Assessing the Ins and Outs of Technological Unemployment*

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Abstract

We analyze how unemployment, job finding and job separation rates react to neutral and investment-specific technology shocks. Neutral shocks increase unemployment and explain a substantial portion of unemployment volatility; investment-specific shocks expand employment and hours worked and mostly contribute to hours worked volatility. Movements in the job separation rates are responsible for the impact response of unemployment while job finding rates for movements along its adjustment path. Our evidence qualifies the conclusions by Hall (2005) and Shimer (2007) and warns against using search models with exogenous separation rates to analyze the effects of technology shocks.

JEL classification: E00, J60, O33.
Key words: Unemployment, technological progress, labor market flows, business cycle models.

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1 Introduction

Since the pioneering contributions of Darby et al. (1985, 1986), Jackman et al. (1989), and Blanchard and Diamond (1990), the literature has recognized the importance of characterizing cyclical employment adjustment in terms of workers flows in and out of unemployment. The conventional wisdom has generally been that recessions, defined as periods of sharply rising unemployment, typically begin with a wave of layoffs and persist over time because unemployed workers have hard time to find new jobs. Hall (2005) and Shimer (2007) have recently challenged this view by showing that over the US business cycle there are substantial fluctuations in the job finding rate (the rate at which unemployed workers find a job), while the job separation rate (the rate at which employed workers lose their job) is comparatively acyclical. However, Fujita and Ramey (2006), Elsby et al. (2007), and Yashiv (2007), looking at the same evidence, attribute to the separation rate a larger role in characterizing US unemployment fluctuations. The conclusions these authors reach are based on simple unconditional correlation analysis, whose interpretation is problematic for at least three reasons: it does not explain what drives fluctuations in finding and separation rates; it raises questions about whether conclusions hold true following any important business cycle shock; it leaves unexplained the direction of causality, since adjustments in job separation rates could, in principle, be responsible for cyclical variations in finding rates.

To address these issues, this paper analyzes the dynamics of the ins and outs of unemployment during technology induced recessions. We focus attention on the response of labor market variables to investment-neutral and investment-specific technology shocks. These shocks are identified as in Altig et al. (2005), Fisher (2006), and Michelacci and Lopez Salido (2007), by imposing that investment specific technological progress is the unique driving force for the secular trend in the relative price of investment goods, while neutral and investment specific technological progress explain long-run movements in labor productivity. We analyze the dynamics they induce along the intensive margin (hours per employee) and the extensive margin (number of employed workers) and characterize unemployment dynamics in terms of the job separation rate and the job finding rate.

As in Blanchard and Quah (1989) and in Fernald (2007), we recognize that low frequency movements could give a misleading representation of the effects of shocks. This is a relevant concern since in the sample the growth rate of both labor productivity and the relative price of investment goods exhibit significant long run swings which have gone together with important changes in labor market conditions. These patterns have been greatly emphasized in the literature on growth and wage inequality (see Violante, 2002 and Greenwood and Yorokoglu, 1997, among others). The productivity revival of the late 90's has also been heralded as the beginning of a new era in productivity growth and it has been a matter of extensive independent research, see for example Gordon (2000) and Jorgenson and Stiroh (2000).

We show that neutral technology shocks, who have positive long run effects on labour productivity substantially increase unemployment in the short run and affect labor market variables primarily along the extensive margin. Positive investment specific technology shocks, on the other hand, expand aggregate hours worked, both because hours per worker increase and because unemployment falls, but the intensive margin contributes most to the adjustments. For both shocks, the impact response of unemployment is almost entirely due to the instantaneous response of the separation rate while movements in the finding rate account for the subsequent unemployment dynamics. Thus, positive neutral shocks can cause recessions and the workers flows they induce are in line with the conventional wisdom: unemployment initially rises because of a wave of layoffs and remains high because the job finding rate takes time to recover.

The practical relevance of these findings depends on how important technology shocks are for labor market fluctuations and how accurately they represent important historical episodes. We show that technology shocks explain around 30 per cent of the cyclical fluctuations in labor market variables with neutral technology shocks mattering primarily for the volatility of unemployment and investment specific technology shocks mainly for hours worked volatility. We also show that neutral technology shocks explain the recession of the late 80's and the subsequent recovery of the early 90's. They initially cause a rise in the job separation and in the unemployment rate; subsequently output builds up until it reaches its new higher long run value, but over the transition path employment remains below normal levels because the job finding rate is persistently below its long run level, making the recovery appear to be "jobless"— a distinctive feature of this business cycle episode.

Our conclusions differ from those of Hall (2005) and Shimer (2007) for three reasons. First, our analysis is conditional on technology shocks, rather than unconditional. Second, our setup allows us to separately measure the contribution of the ins and outs of unemployment on impact and over the adjustment path, rather then at generic business cycle frequencies. Third, our empirical model permits feedbacks in response to technology shocks. This is important since shocks that drive the separation rate up on impact increases unemployment and worker reallocation. This effect is likely to cause an increase in the cost of posting vacancies which can thereby reduce the job finding rate; see Michelacci and Lopez Salido (2007) for a model which produces this effect. Our results thus provides a healthy warning to the ongoing tendency to analyze the effects of technology shocks in search models with exogenous separation rates.

Our evidence also challenges the standard sticky-price explanation for why hours fall in response to neutral technology shocks, see for example Galí (1999). In sticky-price models, when technology improves and monetary policy is not accommodating enough, demand is sluggish to respond and firms take advantage of technology improvements to economize on labor input. This mechanism applies most naturally to the intensive margin since displacing workers is likely to be more costly than changing prices—due to both the direct cost of firing and the value of the sunk investment in training and in job specific human capital that is lost with workers displacement. We find instead that the extensive margin plays a key role and the fall in hours is related to the time consuming process of reallocation of workers across jobs, a finding which is consistent with the Schumpeterian view that the introduction of new neutral technologies causes the destruction of technologically obsolete productive units and the creation of new technologically advanced ones. As shown by Caballero and Hammour (1994, 1996), when the labor market is characterized by search frictions, these adjustments can cause unemployment.

Our work complements the one of Michelacci and Lopez-Salido (2007) in a number of ways. First, while that paper is primarily theoretical, we investigate the dynamics of labor market flows to technology shocks empirically. Second, instead of using job creation and job destruction rates, which are only contaminated proxies of the ins and outs of unemployment and noisy indicators of labor market conditions, we consider workers flow data. Third, the labor market flows we use are representative of the whole US economy while in Michelacci and Lopez-Salido they represent only the manufacturing sector. Finally, this paper uses a longer and more informative data set and analyzes the robustness of the conclusions to changes in a number of auxiliary assumptions.

The rest of the paper is structured as follows. Section 2 discusses the data, the empirical model, and the consequences of low frequency comovements in the variables. Section 3 presents basic results. Section 4 quantifies the relative contribution of job separation rates to the dynamics of technological unemployment. Section 5 measures the contribution of technology shocks to labor market fluctuations. Section 6 interprets the results in light of existing work. Section 7 examines robustness. Section 8 concludes.

2 The empirical model

Let X_t be a $n \times 1$ vector of variables and let X_{1t} and X_{2t} be the first difference of the price of investment, q_t, and labor productivity y_{nt}, respectively. Let $X_t = D(L)\eta_t$ be the (linear) Wold representation of X_t where $D(L)$ has all its roots inside the unit circle and $E(\eta_t\eta_t') = \Sigma_\eta$. In general, η_t is a combination of several structural shocks, which we denote by ϵ_t. We assume that the relationship between η_t and ϵ_t is $\eta = S\epsilon$ where S is a full rank matrix. We also assume that the structural shocks ϵ_t are uncorrelated and normalize their variance so that $E(\epsilon_t\epsilon_t') = I$. Under this normalization, impulse responses represent the effects of shocks of one-standard deviation of magnitude. The restrictions we use to identify investment specific technology shocks and neutral shocks are that the nonstationarities in q_t originate exclusively from investment specific technology shocks and that the non-stationarities in y_{nt} are entirely produced by investment specific and neutral technology shocks. In other words, a neutral technology shock (a z-shock) is the disturbance having zero long-run effects on the relative price of investment goods and non-negligible long-run effects on labor productivity; an investment specific technology shock (a q-shock) affects the long-run level of both labor productivity and the price of investment; and no other shock has long-run effects on these two variables. This implies that the first row of $G = D(1)S$ is a zero vector except in the first position, while the second row is a zero vector except in the first and second position.

These restrictions can be derived from a simple neoclassical growth model where technological progress is non-stationary (see Fisher, 2006 and Michelacci and Lopez Salido, 2007). Note that, in general models with variable capital utilization and adjustment costs, the short run marginal cost of producing capital is increasing and the price of investment goods responds in the short run to change in investment demand. Since the restrictions we impose concern the long run determinants of the price of investment, our identification strategy is robust to the existence of short run increasing marginal costs to produce investment goods.

There is controversy on how the price of investment and GDP should be deflated. Fisher (2006) and Michelacci and Lopez-Salido (2007) deflate both of them by the CPI index. Altig et al. (2005) appear to deflate the relative price of investment with the CPI index, and output with the output deflator (although they are not entirely clear about the issue). In a closed economy, and if we exclude indirect taxes and discount the fact that the CPI only includes a subset of the consumption goods and that its weights measures the prices paid by *urban* consumers, the CPI and the output deflator are similar. However, in an open economy important differences arise because some consumption goods are produced abroad. In our baseline specification, we deflate both variables using a output deflator. In the robustness section we show that this choice has no consequences for the conclusions we reach.

2.1 The data

Our benchmark model has six variables $X = (\Delta q,\ \Delta y_n, h,\ u,\ s,\ f)'$, where Δ denotes the first difference operator. All variables are in logs (and multiplied by one hundred): q is equal to the inverse of the relative price of a quality-adjusted unit of new equipment, y_n is labor productivity, h is the number of per-capita hours worked (thereafter simply hours), u is the unemployment rate and s and f are the job separation rate and the job finding rate, respectively. The dynamics of hours per worker in response to shocks can be obtained assuming that the labor force participation is insensitive to the shocks we consider—we show below that this is a reasonable assumption; those of output per-capita can be derived from the responses of labor productivity and hours. We use 8 lags in the model and stochastically restrict their decay toward zero. We analyze the sensitivity of the results to the choice of lags in the robustness section.

The series for labor productivity, unemployment, and hours are from the USECON database commercialized by Estima and are all seasonally adjusted; q is from Cummins and Violante (2002), who extend the Gordon (1990) measure of the quality of new equipment till 2000:4. The availability of data for q restricts the sample period to 1955:1-2000:4. The original series for q is annual; we use Galí and Rabanal (2004) quarterly interpolated values. Real output (mnemonics `LXNFO`) and the aggregate number of hours worked (`LXNFH`) correspond to the non-farm business sector. The relative price of investment is expressed in output units by subtracting to the (log of the) original Cummings and Violante series the (log of) the output deflator (`LXNFI`) and then adding the log of the consumption deflator ln((`CN`+`CS`)/(`CNH`+`CSH`)). `CN` and `CS` are nominal consumption of non-durable and services while `CNH` and `CSH` are the analogous values of consumption in real terms. The aggregate number of hours worked per capita is calculated as the ratio of `LXNFH` to the working age population (`P16`).

The series for the job separation and the job finding rates are from Shimer (2007). They are quarterly averages of monthly rates. Shimer calculates two different series for the job separation and job finding rate. The first two are available from 1948 up to 2004. Their construction uses data from the Bureau of Labor Statistics for employment, unemployment, and unemployment duration to obtain the *instantaneous* (continuous time) rate at which workers move from employment to unemployment and viceversa. The two rates are calculated under the assumption that workers move between employment to unemployment and viceversa. Since they abstract from workers' labor force participation decisions, they are an approximation to the true labor market rates. Starting from 1967:2, the monthly Current Population Survey public microdata can be used to directly calculate the flow of workers that move in and out of the three possible labor market states (employment, unemployment, and out of the labor force). With this information Shimer calculates an exact instantaneous rates at which workers move from employment to unemployment and viceversa. We use both measures in the analysis: the first two are termed *approximated* rates, the others *exact* rates.

2.2 The low frequency comovements on the VAR

The first graph in the first row of Figure 1 plots hours and the unemployment rate together with NBER recessions (the grey areas). Hours display a clear U-shaped pattern and are highly negatively correlated with unemployment (-0.8). Whether the two series are stationary or exhibit persistent low frequency movements, is matter of controversy in the literature, see for example Francis and Ramey (2005) and Fernald (2007). The second graph plots hours worked per employee (measured as hours over aggregate employment). Clearly, the series exhibit some low frequency changes, primarily at the beginning of the 1970s.

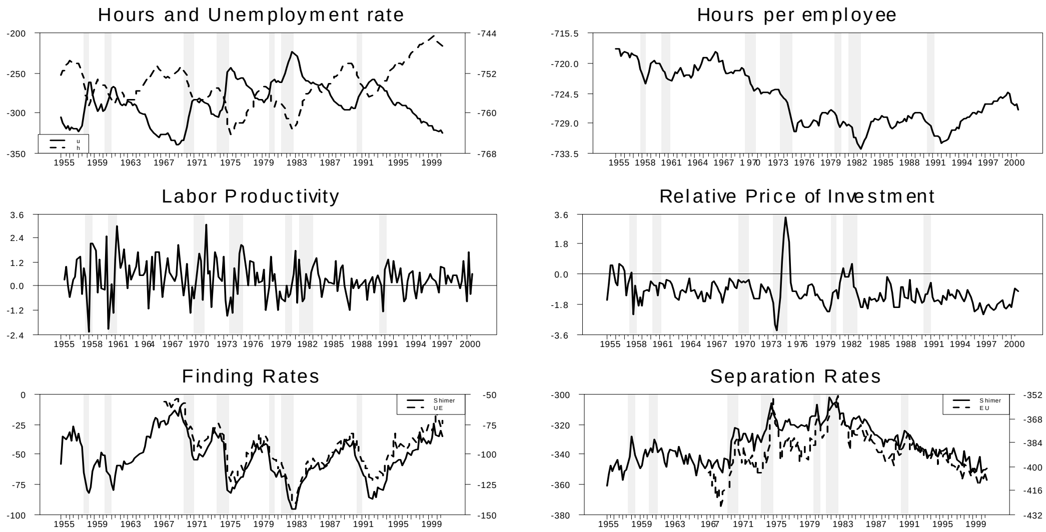


Figure 1: First graph: the dashed line is the aggregate number of hours worked per capita; the continuous line is civilian unemployment both series in logs. Second graph: (logged) hours per employee. Third graph: rate of growth of labor productivity in the non-farm business sector. Fourth graph: growth rate of the relative price of investment goods. Fifth and sixth graph: job finding rate and job separation rate (both in logs), respectively. The solid line corresponds to the approximated rate, the dashed to the exact rate. Shaded areas are NBER recessions.

The two graphs in the second row of Figure 1 plot the first difference of y_n and of the relative price of investment (equal to minus q), respectively. There is a dramatic fall in the value of q in 1974 and its immediate recovery in the following years. Cummins and Violante (2002) attribute this to the introduction of price controls during the

Nixon era. Since price controls were transitory, they do not affect the identification of investment specific shocks, provided that the sample includes both the initial fall in q and its subsequent recovery. The two panels in the third row of Figure 1 display the job finding rate and the job separation rate. Each graph plots approximated and exact rates. The two job finding rate series move quite closely. The exact job separation rate has a lower mean in the 1968-1980 period, higher volatility but tracks the approximated series well. The job finding rate is relatively more persistent than the separation rate (AR1 coefficient is 0.86 vs. 0.73). Given that recessions are typically associated with a persistent fall in the job finding rate, the higher persistence of job finding rate is consistent with Hall (2005) and Shimer (2007) observation that cyclical fluctuations in the unemployment rate are highly correlated with those in the job finding rate.

The low frequency co-movements of the series are highlighted in Figure 2. We follow the growth literature and choose 1973:2 and 1997:1 as a break points, two dates that many consider critical to understand the dynamics of technological progress and of the US labor market (see Greenwood and Yorokoglu, 1997, Violante, 2002, Hornstein et al. 2002). The rate of growth of the relative price of investment goods was minus 0.8 per cent per quarter over the period 55:1 to 73:1 and moved to minus 1.2 per cent per quarter in the period 73:2-97:1. This difference is statistically significant. During the productivity revival of the late 90's the price of investment goods was falling at even a faster rate. The rate of growth of labor productivity exhibits an opposite trend. It was higher in the 55:1 to 73:1 period than in the 73:2-97:1 period, and recovered in the late 90's. Also in this case, differences are statistically significant. Shifts in technological progress occurred together with changes in the average value of the unemployment rate, see the first row of Figure 2.

The graphs in the second row of Figure 2 plot the trend component of labor productivity growth, hours and unemployment obtained by using a Hodrick Prescott filter with smoothing coefficient equal to 1600. The trends are related: there appears to be a negative comovement between productivity growth and the unemployment rate and a positive comovement between productivity growth and hours. The third row of Figure 2 shows that the separation rate exhibits low frequency movements that closely mimic those present in the unemployment rate. The opposite is true for the finding rate.

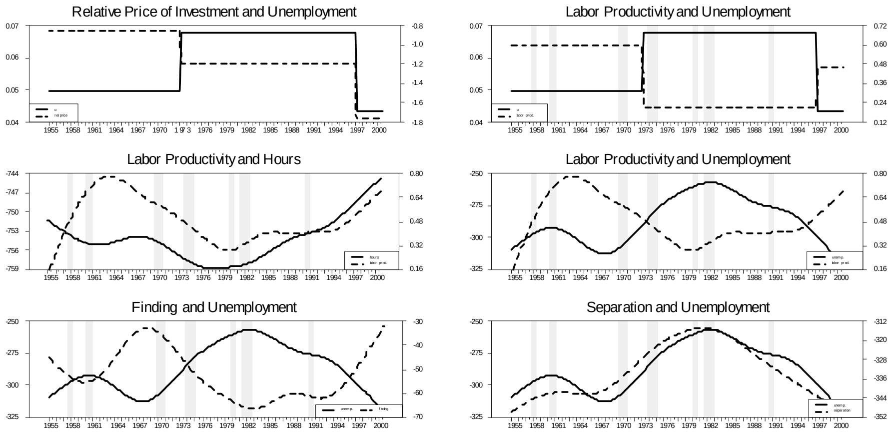


Figure 2: First graph: average quarterly growth rate of the relative price of investment (dotted line) and unemployment rate (solid line). Second graph: average quarterly growth rate of labour productivity (dotted line) and unemployment rate (solid line). Third graph: Hodrick Prescott trend of labor productivity growth (dotted line) and hours per capita (solid line). Fourth graph: Hodrick Prescott trend of labor productivity growth (dotted line) and unemployment rate (solid line). Fifth and sixth graph: Hodrick Prescott trend of finding and separation rates (dotted lines) and unemployment rate (solid line). The smoothing coefficient is $\lambda = 1600$.

2.3 The effects of low-frequencies comovements on impulse responses

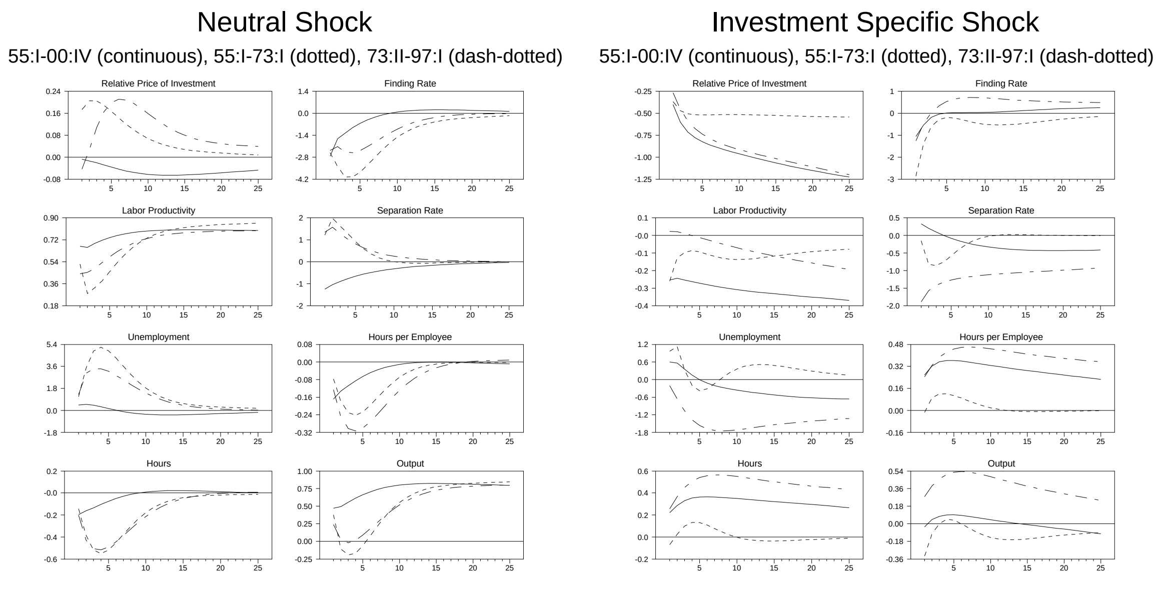
To show why these comovements are problematic when analyzing the responses to technology shocks, we plot the point estimates of the responses obtained for three different samples: 1955:I-2000:IV, 1955:I-1973:I, and 1973:II-1997:I. Panel (a) in Figure 3 displays the responses of labor productivity, the relative price of investment, unemployment, hours, hours per employee, the separation rate, and the finding rate to a neutral shock. Panel (b) deals with the responses to an investment specific shock. The responses of labor productivity and output to either shock in the full sample are similar to those in Fisher (2006) [1].

When considering panel (a), it is apparent that estimated responses to neutral shocks in the two subsample are similar. Yet, they look quite different from the re-

[1] We have a slight initial fall in hours and in the price of investment in response to a neutral shock that Fisher does not have. The presence of additional variables in the VAR explains these differences.

sponses for the full sample. In the full sample, the relative price of investment and the separation rate fall, while they increase in the two subsamples. Moreover the fall in hours and in the job finding rate and the increase in unemployment are much less pronounced in the full sample than in each sub-sample. Finally, output and labor productivity respond faster in the full sample.

Differences in the estimates can be related to the low frequency correlations previously discussed. In the full sample, a permanent change in the rate of productivity growth is at least partly identified as a series of neutral technology shocks. Thus, over the period 1973:II-1997:I when productivity growth is on average lower, the full sample specification finds a series of negative neutral technology shocks. Since in this period the unemployment rate and the separation rate are above their full sample average, while hours and the finding rate are below, biases emerge leading, for example, to a lower response of the unemployment rate and of the separation rate, and a higher response of hours and the job finding rate.



(a) Neutral technology shock

(b) Investment specific technology shock

Figure 3: Responses to a one-standard deviation shocks. Each line corresponds to a six variable VAR(8) with the rate of growth of the relative price of investment, the rate of growth of labour productivity, the (logged) unemployment rate, and the (logged) aggregate number of hours worked per capita, the log of separation and finding rates, estimated over a different sample period.

In discussing the results for panel (b), one should bear in mind two important facts (see Figures 10 and 11 in the Appendix): i) the estimated responses in the first subsample are almost never significant (with the exception of the response of the relative price of investment) and ii) investment specific technology shocks contribute little to the volatility of all variables in the first subsample (again leaving aside the price of investment). In the second sub-period the contribution of investment specific shocks instead becomes important. Hence, it is appropriate to compare estimates for the full sample and the 1973:2-1997:1 sub-period. The bias in the estimated responses for the full sample is in line with the low frequency correlations previously discussed. In the full sample, a permanent change in the rate of growth of the relative price of investment is at least partly identified as a series of investment specific technology shocks. Thus, over the period 1973:II-1997:I when the price of investment falls at a faster rate on average, the full sample specification tends to identify a series of positive investment specific technology shocks. Since over the period, the unemployment rate and the separation rate are also higher than their full sample average, while hours, the job finding rate, and productivity growth are lower, the full sample specification biases estimates towards a higher response of the unemployment rate and of the separation rate, and a lower response of hours, the job finding rate, and productivity.

2.4 Discussion

Our conclusions are robust to a number of standard modifications. For example, they are unaffected if the second subsample is 1973:II-2000:IV (see panels (a) and (b) in Figure 12 in the Appendix) or if we use the population-adjusted hours produced by Francis and Ramey (2005) instead of the standard per-capita hours series.

Commentators have sometimes questioned our choice of break points. Some have suggested that taking a break point as known (when in fact it is not) may bias results, while others have suggested that a perhaps more relevant break point would be, as in the Great Moderation literature, somewhere around the beginning of 1980. Figures 13 and 14 in the Appendix show that moving backward or forward by one year the two chosen break dates does not change the conclusion that, over subsamples, the responses of the variables are similar and different from those of the full sample. Concerning the break around the beginning of the 1980s, visual inspection of Figure 1 clearly indicates that none of the series we consider displays any unusual behavior around that date. One interpretation of this evidence is that, if the events driving the rise and fall of inflation, its volatility and persistence matter for labor market variables, they must matter at much longer run frequencies.

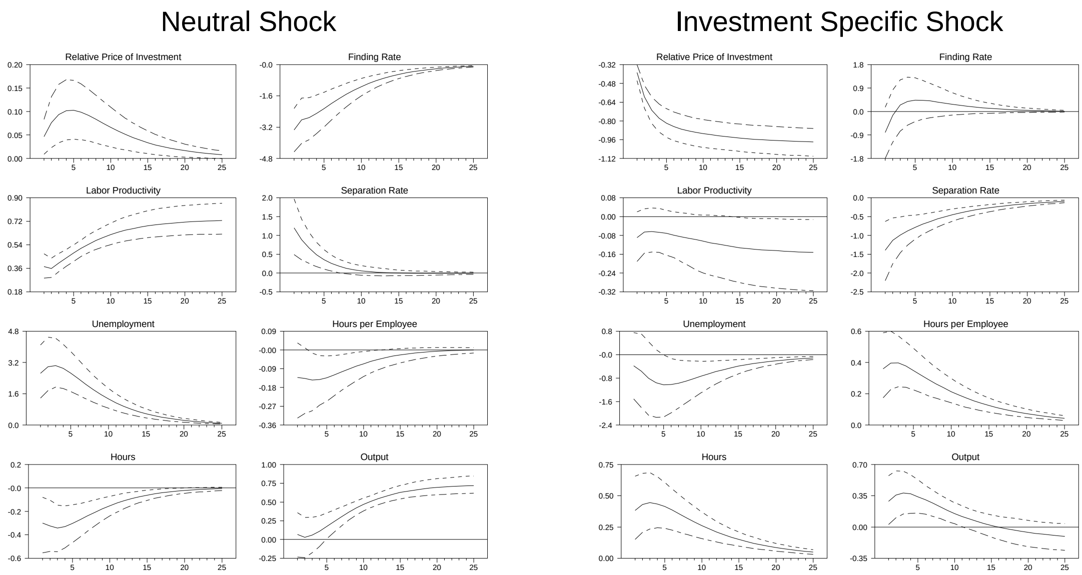
The evidence in Figure 3 indicates that the dynamic responses of the variables of the VAR to the two shocks are very much homogeneous over subsamples. Therefore, the low frequency variations we have highlighted imply that the constant of the VAR needs to be adjusted and this is what we do in this paper. In Canova et al. (2006), we elaborate on this issue and present cases where unaccounted level breaks within a sample produce sign switches or an extreme pattern of persistence in the responses, see also Fernald (2007). It could be argued that a simple way to eliminate the low frequency comovements is to estimate the VAR over sub-samples, but this would be inefficient, since the dynamics are roughly unchanged, and it may cause biases, since imposing long run restrictions in a system estimated over a small sample distorts structural estimates (see Erceg et al. 2005).

It goes without saying that low frequency movements in the data are the object of controversial discussion and our choice of eliminating them could be criticized in, at least, two ways. It could be argued, for example, that after a prolonged period of low productivity growth and in anticipation that productivity will pick up, labor input could be lower in the period of low productivity, making low frequency movements informative about business cycle fluctuations. One way to rationalize our decision of removing low frequency fluctuations is that breaks can not be forecasted so anticipatory effects are not present. It could also be argued that changes in productivity growth also affect agents decisions rule. This would imply that one can get mistaken conclusions from estimating the model for the full sample, just allowing changes in the intercept. This argument is theoretically correct but it does not appear to hold in the data. The dynamics in response to the shocks is very similar in the two subsamples (and different from the full sample where no adjustment for low frequency movements is made) so agent's decision rules appear to be unaffected by the breaks. Furthermore, we will show below that, once breaks in the intercepts are considered, the full sample evidence coincides with the sub-sample one.

3 The full sample results

3.1 Evidence using the approximated rates

Panel (a) in Figure 4 plots the response of the variables of interest to a neutral technology shock when the VAR includes the approximated job finding and job separation rates and the intercept is deterministically broken at 1973:2 and 1997:1. The reported bands correspond to 90 percent confidence intervals. A neutral shock leads to an increase in unemployment and to a fall in the aggregate number of hours. The effects on hours worked per employee are small and, generally, statistically insignificant. The impact increase in unemployment is the result of a sharp rise in the separation rate and of a significant fall in the job finding rate. In the quarters following the shock,



(a) Neutral technology shock (b) Investment specific technology shock

Figure 4: Responses to a one-standard deviation shocks. Full sample with intercept deterministically broken at 1973:II and 1997:I. Six variables VAR(8). Dotted lines are 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 500 times the residuals of the VAR. The continuous line is the median estimate.

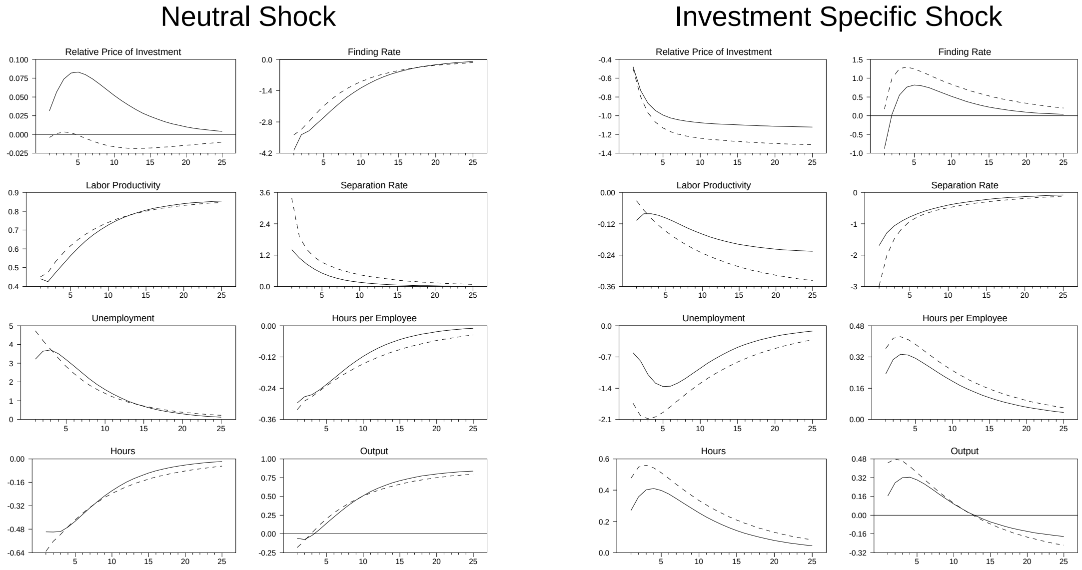
the separation rate returns to normal levels while the job finding rate takes up to fifteen quarters to recover. Hence, the dynamics of the job finding rate explains why unemployment responses are persistent. Output takes about 5 quarters to significantly respond but then gradually increases until it reaches its new higher long-run value. Note that the dynamic responses for the full sample in Figure 4 now look like those of the two subsamples we reported in Figure 3.

Panel (b) in Figure 4 plots responses to an investment specific shock. The responses are very similar to those obtained in the 1973:2-1997:1 sub-sample presented in Figure 3. An investment specific technology shock leads to a short run increase in output and hours per capita and a fall in unemployment. The fall of unemployment on impact is due to a sharp drop in the separation rate. Since this effect is partly compensated by a fall in the job finding rate, the initial fall in unemployment rate is small in absolute terms and statistically insignificant. Consequently, the increase in hours is primarily explained by the sharp and persistent increase in the number of hours worked per employee. Hence, while labor market adjustments to neutral technology shocks occur mainly along the extensive margin, those in response to an investment specific technology shock mainly occur along the intensive margin.

3.2 Evidence using the exact rates

We next use exact job finding and separation rates in the VAR. Panel (a) in Figure 5 presents the responses to a neutral technology shock with the exact rate (dotted line) together with the previously discussed responses obtained with the approximated rates (solid line). The sign and shape of the responses are similar with both specifications. There are however two important quantitative differences. When considering the exact rates, the separation rate rises on impact twice as much, while the finding rate falls slightly less and, over the adjustment path, the separation rate exhibits more persistence when exact rates are used.

Panel (b) in Figure 5 reports responses to an investment specific technology shock when exact and approximated rates are used. Also in this case, the two specifications agree on the sign and shape of the responses. However, there are two significant quantitative differences. When the exact rates are used, the response of the separation rate is more pronounced and falls on impact twice as much. Instead, the job finding rate is now unaffected on impact and remains above normal levels all along the adjustment path. As a result, the fall in the unemployment rate is more pronounced both on impact and during the transition suggesting that the extensive margin plays a more



(a) Neutral technology shock (b) Investment specific technology shock

Figure 5: Exact rates (dotted lines) and approximated rates (solid lines). Both VAR includes dummies corresponding to the breaks in technology growh. Each VAR has 8 lags and six variables. Reported are point estimates of the responses.

important role in accounting for the rise in hours when exact rates are used.

3.3 Omitted variables

Our VAR has enough lags to make the residuals clearly white noises. Yet, it is possible that omitted variables play a role in the results. For example, Evans (1992) showed that Solow residuals are correlated with a number of policy variables, therefore making responses to Solow residuals shocks uninterpretable. To check for this possibility we have correlated our two estimated technology shocks with variables which a large class of general equilibrium models suggest as being jointly generated with neutral and investment specific shocks. We compute correlations up to 6 leads and lags between each of our technology shocks and the consumption to output ratio, the investment to output ratio, and the inflation rate. The point estimates of these correlations together with an asymptotic 95 percent confidence tunnel around zero are in Figure 6. The shocks we use are those obtained in the VAR with the approximated rates, but the results are similar when exact rates are used.

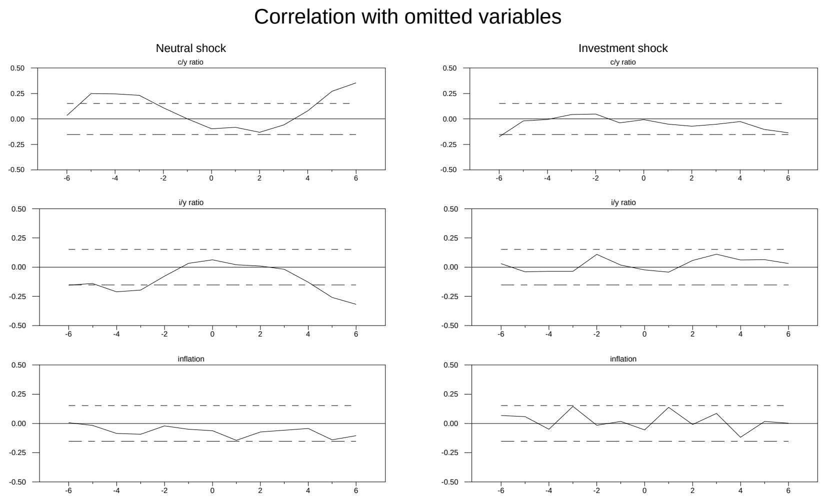


Figure 6: Left column corresponds to neutral technology shocks; right column to investment specific technology shocks. The first row plots the correlation with the consumption-output ratio, the second with the investment-output ratio, the third with the inflation rate. The shocks are estimated from the six variables VAR with approximated rates in the dummy specification. The horizontal lines correspond to an asymptotic 95 percent confidence interval for the null of zero correlation.

The consumption to output and the investment to output ratios help to predict neutral technology shocks at some horizon, while none of the three potentially omitted variables significantly correlate with investment specific shocks. Hence, we investigate what happens when we enlarge the system to include these three new variables. Panels (a) and (b) in Figure 15 in the Appendix present the responses in VAR which includes the original six variables (approximate rates are used) plus the consumption to output and the investment to output ratios and the inflation rate. None of our previous conclusions regarding the dynamics of labor market variables is affected.

4 The role of separation rates

Hall (2005) and Shimer (2007) have challenged the conventional view that recessions—defined as periods of sharply rising unemployment—are the result of higher job-loss rates. They argue that recessions are mainly explained by a fall in the job finding rate. Our responses suggest instead that the separation rate plays a major role in determining the impact effect of technology shocks on unemployment. This is consistent with the evidence of Fujita and Ramey (2006) that the separation rate leads the cycle (by about one quarter) while the finding rate lags it (by about two months).

To further evaluate the role of the separation rate for unemployment fluctuations, we use a simple two state model of the labor market (see Jackman et al. (1989) and Shimer (2007) and (2008)) and assume that the stock of unemployment evolves as:

$$\dot{u}_t = S(l_t - u_t) - Fu_t \tag{1}$$

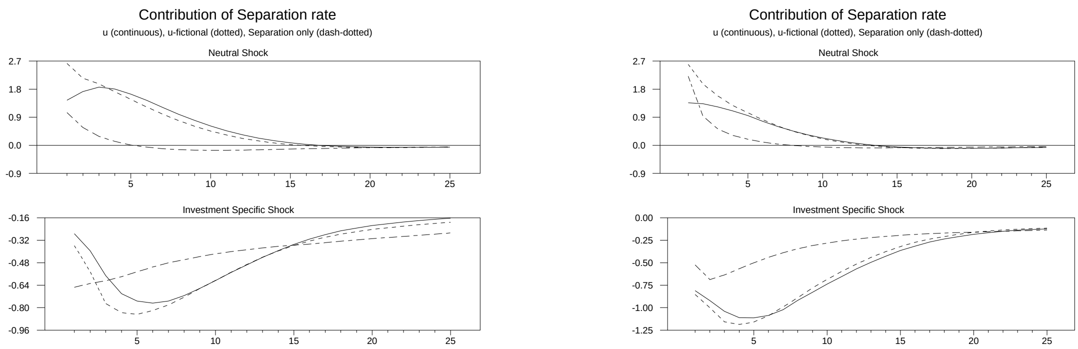
where l_t and u_t are the size of the labor force and the stock of unemployment, respectively; while S and F are the separation and finding rates in levels, respectively. The unemployment rate tends to converge to the following *fictional* unemployment rate:

$$\tilde{u} = \frac{S}{S+F} \equiv \frac{\exp(s)}{\exp(s)+\exp(f)}.$$

Shimer (2007) shows that the fictional unemployment rate $\tilde{u}$ tracks quite closely the actual unemployment rate series, so that one can fully characterize the evolution of the stock of unemployment just by characterizing the dynamics of labor market flows. After linearizing the log of $\tilde{u}$, we can calculate its response using the information contained in the response of (the log of) the separation rate s and the finding rate f. This simple setup allows to measure the contribution of finding and separation rates to the cyclical fluctuations of fictional unemployment $\tilde{u}$ and evaluate how accurately fictional unemployment approximates actual unemployment (if it does workers movements in and out of the labor force play a minor role for unemployment fluctuations).

Panel (a) in Figure 7 reports results for the specification with approximated rates, panel (b) with the exact rates. In both cases, the same nine variable VAR employed in section 5 is used. In each panel, the response of the true unemployment rate appears with a solid line and the response of (logged) $\tilde{u}$ appears with a dotted line. The dash-dotted line corresponds to the response of (logged) $\tilde{u}$ obtained if the job finding rate had remained unchanged at its average level. It therefore represents the contribution of the separation rate to fluctuations in fictional unemployment.

Figure 7 shows that the dynamics of fictional unemployment after a neutral shock are explained to a large extent by fluctuations in the separation rate, especially when considering the specification with exact rates. Consistent with the analysis of previous section, the separation rate explains almost 90 per cent of the impact effect on fictional unemployment. However, its contribution falls to 40 per cent after one quarter and drops to 20 per cent one year after the shock. There are some differences in the impact response of actual and fictional unemployment. Hence, workers movements in and out of the labor force play some role in characterizing the response of the unemployment rate, at least on impact.



(a) Approximated rates

(b) Exact rates

Figure 7: Nine variables VAR with approximated or exact rates. Full sample with deterministic time dummies. Reported are median estimates from 500 bootstrap replications.

Following an investment specific shock, when approximated rates are used, unemployment falls little on impact because the fall in the separation rate makes unemployment decrease while the fall in the job finding rate makes unemployment increase. When considering the specification with exact rates, unemployment falls substantially on impact and this is mainly due to the fall in the separation rate. Since the differences between the response of fictional and actual unemployment are minimal, both with approximated and with exact rates, adjustments in others labor market flows are small in responses to these shocks.

5 The contribution of technology shocks

To put our findings in the right perspective, it is necessary to show that the contribution of technology shocks to fluctuations in the variables of interest is non-negligible. Otherwise, what we uncover is an interesting intellectual curiosity without practical implications. Table 1 reports the forecast error variance decomposition using either the approximated rates or the exact rates. We present results for the VAR with nine variables for the full sample and for the subsample 1973:II-2000:IV. If the consumption and the investment to output ratio, and the inflation rate are omitted, the contribution of technology shocks is marginally larger (on average by about ten percentage points).

Neutral technology shocks explain a substantial proportion of the volatility of unemployment. In the specification with approximated rates, neutral technology shocks explain about 20 per cent of unemployment fluctuations at time horizons between 4 and 8 years while the contribution to the forecast error variance of hours per worker is only five per cent. Investment specific technology shocks instead account for a substantial proportion of the volatility of hours worked: around 20 per cent of the volatility of hours per capita and 30 per cent of the volatility of hours per worker. The contribution of investment specific technology shocks to unemployment volatility is instead small (generally smaller than 10 per cent). Taken together, technology shocks explain a relevant proportion of the labor market volatility: at horizons between 2 and 8 years they explain around 30 per cent of the volatility of unemployment and hours.

The importance of technology shocks is somewhat larger when exact rates are used (see panel C). This is however due to the greater importance of technology shocks in the 1973:II-2000:IV sample period. When we estimate the VAR with approximated rates in the 1973:II-2000:IV sample, we find that technology shocks explain roughly the same amount with approximated and exact rates (see panel B). The main exception is in the contribution of neutral technology shocks to the volatility of the separation rate, which is three times larger with exact rates.

Further evidence on the role of technology shocks in generating cyclical fluctuations can be obtained looking at the historical contribution of technology shocks to fluctuations in logged unemployment, hours, job finding and job separation. The graphs in Figure 8 represent with a solid line the original series and with a dotted line its component due to technology shocks (either neutral or investment specific), as recovered from the nine variables VAR with the exact rates. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600. The areas in grey correspond to the NBER recessions.

It is apparent that technology shocks are an important driving force of cyclical fluctuations in labor market variables, probably more so for unemployment than for hours.

Variable	Neutral				Investment specific			
	Horizon (quarters)				Horizon (quarters)			
	1	8	16	32	1	8	16	32
A. Approximated rates, full sample								
Output	1	6	30	55	3	5	5	4
Hours	8	9	8	7	14	16	21	22
Hours per Worker	5	5	4	4	17	23	29	29
Unemployment	23	21	21	21	3	3	6	6
Finding Rate	17	17	17	17	0	1	2	2
Separation Rate	10	8	7	6	5	8	12	14
B. Approximated rates, 1973:II-2000:IV sample								
Output	1	4	24	43	22	11	10	9
Hours	12	14	12	11	37	18	20	21
Hours per Worker	10	10	8	9	44	30	31	32
Unemployment	12	18	16	14	13	2	2	3
Finding Rate	7	13	12	12	4	1	2	2
Separation Rate	28	28	12	14	2	4	8	12
C. Exact rates								
Output	8	4	17	37	14	8	6	6
Hours	22	19	18	16	24	15	14	14
Hours per Worker	14	12	11	10	35	27	28	28
Unemployment	34	30	29	27	3	1	1	1
Finding Rate	1	25	24	24	0	1	2	3
Separation Rate	34	34	30	26	0	1	1	1

Table 1: Forecast Error Variance Decomposition: percentage of variance explained by neutral or investment-specific technology shocks at different time horizons for the selected variables. All VARs have nine variables with intercept deterministically broken at 1973:II and 1997:I. The variables are the growth in the relative price of investment and in labor productivity, hours per capita, the unemployment rate, the job separation and the job finding rate, the consumption to output ratio, the investment to output ratio, and the inflation rate. Panel A deals with a VAR with approximated rates, Panel B restrict the analysis to the 1973:II-2000:IV sub-sample, Panel C deals with the exact rates.

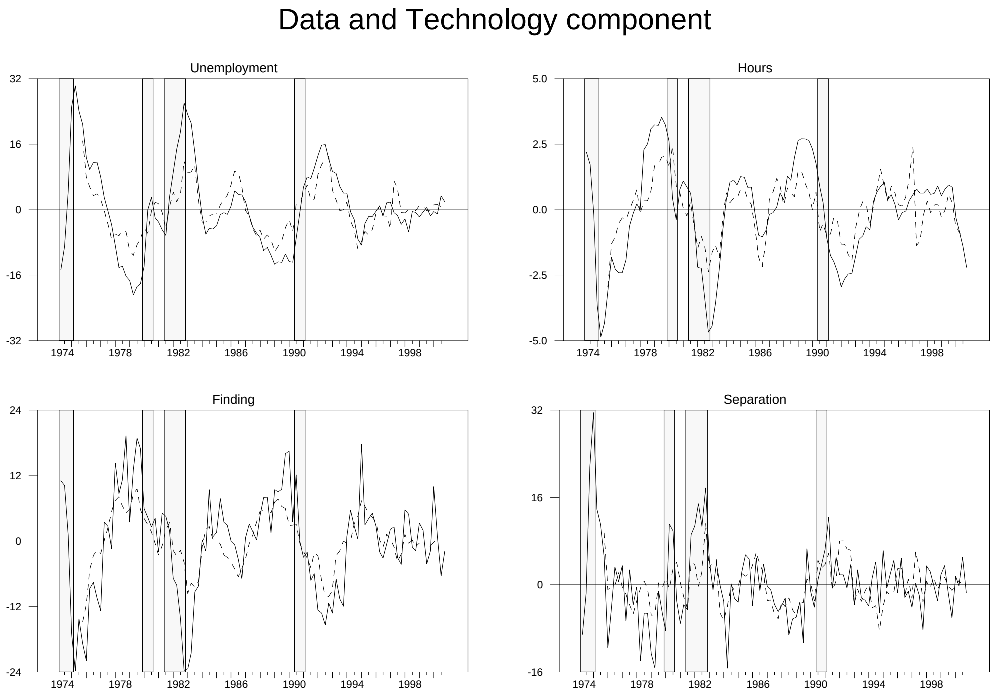


Figure 8: technology shocks to labor market fluctuations. Solid line refers to raw data, the dotted lineto the component due to technology shock (either neutral or investment specific) as recovered from the nine variables VAR with the exact rates. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600.The areas in grey correspond to the NBER recessions.

They account for several important business cycle episodes, including the recession of the late 80's and the subsequent remarkably slow labor market recovery of the early 90's. This episode have been extensively investigated in the literature, yet its causes are still unexplained; see for example Bernanke (2003). A key feature of the episode is that the downturn in employment was severe. Another is that the peak in unemployment occurred about two years later than the trough in output. This is a remarkable exception relative to other business cycle episodes, see McKay and Reis (2007). The graphs in the left column of Figure 9 presents the original output and unemployment series (solid lines) and their component due just to technology shocks (dotted lines), again obtained from the nine variables VAR(8) with the exact rates. All series are detrended with the Hodrick Prescott filter. The vertical lines capture the NBER reces-

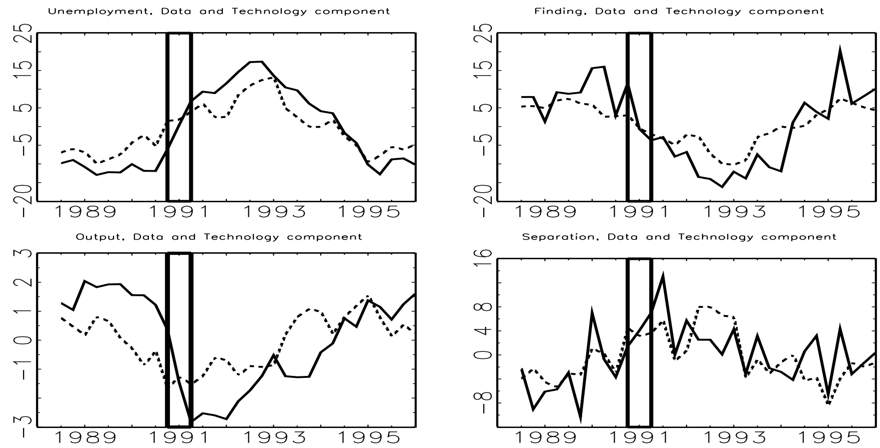


Figure 9: The jobless recovery of the 90s. Solid lines are raw data (either unemployment, finding rates, separation rates or output), the dotted lines the component due to technology shocks (either neutral or investment specific) as recovered from the nine variables VAR with the exact rates. All series are detrended with a Hodrick Prescott filter with smoothing parameter equal to 1600. The vertical lines identifies the NBER recession.

sion. The technology component of the data tracks quite closely the evolution of the raw data. This is mainly due to the evolution of neutral shocks that naturally tend to induce jobless recoveries: following the initial rise in job separation and unemployment, output increases to its new higher long run value, while unemployment remains above trend because of the low job finding rate, which induces a remarkably slow recovery in the labor market, see right column.

6 An interpretation

Our findings indicate that the separation rate is important in characterizing the labor market response to technology shocks. We also find that labor market adjustments to different types of technology shocks are different. Neutral shocks exercise their effects primarily along the extensive margin of the labor market; investment specific shocks along the intensive margin. Moreover, neutral shocks create unemployment, while investment specific shocks increase labor input. These results have important implications for both empirical analysis concerning sources of business cycle fluctuations and theoretical models designed to explain them.

First, failure to empirically distinguish between the two types of disturbances may lead to nonsensical representation of the dynamics following unexpected technological improvements. Second, our results qualify the conclusions by Hall (2005) and Shimer (2007) and show the importance to use search models with endogenous separation for business cycle analysis. The difference in conclusions is due to our focus on correlation conditional on technology shocks rather than on unconditional correlation at generic business cycle frequencies. Third, for interpretation purposes, it is very important to separate the extensive from the intensive margin of labor market and just using total hours may lead to distortions in the analysis. For example, it is well known that hours fall in response to neutral technology shocks and starting with Galí (1999) it is common to interpret this evidence using sticky prices models. In sticky-price models, when technology improves and monetary policy is not accommodating enough, demand is sluggish to respond to the shocks and firms take advantage of technology improvements to economize on labor input. While this mechanism has its own appeal, it most naturally applies to the intensive margin of the labor market since displacing workers must be more costly than changing prices when cost of displacement includes both the direct cost of firing and the value of the sunk investment in training and in job specific human capital that is lost with firing (see e.g. Mankiw, 1985 and Hamermesh, 1993 for a review of the literature). Admittedly, no formal model analyzing the trade-off between changing prices and displacing workers exists in the literature but one can conjecture that when the decision of changing prices is endogenous and menu cost a-la Caballero and Engel (2007) are used, this is the expected outcome. The evidence we have provided indicates instead that labor market adjustments to neutral shocks occur primarily at the extensive margin and the fall in hours is mostly caused by the time consuming process of reallocation of workers across productive units.

A possible alternative interpretation of our finding is that investment specific technological progress has standard neoclassical features, while the transmission of neutral shocks is consistent with the Schumpeterian view that the introduction of new neutral technologies causes the destruction of technologically obsolete productive units and the creation of new technologically advanced ones. When the labor market features search frictions, this process leads to a temporary rise in unemployment. Schumpeterian creative destruction matters for productivity dynamics at the micro level, see Foster et al. (2001) and it is a prominent paradigm in the growth literature, see Aghion and

Howitt (1994), Mortensen and Pissarides (1998), Violante (2002) and Hornstein et al. (2005). Caballero and Hammour (1994, 1996) and Michelacci and Lopez-Salido (2007) show how such a paradigm may also be relevant for business cycle analysis.

7 Robustness

This section briefly describes some robustness exercises we have undertaken. The conclusion is that our technology shocks are unlikely to stand in for other sources of disturbances and that our conclusions stand when we change i) the lag length of the VAR, ii) the way we remove low frequency fluctuations, iii) the timing of identifying restrictions, iv) the price deflator, and v) the labor market data and the series for the relative price of investment.

Other disturbances Despite the fact that our technology shocks do not proxy for omitted variables, it is still possible that they stand in for other sources of disturbances. To check for this possibility, we have correlated the estimated technology shocks obtained from the nine variables VAR with the approximated rates with oil prices (mnemonics `PZTEXP`) deflated by the consumption deflator and federal fund rate shocks (`FFED`), the latter computed filtering FFED with an AR(1). Figure 16 in Appendix 8 shows that correlations are insignificant.

VAR lag length The issue of the length of VAR has been recently brought back to the attention of applied researchers by Giordani (2004) and Chari et al. (2008), who show that the aggregate decision rules of a subset of the variables of a model may have not always be representable with a finite order VAR. This issue is unlikely to be important in our context since we have checked that the residuals of a VAR(8) are white noise and do not stand-in for other potential sources of shocks. To further investigate whether this is an issue, we have reestimated our VAR using 4 and 12 lags. The results using approximated rates are in Figure 18 in Appendix 8. The pattern of responses is unchanged. Our results are independent of chosen lag length one because the stochastic decay restriction we use effectively removes the noise that longer lags tend to produce in the VAR.

Alternative treatments of trends We have considered two alternatives to the dummy approach we employ in the paper to remove low frequency movements in the variables of the VAR: we have allowed up to a fifth order polynomial in time as intercept in the VAR; we filtered all the variables, before entering them in the VAR, with the Hodrick Prescott filter with a smoothing parameter $\lambda = 10000$. Figure 17 in Appendix 8 show that responses have the same shape and approximately the same size as with our benchmark specification.

Medium versus long-run identifying restrictions Uhlig (2004) has argued that disturbances other than neutral technology shocks may have long run effects on labor productivity and that, in theory, there is no horizon at which neutral (and investment specific) shocks fully account for the variability of labor productivity. Literally, this implies the neutral shocks we have extracted may not be structural. To take care of this problem Uhlig suggests to check if conclusions change when medium term restrictions are used. In Panel (a) and (b) of Figure 19 in Appendix 8 we report the responses obtained when the restrictions that the two shocks are the sole source of fluctuations in labor productivity and the price of investment is imposed at the time horizon of 3 years rather than in the long-run. The sign and the shape of responses are almost unchanged. Similar results are obtained if the restrictions are imposed at any horizon of at least one year.

Price deflators In our benchmark VAR, labor productivity and the relative price of investment are deflated with the output deflator. Intuitively, using this deflator is equivalent to use domestic consumption as a numeraire. As we previously mentioned, other authors have either used the CPI deflator or combination of output and CPI deflators. Such choice is potentially problematic since the identifying assumptions we employ are no longer valid using such deflators.

To see this recall that when the price of investment and total factor productivity have unit roots, a standard Solow economy evolves around the (stochastic) trend

$$X \equiv Z^{\frac{1}{1-\alpha}}\ Q^{\frac{\alpha}{1-\alpha}}$$

where Z is the TFP component and Q the price of investment component (see e.g. Michelacci and Lopez-Salido (2007)) and that the quantities $Y \equiv \tilde{Y}/\left(XN\right)$, and $K \equiv$

$\tilde{K}/(XQN)$ converge to $Y^* = (s/\delta)^{\frac{\alpha}{1-\alpha}}$ and $K^* = (s/\delta)^{\frac{1}{1-\alpha}}$, respectively. Consequently, the logged level of aggregate productivity, $y_n \equiv \ln \tilde{Y}/N$, evolves according to

$$y_n = y^* + v + x = y^* + v + \frac{1}{1-\alpha}z + \frac{\alpha}{1-\alpha}q \tag{2}$$

where small letters denote the log of the corresponding quantities in capital letters and v is a stationary term which accounts for transitional dynamics. Hence, the long run component of labour productivity is entirely due to the neutral and the investment specific shock.

Now, let q^c and y_n^c denote the inverse of the relative price of investment and labor productivity (both in logs), when deflated with the Consumer Price Index , P_c, defined as $P_c = \left(\frac{P_c^H}{a}\right)^a \left(\frac{P_c^F}{1-a}\right)^{1-a}$, where P_c^H and P_c^F are the prices of consumption goods produced in the US and abroad; and a represents the share of domestic consumption goods. Tedious calculations show that

$$y_n^c = cte + \frac{1}{1-\alpha-\beta}z + \frac{\alpha+\beta}{1-\alpha-\beta}q^c + \frac{1}{1-\alpha-\beta}(1-a)\left(p_c^H - p_c^F\right) \tag{3}$$

where α and β are the output elasticities to domestic and foreign capital, respectively. Hence, with this choice of numeraire, a permanent change in the real exchange rate could affect long run labor productivity and confused with "neutral" technology shocks (see also Kehoe and Ruhl (2007)). Since the real exchange rate exhibits remarkable persistence, one should worry about mixing neutral and real exchange rate shocks.

When we deflate the relative price of investment with the CPI index and output with the GDP deflator we obtain

$$y_n = cte + \frac{1}{1-\alpha-\beta}z + \frac{\alpha+\beta}{1-\alpha-\beta}q^c + \frac{\alpha+\beta}{1-\alpha-\beta}(1-a)\left(p_c^H - p_c^F\right),$$

and, again, a permanent change in $p_c^H - p_c^F$ has long run effects on productivity.

Our choice of deflator is the right one, in the sense that it implies a well defined balanced growth path in an open economy version of the Solow model, and does not suffer from tmisspecification issues. Nevertheless, it is worth investigating whether the results we obtain would be strongly altered if these alternatively deflators would be used. We have therefore computed responses for the VAR with approximated rates deflating output and the price of investment by the CPI (see Figures 20 in the Appendix). Responses are roughly similar to our benchmark ones. The main difference concerns the response of the price of investment to a neutral technology shock, which is more pronounced in this latter case.

Alternative data sets Elsby et al. (2007) have recently calculated an alternative series for the job finding and job separation rates, by slightly modifying the methodology of Shimer (2007). Jaimovich and Rebelo (2006) have also extended the series for the investment specific technology up to the mid 2000's. Our results are unchanged when these alternative series for labor market flows and for q are used in the VAR.

8 Conclusions

We analyzed the labor market effects of neutral and investment specific technology shocks on unemployment, job finding, job separation rates and other labor market variables. We show that positive neutral technology shocks affect labor market variables primarily along the extensive margin and substantially increase unemployment. Positive investment specific technology shocks, on the other hand, expand aggregate hours worked, both because hours per worker increase and because unemployment falls, but the intensive margin contributes most to the adjustments. For both shocks, the impact response of unemployment is almost entirely due to the instantaneous response of the separation rate while movements in the finding rate account for the dynamic adjustments of unemployment. Thus, positive neutral shocks can cause recessions and the induced flows in and out of unemployment are in line with the conventional wisdom: unemployment initially rises because of a wave of layoffs and remains high because the job finding rate takes time to recover.

We find that technology shocks explain around 30 per cent of the cyclical fluctuations in labor market variables with neutral technology shocks mattering primarily for the volatility of unemployment and investment specific technology shocks for the volatility of hours worked. We also show that our neutral technology shocks accurately characterize the "jobless" recovery of the early 90's and that all our findings are robust to a number of specification choices, to the selection of price deflators and to changes in auxiliary assumptions.

This evidence casts doubts on the recent tendency to use search models with exogenous separation rates to analyze the effects of technology shocks and qualifies the conclusions by Hall (2005) and Shimer (2007). It also challenges the standard sticky price explanation for why hours fall in response to neutral technology shocks, since the mechanism emphasized in these models primarily applies to the intensive margin, while we find that the extensive margin plays a key role in the adjustment. The evidence may instead be consistent with the idea that investment specific technological progress has standard neoclassical features, while neutral technological progress is Schumpeterian. According to this view the introduction of new neutral technologies causes the destruction of technologically obsolete productive units and the creation of new technologically advanced ones. When the labor market is characterized by search frictions, these adjustments lead to a temporary rise in unemployment.

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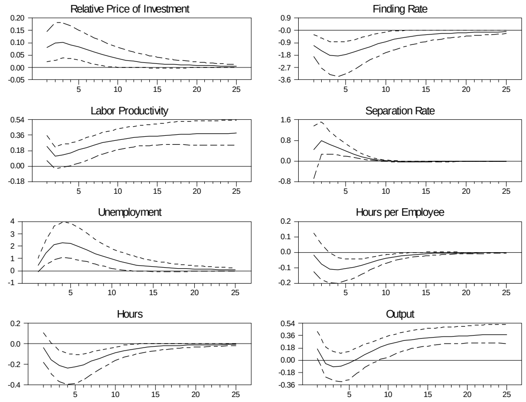
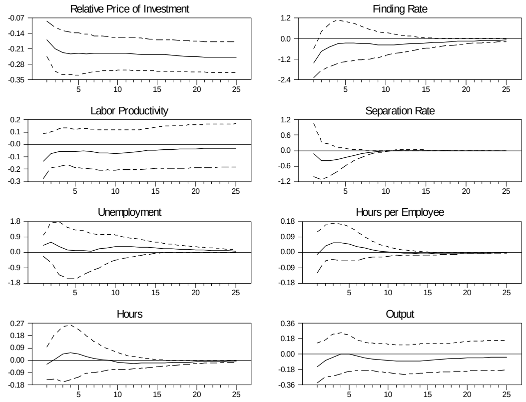
THIS APPENDIX CONTAINS ADDITIONAL EMPIRICAL RESULTS. IT IS PROVIDED FOR BACKING UP STATEMENTS MADE IN THE PAPER AND IT IS NOT INTENDED FOR PUBLICATION.

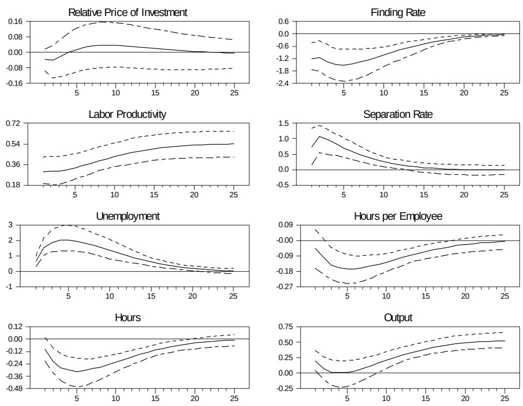


(a) Neutral technology shock

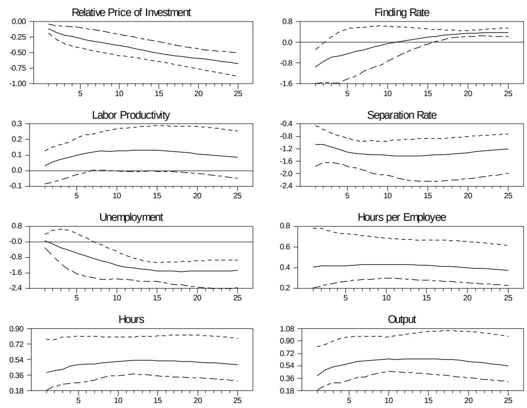


(b) investment specific technology shock

Figure 10: The sample period is 1955:I-1973:I. The VAR has eight lags and contains six variables: the rate of growth of the relative price of investment, t he rate of growth of labour productivity, the (logged) job finding rate, the (logged) job separation rate, the (logged), unemployment rate (logged), and the (logged) aggregate number of hours worked per capita. Dotted lines represent the 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 500 times the residuals of the VAR. The continuous line corresponds to median estimate from bootstrap replications.

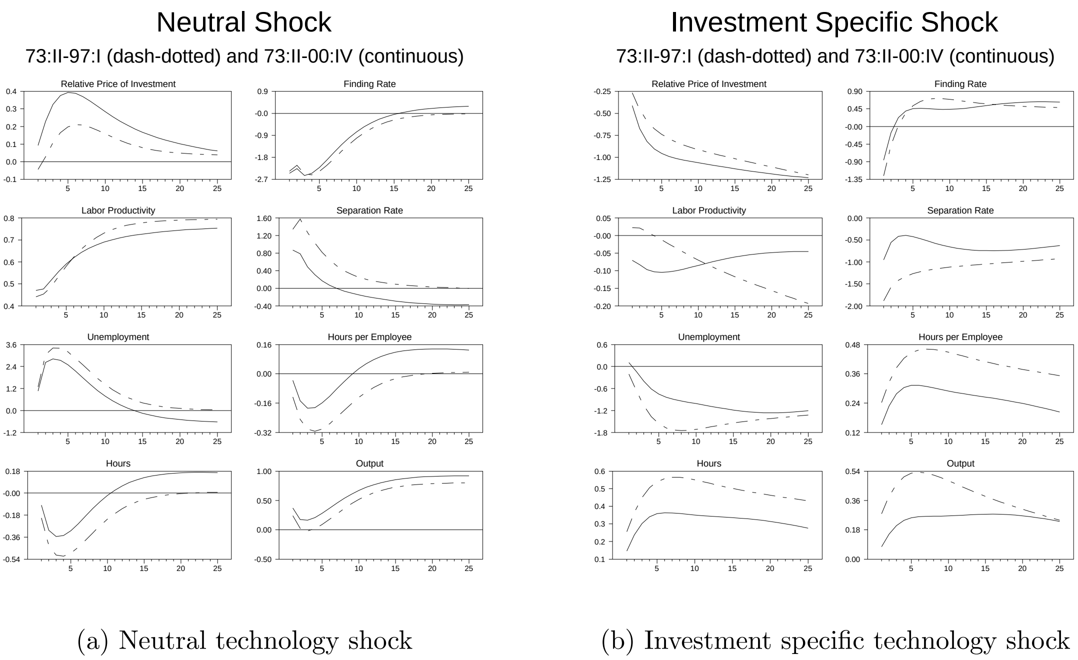


(a) Neutral technology shock



(b) Investment specific technology shock

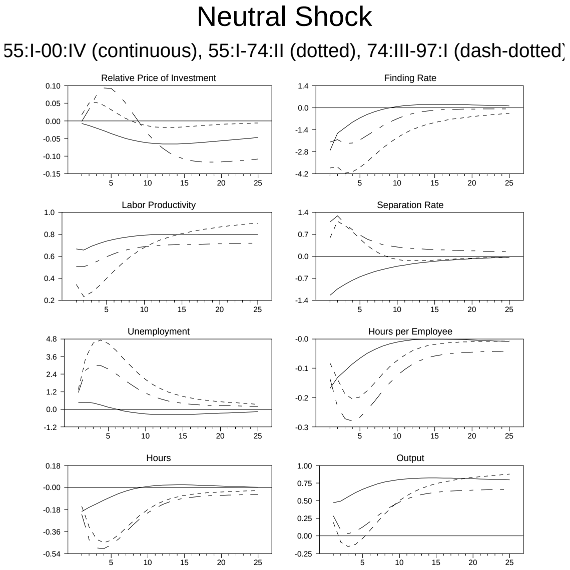
Figure 11: The sample period is 1973:II-1997:II. The VAR has eight lags and contains six variables: the rate of growth of the relative price of investment, the rate of growth of labour productivity, the (logged) job finding rate, the (logged) job separation rate, the (logged), unemployment rate (logged), and the (logged) aggregate number of hours worked per capita. Dotted lines represent the 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 500 times the residuals of the VAR. The continuous line corresponds to median estimate from bootstrap replications.



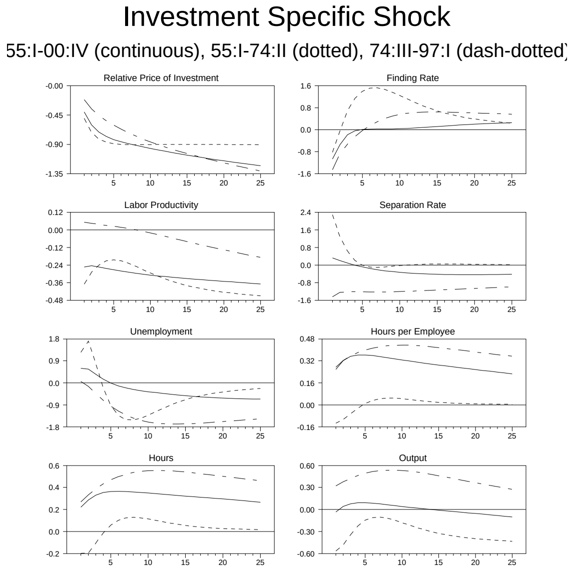
(a) Neutral technology shock

(b) Investment specific technology shock

Figure 12: Response to a neutral or an investment-specific technology shock in two different subperiods: 1973:II-1997:I, and 1973:II-2000:IV. The VAR has 8 lags and six variables: the rate of growth of the relative price of investment, the rate of growth of labour productivity, the (logged) unemployment rate, and the (logged) aggregate number of hours worked per capita, the log of separation and finding rates. The continuous line correponds to the 1973:II-2000:IV period, and the dash-dotted line to the 1973:II-1997:II period. Impulse responses correspond to point estimates.

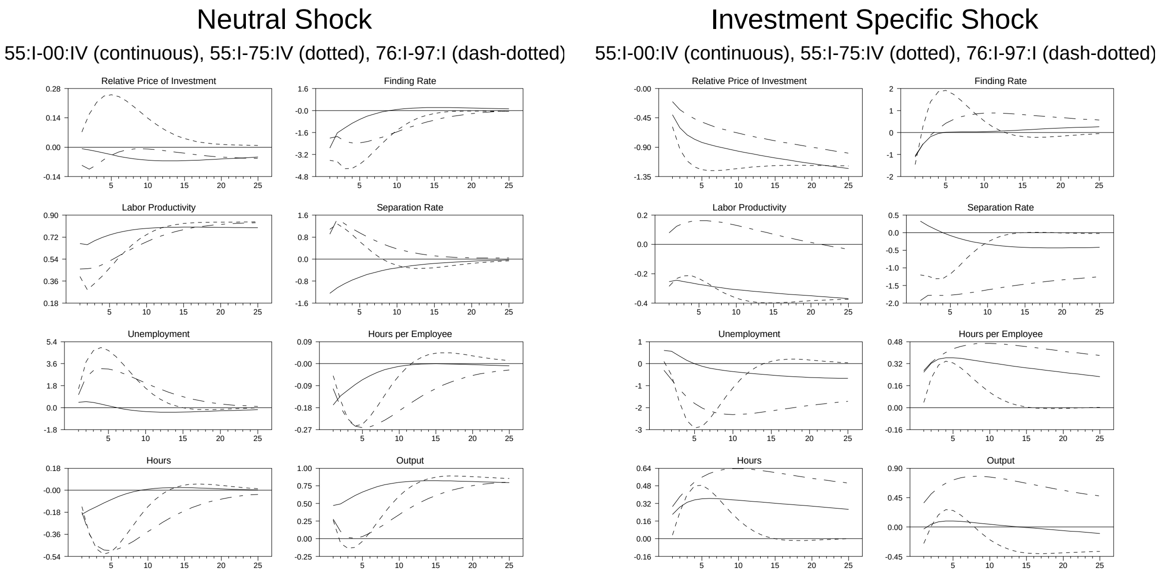


(a) Neutral technology shock



(b) Investment specific technology shock

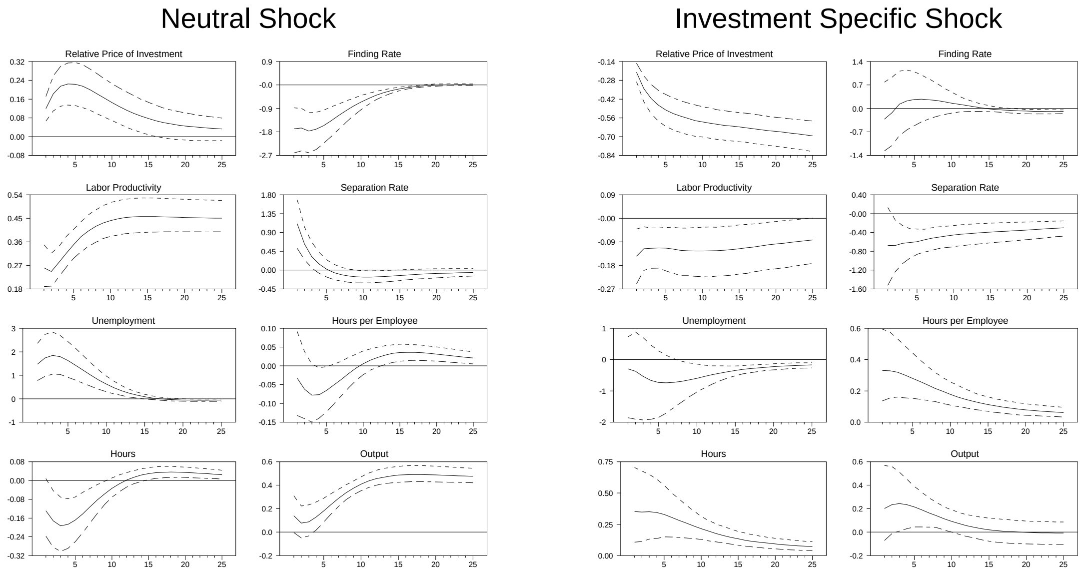
Figure 13: Responses to a one-standard deviation shocks in thre different subsamples. The subsamples are: 1955:I-2000:IV, 1955:I-1974:II, and 1974:III-1997:I. Each line corresponds to a six variable VAR(8) with the rate of growth of the relative price of investment, the rate of growth of labour productivity, the (logged) unemployment rate, and the (logged) aggregate number of hours worked per capita, the log of separation and finding rates, estimated over a different sample period.



(a) Neutral technology shock

(b) Investment specific technology shock

Figure 14: Responses to a one-standard deviation shocks in thre different subsamples. The subsamples are: 1955:I-2000:IV, 1955:I-1975:IV, and 1976:I-1997:I. Each line corresponds to a six variable VAR(8) with the rate of growth of the relative price of investment, the rate of growth of labour productivity, the (logged) unemployment rate, and the (logged) aggregate number of hours worked per capita, the log of separation and finding rates, estimated over a different sample period.



(a) Neutral technology shock

(b) Investment specific technology shock

Figure 15: Response to a neutral or an investment-specific technology shock in a nine variables VAR with approximated rates. 1955:I-2000:IV sample with intercept deterministically broken at 1973:II and 1997:I. Dotted lines represent the 5% and 95% quantiles of the distribution of the responses simulated by bootstrapping 500 times the residuals of the VAR. The continuous line corresponds to median estimate.

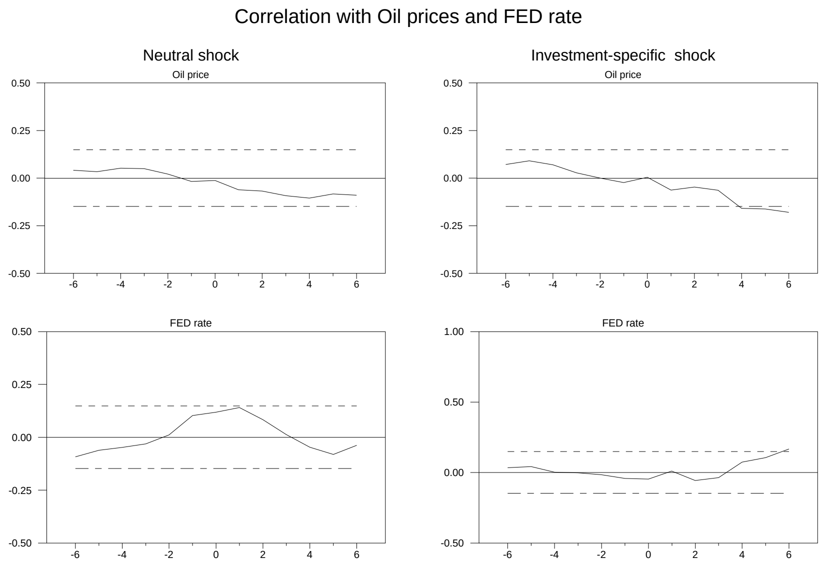
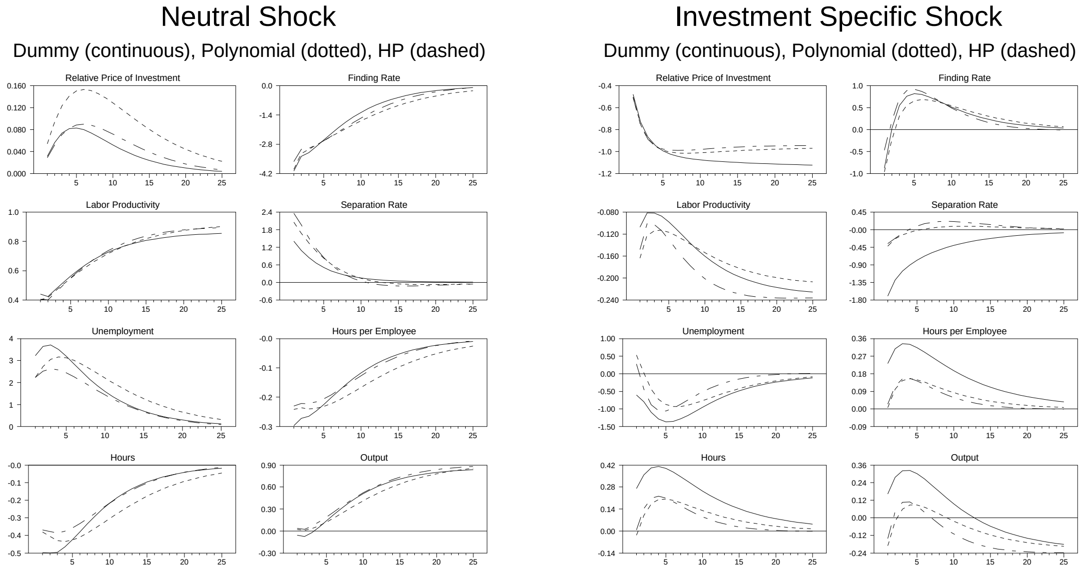


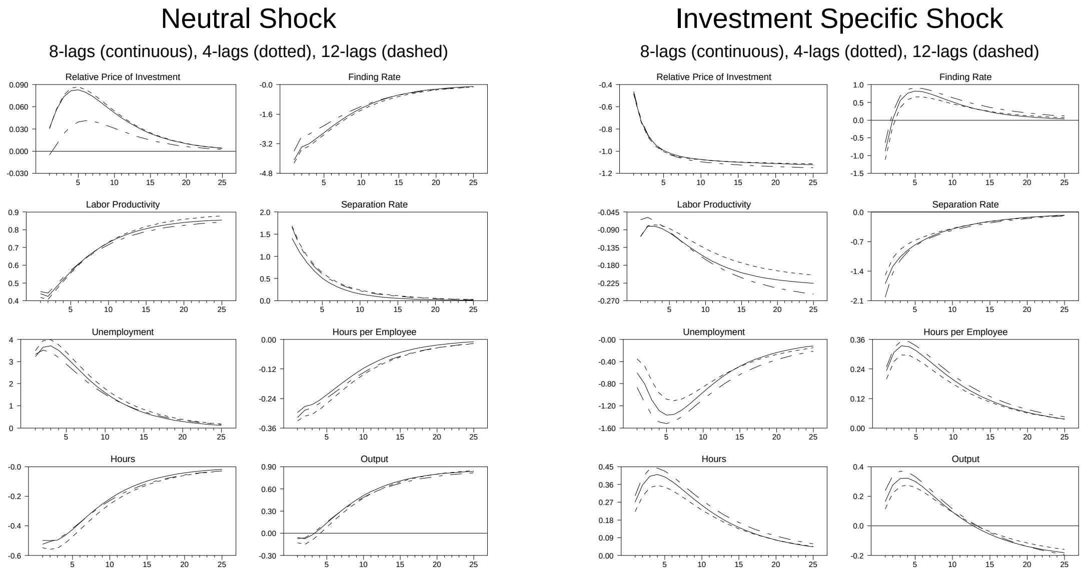
Figure 16: Left column corresponds to neutral technology shocks; right column to investment specific technology shocks. The first row plots the correlation of the corresponding technology shock with relative oil price shocks (i.e. relative to consumption). The second row with Federal fund rate shocks at different time horizons. The shocks are estimated from the nine variables VAR, approximated rates, full sample with deterministic dummies. The horizzontal lines correspond to an asymptotic 95 percent confidence interval centered around zero.



(a) Neutral technology shock

(b) Investment specific technology shock

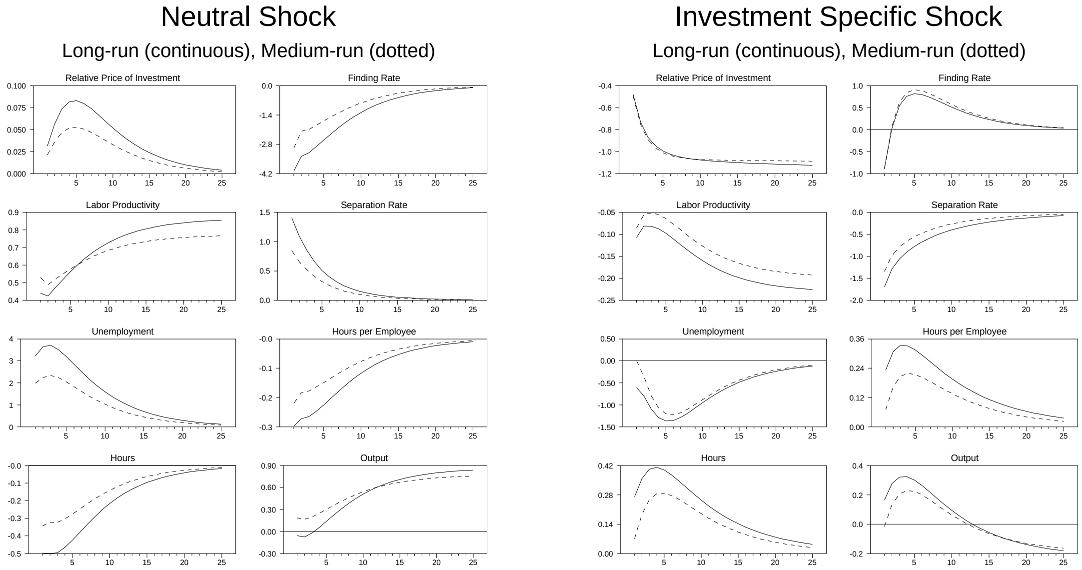
Figure 17: The continous line corresponds to dummy specification, the dotted line to the case where the intercept is a 3rd order polynomial in time. The dashed lines are the responses after detrending the original series with an Hodrick Prescott filter with smoothing parameter $\lambda = 10000$. VAR with approximated rates, with 8 lags, and six variables. Plotted impulse responses correspond to point estimates.



(a) Neutral technology shock

(b) Investment specific technology shock

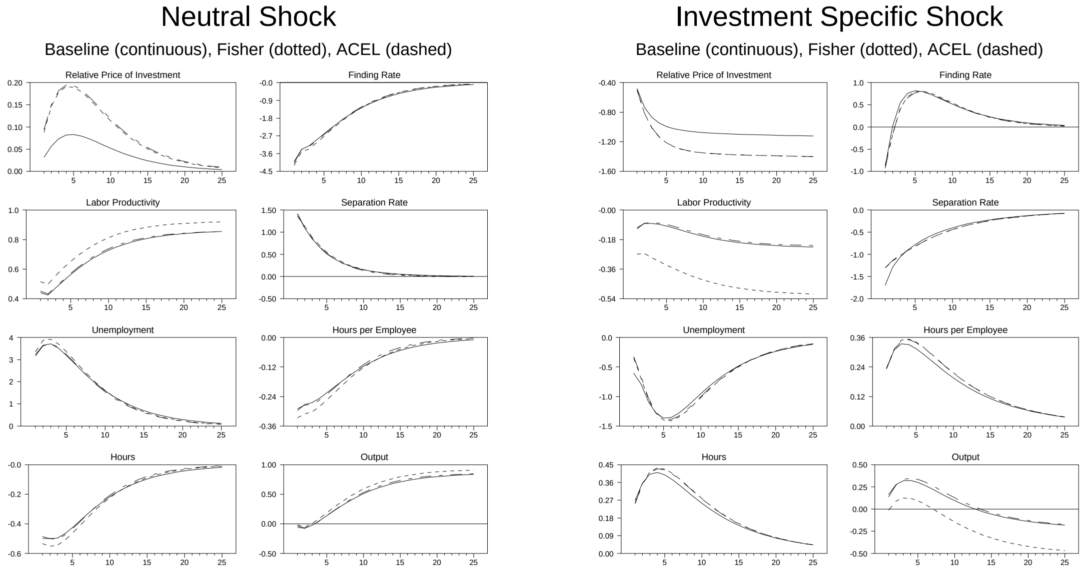
Figure 18: Dummy specification with different lags in the VAR: continous line corresponds to 8 lags, dotted line to 4 lags, dashed line to 12 lags. VAR with approximated rates, with 8 lags, and six variables. Plotted impulse responses correspond to point estimates.



(a) Neutral technology shock

(b) Investment specific technology shock

Figure 19: Dummy specification with identifying restrictions imposed at different time horizons: continous line corresponds to long run restriction, dotted line corresponds to the specification where restrictions are imposed at an horizon of 3 years. VAR with approximated rates, with 8 lags, and six variables. Plotted impulse responses correspond to point estimates.



(a) Neutral technology shock

(b) Investment specific technology shock

Figure 20: Results from VAR in the dummy specification when the variables in VAR are deflated with a different price index: continuous line corresponds to baseline specification, dotted line corresponds to the VAR where output and price of investment are deflated by using the CPI index, the dashed line corresponds to the case where output is deflated with the output deflator and the price of investment with the CPI index. VAR with approximated rates, with 8 lags, and six variables. Plotted impulse responses correspond to point estimates.