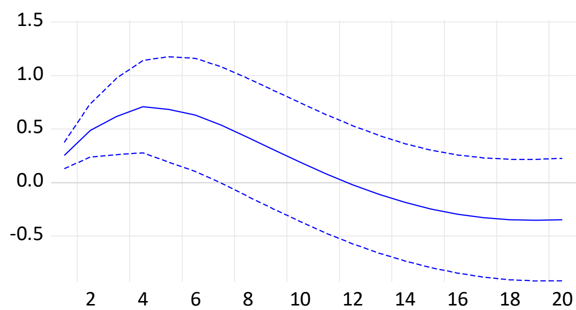
(a) Response of v_t to an i_t shock,

period 1967Q1-1992Q3



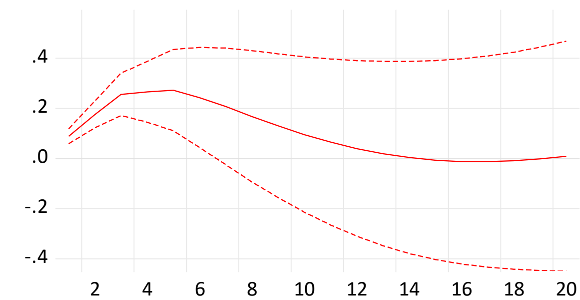
(b) Response of n_t to a v_t shock,

period 1967Q1-1992Q3



(c) Response of v_t to an i_t shock,

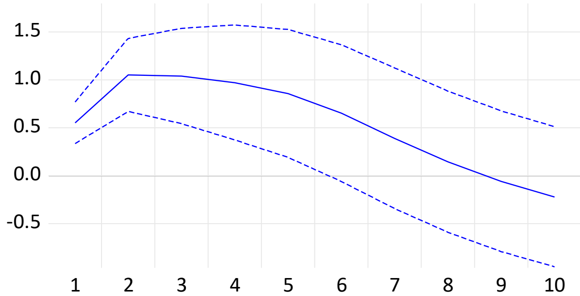
period 1992Q4-2017Q4



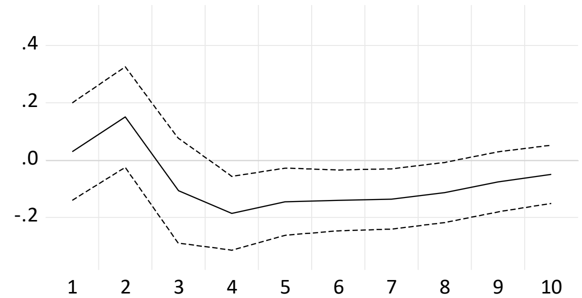
(d) Response of n_t to a v_t shock,

period 1992Q4-2017Q4

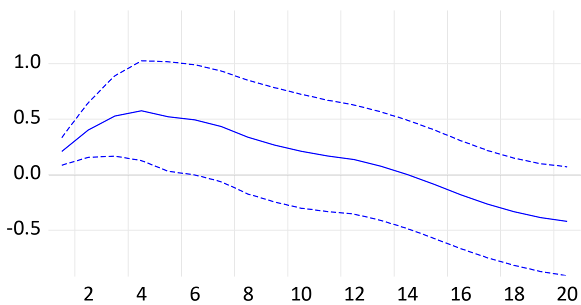
Figure 3. Impulse-response functions obtained from the SVAR models that represent the mass production system's short-run output adjustment. The VARs for the periods 1967Q1-1992Q3 and 1992Q4-2017Q4 included 2 and 4 lags, respectively. These VAR models did not present problems of serial correlation at the 5% level. The estimated VAR for the period 1992Q4-2017Q4 included an exogenous trend since it was found to be jointly significant according to a Wald coefficient test. Notation: v_t = capacity utilization rate; i_t = investment rate; and n_t = employment rate. Dotted lines are the 95% confidence intervals generated via 2,000 Monte Carlo simulations



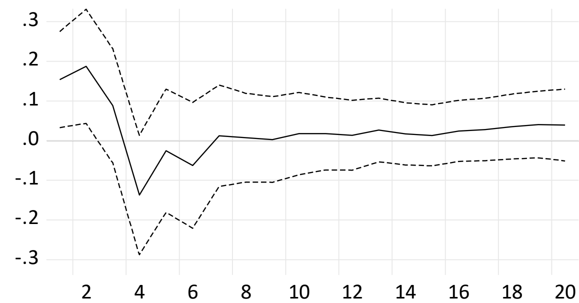
(a) Response of v_t to an i_t shock,
period 1967Q1-1992Q3



(b) Response of $\Delta\pi_t$ to an i_t shock,
period 1967Q1-1992Q3

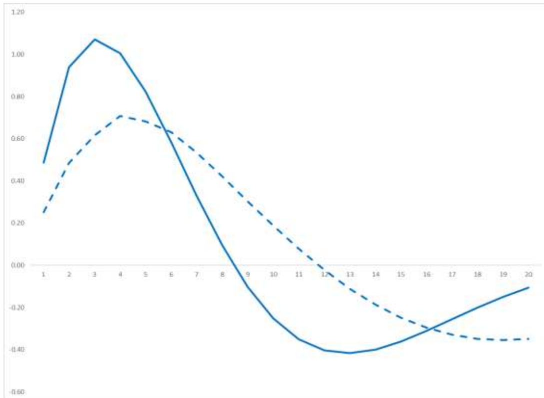


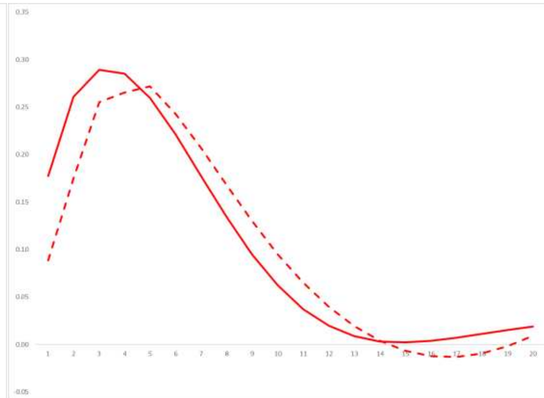
(c) Response of v_t to an i_t shock,
period 1992Q4-2017Q4



(d) Response of $\Delta\pi_t$ to an i_t shock,
period 1992Q4-2017Q4

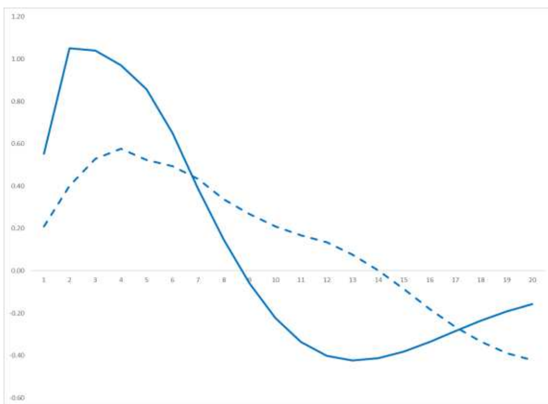
Figure 4. Impulse-response functions obtained from the SVAR models that represent the craft production system's short-run output adjustment. The VARs for the periods 1967Q1-1992Q3 and 1992Q4-2017Q4 included 3 and 6 lags, respectively. These VAR models did not present problems of serial correlation at the 5% level. The estimated VAR for the period 1992Q4-2017Q4 included an exogenous trend since it was found to be jointly significant according to a Wald coefficient test. Notation: v_t = capacity utilization rate; i_t = investment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity. Dotted lines are the 95% confidence intervals generated via 2,000 Monte Carlo simulations

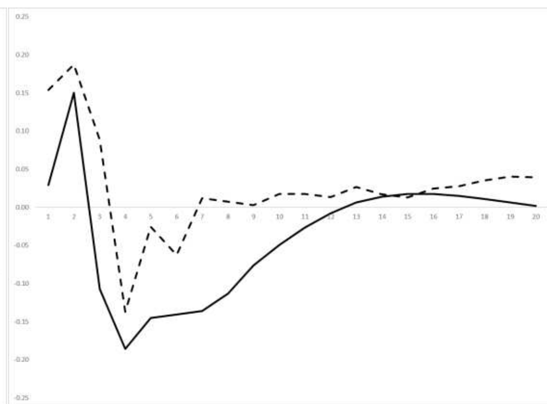




(a) Responses of v_t to an i_t shock, mass production system (Figure 3)

(b) Responses of n_t to a v_t shock, mass production system (Figure 3)

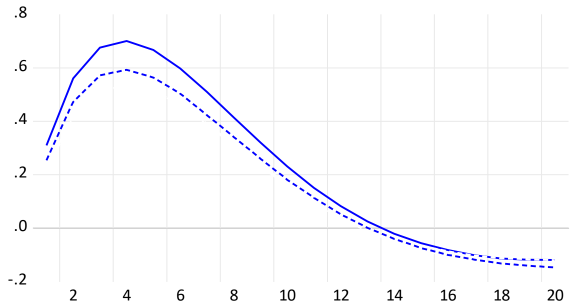




(c) Responses of v_t to an i_t shock, craft production system (Figure 4)

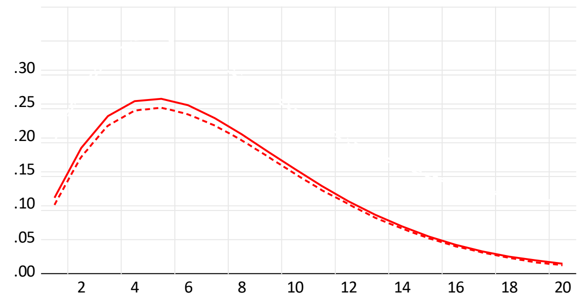
(d) Responses of $\Delta\pi_t$ to an i_t shock, craft production system (Figure 4)

Figure 5. Summary of the impulse-response functions presented in Figures 3 and 4. Straight lines are the mean responses for the period 1967Q1-1992Q3. Dotted lines are the mean responses for the period 1992Q4-2017Q4. Notation: v_t = capacity utilization rate; i_t = investment rate; n_t = employment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity.



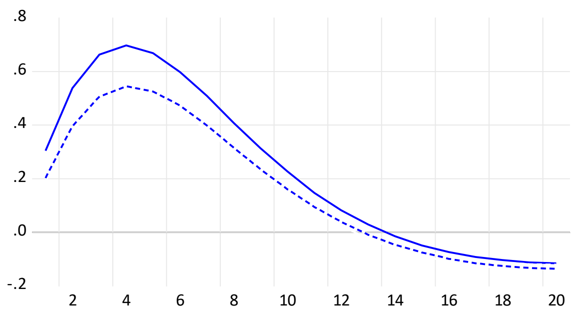
(a) Responses of v_t to an i_t shock,

mass production system



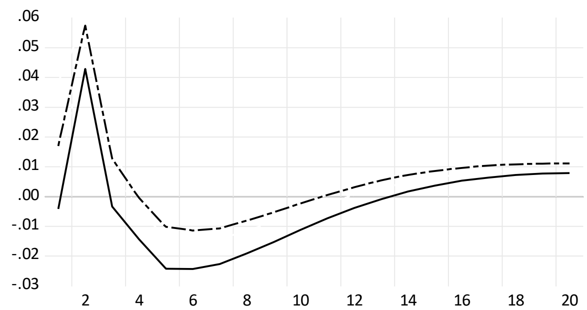
(b) Responses of n_t to a v_t shock,

mass production system



(c) Response of v_t to an i_t shock,

craft production system



(d) Response of $\Delta\pi_t$ to an i_t shock,

craft production system

Figure 6. Summary of the impulse-response functions for the TVP-SVAR models. Straight lines are the mean responses in 1977Q3 (mass production system) or 1978Q3 (craft production system). Dotted lines are the mean responses in 2004Q4. Notation: v_t = capacity utilization rate; i_t = investment rate; n_t = employment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity.

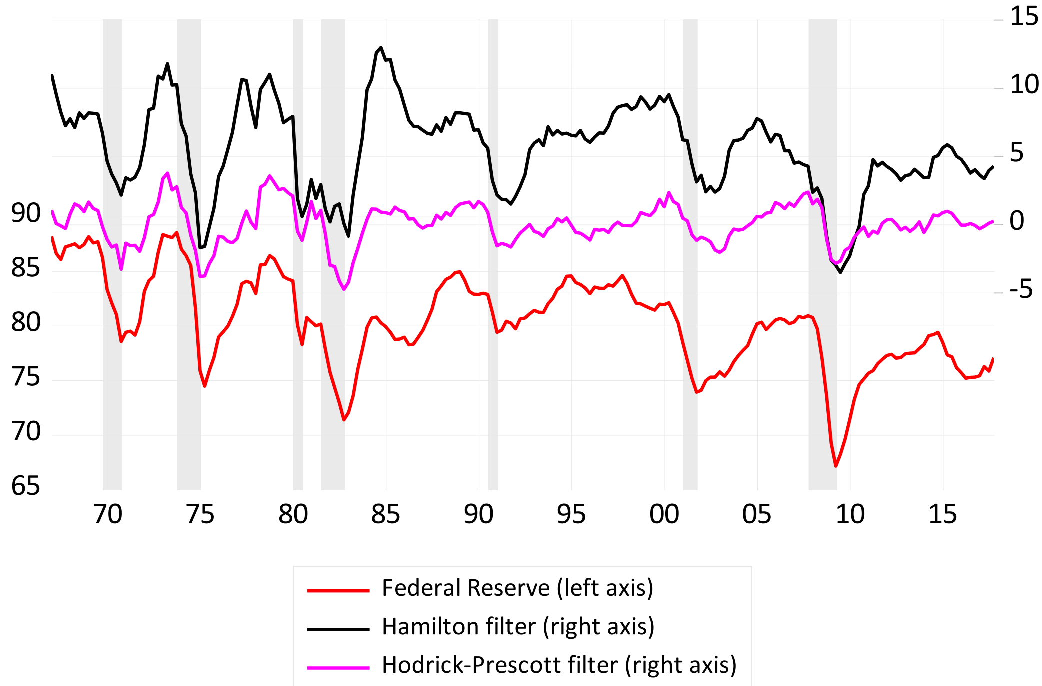
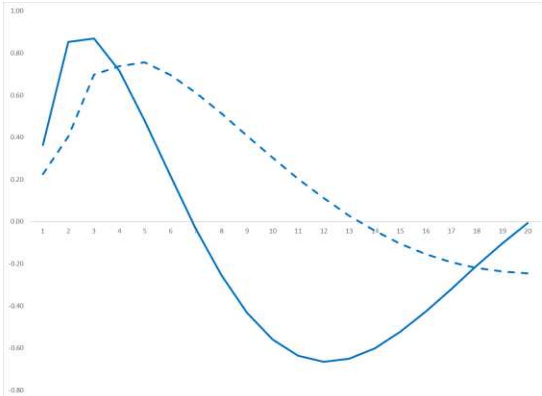
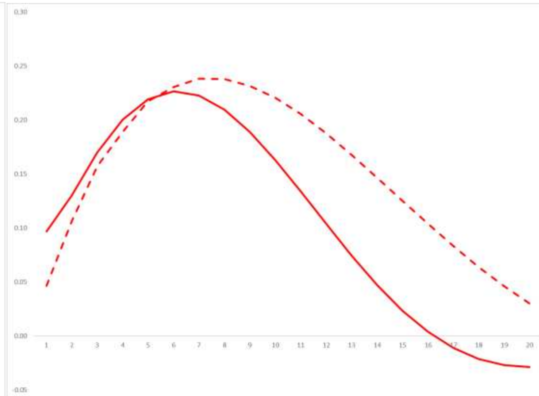


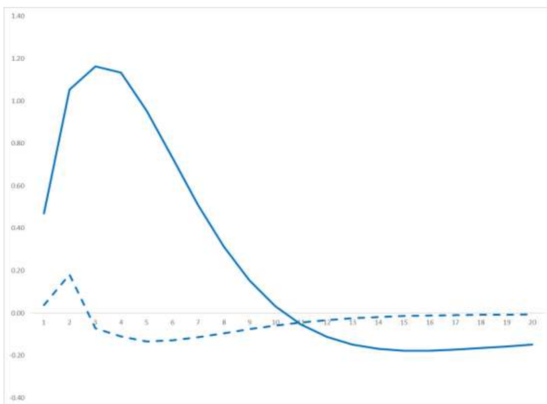
Figure 7. USA, 1967Q1-2017Q4. Capacity utilization rates. (Shaded areas indicate NBER recession dates.)



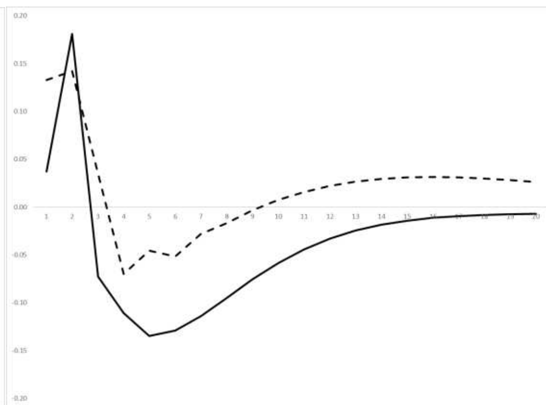
(a) Responses of v_t to an i_t shock, mass production system



(b) Responses of n_t to a v_t shock, mass production system

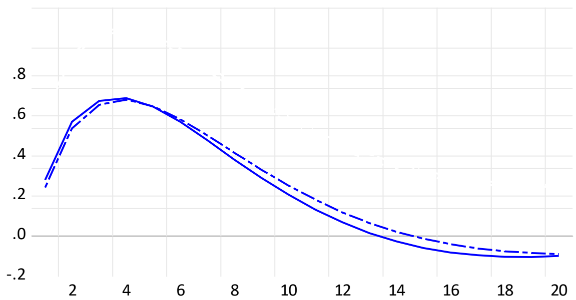


(c) Responses of v_t to an i_t shock, craft production system

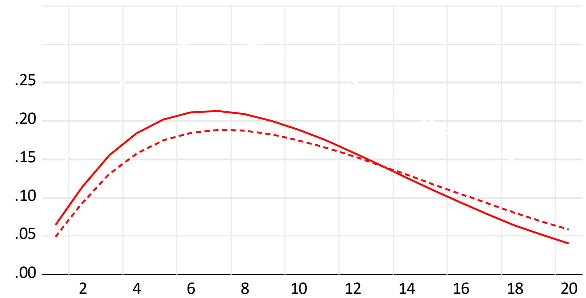


(d) Response of $\Delta\pi_t$ to an i_t shock, craft production system

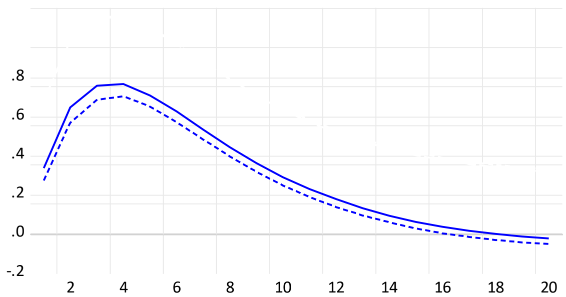
Figure 8. Summary of the impulse-response functions for the SVAR models using the measure of v_t derived from Hamilton's filter. Straight lines are the mean responses for the period 1967Q1-1992Q3. Dotted lines are the mean responses for the period 1992Q4-2017Q4. The estimated VARs for the period 1992Q4-2017Q4 included an exogenous trend since it was found to be jointly significant according to a Wald coefficient test. Notation: v_t = capacity utilization rate; i_t = investment rate; n_t = employment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity.



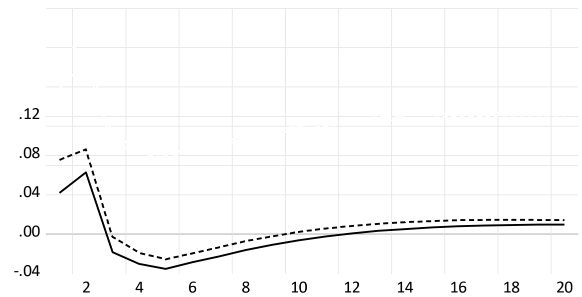
(a) Responses of v_t to an i_t shock, mass production system



(b) Responses of n_t to a v_t shock, mass production system



(c) Response of v_t to an i_t shock, craft production system



(d) Response of $\Delta\pi_t$ to an i_t shock, craft production system

Figure 9. Summary of the impulse-response functions for the TVP-SVAR models using the measure of v_t derived from Hamilton's filter. Straight lines are the mean responses in 1977Q3 (mass production system) or 1978Q3 (craft production system). Dotted lines are the mean responses for 2004Q4. Notation: v_t = capacity utilization rate; i_t = investment rate; n_t = employment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity.

Acknowledgements

We are grateful to Minqui Li, Codrina Rada, Rudiger von Arnim, and seminar participants at the University of Utah for helpful comments on a previous version of this paper. All errors are the authors' responsibility.

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Appendix A. Econometric details: Time-varying parameter structural vector autoregressive (TVP-SVAR) models

Consider the following VAR model:

$$y_t = C_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + u_t, \qquad t = 1, \dots, T \qquad \dots\dots\dots \qquad (\mathrm{A}.1)$$

where y_t is a $kX1$ vector of observed endogenous variables; C_t is a $kX1$ vector of time-varying parameters that multiply constant terms; $B_{i,t}, i = 1, \dots, p$ are kXk matrices of time-varying parameters; and u_t are heteroskedastic unobservable shocks with variance-covariance matrix Ω_t. The latter is defined by:

$$A_t\Omega_\mathrm{t}A_t' = \Sigma_\mathrm{t}\Sigma_\mathrm{t}' \qquad \dots\dots\dots \qquad (\mathrm{A}.2)$$

where A_t is the following lower triangular matrix

$$A_t = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1,t} & \cdots & a_{kk-1,t} & 1 \end{bmatrix} \qquad \dots\dots\dots \qquad (\mathrm{A}.3)$$

and Σ_t is the diagonal matrix

$$\Sigma_\mathrm{t} = \begin{bmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{k,t} \end{bmatrix} \qquad \dots\dots\dots \qquad (\mathrm{A}.4)$$

Therefore:

$$y_t = C_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + A_t^{-1}\Sigma_\mathrm{t}\varepsilon_t \qquad \dots\dots\dots \qquad (\mathrm{A}.5)$$

$$V(\varepsilon_t) = I_k$$

Stacking in a vector B_t all the right-hand side coefficients $B_{i,t}, i = 1, \dots, p$, equation (A.5) can be written as

$$y_t = X_t' B_t + A_t^{-1} \Sigma_t \varepsilon_t \quad \dots\dots\dots \quad (A.6)$$

$$X_t' = I_k \otimes [1, y_{t-1}', \dots, y_{t-p}']$$

where the symbol $\otimes$ denotes the Kronecker product.

The modelling strategy consists of modelling the coefficient processes in (A.6) instead of (A.1). There is a one to one mapping between (A.6) and (A.1) that justifies this approach. Let α_t be the vector of non-zero and non-one elements of the matrix A_t (stacked by rows) and σ_t be the vector of the diagonal elements of the matrix Σ_t. The dynamics of the model's time-varying parameters can be specified as follows:

$$B_t = B_{t-1} + v_t \quad \dots\dots\dots \quad (A.7)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \quad \dots\dots\dots \quad (A.8)$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t \quad \dots\dots\dots \quad (A.9)$$

Hence, both the elements of the vector B_t and the free elements of the matrix A_t are modelled as random walks. The standard deviations (σ_t) are assumed to evolve as geometric random walks, belonging to the class of models known as stochastic volatility.[23]

Finally, all innovations in the model are assumed to be jointly normally distributed with the following assumptions on the variance covariance matrix:

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[23]This is an alternative to Autoregressive Conditional Heteroskedasticity (ARCH) models. The crucial difference is that the variances generated by (A.9) are unobservable components.

$$V = \left(\begin{bmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix} \right) = \begin{bmatrix} I_k & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \quad \ldots\ldots\ldots \quad (A.10)$$

where I_k is a k-dimensional identity matrix, and Q, S and W are positive definite matrices.

The models that depict the mass production and craft production systems were estimated following the standard procedures outlined by Del Negro and Primiceri (2015) and Primiceri (2005). First, we used the Gibbs sampling approach for the posterior numerical evaluation of the parameters of interest. Second, we employed two lags for the estimation of all models. Third, the simulations were based on 10,000 iterations of the Gibbs sample, discarding the first 2,000 for convergence. Finally, the first 10 years (40 observations, because we used quarterly data) were used to calibrate the prior distributions.

Appendix B. Complete set of results obtained from the TVP-SVAR models

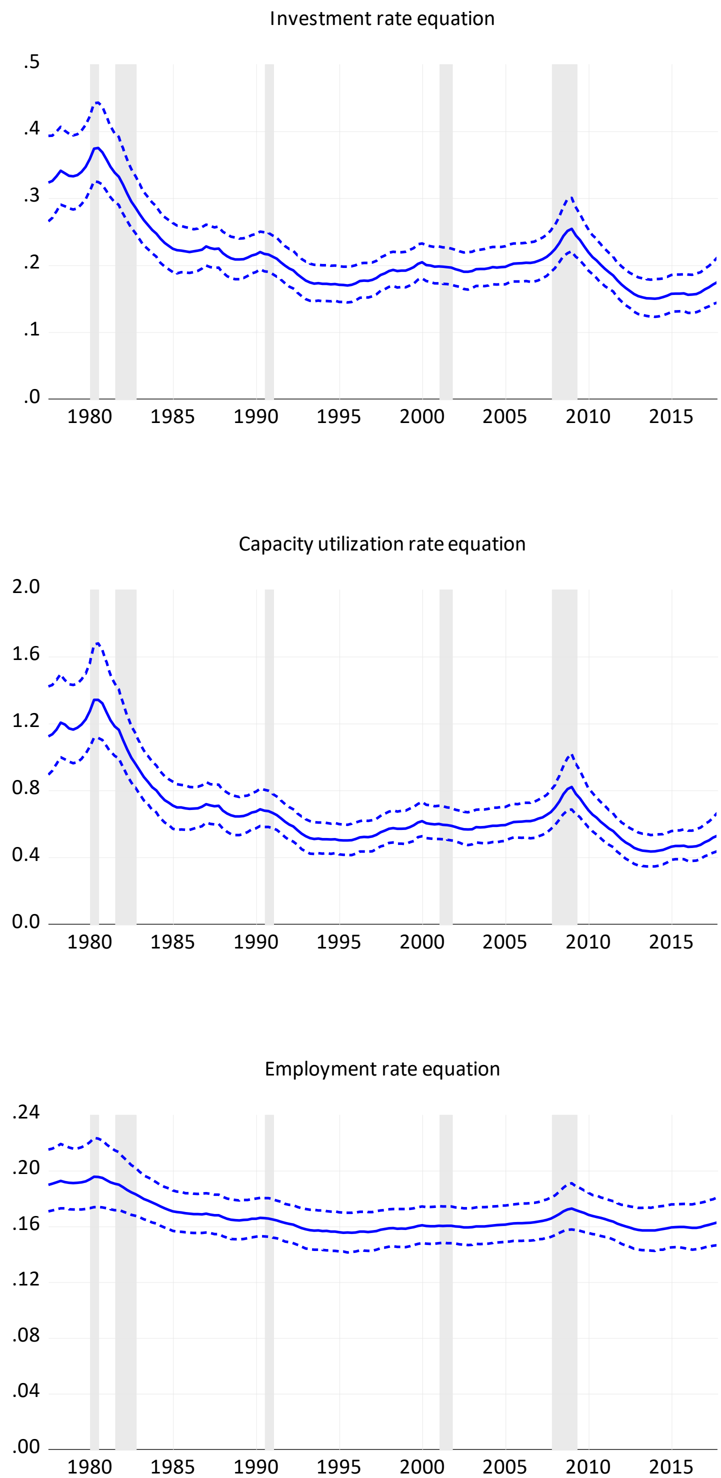
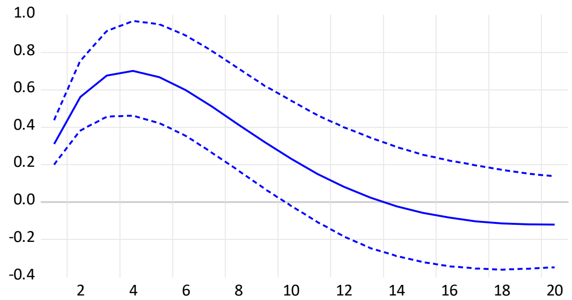
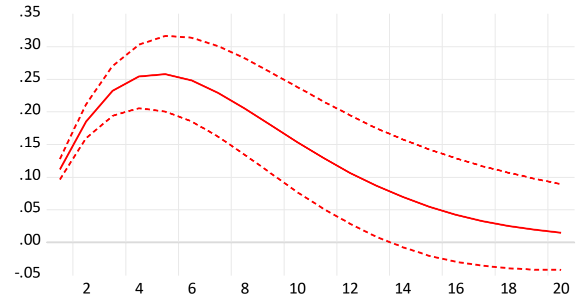


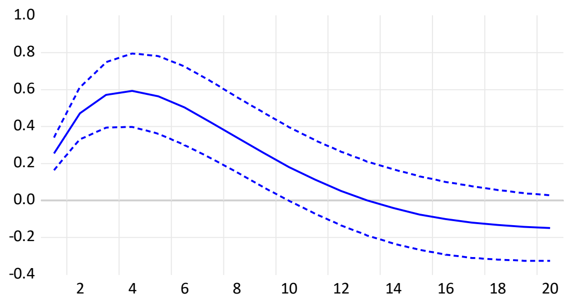
Figure B.1. Posterior means (blue straight lines) with 68% confidence intervals (blue dotted lines) of the standard deviations of each equation in the TVP-SVAR model for the mass production system (Shaded areas indicate NBER recession dates.)



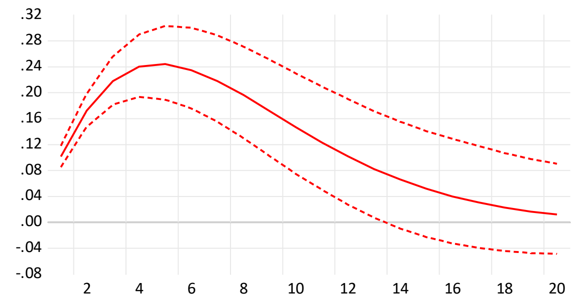
(a) Response of v_t to an i_t shock, 1977Q3



(b) Response of n_t to a v_t shock, 1977Q3



(c) Response of v_t to an i_t shock, 2004Q4



(d) Response of n_t to a v_t shock, 2004Q4

Figure B.2. Impulse-response functions obtained from the TVP-SVAR model that represents the mass production system's short-run output adjustment. Notation: v_t = capacity utilization rate; i_t = investment rate; and n_t = employment rate. Dotted lines are the 68% confidence intervals

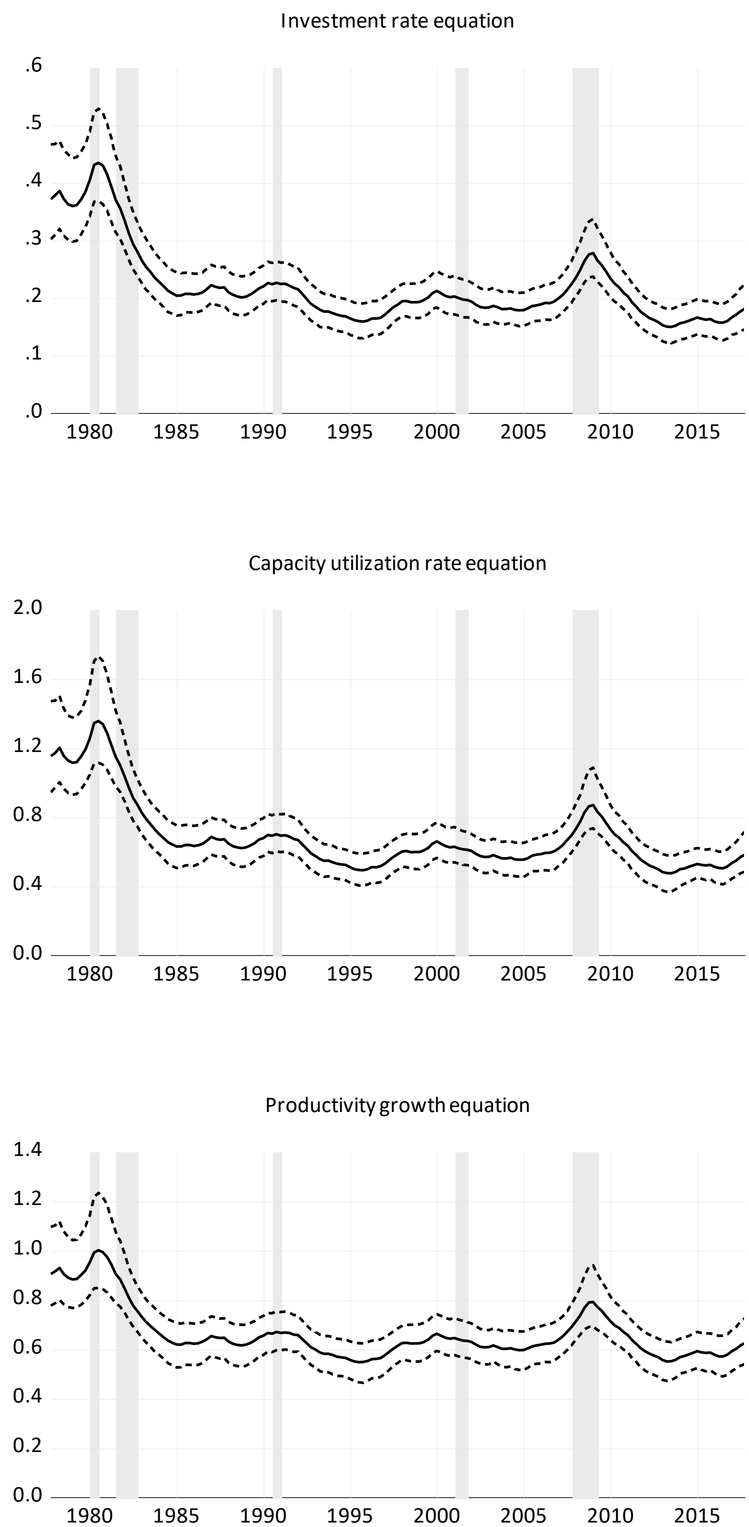
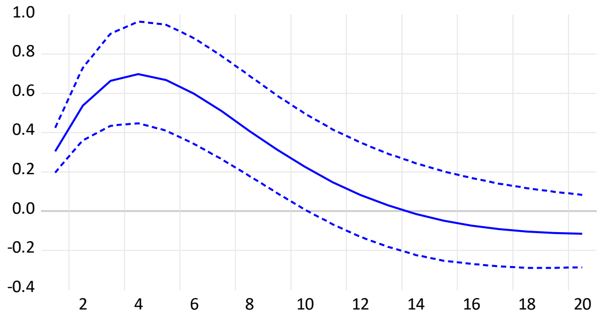
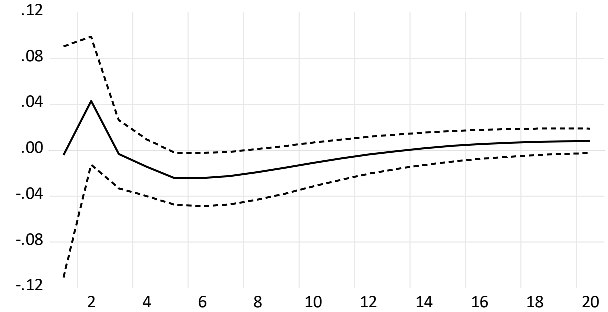


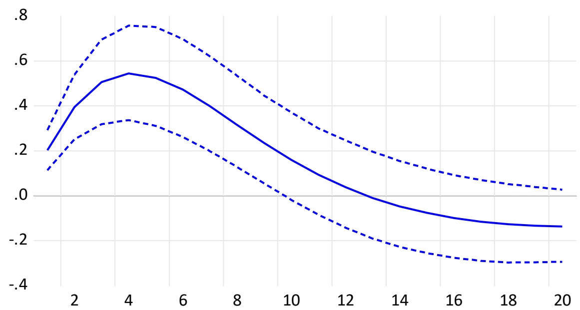
Figure B.3. Posterior means (black straight lines) with 68% confidence intervals (black dotted lines) of the standard deviations of each equation in the TVP-SVAR model for the craft production system (Shaded areas indicate NBER recession dates.)



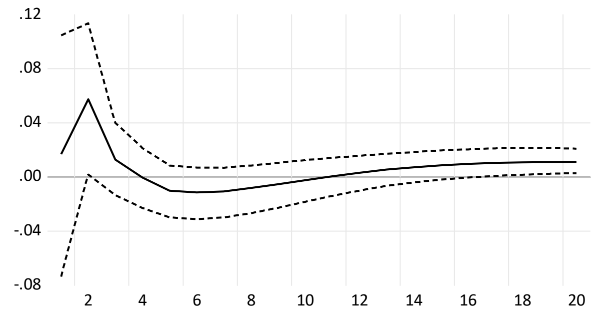
(a) Response of v_t to an i_t shock, 1978Q3



(b) Response of $\Delta\pi_t$ to an i_t shock, 1978Q3



(c) Response of v_t to an i_t shock, 2004Q4



(d) Response of $\Delta\pi_t$ to an i_t shock, 2004Q4

Figure B.4. Impulse-response functions obtained from the TVP-SVAR model that represents the craft production system's short-run output adjustment. Notation: v_t = capacity utilization rate; i_t = investment rate; and $\Delta\pi_t$ = first differences of the natural log of productivity. Dotted lines are the 68% confidence intervals