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LABOR MARKET DYNAMICS: A TIME-VARYING ANALYSIS

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Labor Market Dynamics: a Time-varying Analysis*

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Abstract

This paper studies how key labor market stylized facts and the responses of labor market variables to technology shocks vary over the US postwar period. It uses a benchmark DSGE model enriched with labor market frictions and investment specific technological progress that enables a novel identification scheme based on sign restrictions on a SVAR with time-varying coefficients and stochastic volatility. Key findings are: *i)* the volatility in job finding and separation rates has declined over time, while their correlation varies across time; *ii)* the job finding rate plays an important role for unemployment, and the two series are strongly negatively correlated over the sample period; *iii)* the magnitude of the response of labor market variables to technology shocks varies across the sample period.

JEL Classification: E32, C32.

Keywords: Technology shocks, labor market frictions, Bayesian SVAR methods, sign restrictions.

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1 Introduction

The dynamics of the labor market has been a subject of intense empirical and theoretical research over the past three decades. This paper contributes to this realm of research by studying how the statistical relation among key labor market aggregates and their response to technology shocks change over the US postwar period. To this aim, it develops an estimated time-varying parameter vector autoregression (TVP-VAR) model with stochastic volatility, whose variables' reaction to technology shocks is identified using the cyclical properties of a dynamic, stochastic, general equilibrium (DSGE) model of the business cycle characterized by labor market frictions.

We use a model with labor market frictions to investigate the dynamics of the labor market due to their empirical relevance and theoretical appeal. Empirically, Rogerson and Shimer (2011) summarize evidence showing that labor markets are characterized by frictions that prevent the competitive market mechanism from determining labor market equilibrium allocations, thereby suggesting that their presence is important for a realistic description of the functioning of the labor market. Theoretically, labor market frictions introduce the extensive margin of labor (i.e. (un)employment) into the model, whose dynamics depend on the flows of workers in and out of unemployment. Importantly for the analysis of the paper, we make the rate at which jobs are destroyed endogenous, so that flows in and out of unemployment result from the incentives that workers and firms have to engage in production or terminate their relation. In this way, the theoretical framework details the dynamics of unemployment, job finding and job separation rates, whose reaction to shocks enables a new identification scheme.

The analysis establishes important stylized facts of the US labor market. In particular, it uncovers the following findings:

- The volatility of job finding and job separation rates declines over the sample period, after reaching a peak around the mid-1980s. However, changes in the volatility of the job finding and job separation rates display different patterns over sub-periods.

- The correlation of the labor market variables with GDP growth is relatively stable over time, whereas the correlation between the job finding and job separation rates and the unemployment rate shows significant time variation. In particular, the job finding rate plays an important role for the unemployment rate, and the two series are strongly negatively correlated over the sample period.

• The magnitude of the response of labor market variables to neutral technology shocks varies over time, whereas the response to investment specific technology shocks is substantially constant. Neutral technology shocks decrease unemployment.

• Across the sample period, neutral technology shocks explain approximately half of the movements in unemployment and the job finding rate, whereas they explain only 20% of fluctuations in the job separation rate. Investment specific technology shocks contribute to, on average, less than 20% of fluctuations in unemployment, job finding and job separation rates.

• The time-varying trends of the job separation rate and the unemployment rate show a similar pattern, and they peak in the early 1980s.

The contribution of this paper is threefold. First, to the best of our knowledge no papers have yet investigated how the statistical relation among key labor market variables and their response to technology shocks change over time. A few studies, detailed below, investigate the time-varying response of macroeconomic variables to shocks, but none of them focuses on the dynamics of the labor market.

Second, the theoretical framework embeds endogenous job destruction in a model in which technology shocks are distinguished between neutral and investment specific technological processes, since the latter are key to study the dynamics of the technological progress, as shown in Greenwood, Hercowitz and Krusell (1997), Fisher (2006) and Justiniano and Michelacci (2011). Therefore the model provides new insights into the time-varying effect of investment specific technology shocks on labor market variables, and, importantly for our analysis, enables a novel identification scheme.

Finally, we propose a novel identification scheme based on sign restrictions that uses information from real activity, job finding and separation rates and unemployment. In this way, our high-frequency identification scheme imposes a minimal set of constraints on the model compared to low- or medium-frequency identification restrictions. This is particularly important in the context of labor market variables, since Fernald (2007) points out that any procedure that includes low- or medium-frequencies generates an artificial positive comovement between labor input and neutral technology shocks that disappears once controlling for long cycles. In general, Faust and Leeper (1997) and Chari, Kehoe and McGrattan (2008) show that long-run restrictions may generate unreliable estimates as they are unable to accurately recover true underlying impulse response functions when estimated using data generated from a structural model.

Before proceeding we relate this study to the literature. This paper contributes to two strands of the literature. First, it contributes to the literature that studies the cyclical properties of the labor market. Shimer (2012), Elsby, Michaels and Solon (2009), Elsby, Hobijn and Sahin (2010) and Elsby, Hobijn and Sahin (2013) identifies important labor market stylized facts using business cycle statistics. We enrich this realm of research by allowing for time variation in the analysis, thereby uncovering changes in labor market dynamics across time. In addition, we also allow for both neutral and investment specific technology shocks, so as to provide a more comprehensive assessment of the influence of technological process on the dynamics of the labor market. Michelacci and Lopez-Salido (2007) and Ravn and Simonelli (2008) use theoretical models with labor market frictions to identify the effect of technology shocks using a SVAR. Compared to these studies, we use worker flows and allow for time variation of coefficients and stochastic volatility in the estimation. Similarly to us, studies by Gali and Gambetti (2009), Primiceri (2005), Cogley, Primiceri and Sargent (2010) and Benati and Surico (2008) investigate the time-varying response of macroeconomic variables such as output, inflation, monetary aggregates and the nominal interest rate to shocks. However, our focus is on the dynamics of the labor market, and we identify shocks using short-run restrictions.

Second, this paper contributes to the literature on the identification of technology shocks. Similarly to us, Uhlig (2004), Dedola and Neri (2007), Paustian (2007), Pappa (2009), Canova and Paustian (2011) and Mumtaz and Zanetti (2012), use short-run identification schemes to investigate the reaction of labor input to technology shocks. However, none of these studies, with the exception of Mumtaz and Zanetti (2012), uses restrictions based on labor market variables. In particular, this last study identifies technology shocks using labor market variables such as hiring and labor market tightness. Instead, we identify technology shocks based on their effect on real activity, job finding and separation rates and unemployment, whose interaction provides a theoretically consistent characterization of the relation among labor market variables. Finally, all these mentioned studies focus on the impact of technology shocks, whereas our paper focuses on how the statistical relations among key labor market aggregates and their responses to technology shocks change over the US postwar period.

The remainder of the paper is organized as follows. Section 2 lays out the theoretical model, describes the model's solution and calibration. Section 3 details the sign restrictions from the theoretical model. Section 4 describes the TVP-VAR model with stochastic volatility and the implementation of the identification scheme. Section 5 presents the results. Section 6 concludes.

2 The theoretical model

We now present a model with search and matching frictions that resembles Mumtaz and Zanetti (2012). However, we enrich the theoretical framework with endogenous job destruction, as in Mortensen and Pissarides (1994) and Thomas and Zanetti (2009), which relates movements in both job creation and finding rates to changes in the endogenous variables and exogenous changes to technology. In addition, we also embed the investment specific technology progress as in Greenwood et al. (1997).

The model economy is populated by three types of agents: households, firms and a fiscal authority. Households consist of a large number of members, a fraction of which are unemployed and searching for jobs. On the other side of the labor market, firms hire workers. The fiscal authority simply balances the budget in every period. The rest of this section describes the agents' tastes, technologies, and the structure of the labor market in detail.

2.1 Firms

Employment relationships are taken to consist of two agents, a worker and a firm, which engage in production through discrete time until the relationship is severed. There exists a continuum of firms indexed on the unit interval. Inside any firm i, the timing of hiring and firing proceeds as follows. At the start of the period, a fraction λ^x of last period's workers are exogenously separated from the firm. Aggregate shocks are then realized, after which the firm hires a number h_{it} of workers. Once the hiring round has taken place, continuing workers receive an i.i.d. idiosyncratic productivity shock, z. Let $G(z)$ and $g(z)$ denote the cumulative distribution function and the density of z, respectively. Those workers whose new idiosyncratic productivity falls below a certain reservation productivity z_{it}^R (to be determined below) become unprofitable and their jobs are destroyed, whereas the remaining workers start producing immediately. The law of motion of the firm's workforce, n_{it}, is therefore given by

$$n_{it} = \left[1 - G(z_{it}^R)\right](1 - \lambda^x) n_{it-1} + h_{it}, \tag{1}$$

where $G(z_{it}^R)$ is the fraction of new and continuing workers that are endogenously separated from the firm and h_{it} is the number of new hires at time t.

The firm's production function is given by

$$y_{it} = a_t k_{it}^{\theta} n_{it}^{1-\theta} \int_{z_{it}^R} z \frac{g(z)}{1 - G(z_{it}^R)} dz \equiv a_t k_{it}^{\theta} n_{it}^{1-\theta} H(z_{it}^R), \tag{2}$$

where $H(z_{it}^R)$ is the conditional expectation $E[z \mid z \geqslant z_{it}^R]$, and a_t is the neutral technology shock, which follows the autoregressive process

$$\ln a_t = \rho_a \ln a_{t-1} + \varepsilon_t^a, \tag{3}$$

with $0 < \rho_a < 1$, and where the zero-mean, serially uncorrelated innovation ε_{at} is normally distributed with standard deviation σ_a.

2.1.1 Profit maximization

Subject to equations (1) and (2), the firm maximizes its profits,

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left\{ y_{it} - n_{it}\overline{w}_{it} - k_{it}q_t - h_{it}\chi_t \right\}, \tag{4}$$

where E_0 refers to the expectations at time $t = 0$, $\beta^t \lambda_t$ measures the marginal utility value to the representative household of an additional dollar in profits received during period t, $\overline{w}_{it} \equiv \int_{z_{it}^R} w_{it}(z) \frac{g(z)}{1-G(z_{it}^R)} dz$ is the average real wage for firm i, $w_{it}(z)$ is the real wage paid to the worker with idiosyncratic productivity z, q_t is the remuneration rate for each unit of capital k_{it}, and χ_t is the real cost of hiring (defined below), which is taken as given by each firm i. Thus the firm chooses $\{k_{it}, n_{it}, z_{it}^R\}_{t=0}^{\infty}$ to maximize equation (4) subject to equations (1) and (2). By substituting equations (1) and (2) into equation (4) for y_{it} and h_{it} respectively, the first order conditions are

$$q_t = \theta y_{it}/k_{it} \tag{5}$$

$$\overline{w}_{it} = (1-\theta) y_{it}/n_{it} - \chi_t + \beta E_t(\lambda_{t+1}/\lambda_t) \left[1 - G(z_{it}^R)\right] \chi_{t+1}, \tag{6}$$

$$a_t k_{it}^{\theta} n_{it}^{-\theta} \left[H(z_{it}^R) - z_{it}^R\right] - \left[\overline{w}_{it} - w_{it}(z_{it}^R)\right] - \beta E_t(\lambda_{t+1}/\lambda_t) \left[1 - G(z_{it}^R)\right] \chi_{t+1} = 0. \tag{7}$$

Equation (5) states that the rate of capital remuneration, q_t, equals the marginal product of capital in each period t, $\theta y_{it}/k_{it}$. Equation (6) equates the average real wage, $\overline{w}_{it}$, to the marginal rate of transformation. The marginal rate of transformation depends on the marginal product of labor, $(1-\theta)y_{it}/n_{it}$, but also, due to the presence of labor market frictions, on present and future foregone costs of hiring. The latter two components are the cost of hiring an additional worker, χ_t, net of the savings in hiring costs resulting from the reduced hiring needs in period $t+1$ if the job survives job destruction, $\beta(\lambda_{t+1}/\lambda_t)\left[1 - G(z_{it}^R)\right] \chi_{t+1}$. In a model without labor market search only the marginal product of labor appears. Finally, equation (7) states that the value of the worker with idiosyncratic productivity z_{it}^R is exactly equal to zero, i.e. the firm is indifferent between keeping this worker or not.

2.2 Households

There exists a representative household. A fraction n_t of its members are employed. The remaining members are unemployed and searching for jobs. All members pool their resources so as to ensure equal consumption.[1] The household maximizes utility from consumption,

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(c_t) - \xi n_t^{1+\phi}/(1+\phi) \right], \tag{8}$$

subject to the following period budget constraint,

$$\int_0^1 n_{it} \overline{w}_{it} di + k_t q_t + (1 - n_t) b_t + \Pi_t = c_t + \tau_t + i_t, \tag{9}$$

where $\int_0^1 n_{it} \overline{w}_{it} di$ is the remuneration of labor, $k_t q_t$ is the remuneration from renting k_t units of capital at the rate q_t, b_t is the worker outside option (defined below), Π_t are real profits reverted from the firm sector to households in a lump-sum manner, i_t are the units of output invested and τ_t are real lump-sum taxes. By investing i_t units of output during period t, the household increases the capital stock k_{t+1} available during period $t+1$ according to

$$k_{t+1} = (1 - \delta_k) k_t + \upsilon_t i_t, \tag{10}$$

where the depreciation rate satisfies $0 < \delta_k < 1$ and the disturbance υ_t is the Greenwood et al. (1997) investment specific technology shock, which follows the autoregressive process

$$\ln(\upsilon_t) = \rho_\upsilon \ln(\upsilon_{t-1}) + \varepsilon_{\upsilon t}, \tag{11}$$

with $0 < \rho_\upsilon < 1$, and where the zero-mean, serially uncorrelated innovation $\varepsilon_{\upsilon t}$ is normally distributed with standard deviation σ_υ. Thus the household chooses $\{c_t, k_{t+1}, i_t\}_{t=0}^{\infty}$ to maximize its utility (8) subject to the evolution of capital stock (10) and the budget constraint (9) for all $t = 0, 1, 2, ...$ Substituting equation (10) into (9) for i_t and letting λ_t denote the

[1] The assumption of perfect insurance of unemployment risk is standard in the search and matching literature.

non-negative Lagrange multiplier on the resulting equation, the first order conditions are

$$\lambda_t = 1/c_t, \tag{12}$$

and

$$\lambda_t/\upsilon_t = \beta E_t \lambda_{t+1}[q_{t+1} + (1-\delta_k)/\upsilon_{t+1}]. \tag{13}$$

According to equation (12), the Lagrange multiplier equals the household's marginal utility of consumption. Equation (13) is the standard Euler equation for capital, which links the intertemporal marginal utility of consumption with the real remuneration of capital.

2.3 The labor market and wage bargaining

At the beginning of period t, there is a pool of jobless individuals who are available for hire, and whose size we denote by U_t. For all $t = 0, 1, 2, ...$, the fraction of aggregate employment and hires supplied by the representative household must satisfy $n_t = \int_0^1 n_{it} di$, and $h_t = \int_0^1 h_{it} di$ respectively, while the aggregate reservation productivity satisfies $z_t^R = \int_0^1 z_{it}^R di$. Accounting for job destruction, the pool of the household's members who are unemployed and available to work before hiring takes place is:

$$U_t = 1 - \left[1 - G(z_t^R)\right](1 - \lambda^x) n_{t-1}. \tag{14}$$

Firms are assumed to be large, such that the probability of the firm hiring a worker is the ratio of new hires over the number of unemployed workers such that:

$$x_t = h_t/U_t, \tag{15}$$

with $0 < x_t < 1$, given that all new hires represent a fraction of the pool of unemployed workers. The job creation rate, x_t, is also an index of labor market tightness, since it indicates the proportion of hires over the number of workers in search of a job. The cost of hiring a worker is equal to χ_t and, as in Blanchard and Gali (2010) and Mandelman and Zanetti

(2014), is a function of labor market tightness x_t:

$$\chi_t = Bx_t^{\alpha}, \tag{16}$$

where α is the elasticity of labor market tightness with respect to hiring costs, such that $\alpha \geq 0$; and B is a scale parameter, such that $B \geq 0$. As pointed out in Rotemberg (2008), this formulation expresses the idea that the tighter the labor market the more costly hiring may be. Note that given the assumption of full participation, the unemployment rate, defined as the fraction of household members without a job after hiring takes place, is

$$u_t = 1 - n_t. \tag{17}$$

Each firm negotiates wages with its employees on a period-by-period basis. As is standard in the search and matching literature, we assume Nash wage bargaining, which implies that the firm and each worker split the joint surplus of their employment relationship. The joint surplus is the sum of the firm's surplus and the worker's surplus. The worker with idiosyncratic productivity z enjoys the following surplus, $S_{it}^{w}(z) = W_{it}(z) - U_{it}(z)$, where $W_{it}(z)$ and $U_{it}(z)$ are the present-discounted values of employed and unemployed workers respectively, and

$$W_{it}(z) = w_{it}(z) + E_t\beta_{t,t+1}[(1-\rho^x)\int_{z_{it+1}^R}^{\infty} W_{it+1}(z)dF(z) + \rho_{t+1}(z)U_{it+1}(z)], \tag{18}$$

and

$$U_{it}(z) = b_t + E_t\beta_{t,t+1}[x_t W_{it+1}(z) + (1-x_t)U_{it+1}(z)], \tag{19}$$

where $\beta_{t,t+1} = \beta\lambda_{t+1}/\lambda_t$ is the stochastic discount factor, and ρ_{t+1} is the total job separation rate at time $t+1$, defined as

$$\rho_{t+1}(z) = \lambda^x + (1-\lambda^x)G(z_t^R). \tag{20}$$

Equation (18) states that the value of a job for a worker is given by the wage and the expected-discounted net gain from continuing to work. Equation (19) states that the value of unemployment is made up of the yield b_t and the expected-discounted capital gain from the change of state. As described by Pissarides (2000), we assume that b_t equals the marginal rate of substitution between consumption and leisure, which represents the disutility value of being unemployed, such that

$$b_t = \xi n_t^{\phi} / \lambda_t. \tag{21}$$

The firm's surplus from an established employment relationship, denoted by S_t^f, is simply given by $S_t^f = B x_t^{\alpha}$, since any current worker can be immediately replaced with someone who is unemployed by paying the hiring cost.

Let $\eta \in (0,1)$ denote the household's bargaining power. Nash bargaining implies the following surplus-sharing rule, $\eta S_t^f = (1-\eta) S_{it}^w(z)$. Combining the latter equation with the expressions for S_t^f and $S_t^w(z)$, we obtain the following solution for the real wage,

$$w_{it}(z) = \eta \left[(1-\theta) a_t z y_t / n_t + x_t \chi_t \right] + (1-\eta) b_t. \tag{22}$$

Equation (22) states that workers receive a wage made up of two parts. First, for a fraction η, from the revenue product generated, $(1-\theta) a_t z y_t / n_t$, and a reward for the saving in hiring costs, $x_t \chi_t$. Second, for a fraction $1-\eta$, from the real return of unemployment, b_t. The reservation wage $w_{it}^R(z_t^R)$ is derived by assuming $z = z_t^R$ in equation (22).

2.4 Fiscal authority

The fiscal authority is assumed to adjust lump-sum taxes, τ_t, so as to balance its budget in every period,

$$\tau_t = (1-n_t) b_t. \tag{23}$$

2.5 Model solution and calibration

In a symmetric, dynamic equilibrium, all firms make identical decisions, which allows us to suppress the i subscripts. Combining the firm's profit conditions (4), the household's budget constraint (9) and the fiscal authority's budget constraint (23) produces the aggregate resource constraint

$$y_t = c_t + i_t + h_t\chi_t. \tag{24}$$

Equating the remuneration of capital from equation (5) to equation (13), and also accounting for equations (1)-(3), (6), (7), (10), (11), (12), (14)-(17), (20)-(22), (24), and the definition of w_t^R, the model describes the behavior of the 18 endogenous variables $\{y_t, c_t, \lambda_t, n_t, k_t, U_t, u_t, h_t, i_t, \chi_t, x_t, z_t^R, \rho_{t+1}, \overline{w}_t, w_t^R, b_t, a_t, \upsilon_t\}$, and the persistent autoregressive processes of the exogenous shocks $\{\varepsilon_{at}, \varepsilon_{\upsilon t}\}$. The system is approximated by loglinearizing its equations around the stationary steady state and the solution is derived using Klein (2000).

The model is calibrated on quarterly frequencies using US data. Since the model is used to identify the sign of the variables' response to shocks, we need to ensure that the reactions are robust across a broad range of parameters' calibration. For this reason, as in Dedola and Neri (2007), Pappa (2009) and Mumtaz and Zanetti (2012), we assume that most of the parameters' values are uniformly and independently distributed over a wide range of plausible values. The range value for each parameter is described below and reported in Table 1. In a model with endogenous job destruction, the steady state is highly sensitive to the calibration of labor market parameters, as documented in Christiano, Trabandt and Walentin (2010). For this reason, in order to ensure a plausible steady state and the existence of a unique solution, we fix the value of certain labor market parameters, while allowing changes in all the remaining parameters, as detailed below. We start by describing the calibration of the parameters that are allowed to vary.

We allow the real interest rate to vary between 2 and 6.5 percent annually, which are the values that are commonly used in the literature, and they pin down the quarterly discount factor β between 0.985 and 0.995. Consistent with US data, the steady-state value of the exogenous job separation rate, λ^x, is allowed to vary between 2.5 and 3.5 percent, which is almost one half the total separation rate,[2] and the steady-state value of the capital destruction rate, δ_k, is set between 0 and 5 percent, as in King and Rebelo (1999). The parameter of the production capital share, θ, is set between 0.2 and 0.4 in line with studies such as Ireland

[2] den Haan, Ramey and Watson (2000) set λ^n/ρ to 32%, whereas Pissarides (2007) estimates that endogenous separations account for 60% of all separations. The midpoint of these estimates is 46%.

(2004) and King and Rebelo (1999). We need to set a value for B, which determines the steady-state share of hiring costs over total output, $\chi h/y$. Since precise empirical evidence on this parameter is unavailable, in line with Blanchard and Gali (2010), we choose B such that hiring costs represent between 0.05 and 1 percent of total output, which covers reasonable lower and upper bounds for this parameter. The steady-state values of the neutral and investment specific technological progresses, a and υ are conveniently set equal to 1, as they do not affect the dynamics of the system. The autoregressive coefficients of the neutral and investment specific technological progresses, ρ_a and ρ_υ, are free to vary between 0.75 and 0.99 in line with King and Rebelo (1999) and Ireland (2003). The standard deviation of the neutral and investment specific technological progresses, σ_a and σ_υ, are normalized to be equal to 1%.

The rest of the parameters are fixed. As in Blanchard and Gali (2010), to satisfy the Hosios condition, which ensures that the equilibrium of the decentralized economy is Pareto efficient, we impose that the relative bargaining power of the worker, $\eta/(1-\eta)$, is equal to the elasticity of labor market tightness with respect to hiring costs, α, such that $\eta/(1-\eta) = \alpha$.[3] As estimated in Petrongolo and Pissarides (2001), the household's bargaining power, η, is set equal to 0.5, which implies that the elasticity of labor market tightness with respect to hiring costs, α, is equal to 1, as in Blanchard and Gali (2010). We calibrate the inverse of the Frisch intertemporal elasticity of substitution in labor supply, ϕ, equal to 0.3, which is in between the micro- and macro-evidence as detailed in Card (1994) and King and Rebelo (1999).[4] In line with Blanchard and Gali (2010), we calibrate the parameter of the disutility of labor, ξ, equal to 0.5. The idiosyncratic productivity shock z is lognormally distributed: $\log(z) \sim N(\mu_z, \sigma_z)$. We calibrate the value for μ_z equal to 0.4, and the value of its standard deviation, σ_z, equal to 0.4, in order to closely mimic the estimated wage density distribution for the US (as reported in Figure 3b by Jolivet, Postel-Vinay and Robin (2006)). To simplify notation, we denote the endogenous separation rate $G(z^R)$ with λ^n, such that $\lambda^n \equiv G(z^R)$. Given the values of μ_z, σ_z and λ^n, the reservation productivity equals $z^R = G^{-1}(\lambda^n)$, where

[3] See Hosios (1990) for the formal derivation of this condition.

[4] We have performed robustness analysis on this parameter and the qualitative results are robust to alternative calibrations.

$G(\cdot)$ is the cdf of the lognormal distribution. In steady state, equations (6) and (7) form the following 2-equation system, $\overline{w}-(1-\theta)y/n+\chi_t\left\{1-\beta\left[1-\lambda^n\right]\right\}=0$ and $\left[H(z^R)-z^R\right]y/n-\left[\overline{w}-w(z^R)\right]-\beta\left[1-\lambda^n\right]\chi=0$, which can be used to solve numerically for the steady-state value of employment, n, and the steady-state reservation productivity, z^R. For an average calibration of the model (i.e. using the mean values of the parameter ranges in Table 1) the implied steady-state values are $n=0.92$ and $z^R=0.43$. Average idiosyncratic productivity then equals $\bar{z}\equiv\int_{z^R} z\frac{g(z)}{1-G(z^R)}dz=1.62$.

3 The theoretical restrictions

To derive the sign restrictions to impose on the empirical TVP-VAR model we use the theoretical model to determine how each variable reacts to shocks. To produce robust responses to one positive percentage point neutral and investment specific technology shocks we simulate the theoretical model by drawing 10,000 times from the parameters' ranges. As in Dedola and Neri (2007), Pappa (2009) and Mumtaz and Zanetti (2012), to eliminate extreme responses, we discard the regions of the two distributions below and above 2.5 and 97.5 percentiles respectively. To illustrate how the variables of the theoretical model react to each shock, Figure 1 plots the impulse responses of variables to a one positive percentage point deviation of the neutral and investment specific technology shocks respectively. Independently from the shock considered, capital and investment show similar dynamics, as they both rise. In addition, the impact response of output growth could be either positive or negative for both shocks, depending on the model's calibration. However, the impact response is more pronounced in the case of a neutral technology shock, which corroborates the findings in Greenwood et al. (1997) and Fisher (2006). The impact reactions of consumption, hiring and the job finding rate to a neutral technology shock are positive, whereas the response of the job destruction rate is negative. The intuition of these results is straightforward. In response to a positive technology shock, hiring increases as firms expand production by increasing labor input, while job destruction falls since the productivity of the marginal job increases. Consequently, the unemployment rate falls, which combined with the increase in hiring generates a rise in the job finding rate. On the other hand, in the face of an investment specific technology shock, the unemployment rate rises since capital is more productive and, as described, firms respond to this by expanding production. As a consequence, hiring and the number of workers both decrease, thereby decreasing the job finding rate. Importantly for the analysis of this paper, since the job finding rate and the unemployment rate have opposite reactions to neutral or investment specific technology shocks we are able to disentangle the effects of these two shocks in the data. To implement the identification scheme we impose the described sign restrictions, as summarized in Table 2, on the first-period reaction of the TVP-VAR model. Note that we include GDP growth in the empirical model, but leave its reaction unconstrained as the impact reaction in the theoretical model could be either positive or negative, depending on the model's calibration.

4 The empirical model

In this section, we describe the empirical TVP-VAR model with stochastic volatility, the identification scheme based on sign restrictions, the Bayesian estimation and the data.

We consider the following VAR model

$$Z_t = c_t + \sum_{l=1}^{L} \phi_{l,t} Z_{t-l} + v_t, \tag{25}$$

where Z_t contains the job finding rate, the job separation rate, GDP growth and the unemployment rate. Our benchmark model allows for time variation in the parameters. We postulate the following law of motion for the coefficients $\tilde{\phi}_{l,t} = \tilde{\phi}_{l,t-1} + \eta_t$, where $\tilde{\phi}_{l,t} = \{c_t, \phi_{l,t}\}$. As in Cogley and Sargent (2005), the covariance matrix of the innovations v_t is factored as $VAR\,(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})'$. The time-varying matrices H_t and A_t are defined as:

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 \\ 0 & 0 & 0 & h_{4,t} \end{bmatrix} \qquad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix} \tag{26}$$

with the $h_{i,t}$ evolving as geometric random walks, $\ln h_{i,t} = \ln h_{i,t-1} + \tilde{\nu}_t$. Following Primiceri (2005), we postulate the non-zero and non-one elements of the matrix A_t to evolve as driftless random walks, $\alpha_t = \alpha_{t-1} + \tau_t$. The time-varying VAR model can be written compactly as

$$y_t = x_t' \tilde{B}_t + A_t^{-1} H_t^{1/2} \varepsilon_t \tag{27}$$

where $y_t = vec\,(Z_t)$, $x_t = I \otimes [1, Z_{t-1}, Z_{t-2}, ...]$, $\tilde{B}_t = vec\left([c_t, \phi_{1,t}, \phi_{2,t}...]\right)$ and $VAR\,(\varepsilon_t) = I$.

The time-varying VAR model in equation (27) represents a flexible framework which is particularly suited to our analysis that considers changes in the role and transmission of technology shocks. Consider re-writing equation (27) as

$$y_t = x_t \tilde{B}_t + \tilde{A}_{0,t} \varepsilon_t, \tag{28}$$

where $\tilde{A}_{0,t}$ represents a time-varying structural impact matrix such that: $\Omega_t = \tilde{A}_{0,t} \tilde{A}_{0,t}'$.

The structural VAR in equation (28) allows flexibility along several dimensions. First, the magnitude of the contemporaneous relationships amongst v_t are allowed to be different across time. This seems particularly appropriate for the US which has experienced several structural shifts. Within a simple economic model, these structural changes imply a change in the contemporaneous reaction of macroeconomic variables to structural shocks. Therefore, an empirical model with fixed impact matrix $\tilde{A}_0$ is unable to account for this feature of the data. Moreover, structural changes in the economy may have occurred along several dimensions, implying independent shifts in different (structural) equations of the model. By allowing for independent time variation in each contemporaneous and lagged coefficient, it is likely that the model is a good proxy for structural change with these features. In a similar vein, the time-varying VAR has a flexible formulation for volatility allowing shifts in shock volatility that are independent from changes in the coefficients B_t.

4.1 Identification of structural shocks

As mentioned, the structural analysis using the VAR model is based on the identification of the signs of the responses of the endogenous variables to neutral and investment specific technology shocks, as described in the previous section and summarized in Table 1.

In the empirical analysis below we impose these restrictions on the contemporaneous impulse responses estimated using the VAR model in equation (25). The sign restrictions are imposed using the procedure described in Rubio-Ramírez, Waggoner and Zha (2010), and the identification scheme is implemented as follows. Let $\Omega_t = P_t P_t'$ be an arbitrary decomposition of the VAR covariance matrix Ω_t, and let $\tilde{A}_{0,t} \equiv P_t$. We draw an $N \times N$ matrix, J, from the $N(0,1)$ distribution. We take the QR decomposition of J. That is, we compute the matrices Q and R such that $J = QR$. This gives us a candidate structural impact matrix as $A_{0,t} = \tilde{A}_{0,t} Q$. We check if the rows of the A_0 matrix are consistent with the restrictions in Table 1. If this is the case we store $A_{0,t}$. If the sign restrictions are not satisfied, we draw another J and repeat the above.

With time-varying coefficients, the calculation of impulse responses is complicated by the possibility of coefficient variation over the impulse response horizon. To tackle this issue, we follow the procedure in Koop, Pesaran and Potter (1996) and use Monte Carlo integration to account for future coefficient uncertainty. In particular, the impulse response functions at each point in time are defined as:

$$IRF_t = E\left(Y_{t+k} \backslash \Psi_t, Y_{t-1}, \mu\right) - E\left(Y_{t+k} \backslash \Psi_t, Y_{t-1}\right) \tag{29}$$

where Ψ_t denotes all the parameters and hyperparameters of the VAR, k is the horizon under consideration and μ denotes the shock. Equation (29) states that the impulse response functions are calculated as the difference between two conditional expectations. The first term in equation (29) denotes a forecast of the endogenous variables conditioned on one of the structural shocks, μ. The second term is the baseline forecast, i.e. conditioned on the scenario where the shock equals zero. Koop et al. (1996) describe how to approximate these conditional expectations via a stochastic simulation of the VAR model.

4.2 Estimation and data

The TVP-VAR model is estimated using the Bayesian methods described in Kim and Nelson (1999). In particular, we employ a Gibbs sampling algorithm that approximates the posterior distribution. A detailed description of the prior distributions, the sampling method and evidence of convergence are provided in an appendix available upon request from the authors. Here we summarize the basic algorithm which involves the following steps:

1. The VAR coefficients $\tilde{B}_t$ and the off-diagonal elements of the covariance matrix A_t are simulated by using the methods described in Carter and Kohn (2004). As is common practice in this literature (see Cogley and Sargent (2005)), we impose the constraint that $\tilde{B}_t$ should be stable at each point in time.

2. The volatilities of the reduced form shocks, H_t, are drawn using the date by date blocking scheme introduced in Jacquier, Polson and Rossi (2004).

3. The hyperparameters Q and S are drawn from an inverse Wishart distribution while the elements of G are simulated from an inverse gamma distribution.

The lag length is set at 2. We compare the relative fit of a TVP-VAR(1) and TVP-VAR(2) using deviance information criterion (DIC).[5] The estimated DIC is virtually identical for the VAR with these two lag lengths (-7255.74 for the TVP-VAR(1) and -7254.35 for the TVP-VAR(2)). Therefore we select two lags but check our results using a TVP-VAR(1). The results from the TVP-VAR(1) are very similar to the benchmark estimates presented below.[6]

The data are quarterly, seasonally adjusted, and cover the period 1948:Q2-2007:Q1. Real GDP and the unemployment rate are obtained from the FRED database (mnemonics GDPC96 and UNRATE respectively). Data on job creation and job separation probabilities are from Shimer (2012), and are quarterly averages of monthly transition probabilities, corrected for time-aggregation. As in Cogley and Sargent (2005) we obtain starting values and set priors using a training sample of 10 years with the estimation carried out from 1959:Q1.

[5] The DIC can be thought of as a generalisation of the Akaike information criterion (see Berg, Meyer and Yu (2004) for details). The calculation of the DIC requires the evaluation of the likelihood function of the TVP-VAR. We accomplish this via a particle filter.

[6] These results are available upon request from the authors.

5 Results

This section documents the results. In particular, it shows time-varying statistics for the volatility and correlation among variables, the impulse response functions, the forecast error variance decomposition, the trends and an index of persistence and predictability of the variables.

5.1 Volatility and correlation

Figure 2 plots the time-varying unconditional variance (solid line) of each endogenous variable and the estimated variance when either the neutral technology shock (dashed line), or the investment specific technology shock (dotted line) is set to zero. The unconditional volatility is calculated as $vec\left[VAR\left(Z_t\right)\right] = \left(I - \bar{\phi}_{l,t} \otimes \bar{\phi}_{l,t}\right)^{-1} vec\left(\Omega_t\right)$. Given the structural impact matrix $A_{0,t}$ (with diagonal elements normalized to 1), the variance of structural shocks can be recovered as $\tilde{H}_t = A_{0,t}^{-1\prime} \Omega_t A_{0,t}^{-1}$. We set the variance of either the neutral technology shock or the investment specific technology shock in $\tilde{H}_t$ to zero. We use this counterfactual estimate (denoted $\tilde{H}_t^*$) to build a counterfactual covariance matrix $\Omega_t^* = A_{0,t}' \tilde{H}_t^* A_{0,t}$ and recalculate $VAR\left(Z_t\right)$.

The volatility of the job finding rate is fairly constant over the sample period, although there is a slight decrease in the median after the early 1980s. It is clear from the figure that the unconditional volatility of the job finding rate is largely driven by the neutral technology shock. This shock explains about 60% of the variance during the 1960s until the mid-1970s and from the mid-1980s onwards. The peak in the job finding volatility during the late 1970s-early 1980s displays a decline in the contribution of the neutral technology shock to around 40%. The contribution of the investment specific technology shock is also fairly constant, at approximately 10% throughout the sample period.

The volatility of the job destruction rate increases substantially during the early 1980s and rapidly decreases afterwards to return to its 1960s' level. Interestingly, the unconditional variance of the job destruction rate displays a pattern that mimics the unconditional volatility of the job finding rate for the post-1980s period, but it differs in the pre-1970s and early 2000s periods. In the pre-1970s the unconditional volatility of the job destruction rate increases, whereas it remains largely unchanged for the job finding rate. In the early 2000s the unconditional volatility of the job destruction rate increases, whereas it increases for the job finding rate. Finally, the contribution of neutral and investment specific technology shocks is similar throughout the sample period.

The estimated volatility of GDP growth is high during the 1970s and the first half of the 1980s and shows a sharp decline around 1984, which corroborates the findings in Stock and Watson (2003), who detect a significant fall in the volatility of output around the early 1980s. The volatility of GDP growth is substantially smaller throughout the sample period if the variance of the neutral technology shock is set to zero. In fact, this shock explains about 60% of the variance of GDP growth. The contribution of the investment specific technology shock is smaller, ranging at around 10% throughout the sample period.

Finally, the volatility of the unemployment rate increases until the mid-1980s and then shows a sharp decline. The neutral technology shock contributes 50% to this variance over most of the sample period except during the early 1980s when this contribution falls to 40%. The contribution of the investment specific technology shock is fairly constant at 10% throughout the sample period.

Overall, these results show that the volatility of labor market aggregates remarkably declines after the early 1980s, and then stabilizes at a level similar to that of the 1960s. This observed pattern is consistent with the numerous studies that investigate the changes in the volatility of output and other macroeconomic aggregates, as in Stock and Watson (2003). However, we find that movements in the volatility of job finding and job destruction rates display different patterns over sub-periods. Also, the time-varying volatility of the job finding rate is high, roughly twice the volatility of GDP growth. Moreover, the volatility of the job finding rate is higher than the volatility of the job destruction rate throughout the sample period, which supports the evidence based on summary statistics in Shimer (2012).

Figure 3 shows the time-varying correlations among the endogenous variables as implied by the TVP-VAR model (solid line), the 68% error band (shaded area), and the correlations conditional on setting the variance of either the neutral technology shock (dashed line), or the investment specific technology shock (dotted line) to zero. We calculate the unconditional correlation matrix at each point in time by using the unconditional covariance matrix of the variables $vec\left[VAR\left(Z_t\right)\right] = \left(I - \bar{\phi}_{l,t} \otimes \bar{\phi}_{l,t}\right)^{-1} vec\left(\Omega_t\right)$. There are large changes in the correlation between the job finding rate and the job destruction rate across time. In particular, the correlation is significantly negative until the mid-1980s, and it then decreases and remains insignificantly different from zero after the mid-1990s. Removing the influence of the investment specific technology shock has limited influence on the evolution of this correlation. Without the neutral technology shock, however, this correlation goes to zero (and becomes positive) quicker in the post-1985 period. In general, a negative correlation between the job finding and destruction rates has been detected by several studies. However, focusing on its variation across time shows that the correlation weakens over time, and virtually vanishes from the late 1990s onwards.[7] This change in the sign of the correlation is likely linked with changes in labor market institutions during the early-1990s that might have altered the response of job finding and destruction to shocks, as detailed in Zanetti (2011) and Zanetti (2014). Extending the analysis to consider the role of labor market institutions explicitly and their effect of the job finding and destruction rates would certainly be a useful extension for future research.

The correlation between the job finding rate and the unemployment rate is strongly negative throughout the sample period and it weakens after 1990. Without the neutral technology shock, the correlation is smaller in magnitude and declines at a higher rate after 1990. The post-1985 period is also associated with a decrease in the correlation between the job destruction rate and the unemployment rate (from a peak of 0.8 in the mid-1980s to a low of 0.4 in 2003/2004). However, the identified technology shock has limited influence on the time-path of this correlation. A comparison of the correlations between the unemployment rate and the job finding and job destruction rates enables us to evaluate which variable is more strongly correlated with the unemployment rate. Interestingly, the job finding rate displays

[7] Note that the fact that the unconditional and conditional correlation is similar across investment-specific and neutral technology shocks is not necessarily evidence that the destruction rate is well approximated by an endogenous rate, since for both scenarios the job destruction is endogenous. Such a similarity simply suggests that both margins have a similar response throughout the sample period to investment-specific and neutral technology shocks.

a sample average correlation with the unemployment rate around -0.85%, whereas the job destruction rate has a correlation with the unemployment rate around 0.65% throughout the sample period. This supports the view that although the job finding and job destruction rates jointly determine unemployment, the flow out of unemployment (i.e. the job finding rate) plays a relatively more important role for the dynamics of unemployment. However, the correlations of both the job finding and job destruction rates with the unemployment rate decline substantially from 2000 onwards.

The correlation between the job finding rate and GDP growth is estimated to be insignificantly different from zero over the sample period with the neutral technology shock playing an important part. In contrast, the correlation between job destruction and GDP growth is negative, and it becomes insignificantly different from zero from the early 2000s onwards.[8] Finally, the correlation between GDP growth and the unemployment rate is close to zero across the sample period.

Overall, it is worth noting that the correlation of the variables with GDP growth is relatively stable over time, whereas the correlation between the job finding rate, the job destruction rate and the unemployment rate shows significant variation across time. This evidence of changes in the joint dynamics of labor market variables, underlines that the statistical relation between the job finding and destruction rates with the unemployment rate is time-varying.

5.2 Impulse response functions

Figures 4 and 5 plot the cumulated impulse response to neutral and investment specific technology shocks. Both shocks are normalized to increase GDP growth by 1% on impact at each point in the sample period. This normalization allows us to focus on possible changes in the responses of the labor market variables.[9] The left panels in each figure present the

[8] Note that the unconditional correlation and the correlation without investment-specific technology shocks are around zero during the sample period, with a wide error band surrounding the estimates. Instead the correlation without neutral technology shock is positive and increases slightly from the 1980s onwards, in line with the estimates of the investment-specific technological process in Fisher (2006).

[9] Note that the time-varying nature of the VAR means that we take low-frequency movements in the data into account when estimating impulse responses.

median impulse response at each point in time. The X-axis in these panels represents the time periods while the Y-axis is the impulse response horizon. The remaining panels show the average cumulated impulse response in each decade of the sample for the TVP-VAR (solid line) together with the response from a standard fixed coefficient VAR (dashed line) estimated over the entire sample period. Before considering the variables' response to each shock, looking across the different impulse response functions provides a few useful insights. First, allowing for time variation in the VAR is important to describe the responses of variables to shocks, as most of the variables' responses from the fixed coefficient VAR significantly differ from those of the TVP-VAR. For instance, the reaction of the job destruction rate from the fixed coefficient VAR is systematically higher compared to its TVP-VAR counterpart. Second, neutral and investment specific technology shocks increase GDP, and they have an opposite effect on labor market variables. The neutral technology shock decreases the unemployment rate by increasing the job finding rate and decreasing the job destruction rate, whereas the investment specific technology shock leaves the unemployment rate substantially unchanged. As discussed, Michelacci and Lopez-Salido (2007) have also analyzed the effect of technology shocks using a SVAR model and find that the neutral technology shock increases job destruction thereby increasing unemployment, whereas the impact of the investment specific technology shock on unemployment is contractionary. Our analysis has a number of important differences from this study. First, we use a different identification strategy. While these authors use long-run restrictions to identify technology shocks, we use high-frequency restrictions. Our approach has a number of advantages, as detailed in the outset. Second, we allow for time variation in the analysis. Third, the data series differ. While these authors use quarterly data series for job flows from Davis, Haltiwanger and Schuh (1998) that cover the period 1972-1993, we use job flows data from Shimer (2012) that cover the period 1948-2007.

Figure 4 shows the response to the neutral technology shock. The top panel shows that the response of the job finding rate to the shock is significant and positive throughout the sample period, with the cumulated effect ranging from around 2% to 6%. The response of the job finding rate to the neutral technology shock displays significant time variation. The top left panel shows a large increase in the cumulated response of the job finding rate at the end of the 1980s, especially at longer horizons. This can be seen quite clearly from the average impulse response functions with the estimates over the period 1990-2007, which are larger than the previous years. Note that over this period the fixed coefficient VAR tends to underestimate the response of the job finding rate on average. There is limited evidence of time variation in the response of the job destruction rate to the neutral technology shock until the period 1990-2000. Similarly, the response of the unemployment rate to the neutral technology shock is similar across periods until the late 1980s, and increases afterwards.

To investigate further the time-varying relations between job finding and destruction rates and the unemployment rate, the top panel of Figure 6 shows the cumulated responses of these variables to the neutral technology shock after two years. The entries point out that the response of the job destruction rate is remarkably constant from the early 1970s, whereas the responses of the job finding rate and the unemployment rate are stronger after 1980. The response of the job creation rate almost doubles, whereas the response of the unemployment rate decreases by approximately the same amount. This reinforces the results based on time-varying cross correlations between unemployment and job finding and destruction rates, and it is in line with the evidence in Shimer (2012), who, using descriptive statistics, points out that movements in the job finding rate are key drivers of unemployment fluctuations. Interestingly, the figure also shows that the response of output to the neutral technology shock increases from 1980 onwards, in line with the findings in Gali and Gambetti (2009).

Figure 5 shows the response to the investment specific technology shock. Entries show that the response of the job destruction rate to the shock displays significant time variation. Over the period 1960-2000, the job destruction rate declines by around 0.3% in response to this shock at the two-year horizon. However, from 2000 onwards the magnitude of the response increases to around 0.5%. The bottom panel of Figure 6 shows the cumulated responses of these variables after two years. The reactions of the variables to an investment specific technology shock are substantially constant over time, and often around zero, suggesting that changes in labor market dynamics are more likely explained by the neutral technology shock.[10]

[10] In order to evaluate the empirical role of the endogeneity of the job destruction rate, we re-estimate a version of the model where no restriction is placed on job destruction rate. Removing this restriction has a large impact on the response to investment specific shocks, suggesting that the restriction on job destruction is

5.3 Forecast error variance decomposition

To understand the extent to which the movements of each variable are explained by the shocks, Figures 7 and 8 report the forecast error variance decompositions to a neutral and investment specific technology shock respectively for the TVP-VAR model (solid line), the 68% error band (shaded area), and the median response from the fixed coefficient VAR (dashed line). The left panels present the forecast error variance decompositions to the shock at each point in time. The X-axis in these panels represents the time periods, while the Y-axis is the forecast error variance decomposition at different forecast horizons. The remaining panels show the forecast error variance decompositions in each decade of the sample.

Looking across the entries shows that the contribution of each shock to movements in the data varies over time. As shown in Figure 7, the contribution of the neutral technology shock to the job finding and job destruction rates decreases over the sample period. In the period 1960-1970 neutral technology shocks explain approximately 51% and 28% of movements of these series at low frequencies, whereas their contribution declines to approximately 40% and 15% over the period 2000-2007. The contribution of the neutral technology shock to GDP growth displays a similar pattern, since this shock explains approximately 55% of GDP growth over the period 1960-1990, but the contribution decreases to approximately 45% over the period 2000-2007. Finally, the contribution of the neutral technology shock to the unemployment rate shows a low degree of time variation, as it is at approximately 52% over the period 1970-1990, and at around 47% on average over the subsequent periods.

As shown in Figure 8, the contribution of the investment specific technology shock explains approximately 18% of the job creation and destruction rates at low frequencies over the period 1960-1970, while the contribution almost doubles over the period 2000-2007. The investment specific technology shock explains on average 8% of GDP growth at high frequencies over the sample period 1960-1980 and its contribution increases to approximately 18% on average over the period 1990-2007. The investment specific technology shock contributes to around 18% on average to short-run fluctuation in the unemployment rate, although its contribution declines

important for identification of the shocks in our model. A companion appendix that documents these results is available on request from the authors.

to approximately 14% at low frequencies. On average, the investment specific technology shock contributes less than 20% on average of fluctuations in the unemployment rate, job finding and job destruction rates.

In general, neutral and investment specific technology shocks contribute significantly to explain the variance of the variables, although the explanatory power of the investment specific technology shock is lower than the neutral technology shock, which corroborates the findings in Zanetti (2008) obtained by estimating standard real business cycle.[11] Both neutral and investment specific technology shocks contribute to explain around 55% on average of unemployment fluctuations at low frequencies, in line with Fisher (2006) and Christiano, Eichenbaum and Vigfusson (2004). Moreover, although both neutral and investment specific shocks explain the bulk of the variables' fluctuations, they are unable to explain the whole variance of the variables, therefore indicating that other shocks are important to describe the dynamics in the data. For both shocks, the forecast error variance decompositions are always statistically significant albeit a sizable degree of uncertainty surrounds the estimates.

6 Conclusion

This paper has investigated how the statistical relations among key labor market aggregates and their responses to technology shocks have changed over the US postwar period. The analysis is conducted using an estimated VAR that allows for time-varying coefficients and stochastic volatility, whose variables' reactions to shocks are identified using a novel identification scheme based on the cyclical properties of a DSGE model of the business cycle characterized by labor market frictions. The results clearly point out that the dynamics of labor market variables significantly change over time, suggesting that allowing for time variation is an important dimension for a comprehensive assessment of labor market dynamics. We establish several results. The volatility of job finding and job destruction rates has declined

[11] Note that our results are different from those of Justiniano and Primiceri (2008) who find that investment-specific technology shocks account for the bulk of the decline in the variability of output and hours at business cycle frequencies. Our approach and information set differ from those of this study since we use a time-varying VAR model that accounts for key labor market variables, therefore including data for unemployment, job creation and job separation probabilities. The abovementioned study instead uses a general equilibrium model that does not account for these labor market series. In addition, our model abstracts from nominal rigidities.

over time, after reaching a peak around the mid-1980s. However, changes in the volatility of the job finding and job destruction rates display different patterns over sub-periods. The correlation of the labor market variables with GDP growth is relatively stable over time, whereas the correlation between the job finding and job destruction rates and the unemployment rate shows significant time variation. The job finding rate plays an important role for the unemployment rate, and the two series are strongly negatively correlated over the sample period. The response of labor market variables to neutral technology shocks varies over time. Moreover, neutral technology shocks decrease unemployment, whereas investment specific technology shocks have a limited impact on unemployment. Finally, across the sample period, neutral technology shocks explain approximately half of the movements in the unemployment rate and the job finding rate, whereas they explain only 20% of fluctuations in the job destruction rate. Investment specific technology shocks contribute to below 20% on average of fluctuations in unemployment, job finding and job destruction rates.

The analysis of this paper suggests that most of the variation in the unemployment rate over time is explained by job creation. It also points out that changes in labor market dynamics involve deep variation in the functioning of the labor market, suggesting that structural changes play a role to account for the time-varying dynamics of labor market variables. Extending the model to investigate what structural changes could account for the observed variations in labor market dynamics remains an outstanding task for future research. This would prove to be a difficult task however, because it requires the estimation of fully-fledged DSGE models with time-varying parameters, as recently outlined in Fernández-Villaverde and Rubio-Ramírez (2008).

Finally, the empirical model could be extended to allow for additional variables, so as to investigate the time-varying statistical relations of labor market variables with a broader set of macroeconomic aggregates. This extension is also open for future research.

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Table 1. Parameters' Values

Parameter		Value
β	Discount factor	[0.985 , 0.995]
λ^x	Exogenous job destruction rate	[2.5 , 3.5]
δ_k	Capital destruction rate	[0 , 0.05]
θ	Capital share	[0.2 , 0.4]
$\chi h/y$	Share of hiring costs over total output	[0.005 , 0.01]
ρ_a	Autoregressive coefficient, neutral technological progress	[0.75 , 0.99]
ρ_υ	Autoregressive coefficient, investment specific technological progress	[0.75 , 0.99]
α	Elasticity of labor market tightness	1
η	Household's bargaining power	0.5
ϕ	Inverse of the Frisch intertemporal elasticity	0.3
ξ	Disutility of labor	0.5
μ_z	Mean of the idiosyncratic productivity shock	0.4
σ_z	Variance of the idiosyncratic productivity shock	0.4

Notes: The table shows the parameters' values that are used to simulate the theoretical model.

Table 2. Sign Restrictions on the First-period TVP-VAR Variables

	Neutral technology shock	Investment specific technology shock
Variable		
GDP growth	free	free
Job finding rate	+	−
Job destruction rate	−	−
Unemployment rate	−	+

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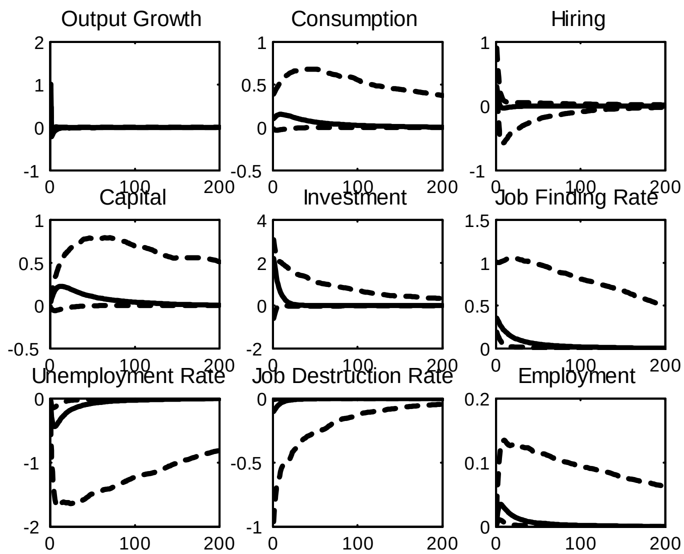
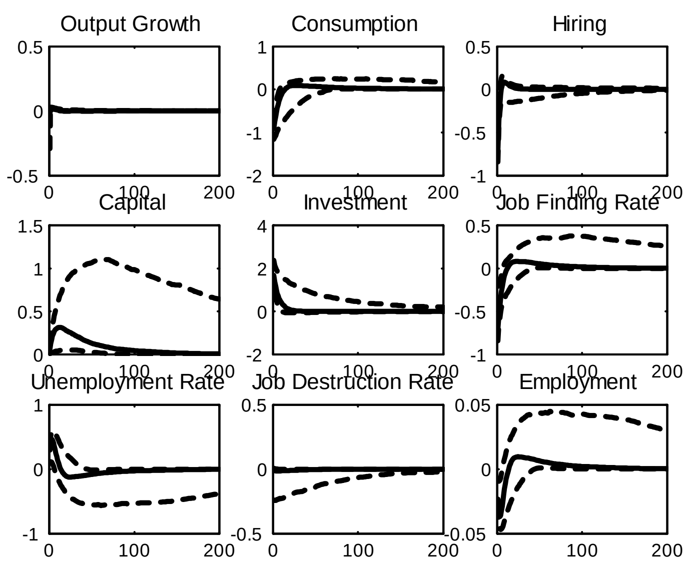
Notes: Entries show sign restrictions on the first period TVP-VAR variables to neutral and investment specific technology shocks.

Figure 1. Theoretical Impulse-Response Functions

A: Neutral Technology Shock

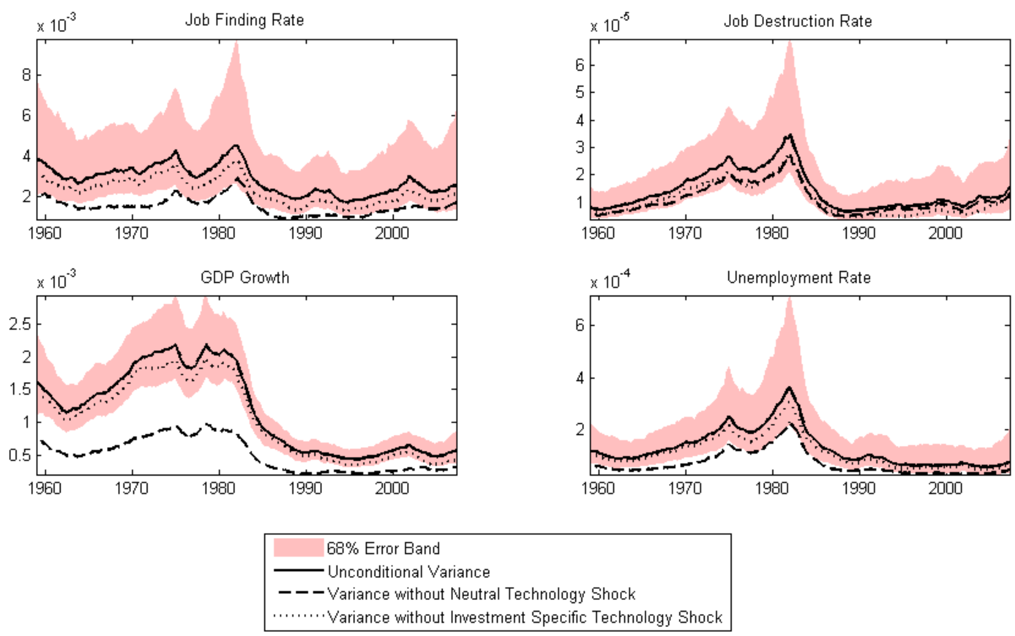


B: Investment Specific Technology Shock



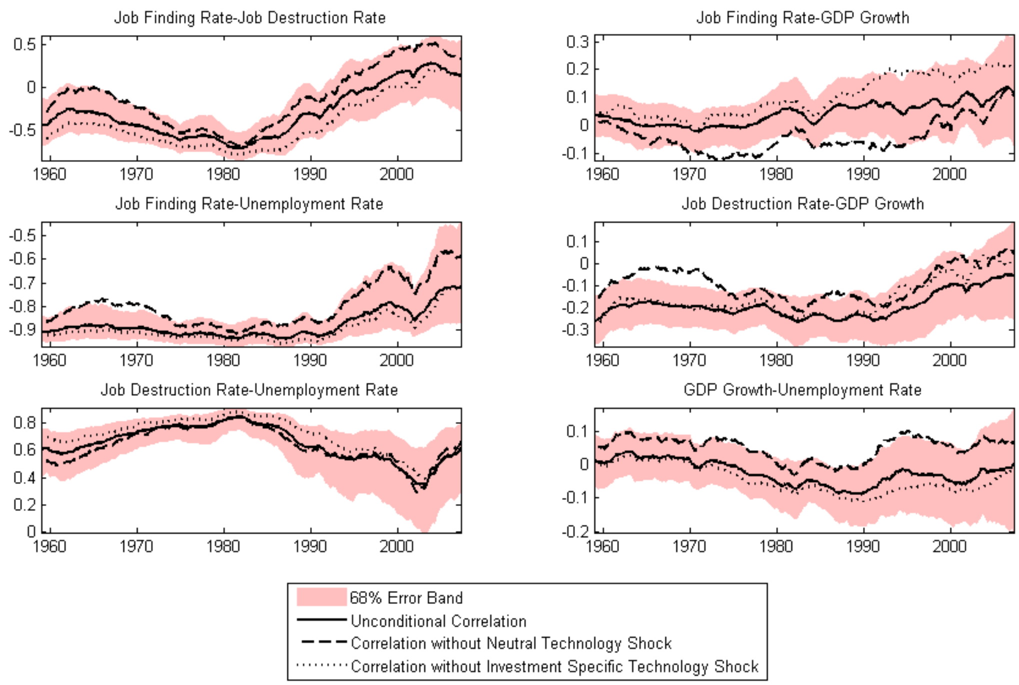
Notes: Panel A (Panel B) shows the percentage-point response of one of the model's variables to a one-percentage-deviation neutral (investment specific) technology shock. The solid line reports the median responses and the dashed lines report the 2.5 and 97.5 percentiles of the responses.

Figure 2. Time-varying Unconditional Volatilities



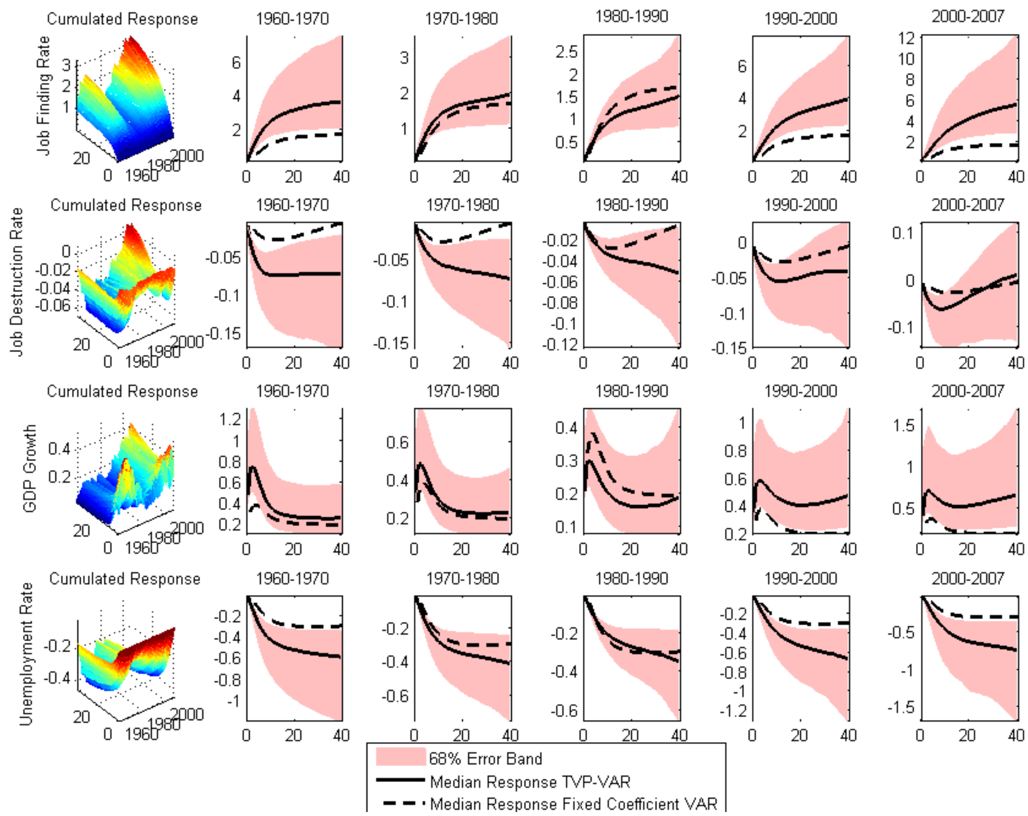
Notes: Each entry shows the unconditional variance (solid line) of each endogenous variable and the estimated variance when either the neutral technology shock (dashed line), or the investment specific technology shock (dotted line) is set to zero.

Figure 3. Time-varying Correlations



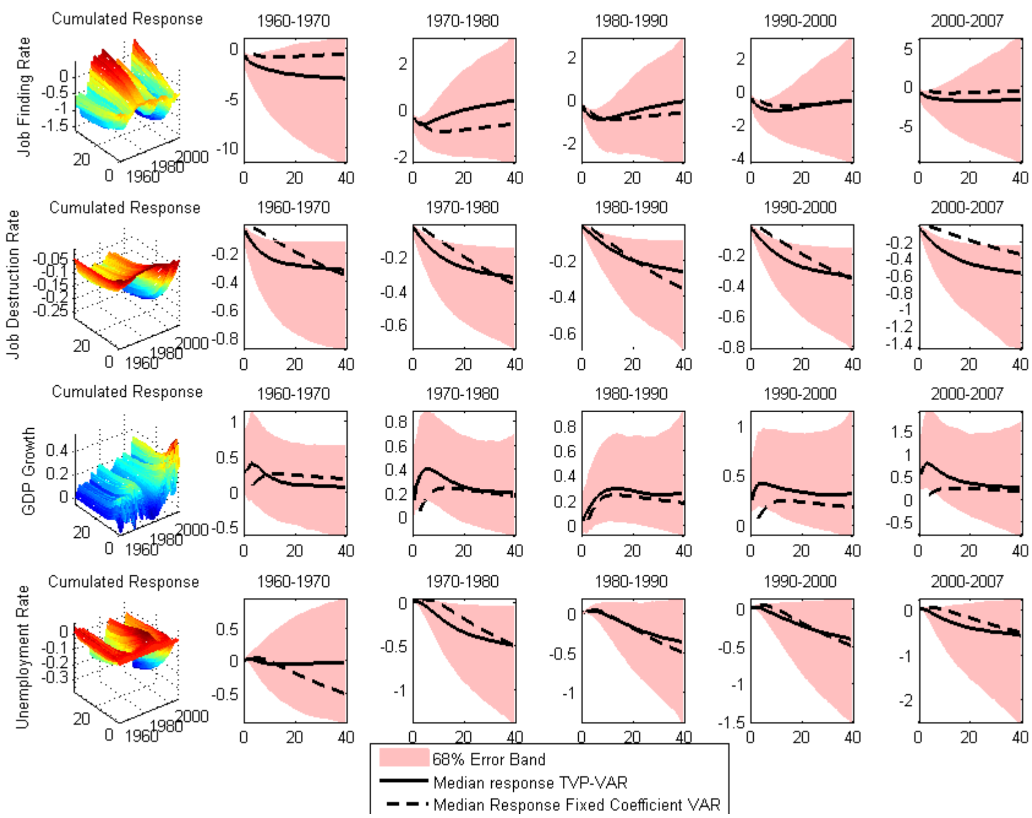
Notes: Figure 3 shows the time-varying correlations among the endogenous variables as implied by the TVP-VAR model (solid line), the 68% error band (shaded area), and the correlations conditional on setting the variance of either the neutral technology shock (dashed line) or the investment specific technology shock (dotted line) to zero.

Figure 4. Empirical Impulse-Response Functions to a Neutral Technology Shock



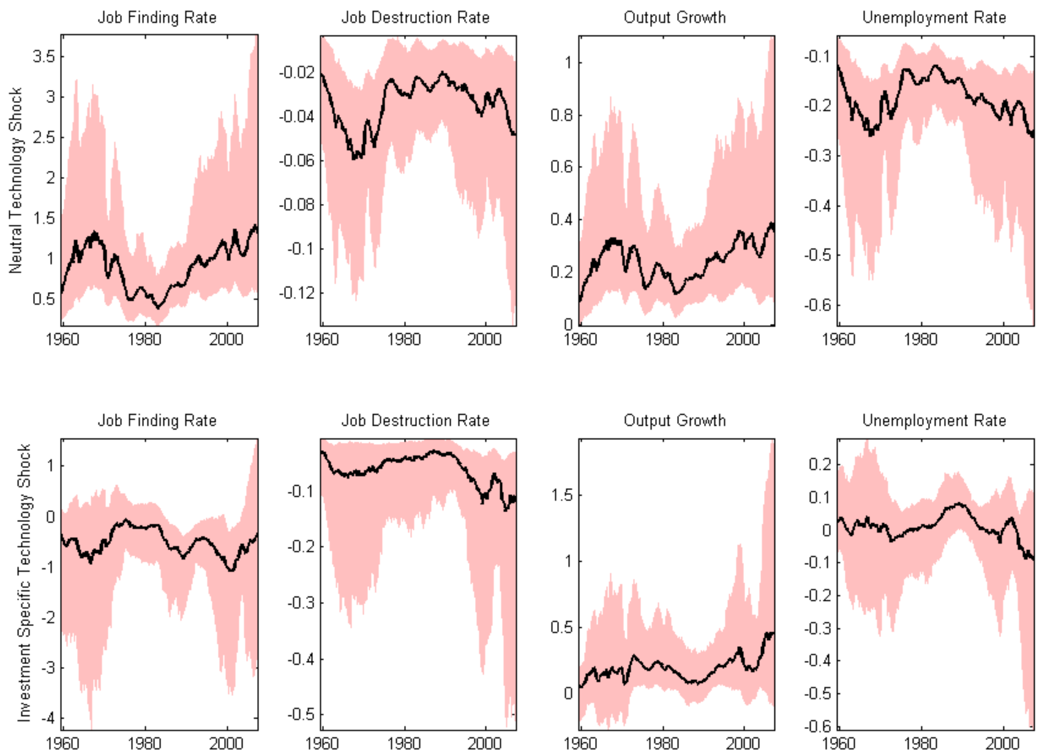
Notes: Cumulated impulse responses to a neutral technology shock. The shock is normalized to decrease the unemployment rate by 1% on impact at each point in the sample period. The left panels present the median impulse response at each point in time. The X-axis in these panels represents the time periods while the Y-axis is the impulse response horizon. The remaining panels show the average cumulated impulse response in each decade of the sample for the TVP-VAR (solid line), its 68% error band (shaded area), together with the response from a standard fixed coefficient VAR (dashed line) estimated over the entire sample period.

Figure 5. Empirical Impulse-Response Functions to an Investment Specific Technology Shock



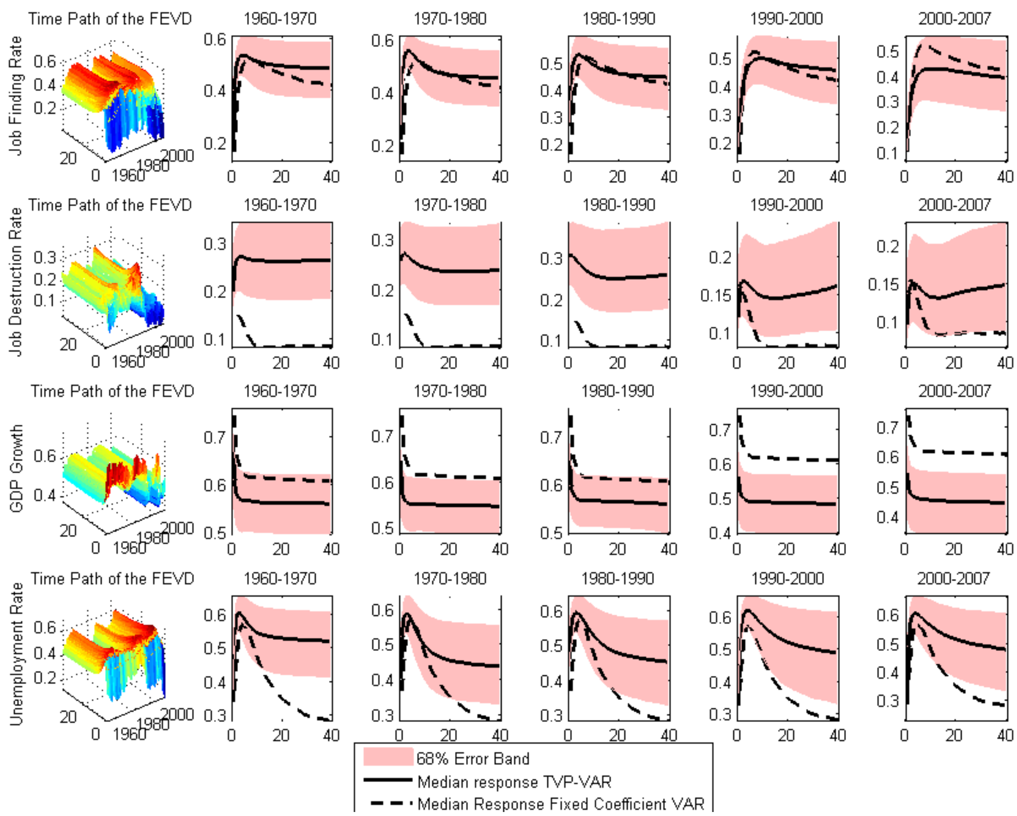
Notes: Cumulated impulse responses to an investment specific technology shock. The shock is normalized to decrease the unemployment rate by 1% on impact at each point in the sample period. The left panels present the median impulse response at each point in time. The X-axis in these panels represents the time periods while the Y-axis is the impulse response horizon. The remaining panels show the average cumulated impulse response in each decade of the sample for the TVP-VAR (solid line), its 68% error band (shaded area), together with the response from a standard fixed coefficient VAR (dashed line) estimated over the entire sample period.

Figure 6. Empirical Cumulated Impulse-Response Functions after 2 Years



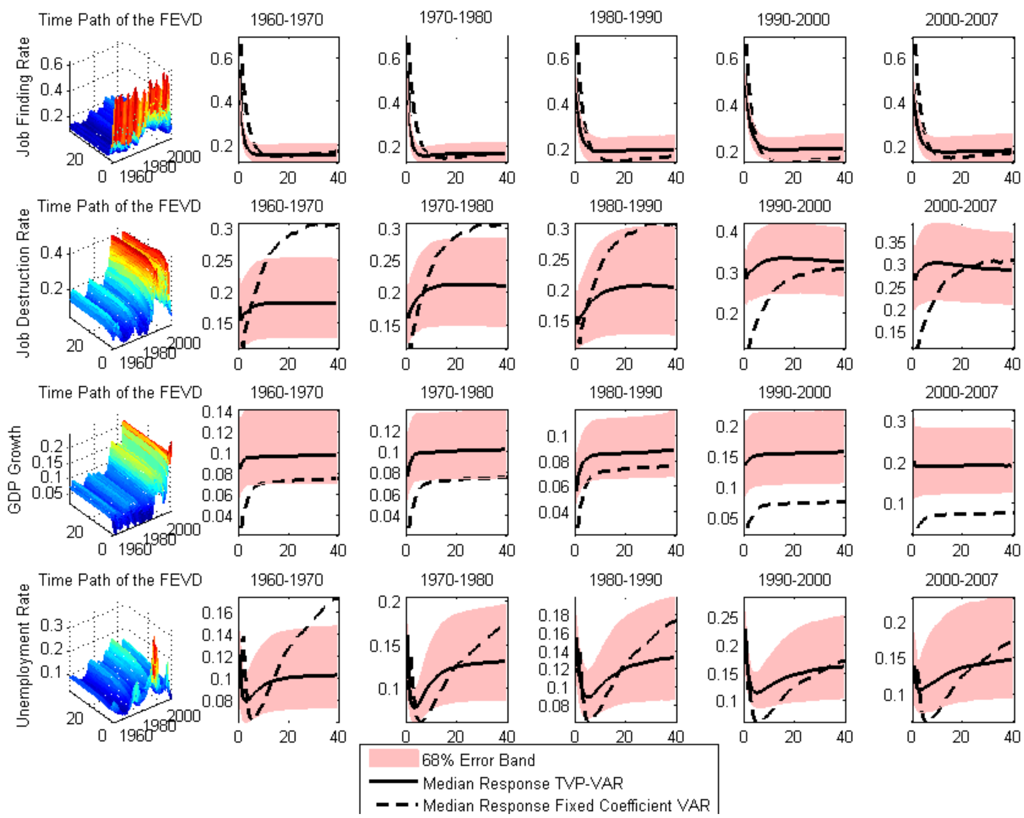
Notes: The top row shows the cumulated responses after 2 years from the TVP-VAR model to a neutral technology shock. The bottom row shows the cumulated responses after 2 years from the TVP-VAR model to an investment specific technology shock. Each plot shows the 68% error band.

Figure 7. Forecast Error Variance Decompositions, Neutral Technology Shock



Notes: The left panels present the forecast error variance decompositions to a neutral technology shock at each point in time. The X-axis in these panels represents the time periods, while the Y-axis is the forecast error variance decomposition at different forecast horizons. The remaining panels show the forecast error variance decompositions to a neutral technology shock from the TVP-VAR model (solid line), its 68% error band (shaded area), and the median response from the fixed coefficient VAR (dashed line).

Figure 8. Forecast Error Variance Decompositions, Investment Specific Technology Shock



Notes: The left panels present the forecast error variance decompositions to an investment specific technology shock at each point in time. The X-axis in these panels represents the time periods, while the Y-axis is the forecast error variance decomposition at different forecast horizons. The remaining panels show the forecast error variance decompositions to a neutral technology shock from the TVP-VAR model (solid line), its 68% error band (shaded area), and the median response from the fixed coefficient VAR (dashed line).