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Javier Ordóñez
Hector Sala
José I. Silva

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Javier Ordóñez
Universitat Jaume I de Castelló

Hector Sala
*Universitat Autònoma de Barcelona
and IZA*

José I. Silva
Universitat de Girona

ABSTRACT

Oil Price Shocks and Labor Market Fluctuations[*]

We examine the impact of real oil price shocks on labor market flows in the U.S. We first use smooth transition regression (STR) models to investigate to what extent oil prices can be considered as a driving force of labor market fluctuations. Then we develop and calibrate a modified version of Pissarides' (2000) model with energy costs, which we simulate in response to shocks mimicking the behavior of the actual oil price shocks. We find that (i) these shocks are an important driving force of job market flows; (ii) the job finding probability is the main transmission mechanism of such shocks; and (iii) they bring a new amplification mechanism for the volatility and should thus be seen as complementary of labor productivity shocks. Overall we conclude that shocks in oil prices cannot be neglected in explaining cyclical labor adjustments in the U.S.

JEL Classification: E22, E32, J63, J64

Keywords: oil prices, unemployment, vacancies, business fluctuations

Corresponding author:

Hector Sala
Department d'Economia Aplicada
Universitat Autònoma de Barcelona
08193 Bellaterra
Spain
E-mail: hector.sala@uab.es

1   Introduction

This paper investigates to what extent shocks in oil prices are significant in accounting for labor market fluctuations. We take a workers flow perspective and focus on the unemployment fluctuations resulting from the job finding and job separation rates. In this way we complement and push forward the work by Davis and Haltiwanger (2001) on the US manufacturing sector. These authors took a *job flows* approach to assess the effects of the oil price shocks on job creation and job destruction, and found them to account for 25 percent of the employment volatility. Here, instead, we take a *workers flow*[1] perspective and find significant effects on vacancies and unemployment.

Although this flow perspective has become very popular in business cycle analysis of the labor market, a consensus on the main source behind the volatility of unemployment is still far to be reached. While some authors argue that the job finding rate is the main cause of unemployment fluctuations (Hall, 2005; Shimer, 2007), others claim that job separations are the central one (Elsby *et al.* 2009; Fujita and Ramey, 2009). In particular, Shimer (2007) argues that 75 percent of the unemployment volatility is driven by the job finding rate, whereas Fujita and Ramey (2009) place the explanatory power of job separations between 40 and 50 percent.

This controversy is not central to this paper. Circumventing this analysis there is an important consideration related to what we understand as sources of shocks or, in other words, to what we consider as driving forces of the job finding and job separation rates. In the flow approach, the behavior of the key labor market variables is generally examined in response to aggregate technological shocks. In this paper, on the contrary, we concentrate on shocks in real oil prices, which have traditionally received much attention in other economic fields, and we contribute to this literature by bringing into the scene the analysis of their impact on the US labor market fluctuations.

A related strand of literature focuses on the identification of shocks through structural vector autoregression (SVAR) models. Braun *et al.* (2009), for example, examine the reaction of some labor market variables in response to shocks that are identified as demand and supply shocks. In turn, in the particular context of energy prices, Kilian (2009) disentangles demand from supply-side oil price shocks to evaluate their impact on GDP and inflation. Although vector autoregressions provide useful starting points for analyzing multivariate relationships between variables, concern about the short-comings of linear models has led to considerable research on univariate models and their enhanced possibilities to account for macroeconomic asymmetries (see Granger and Teräsvirta, 1993, for a summary). Moreover, nonlinear phenomena of economic relevance include nonlinear effects of policy changes, capacity constraints and adjust-

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[1]As explained in Shimer (2007, Section 4.1), the difference between the *workers flow* and the *jobs flow* approach is not trivial.

ment costs, which might well characterize labor and energy markets. This was verified in Mork (1989), which is the first study that substantiates the nonlinear impact of oil price shocks on economic activities, and confirmed in Papapetreo (2001), who investigates their impact on employment. Given these considerations, this paper follows the nonlinear methodological route.

We consider actual shocks in real oil prices and investigate their cyclical effects on the US unemployment rate through their impact on the job finding and job separation rates. By actual shocks we interpret the specific impact of oil price changes on our four variables of interest (unemployment, vacancies, and the job finding and job separation rates), which we compute using the smooth transition regression (STAR) approach.[2] In particular, we estimate a multivariate STAR model in which the cyclical component of these four variables is modeled against the cyclical component of the real oil prices, which is the transition function. This procedure has two particular advantages. First, it allows a nonlinear specification of the relationship between the variables (which in our case is to be expected) and, second, it is designed to capture regime switching (which is crucial to identify the shocks and the corresponding transitions between equilibria).

The objective of this exercise is to learn the actual responses of our variables of interest to the actual shocks in real oil prices which are nonlinear. Important results of the econometric analysis are (i) that, both, vacancies and unemployment are sensitive to oil price shocks and, especially, (ii) the larger responses in the job finding rate than in the job separation rate which point to the former as main driving force under the fluctuations in the labor market in response to oil price shocks.

This insightful econometric exercise does not reveal the transmission mechanisms connecting oil prices with the labor market variables. The study of these transmission channels and amplification mechanisms can only be undertaken through a theoretical model. We thus take Pissarides' (2000) search and matching model as benchmark, and augment it by considering (i) oil prices and, consequently, (ii) endogenous capital utilization and (iii) energy consumption. In this context shocks in real oil prices will cause business cycle adjustments by affecting both the use of existing capital stock and the marginal cost of new capital stock.

It is important to note that our model is consistent with the fact that energy is an essential determinant of capacity utilization. In particular, along the lines of Finn (1995, 2000), we assume that a higher rate of capacity utilization causes faster depreciation, and thus generates extra energy costs. At the same time, it is well known that the use of energy in the short run is not excessively sensitive with respect to rises in energy prices (Atkenson and Kehoe, 1999). In the context of our business cycle model, we capture this fact by assuming adjustment costs in capital services so that higher energy

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[2]STAR models are a generalization of discrete switching models. See Section 2 for details.

costs decrease the response of capital services to changes in energy prices. Because capital services and energy consumption move in parallel, energy consumption will also display a mild reaction in response to energy price shocks. Figure 1 provides support to our modeling strategy by uncovering the close connection between the interannual quarterly growth rates of energy consumption and the rate of capacity utilization in the U.S. The two series display, respectively, a standard deviation of 4.61 and 4.37 percent with respect to their mean and a contemporaneous correlation coefficient of 0.83.[3]

Figure 1. Energy consumption and rate of capacity utilization
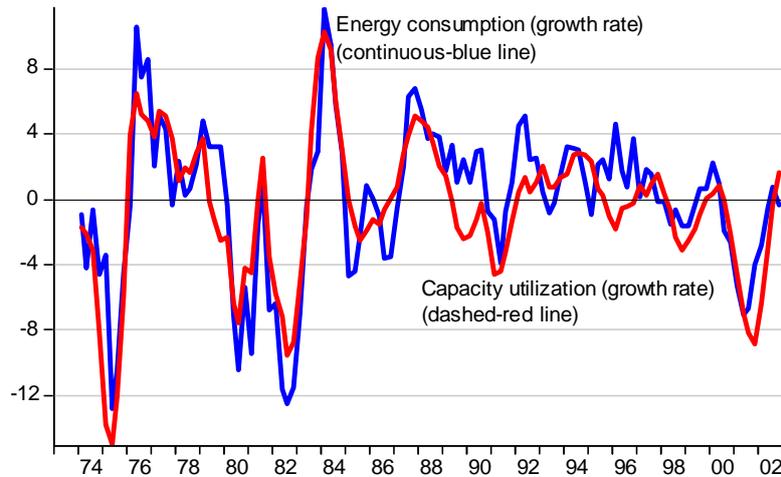
We calibrate our model to the US and use it to simulate the consequences of actual shocks in real oil prices. Actual because they have been characterized in the STAR analysis and they are now reproduced in terms of their main statistical features: persistence and volatility. Through this analysis we generate *simulated* responses of unemployment, vacancies, and the job finding and job separation rates, which we compare with the equivalent *estimated* responses obtained through the econometric STAR analysis. This comparison provides a straightforward check of the extent to which actual shocks in oil prices are significant in accounting for labor market fluctuations, which is the main objective of the paper.

Our main quantitative findings are the following. Real oil prices are an important driving force of labour market fluctuations. Around two thirds of the volatility of the unemployment rate, and more than 90 percent of the vacancies' volatility is explained when the job market is confronted to a negative shock in oil prices. The main transmission channel of these effects is the job finding probability which both our econometric and simulation exercises uncover as substantially more responsive than the job separation probability. The model, however, yields a better fit of the job separation rate

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[3]Information on the source and precise definition of these varaibles is provided in the fourth paragraph of Section 6.

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response. When the impact of the oil price shocks is examined in a broader macro-economic context including the presence of technological shocks, we confirm that it contributes to enhance the volatility produced by the standard Pissarides' model. Finally, an important finding is that throughout the different analyses conducted, the impact of these shocks is always consistent with the observed negative relationship between vacancies and unemployment (that is, with the Beveridge curve).

The rest of the paper is structured as follows. In Section 2 we deal with the presentation and estimation of the STAR models. In Section 3 we present the augmented version of Pissarides' (2000) model. In Sections 4 and 5, respectively, we calibrate and simulate the model. Section 6 assesses the impact of the oil price shocks in a broader macroeconomic context, and Section 7 concludes.

2   Do oil prices drive labor market fluctuations?

In this Section we examine to what extent the trajectories of unemployment, vacancies, and the job finding and job separation rates are driven by shocks in the real oil prices. This analysis is conducted through the estimation of STAR models.

2.1   STAR models

STAR models are a useful tool to model economic series which, very often, are characterized by nonlinearities and multiple equilibria. These models can be formulated as

$$y_t = (\alpha + \sum_{i=1}^{p} \phi_i y_{t-i})(1 - G(\gamma, x_{t-d} - c)) + (\tilde{\alpha} + \sum_{i=1}^{p} \tilde{\phi}_i y_{t-i})G(\gamma, x_{t-d} - c) + \varepsilon_t, \quad (1)$$

where α, $\tilde{\alpha}$, ϕ_i, $\tilde{\phi}_i$, γ and c are parameters to be estimated, and ε_t is an i.i.d. error term with zero mean and constant variance σ^2. The transition function $G(\gamma, x_{t-d} - c)$ is continuous, non decreasing and bounded between 0 and 1. The exogenous variable x_{t-d} is the so called transition variable and determines the regimes of the endogenous variable.

This STAR model can be interpreted as a regime-switching model allowing for two regimes associated with the extreme values $G(\gamma, x_{t-d} - c) = 0$ and $G(\gamma, x_{t-d} - c) = 1$, each corresponding to a specific state of the economy. When x_{t-d} deviates from the constant threshold value c, there is a transition between regimes whose speed is governed by the γ parameter.

Two popular choices of transition functions are the first-order logistic function,

$$\text{LSTAR: } G(\gamma, x_{t-d} - c) = (1 + exp\{-\gamma(x_{t-d} - c)\})^{-1}, \ \ \gamma > 0, \tag{2}$$

and the exponential function,

$$\text{ESTAR: } G(\gamma, x_{t-d} - c) = 1 - exp\{-\gamma(x_{t-d} - c)^2\}, \ \ \gamma > 0. \tag{3}$$

The first one delivers the logistic STAR (LSTAR) model and encompasses two possibilities depending on the transition speed γ. When $\gamma \to \infty$, the logistic function approaches to a constant and the LSTAR model becomes a two-regime threshold autoregressive (TAR) model. When $\gamma = 0$, the LSTAR model reduces to a linear AR model. Due its different responses to positive and negative deviations of x_{t-d} from c, the LSTAR specification is convenient for modelling asymmetric behavior in time series. This is not the case of the exponential STAR (ESTAR) specification, in which these deviations have the same effect. Consequently, this model is only able to capture non-linear symmetric adjustment.

Following Granger's (1993) "specific-to-general" strategy for building nonlinear time series models, Granger and Teräsvirta (1993) and Teräsvirta (1994) develop a technique for the specification and estimation of parametric STAR models. This procedure can be summarized in four steps (van Dijk *et al.*, 2002): (i) Specification of a linear AR model of order p for the time series under investigation; (ii) Test of the null hypothesis of linearity against the alternative of STAR; (iii) Selection of the appropriate transition function for the transition variable, if linearity is rejected; (iv) Model estimation, which is then used for descriptive or forecasting purposes.

Testing linearity against STAR is a complex matter because, under the null of linearity, the parameters in the STAR model are not identified. Granger and Teräsvirta (1993) suggest a sequence of tests to evaluate the null of an AR model against the alternative of a STAR model. These tests are conducted by estimating the following auxiliary regression for a chosen set of values of the delay parameter d, with $1 < d < p$:[4]

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \sum_{i=1}^{p} \beta_{2i} y_{t-i} x_{t-d} + \sum_{i=1}^{p} \beta_{3i} y_{t-i} x_{t-d}^2 + \sum_{i=1}^{p} \beta_{4i} y_{t-i} x_{t-d}^3 + \epsilon_t. \tag{4}$$

The null of linearity against a STAR model corresponds to: $H_0 : \beta_{2i} = \beta_{3i} = \beta_{4i} = 0$ for $i = 1, 2, ..., p$. The corresponding LM test has an asymptotic χ^2 distribution with $3(p+1)$ degrees of freedom under the null of linearity. If linearity is rejected for more than one value of d, the value of d corresponding to the lowest p-value of the joint test is chosen.

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[4]Equation (4) is obtained by replacing the transition function in the STAR model (1) by a suitable Taylor series approximation (see Granger and Teräsvirta, 1993).

In small samples, it is advisable to use F-versions of the LM test statistics because these have better size properties than the χ^2 variants (the latter may be heavily oversized in small samples). Under the null hypothesis, the F version of the test is approximately F distributed with $3(p+1)$ and $T - 4(p+1)$ degrees of freedom. Escribano and Jordà (2001) propose an extension of the Teräsvirta (1994) linearity test by adding a fourth order regressor.[5] Below we use both tests.

If linearity is rejected, we need to test for LSTAR against ESTAR nonlinearity. For this purpose, Granger and Teräsvirta (1993) and Teräsvirta (1994) propose the following sequence of tests within the auxiliary regression (4):

$H_{03} : \beta_{4i} = 0 \;\; i = 1, 2, ..., p$

$H_{02} : \beta_{3i} = 0 | \beta_{4i} = 0 \;\; i = 1, 2, ..., p$

$H_{01} : \beta_{2i} = 0 | \beta_{3i} = \beta_{4i} = 0 \;\; i = 1, 2, ..., p.$

An ESTAR model is selected if H_{02} has the smallest p-value, otherwise the selected model is the LSTAR. Escribano and Jordà (2001) also suggest a modification of this sequence of tests and propose two test statistics, H_{0E} and H_{0L}, for distinguishing between LSTAR and ESTAR models. An LSTAR is chosen if the minimum p-value is obtained for H_{0L}.

As noted before, linear model shortcomings have led to increasing research in nonlinear models. However, the complexity of multivariate nonlinear modeling leads us to test whether economic reasoning and data allow us to simplify this modeling. One possible simplification stems from the presence of common nonlinear components. Therefore, let us assume that within a given set of variables there is a nonlinear behavior of each individual variable with respect to the same transition variable. If this is the case, we can test whether there is a nonlinear comovement within this set of variables. In order to address this issue we test for common LSTAR nonlinearities following the methodology proposed by Anderson and Vahid (1998) based upon canonical correlations. Accordingly, let

$$y_t = \pi_{A0} + \pi_A(L)y_t + F(z_t)[\pi_{B0} + \pi_B(L)y_t] + \epsilon_t$$

be the multivariate version of the LSTAR model, where y_t is the vector of variables under analysis, $\pi_i(L)$ is a matrix polynomial of degree p in the lag operator, ϵ_t is i.i.d., and $F(z_t)$ is a diagonal matrix containing the transition functions for each series. Testing for common nonlinearities consists in testing whether some α exists such that $\alpha'y_t$ does not exhibit the type of nonlinearity that is present in the mean of each individual y_t. The test statistic is based on canonical correlations and is asymptotically distributed as $\chi^2_{(3p-1)5s+s^2}$, where p denotes the maximum lag length and s is the number of common

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[5]They claim that this provides better results when the data are mainly in one of the regimes and when there is uncertainty about the lag length of the autoregressive part. The corresponding LM test statistic has an asymptotic χ^2 distribution with $4(p+1)$ degrees of freedom under the null of linearity.

nonlinearities. Rejection of the null hypothesis provides evidence of the presence of at most s common nonlinearities.

Once the selected STAR models are estimated, they can be used to characterize the dynamic behavior of the endogenous variables' (y) through their impulse functions in response to the shocks ε. As shown in Teräsvirta (1994) analogous impulse response functions (IRFs) can be obtained by eventual forecast.

2.2   Variables and data

The variables we consider for y in equation (1) are vacancies (v), the unemployment rate (u), the job finding rate (ζ), and the job separation rate (s). In all four STAR models the transition function, x in equation (1), is the real oil price (p). We work with quarterly data (each datapoint corresponding to the average value of the variable in that quarter and we always use the first seasonal log difference of the variables $-\Delta p$, Δu, Δv, $\Delta\zeta$, and $\Delta s-$, which we take as the best proxy to their cyclical component. A popular alternative would be to use the Hodrick-Prescott filter, however we disregard this possibility in view of the spurious dynamics that, as shown by Cogley and Nason (1995), this two-sided filter may introduce in the analysis.

Our data is gathered from different sources. For the oil price we take the average world crude price (expressed in U.S. dollars per barrel) supplied by the International Monetary Fund (code 00176AAZZF).[6] To obtain real magnitudes we divide by the implicit GDP price deflator from the National Income and Product Accounts (NIPA) seasonally adjusted by the U.S. Bureau of Economic Analysis (BEA). The unemployment rate (seasonally adjusted) is constructed by the Bureau of Labor Statistics (BLS) from the Current Population Survey (CPS). As the proxy of vacancies we follow Shimer (2005) and use the Conference Board (CB) help-wanted advertising index, which is measured as the number of help-wanted advertisements in 51 major newspapers. Unfortunately, this series is only available until 2003. For the job finding and job separation rates we use the novel measures computed by Shimer (2007).[7] Our sample period runs from the first quarter of 1957 to the third quarter of 2003.

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[6] The U.S. West Texas Intermediate oil price is only available since 1959. However, both series display a correlation coefficient of 0.996 between 1959 and 2003.

[7] Shimer (2007) takes public data from the CPS on the number of employed, unemployed, and recent unemployed workers (less than five weeks). He considers a two-state continuous time model (employed or unemployed) and calculates the job finding and job separation probabilities by assuming that unemployed workers find jobs and employed workers loose jobs according to a Poisson process. Details are given in http:// robert.shimer.googlepages.com/flows and Shimer (2007).

2.3 Results

Linearity tests are only valid under the assumption of stationarity. We thus start by confirming that our variables are stationary and we follow the procedure in Sollis (2009) to test for the null of a unit root against the alternative of nonlinear stationarity. Table 1 shows that the null of unit root is clearly rejected for all variables, with the only exception of oil prices when the lag is chosen according to the multivariate AIC criterion. Once unit root is rejected, it is possible to test the null of symmetric against asymmetric nonlinear stationarity. Results are shown in the lower part of Table 1 and, accordingly, symmetric nonlinearity is rejected for all variables. We conclude that the variables are globally nonlinear stationary and asymmetric.

Table 1. Sollis *et al.* (2009) nonlinear unit root test.

Contrast: Unit root (H_0) versus nonlinear stationarity (H_1).

	AIC		BIC		HQ		MAIC	
Variable	lag	cv	lag	cv	lag	cv	lag	cv
Δp	5	4.26*	2	10.70***	5	4.26*	8	2.98
Δu	8	5.35**	4	13.30***	4	13.30***	4	13.30***
Δv	5	8.66***	5	8.66***	5	8.66***	0	18.16***
$\Delta \zeta$	5	4.24*	1	13.57***	5	4.24*	5	4.24*
Δs	4	5.10**	1	13.57***	4	5.10**	4	5.10**

Contrast: Symmetric (H_0) versus Asymmetric (H_1) nonlinear stationarity.

Δp	8.26***	18.81***	8.26***	5.50**
Δu	5.06**	6.85***	6.85***	6.85***
Δv	5.96***	5.96***	5.96***	12.56***
$\Delta \zeta$	8.26***	21.92***	8.26***	8.26***
Δs	9.71***	21.92***	9.71***	9.71***

Notes: Critical values (cv) at the 10, 5 and 1 per cent for the Sollis (2009) test are 3.496, 4.297, and 6.066, respectively. They have been computed by Monte Carlo simulation with 10,000 replications. *, ** and *** denote rejection of the null hypothesis of unit root against nonlinear stationarity at, respectively, 10, 5 and 1 percent.

Table 2 presents the test statistics for the null hypothesis of linearity against STAR nonlinearity. These tests are performed for each variable using real oil prices as transition variable, i.e. x_t in equations (1) and (4). According to the results, linearity is rejected for all variables using both Granger and Teräsvirta (1993) and Escribano and Jordà (2001) linearity tests. This robust result has a twofold implication. First,

all variables exhibit a nonlinear behavior within two extreme regimes and, second, the transition between both regimes is driven by real oil prices.

Adjustment to changes in the transition variable can be either symmetric or asymmetric. As pointed out before, if the transition function is exponential the implied adjustment will be symmetric, whereas if the transition function is logistic the adjustment is asymmetric. This is not a trivial choice, since in our case an asymmetric behavior would imply that positive shocks to real oil prices have a different impact on the dynamics of the labor market than negative shocks. Table 2 presents the Granger and Teräsvirta (1993) and Escribano and Jordà (2001) test for choosing between the ESTAR and the LSTAR model. According to the first set of tests statistics, the LSTAR representation of the data is preferred to the ESTAR one, i.e. H_{02} does not present the smallest p-value for the unemployment and job separation rates. According to Escribano and Jordà's (2001) test statistics, the LSTAR function is preferred for all variables since H_{0L} presents a lower p-value than H_{0E}. Therefore not only unemployment, vacancies, and the job finding and job separation rates present a nonlinear behavior for different values of real oil prices; on top of that, this behavior is asymmetric. This result give further insights in the asymmetric nature of labor market flows we have found using the Sollis (2009) unit root test since, at least partially, the asymmetric behavior of labor market variables is explained by an asymmetric response of these variables to real oil prices changes.

Table 2. Linearity tests.

	Δu	Δv	$\Delta \zeta$	Δs
		Linearity test		
Granger-Tërasvirta	0.001	0.000	0.015	0.070
Escribano-Jordà	0.009	0.000	0.027	0.027
		LSTAR versus ESTAR		
H_{01}	0.053	0.036	0.053	0.011
H_{02}	0.077	0.004	0.031	0.607
H_{03}	0.008	0.084	0.326	0.460
H_{0L}	0.087	0.002	0.002	0.153
H_{0E}	0.120	0.019	0.962	0.155
		Multivariate linearity test		
	0.005	0.003	0.000	0.025

Note: p-values are shown.

Table 3 presents the results for the common STAR nonlinearities test proposed by Anderson and Vahid (1998). These results are obtained using real oil prices as the

(common) transition variable. Taking, as standard, 5 percent as critical value, the null that there are no nonlinear factors in the system is rejected, whereas the null that there is only one such factor is not rejected. These tests, therefore, provide evidence that the nonlinear behavior of the labor market variables is generated by a common driving force: the real oil prices. The detection of a common component enables parsimony, which is specially important when estimating nonlinear multivariate models.

Table 3. Tests for common LSTAR nonlinearities.

Null hypothesis	Alternative hypothesis	p-value
The system is linear	At least one of the variables has a LSTAR nonlinearity	0.007
The system has at most 1 common LSTAR nonlinearity	The system has at least 2 common LSTAR nonlinearities	0.192
The system has at most 2 common LSTAR nonlinearities	The system has at least 3 common LSTAR nonlinearities	0.736
The system has at most 3 common LSTAR nonlinearities	The system has at least 3 common LSTAR nonlinearities	0.989
The system has at most 4 common LSTAR nonlinearities	The system has at least 4 common LSTAR nonlinearities	0.999

We have now determined that the labor market variables share a nonlinear component driven by oil prices as exogenous transition variable. As a consequence, to correctly capture the relationship between oil prices and these variables we proceed to estimate a multivariate non-linear model.

We start by regressing oil prices according to the following LSTAR process

$$\Delta p_t = \underset{(0.07)}{0.34}\Delta p_{t-1} - \underset{(0.15)}{0.51}\Delta p_{t-2} + \left(\underset{(0.21)}{0.73}\Delta p_{t-1} - \underset{(0.20)}{0.55}\Delta p_{t-2} \right) \times F(\Delta p_{t-3}) + \epsilon_t, \qquad (5)$$

which provides estimates of the transition parameter γ that will be used as the initial value in the estimation of the multivariate nonlinear model.[8] The resulting estimates of the nonlinear model are shown in Table 4 (with the lag-length chosen according to the multivariate AIC criterion) and the impulse-response functions (IRFs) pictured in Figure 2. These IRFs, and the corresponding 5 percent error bands, are obtained through Monte Carlo simulation.[9]

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[8]To obtain this initial value, an alternative procedure would be to conduct a grid search for the whole multivariate nonlinear model. However, given that all variables share the same common nonlinearity, i.e. the same value for γ, we find our procedure more clear and informative.

[9]We conducted 10,000 replications and used antithetical acceleration to improve convergence of draws. On the odd values for draws, a draw is made from the inverse Wishart distribution of the covariance matrix.

The fact that as value of the transition parameter we use the estimate shown in Table 4 *de facto* implies that the model becomes linear in the parameters. Ideally, we would compute IRFs based on the estimation of a multivariate model, nonlinear in both variables and parameters. However, when in the model we contrast the existence of a common nonlinear component, the matrix of transition functions becomes a diagonal matrix with equal elements and, therefore, equal γ parameters. As a consequence, the non-linear system becomes more parsimonious and tractable and facilitates the estimation process and the subsequent Monte Carlo simulations. This strategy of estimation has an additional advantage. Having a linear model in the parameters enables the comparison between the resulting empirical IRFs (shown in Figure 2) and the theoretical IRFs obtained through simulation of the theoretical model linearized at the steady state. This is so because the empirical IRFs can be interpreted as an average of the IRFs that would be obtained for each of the regimes within the nonlinear model under the oil price shock. This yields comparability with respect to the IRFs obtained through the model's simulation.

Table 4 presents the estimated multivariate nonlinear model where the transition function has been restricted in each equation to be the same following the test for common LSTAR nonlinearities.

Table 4. Estimated nonlinear system.

$$\Delta u_t = -\underset{(0.10)}{0.61}\Delta u_{t-1} - \underset{(0.05)}{0.31}\Delta v_{t-1} - \underset{(0.07)}{0.93}\Delta \zeta_{t-1} - \underset{(0.08)}{0.48}\Delta \zeta_{t-2} + \underset{(0.08)}{0.48}\Delta s_{t-2} +$$

$$\left(\underset{(0.02)}{0.03}\Delta p_{t-2} + \underset{(0.02)}{0.07}\Delta p_{t-4} + \underset{(0.06)}{0.16}\Delta v_{t-4} + \underset{(0.11)}{0.46}\Delta s_{t-2} \right) \times F(\Delta p_{t-3}) + \epsilon_{1t}$$

$$\Delta v_t = \underset{(0.09)}{0.33}\Delta u_{t-1} + \underset{(0.07)}{0.18}\Delta u_{t-4} + \underset{(0.13)}{0.89}\Delta v_{t-1} + \underset{(0.10)}{0.41}\Delta \zeta_{t-1} - \underset{(0.07)}{0.14}\Delta \zeta_{t-3} - \underset{(0.07)}{0.36}\Delta s_{t-1} +$$

$$\left(-\underset{(0.03)}{0.06}\Delta p_{t-3} - \underset{(0.03)}{0.11}\Delta p_{t-4} - \underset{(0.22)}{0.57}\Delta v_{t-1} + \underset{(0.15)}{0.30}\Delta v_{t-4} \right) \times F(\Delta p_{t-3}) + \epsilon_{2t}$$

$$\Delta \zeta_t = \underset{(0.05)}{0.51}\Delta v_{t-1} + \underset{(0.05)}{0.12}\Delta \zeta_{t-4} - \underset{(0.05)}{0.13}\Delta s_{t-2} +$$

$$\left(\underset{(0.11)}{0.37}\Delta u_{t-2} - \underset{(0.02)}{0.06}\Delta p_{t-3} - \underset{(0.03)}{0.08}\Delta p_{t-4} - \underset{(0.13)}{0.56}\Delta \zeta_{t-1} \right) \times F(\Delta p_{t-3}) + \epsilon_{3t}$$

$$\Delta s_t = -\underset{(0.08)}{0.26}\Delta \zeta_{t-1} + \underset{(0.09)}{0.22}\Delta \zeta_{t-4} - \underset{(0.08)}{0.43}\Delta s_{t-2} - \underset{(0.08)}{0.24}\Delta s_{t-3} - \underset{(0.07)}{0.20}\Delta s_{t-4} + \underset{(0.02)}{0.07}\Delta p_{t-3} +$$

$$\left(\underset{(0.17)}{0.45}\Delta u_{t-2} + \underset{(0.15)}{0.38}\Delta v_{t-4} - \underset{(0.15)}{0.38}\Delta v_{t-4} \right) \times F(\Delta p_{t-3}) + \epsilon_{4t}$$

where: $F(\Delta p_{t-3}) = (1 + exp[-\underset{(0.59)}{2.13}\,\Delta p_{t-3}])^{-1}$

Note: standard errors in parentheses.

Figure 2 plots the IRFs of unemployment, vacancies, and the job finding and job separation probabilities in response to a one-off shock on real oil prices. The shock we examine is always unfavorable (oil prices rise) and its size is normalized to one standard deviation. Cumulative responses to this shock are given in Table 6.

Figure 2. IRFs to a one-off shock in real oil prices
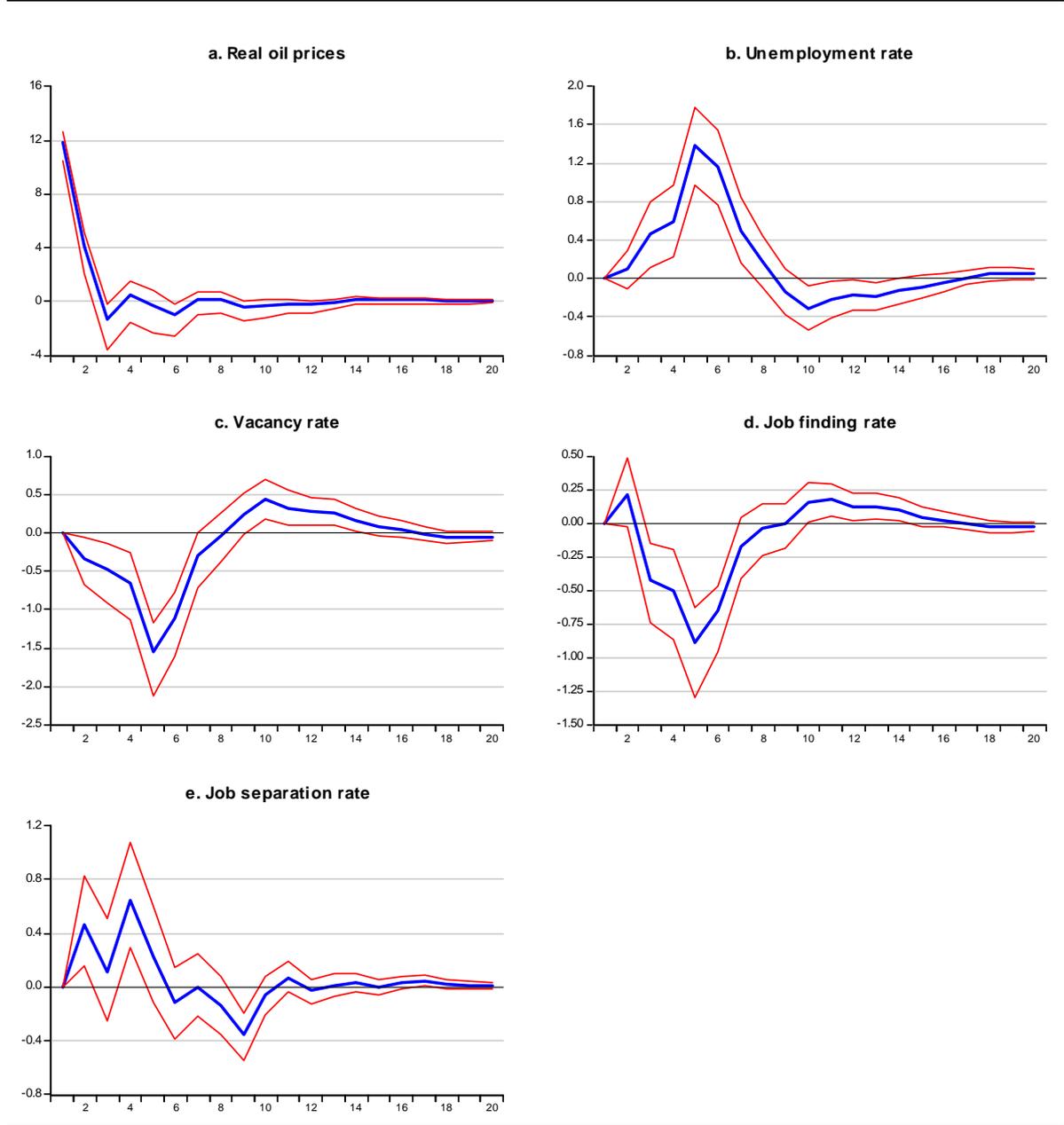
As shown in Figure 2a, the oil price shock has a strong initial impact (oil prices immediately rise by 11.89 percent) and vanishes quickly (its impact is statistically zero already in the third period). In consistency with this dynamic behavior, the theoretical model below assumes that the oil price shock follows the same LSTAR process.

As expected, an unfavorable shock rises unemployment, reduces vacancies, depresses the job finding rate, and promotes job destruction. The corresponding 5 percent confidence intervals indicate that all these responses are significant not only when the shock takes place but also for a number of periods. Therefore, beyond the fact that the labor market is significantly affected by an oil price shock, a first important result is the delayed and gradual responses of the variables due to the costly adjustments taking place. Although the adjustments are reflected in all variables, their dynamics vary. The unemployment and vacancy rates display a similar response (of different sign but similar magnitude) which picks up in the fifth period and subsequently dies out to zero (Figures 2b and 2c). A similar qualitative response can be seen in the job finding rate (Figure 2d), but with an initial positive response that is hard to rationalize and a smaller pick effect. In these three cases there is also some overshooting (only starting in the 9th or 10th periods) before the IRFs converge to zero. In contrast, the job separation rate (Figure 2e) displays a different reaction which is more volatile, less persistent, and smaller in magnitude.

The cumulative responses of the variables allow us to complete the analysis (note that these cumulative responses are plotted in Figure 3 below). In response to an overall increase of 13.68 percent in oil prices, the unemployment and job separation rates would rise by 3.22 and 0.94 percent respectively, while the vacancies and job finding rates would decrease by 2.85 and 1.79 percent. Therefore, there is a larger response in terms of unemployment and vacancies which, in turn and as expected, reproduce a negative Beveridge curve with slope -0.89 (=-2.85/3.22). It is also important to remark the key role of the job finding rate in explaining the movements in the Beveridge curve. Its response almost doubles the size of the job separation rate response and emerges as the main driving force of the adjustments in the labor market in response to an oil-price shock.

Table 5. Estimated cumulative responses to a one-off shock in oil prices

	Δp	Δu	Δv	$\Delta \varsigma$	Δs
Cumulative responses (percent)	13.68	3.22	-2.85	-1.79	0.94

3 The model

In this section we extend Pissarides' (2000) search and matching model to include real oil prices which further entails the endogenization of capital utilization and energy (oil) consumption. This extension generates a new set of economic relationships which has not yet been considered in the context of these models. In particular, energy prices affect both the capacity utilization rate of existing capital stock and the marginal cost

of new capital, and creates a channel whereby the labor factor, and thus the job finding and job separation rates, are affected. It is in this context that we study the effects of real oil price shocks on labor market fluctuations.

The economy is integrated by a continuum of risk-neutral, infinitely-lived workers and firms. Workers have linear utility over consumption of a homogeneous good. Workers and firms discount future payoffs at a common and constant rate, $1 > \delta > 0$, and capital markets are perfect. In addition, time is discrete.

Workers can be either unemployed or employed. Unemployed individuals enjoy a constant instantaneous utility b each period. Those who are employed earn a wage w.

Before a position is filled, the firm has to open a job vacancy with constant flow cost c. As in Pissarides (2009), when workers and firms start an employment relationship, the firm pays fixed training costs ξ. These costs are sunk because they take place once the wage bargain is concluded and the worker takes up the position. Firms have a constant-returns-to-scale Cobb-Douglas production technology with two production factors, capital and labor. Firms hire capital once the new worker has arrived and a wage rate has been agreed. The intensity in the use of capital is non-constant and governed by the capital utilization rate, h. Defining k as the capital stock per employee, the output per worker is $z_t f(k_t h_t) = z_t (k_t h_t)^{1-\alpha}$, where α is a technological parameter bounded between 0 and 1 and z is the match-specific productivity term, which is assumed to be independent and identically distributed across firms and time with a cumulative distribution function $G(z)$ and support $[0, \overline{z}]$.

Two particular features of this modeling need be remarked. First, similar to Finn (1995, 2000), higher capital utilization increases the capital depreciation rate $\rho(h_t)$, and generates energy costs equal to the product of energy prices, p_t, and energy consumption per worker, $e(k_t h_t)$. Specifically, we assume that $\rho(h_t) = \mu h_t$ and $e(k_t h_t) = \omega h_t k_t$, where the parameters $\mu > 0$ and $\omega > 0$. In this context, the per worker energy consumption, $e(k_t h_t)$, captures the idea that energy is essential to determine the rate of capital utilization (note that the larger h the more use of energy per unit of capital k at the constant rate ω). Second, we capture the fact that energy use does not change much in the short-run in response to energy price changes (Atkenson and Kehoe, 1999) by adding adjustment costs to capital services. Thus, the presence of adjustment costs reduces the response of capital services, $k_t h_t$, to changes in energy prices, p_t, and, since $k_t h_t$ and energy consumption $e(k_t h_t)$ are complementary, the latter also moves slowly over time in response to a shock in p_t.

We assume that energy prices, p_t, follow a LSTAR process similar to the estimated one for oil prices in (5) so that the energy price shocks can be adequately modeled. At the end, each productive firm yields an instantaneous profit equal to output per worker, $z_t f(k_t h_t)$, minus the wage, w_t, the capital costs, $(1 - \frac{1}{\delta}) k_t h_t + \rho(h_t) k$, and the energy

costs per employee $p_t e(k_t h_t)$.

There is a time-consuming and costly process of meeting workers and job vacancies, captured by a constant-return-to-scale meeting function $m(u_t, v_t)$, where u_t denotes the unemployment rate and v_t is the vacancy rate. We follow den Haan *et al.* (2000) and assume that $m(u_t, v_t) = \frac{u_t v_t}{(u_t^{\varphi} + v_t^{\varphi})^{1/\varphi}}$ with $\varphi > 0$. This functional form ensures that the ratios $\frac{m(u_t, v_t)}{u_t}$ and $\frac{m(u_t, v_t)}{v_t}$ lie between 0 and 1. Unemployed workers meet job opening positions with probability $\frac{m(u_t, v_t)}{u_t} = g(\theta_t)$, where θ is the vacancy-unemployment ratio $\frac{v}{u}$, and vacancies meet workers with probability $\frac{m(u_t, v_t)}{v_t} = q(\theta_t)$. Note that given the properties of the meeting function, these probabilities only depend on θ; therefore, the higher the number of vacancies with respect to the number of unemployed workers, the easier is for each of these workers to meet a job $g'(\theta) > 0$, and the more difficult is for a firm to fill its vacancy $q'(\theta) < 0$.

Firms open vacancies until the expected value of doing so becomes zero. Therefore, in equilibrium the value of vacancies V_t must equal zero. Imposing the free entry condition ($V_t = 0$), the marginal condition for labor demand is

$$0 = -c + \delta q(\theta_t) E_t \left[\int_{\widetilde{z}_{t+1}}^{\bar{z}} (J_{t+1}(z) - \xi) dG(z) \right], \tag{6}$$

where E_t is the expectation operator. Note that expectations are taken over the distribution of next periods' energy price. In turn, $J(z_t)$ is the value of a filled job which is represented by the following Bellman equation

$$J(z_t) = z_t f(k_t h_t) - (\frac{1}{\delta} - 1)k_t h_t - \rho(h_t)k_t - p_t e(k_t h_t) - w_t + \delta(1 - \phi)E_t \left[\int_{\widetilde{z}_{t+1}}^{\bar{z}} (J_{t+1}(z)) dG(z) \right]. \tag{7}$$

Each period workers may be exogenously separated with constant probability ϕ. Moreover, firms endogenously terminate the matches with productivity below some threshold, $\widetilde{z}_t$. This productivity threshold is defined such that nonprofitable matches are severed,

$$J(\widetilde{z}_t) = 0. \tag{8}$$

It follows that employees separate with probability s_t, and unemployed workers find jobs with probability ζ_t, where

$$s_t = \phi + (1 - \phi)G(\widetilde{z}_t), \tag{9}$$

$$\zeta_t = g(\theta_{t-1})(1 - G(\widetilde{z}_t)). \tag{10}$$

From the workers' side, the Bellman equations for the unemployed and employed

workers are given by

$$U_t = b + \delta E_t \left[g(\theta_t) \left(\int_{\widetilde{z}_{t+1}}^{\bar{z}} W_{t+1}(z) dG(z) + G(\widetilde{z}_{t+1}) U_{t+1} \right) + (1 - g(\theta_t))(1 - G(\widetilde{z}_{t+1})) U_{t+1} \right],$$
(11)

and

$$W_t(z_t) = w_t(z_t) + \delta E_t \left[(1 - \phi) \left(\int_{\widetilde{z}_{t+1}}^{\bar{z}} W_{t+1}(z) dG(z) + G(\widetilde{z}_t) U_{t+1} \right) + \phi U_{t+1} \right].$$
(12)

The unemployment rate, u_t, evolves according to the following backward-looking differential equation:

$$u_t = u_{t-1} + s_t(1 - u_{t-1}) - \zeta_t u_{t-1}.$$
(13)

Firms take wages as given and both rent and use as much capital as it is necessary to maximize J_t with respect to k_t and h_t. The equilibrium condition for the firm's capital stock requires the marginal product of capital to equal its marginal cost:

$$z_t f'_k(k_t h_t) = (\frac{1}{\delta} - 1)h_t + \rho(h_t) + p_t e'_k(k_t h_t).$$
(14)

Moreover, the condition regulating capacity utilization is

$$z_t f'_h(k_t h_t) = (\frac{1}{\delta} - 1 + \rho'(h_t))k_t + p_t e'_h(k_t h_t),$$
(15)

which sets the marginal benefit of capital utilization equal to its marginal cost. On the one hand, $(\frac{1}{\delta} - 1 + \rho'(h_t))k_t$ represents the marginal cost in terms of increased capital rents and depreciation from using capital at a higher rate. On the other hand, $p_t e'_h(k_t h_t)$ captures the increase in energy costs caused from higher capital utilization.

Observe that (14) and (15) represent a system of two equations in two unknowns, k_t and h_t, which are jointly determined when shocks in energy prices hit the economy.

To close the model, we also assume that wages are determined through bilateral Nash bargaining between workers and firms. The first-order condition yields the following equation

$$(1 - \beta)(W(z_t) - U_t) = \beta J(z_t),$$
(16)

where $\beta \in (0, 1)$ denotes the workers' bargaining power relative to the firms'. Under this assumption, the equilibrium wage is

$$w_t = \beta \left[z_t f(k_t h_t) - (\frac{1}{\delta} - 1)k_t h_t - \rho(h_t)k_t - p_t e(k_t h_t) + \theta_t c + \zeta_t \xi \right] + (1 - \beta)b.$$
(17)

For a given p^*, an equilibrium is a sextuple $(\widetilde{z}^*, k^*, h^*, \theta^*, w^*, u^*)$ that satisfies condition (13) for $u_t = u_{t-1} = 0$, the equilibrium conditions for the firm's capital rent (14)

and capital utilization (15), the job creation condition (6), the job destruction condition (8), and the wage equation (17).

The solution of the model is recursive. Capital stock and the rate of capital utilization per employee are determined first; the threshold $\widetilde{z}^*$, labor market tightness θ^*, and the wage w^* are determined next; and unemployment u^* is determined last.

4 Calibration

In this section we calibrate the model at quarterly frequencies by matching the steady-state properties of the model to US data.

Regarding the target values, we place the inverse of the quarterly output-capital ratio $k^*(1 - u^*)/y^*$ at 10, and the depreciation rate $\rho(h^*)$ at 2.5 percent per quarter. These are standard values generally used in the Real Business Cycle (RBC) literature. The average rate of capacity utilization, h, is set at 81 percent based on data for the industrial sector from the Federal Reserve Board. And the average share of energy expenditures over GDP, $p^*e^*(1 - u^*)/y^*$, is placed at 2.3 percent following Edelstein and Kilian (2007).[10]

The remaining targets are related to labor market outcomes. The average unemployment rate, u^*, is set at 10.4 percent following Yashiv (2006);[11] the steady-state job separation probability, s^*, at 0.10 percent per quarter following Shimer (2005); and the elasticity of the matching function with respect to unemployment, $\varepsilon_{m,u}$, at 0.72 according to the estimate reported in Shimer (2005). In turn, we target the vacancy and training costs using information reported by Barron *et al.* (1997) and Silva and Toledo (2009a). According to Barron *et al.* (1997) it takes 17 days on average to fill a vacancy. During this time the number of man-hours spent by the firm personnel recruiting, screening, and interviewing applicants to hire one individual for a vacant position is equal to 13.5. According to Silva and Toledo (2009a), the total average cost of these 13.5 hours amount to about 4 percent of the quarterly wage of a full productive worker. We thus set $c/w^* = 0.04$. Barron *et al.* (1997) report that new workers spend 142 hours on training during the first three months in the firm while experienced workers spend 87.5 hours training new employees (on average). The total average training cost of these man-hours is equivalent to 55 percent of the quarterly wage of a new hired worker. We follow Silva and Toledo (2009b) who calculate that only 28 percent of these

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[10]This share corresponds to the average sum, between 1977 and 2006, of the nominal value added in oil and gas extraction, imports of petroleum, and petroleum products divided by the US nominal GDP.

[11]Yashiv (2006) computes this average unemployment rate by considering not only the officially unemployed but also those not in the labor force who acknowledge to want a job. In this way, this value reflects the fraction of unmatched workers in the US. This computed unemployment rate is extremely correlated with the official rate (0.98).

costs are sunk, and fix $\xi/w^* = 0.55 \times 0.28 = 0.154$.

Notice that we are selecting parameter values based on long-run estimates or microeconomic data, which are not necessarily those giving the best time series responses for the unemployment, vacancy, job finding and job separation rates.

Table 6. Calibrated parameter values for the U.S. economy.

Parameters		Value	Target or Calibration
Energy price	p^*	1	Normalized
Mean of the distribution of z	v	0.000	Normalization
Standard deviation of z	σ_z	0.20	Other studies
Exogenous separation probability	ϕ	0.065	JOLTS data
Discount rate	δ	0.990	Match interest rate
Employment opportunity cost	b	1.439	Solves (8)
Parameter of the matching function	φ	2.963	Match $\varepsilon_{m,u}$
Worker's bargaining power	β	0.458	Solves (6)
Vacancy cost	c	0.079	Barron *et al.* (1997)
Training costs	ξ	0.369	Barron *et al.* (1997)
Depreciation rate parameter	μ	0.031	Match average depreciation rate
Energy usage	ω	0.003	Match energy share
Labor share	α	0.66	NIPA data

Having dealt with the targets, we need to find values for the following parameters: φ (discount factor), α (technology), μ (depreciation), ω (energy usage), φ (matching function), ϕ (exogenous job separation), c (vacancy cost), ξ (training costs), β (workers bargaining power), ϕ (exogenous job separation), b (employment opportunity cost); and also for the stochastic processes governing p (real oil prices) and z (random variable).

From our targets on the rates of capital depreciation and capacity utilization, we obtain:

$$\mu = \frac{p(h^*)}{h^*} = 0.0309.$$

The relative price of energy in the steady-state is normalized so that $p^* = 1$. Together with the targets on the unemployment rate, the output-capital ratio, and the average share of energy expenditures share, the use of energy consumption function $e(k^*h^*)$ yields:

$$\omega = \frac{\left(\frac{e^* p^* (1-u^*)}{y^*}\right)}{h^* (k^*/y^*) p^* (1 - u^*)} = 0.003.$$

We set the discount factor $\delta = 0.99$, which implies a reasonable quarterly interest rate of nearly 1 percent in the steady state. We also set the production function parameter

$\alpha = 0.66$, which is consistent with an average labor share of around two thirds given by the NIPA.

Regarding the exogenous separation probability ϕ, we interpret exogenous separations as worker-initiated separations. Hence, endogenous separations, $G(\widetilde{z}^*)$, are associated with the layoff rate. According to the U.S. Job Opening Labor Turnover Survey (JOLTS), layoffs represent on average about 35 percent of total separations. Thus, using equation (9) we set $\phi = 0.065$ and $G(\widetilde{z}^*) = 0.0374$.

Following den Haan *et al.* (2000), the idiosyncratic productivity, z, is assumed to be log-normally distributed with mean ν and standard deviation σ_z, whose values are set, respectively, at 0.0 and 0.2.[12] Thus, the calibrated threshold and the expected value of productive matches are equal, respectively, to $\widetilde{z}^* = 0.700$ and $\widehat{z} = 1.035$.

Given α, h^*, $\rho(h^*)$, ω, p^*, and $\widehat{z}$, we obtain k^* from the equilibrium condition for the firm's capital stock (14),

$$k^* = \left(\frac{(1-\alpha)\widehat{z}h^{*(1-\alpha)}}{(\frac{1}{\delta} - 1)h^* + \rho(h^*) + p^*\omega h^*} \right)^{\frac{1}{\alpha}} = 26.163.$$

Then, with, $k^*(1 - u^*)/y^* = 10$ and $p^*e^*(1 - u^*)/y = 0.023$, the calibrated values of total output and energy consumption are, respectively, $y^* = 2.616$ and $e^* = 0.067$.

Given our target job separation probability of $s_t = 0.10$, and using the unemployment equation (13), the equilibrium job meeting probability is $g(\theta^*) = 0.895$.

We select the matching technology parameter φ in order to match our target elasticity $\varepsilon_{m,u}$. Since the matching elasticity depends on θ as well, we need to solve the following system of equations for φ and θ^*,

$$\varepsilon_{m,u} = \frac{\theta^\varphi}{(1 + \theta^\varphi)},$$
$$g(\theta^*) = \frac{\theta^*}{(1 + \theta^\varphi)^{\frac{1}{\varphi}}}.$$

The first equation is the average elasticity of the matching function with respect to unemployment in the steady state. The second is the equilibrium job meeting probability. From this computation, we obtain, $\varphi = 2.963$ and $\theta^* = 1.375$.

The remaining parameters are vacancy flow costs c, training costs ξ, the employment opportunity cost b, and the wage bargaining parameter β. We chose β and b to satisfy the job creation and job destruction conditions (6) and (8). Parameters c and ξ are chosen to target the hiring and training costs. This requires to solve for w using the wage equation (17) and yields $c=0.0793$, $\xi=0.369$, $\beta=0.458$, $b=1.439$, and $w^*=1.845$.

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[12]For the standard deviation of the idiosyncratic shock, the literature provides a range of values between 0.1 (den Haan *et al.*, 2000) and 0.4 (Trigari, 2005) and we choose the intermediate case.

5 Simulated results

Next we use our matching model to simulate the labor market behavior in response to a particular exogenous process in the growth rate of the real oil price, Δp. This process reproduces the main statistical features (in terms of persistence and standard deviation) of the actual shocks experienced by the US oil prices.[13] We evaluate the model by comparing the extent to which the simulated cumulative responses obtained through this model fit the empirical ones estimated in Section 2. Figure 3 pictures the estimated (continuous-blue line) and simulated (dashed-red line) cumulative IRFs, while Table 7 gives the corresponding cumulative percent changes and the overall percent fit.

From a qualitative point of view, the sequence of unfavorable shocks and model's responses is as follows. First, an increase in real oil prices, p, rises both the user cost of capital and its marginal cost. Second, to restore the equilibrium conditions for capital and the rate of capacity utilization, both k and h decrease immediately to their new equilibrium after the shock. Third, since energy is essential to capital utilization, energy usage, e, is also reduced. Fourth, with less capital stock and lower capital utilization, the marginal product of labor becomes smaller and firms do not have the incentive to employ additional workers. Therefore, to avoid job creation firms need to close vacancies, v (job creation effect), which reduces the rate at which workers meet jobs $g(\theta)$ and, in turn, increases the unemployment rate, u, and reduces the workers' wages, w. Moreover, with the reduction in the marginal product of labor, low productive jobs are severed, which in turn increases the job destruction probability, s, and the flow of workers into unemployment (job destruction effect).

At the end, higher real oil prices increase unemployment but have uncertain effects on vacancies. On the one hand, the job creation effect reduces the number of vacancies but, on the other hand, the job destruction effect increases the number of unemployed available and, therefore, it is easier for firms to recruit new workers and they have new incentives to open vacancies. If the job creation effect dominates the job destruction effect, vacancies are reduced after the shock.

From a quantitative point of view, we first solve the model by using a first-order log-linearization procedure implemented in Dynare for Matlab, and we then compute the simulated IRFs. Although this linearization makes the exercise inherently unable to capture the nonlinear response of the labor market variables to shocks, we should recall that the estimated IRFs can be interpreted as an average of the IRFs that would be obtained for each of the regimes within the nonlinear model under the oil shock. In

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[13]The stochastic process of oil price growth rate, Δp_t, is considered exogenous and simulated according to the LSTAR process estimated in equation (5) . The values of the autoregressive parameters and the standard deviation of the white noise process are calibrated to match the actual autocorrelation coefficient (0.268) and standard deviation (0.127) of Δp_t observed between 1957 and 2003.

this way, our analysis should be interpreted with caution since we can not distinguish the different effects (if any) that the shock may have in the different regimes.

With this caveat in mind, it is interesting to see that the model accounts for a number of features identified through our previous econometric analysis. First of all, the model displays a negative relationship between vacancies and unemployment, and is thus qualitatively consistent with the downward-sloping Beveridge curve observed in the data. Second, the model is able to reproduce 64.6 percent of the cumulative unemployment response, and 94.0 percent of the vacancies' response. Therefore their negative relationship is precisely captured since the simulated labor market tightness amounts to -1.29 ($= -2.68/2.08$) which is not far from the estimated one (which is -0.89$= -2.85/3.22$). Third, also in accordance with our econometric analysis, the cumulative response of the job finding rate is higher than the response in the job separation probability, even though both are underestimated by the model. The simulated cumulative impact of the job finding rate fails short by 20 percent (-1.43 versus -1.79), while that of the job destruction rate does it by less than 6 percent (0.89 with respect to 0.94 in the data). As a consequence, the simulated cumulative response of the job finding rate is 70 percent larger than the one of the job separation rate, a figure somewhat smaller than the 90 percent obtained in the econometric analysis. Irrespective of these concrete values, it seems safe to conclude that the main driving force under the unemployment fluctuations in response to oil price shocks is the job finding probability.

Table 7. Cumulative responses to a one-off shock in real oil prices.

	Δp	Δu	Δv	$\Delta \varsigma$	Δs
Estimated cumulative responses (percentage points)	13.68	3.22	-2.85	-1.79	0.94
Simulated cumulative responses (percentage points)	13.67	2.08	-2.68	-1.43	0.89
Fit (percent)	99.9	64.6	94.0	80.2	94.4

Turning now to the path followed by the cumulative IRFs, we should note, first of all, that we reproduce the initial jump of 11.89 percent in real oil prices in response to the shock (Figure 3a), that we also match its path up to the 5th quarter, but that the series deviates afterwards to end-up converging to the same cumulated value (13.7 percent). This discrepancy, however, is not the cause under the relatively poor performance of the model in reproducing the dynamic trajectories of the labor market variables in the aftermath of the shock as shown in Figures 3b to 3e. The reason for these deviations needs to be found in the propagation mechanisms imbedded in the model. Due to

the forward looking behavior of the firms and the absence of planning lags in posting vacancies and laying off workers, oil price shocks are quickly translated into the labor market, especially through an almost immediate adjustment in the vacancy and job separation rates. As a consequence, subsequent labor market adjustments exhibit little of the persistence observed in the data.

Figure 3. Cumulative IRFs to a one-off shock in real oil prices.
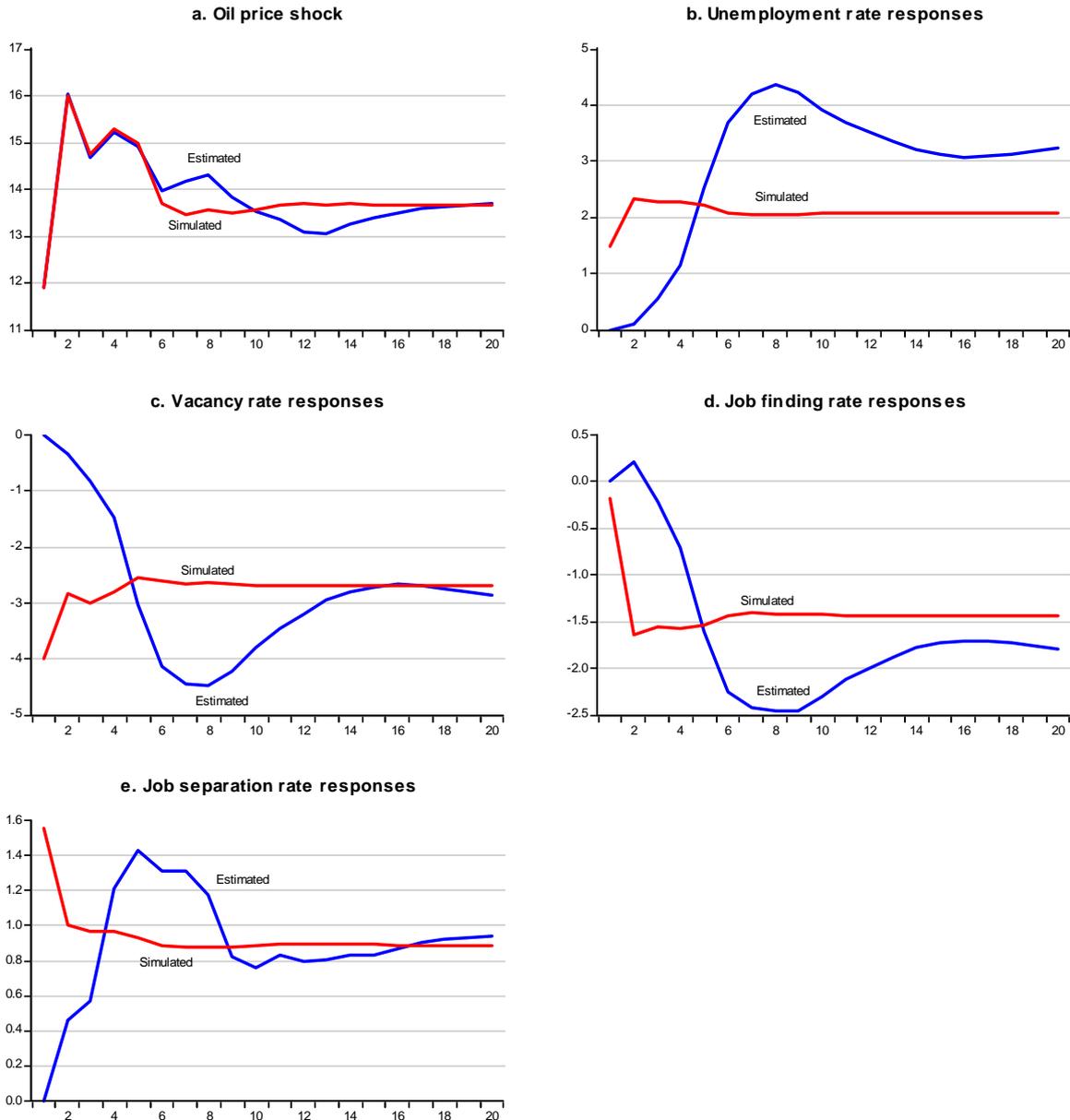
Summarizing, our model provides a good description of the cumulative responses of the labor market variables and is helpful in identifying the channels whereby the job finding rate is a driving force of labor market fluctuations produced by oil price shocks. However, the model is not able reproduce the dynamic behavior of these variables,

mainly because of the initial excessive sensitivity to the shock of the vacancy and job destruction rates.

6 Oil prices in a broader macroeconomic context

Although the Pissarides matching model has become a standard theory of equilibrium unemployment, its ability to match the observed cyclical fluctuations of US the unemployment rate was critically questioned by Shimer (2005). Its main criticism lies in the discrepancy between the similar expected volatilities of the vacancy-unemployment ratio and labor productivity under a reasonable calibration strategy, and the fact that the first of these standard deviations turns out to be at least 8 times larger than the latter. This discrepancy, which is generally known as the unemployment volatility puzzle, has prompted a dense literature trying to improve the empirical performance of the Pissarides model by extending its original formulation. Consideration of new sources of shocks in one of such extensions and the oil price shocks a natural complement to the standard labor productivity (or technological) shocks.

Along these lines, we next complete our assessment of the quantitative effects of the oil price shocks on labor market fluctuations by considering further macroeconomic variables and neutral technological shocks. We proceed in two steps. First, we show statistics describing the short-run behavior of the variables, including measures of their standard deviations and their cross-correlations with respect to Δp, at leads and lags of up to four quarters. Then, we simulate again our theoretical model in two scenarios, one in which the two independent and exogenous shocks on labor productivity and oil prices are considered, and another one in the absence of the oil price shock. At that point, by comparing how the simulated model in the presence and absence of the oil price shock fits the actual volatilities and contemporaneous correlations, we will be able to assess to what extent such shocks determine labor market and other macroeconomic fluctuations.

Up to this point we have worked with a restricted set of variables at the cost of disregarding other interesting macroeconomic relationships that have become popular in the context of the unemployment volatility puzzle. The reasons were, on the one hand, the requirement of sufficient degrees of freedom to estimate the multivariate STAR model in Section 2, which left some variables out; and, on the other hand, the correspondence needed between the variables considered in the econometric and the theoretical analyses. In order to overcome this restriction, in this section we briefly expand our analysis by considering other relevant macroeconomic variables such as energy consumption (e), capital utilization (h), total output (y), investment (i), wages (w), and labor productivity (y/n). In this way we are able to connect our results to

those generally obtained in the related literature.

Energy consumption is the index of total energy consumed in the industrial sector (from the US Energy Information Administration); capital utilization is the rate of capacity utilization in the industrial sector (from the Federal Reserve); total output is the real gross domestic product and investment is the real gross private domestic investment in equipment and software (both from the NIPA and seasonally adjusted by the US BEA). In turn, data on wages and labor productivity are taken from Shimer (2005). Wages is a real hourly compensation index and labor productivity is the seasonally adjusted real average output per person (both in the non-farm business sector, and both constructed by the BLS from the NIPA).

Since the time-series on e and h are only available 1967 and 1973 onwards respectively, we deal with a new sample period running from the first quarter of 1973 to the third quarter of 2003. As before, all series, including the labor market variables (u, v, ζ, and s) as well as the real oil price p, are first transformed in logs and then differentiated (Δ).

The unconditional correlations displayed in Table 8 offer some important pieces of information that endorse our previous results. The first one is the negative relationship between changes in oil prices and changes in both capital utilization –and consequently in energy consumption– and new investments. In parallel, firms also respond by posting less vacancies and destroying more jobs. As a result, the job finding rate decreases and unemployment increases. A second piece of evidence is the appearance of real oil prices as a leading indicator of the labor market performance, given that the maximum correlation is, in most cases, reached after four lags. For example, the contemporaneous correlation between Δu and Δp is very low and negative -0.039, but becomes highly positive (0.424) with Δp_{t-4}. This result is in line with the gradual adjustment of the labor market variables uncovered by the estimated IRFs in Section 2.3 in response to an unfavorable oil price shock.

We next simulate our matching model with independent and exogenous shocks in both oil prices and labor productivity. For the oil price shock we use the same stochastic process than in Section 5 based on the LSTAR process estimated in section 2.3. However, the process is now calibrated to reproduce the persistence (0.259) and standard deviation (0.158) of the US real oil price growth rate between 1973 and 2003. For the labor productivity shock we incorporate a new stochastic process by adding an aggregate component A_t to output per worker $A_t z_t f(k_t h_t)$ and assuming that its logarithm follows an AR(1) process so that $log(A_t) = \lambda log(A_{t-1}) + \epsilon_t$ with $\epsilon_t \sim N(0, \sigma_A)$. The values of the autoregressive parameter and the standard deviation of the white noise process are calibrated to match the actual autocorrelation coefficient (0.11) and standard deviation (0.085) of $\Delta (y/n)$, and we thus set $\lambda = 0.90$ and $\sigma_A = 0.0085$. As

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before, the model is solved by linearizing around the deterministic steady state and we also use Dynare for Matlab to compute the moments of the simulated series. Tables 9 shows the results (the baseline model considers both shocks while $\sigma_{\Delta p} = 0$ indicates that the oil price shock has been suppressed).

Table 8. Standard deviations and cross-correlations: real oil price versus other variables. US quarterly data, 1973-2003.

t					Δp_t				
	+4	+3	+2	+1	0	-1	-2	-3	-4
Δu (5.039)	-0.131	-0.014	-0.026	-0.096	-0.039	0.011	0.096	0.225	0.424
Δv (6.014)	0.088	0.035	0.031	0.087	0.033	-0.061	-0.090	-0.213	-0.383
$\Delta \zeta$ (4.340)	0.018	0.088	0.020	-0.011	0.089	0.044	-0.082	-0.248	-0.297
s (4.253)	0.102	0.109	-0.067	-0.082	0.025	0.131	0.156	0.204	0.084
Δw (0.603)	0.149	-0.034	0.015	0.015	-0.387	-0.272	0.036	-0.009	0.005
$\Delta(y/n)$ (0.854)	0.182	0.050	-0.062	-0.055	-0.204	-0.173	-0.162	-0.112	-0.157
i (2.563)	0.198	0.155	0.021	0.089	0.039	-0.066	-0.085	-0.110	-0.290
Δh (1.501)	0.033	0.031	-0.015	0.094	0.081	-0.059	-0.094	-0.158	-0.388
Δe (2.278)	0.033	0.078	-0.064	0.107	0.076	-0.006	-0.022	-0.083	-0.113
y (0.851)	0.194	0.127	-0.036	0.066	-0.066	-0.105	-0.155	-0.149	-0.267

Note: standard deviations in parentheses, In turn the standard deviation of Δp is 15.837.

When both shocks are considered (row 2 in Table 9), the simulated model performs well in matching the volatilities of all variables with the exception of wages. In some cases there is some underestimation –it generates, respectively, 91, 81, 85, and 80 percent of the observed standard deviations of unemployment, the job finding rate, investment, and capital utilization–, and in some others the volatility is overestimated –it reproduces 106 percent of the volatility observed in energy consumption, and yields standard deviations that are between 16 and 56 percent larger than in the data for the remaining variables–.

On the contrary, when the oil price shock is suppressed (row 3 in Table 9) all simulated volatilities fall, some of them significantly (again with the exception of wages). In other words, oil prices are an important transmission channel and play a relevant role in amplifying labor market fluctuations. In particular, when the oil price shock is operative, the standard deviations of the labor market variables increase between 12 percent (in the case of unemployment) and 33 percent (in the case of labor productivity). Regarding the rest of macroeconomic variables, the oil price channel contributes to rise by 24 percent the volatility of output, by 55 percent that of investment, and allows to multiply by 4 (from 0.30 to 1.20) the standard deviation of capital utilization.

Table 9. Simulated standard deviations (percent)

	Δy	Δi	Δe	Δh	Δu	Δv	$\Delta \zeta$	Δs	$\Delta(y/n)$	Δw
US Data	0.85	2.56	2.28	1.50	5.04	6.01	4.34	4.25	0.85	0.603
Parameterization										
Baseline	1.33	2.17	2.42	1.20	4.57	9.14	3.51	4.91	0.85	2.13
$\sigma_{\Delta p}= 0$	1.07	1.40	1.56	0.30	4.04	7.58	2.99	4.46	0.64	2.08

These results should come as no surprise since an oil price shock has a direct impact on the optimal conditions (14) and (15), which are the ones governing capital accumulation and capital utilization, respectively. In parallel, energy consumption becomes also less volatile due to its high complementarity with capital services kh.

Table 10. Simulated cross-correlations

	US Data	Parameterization	
		Baseline	$\sigma_{\Delta p}= 0$
$corr(\Delta y, \Delta i)$	0.583	0.941	0.961
$corr(\Delta y, \Delta e)$	0.349	0.941	0.961
$corr(\Delta y, \Delta h)$	0.742	0.767	0.958
$corr(\Delta y, \Delta u)$	-0.686	-0.946	-0.948
$corr(\Delta y, \Delta v)$	0.648	0.844	0.910
$corr(\Delta u, \Delta v)$	-0.818	-0.824	-0.878
$corr(\Delta y, \Delta \zeta)$	0.407	0.330	0.235
$corr(\Delta y, \Delta s)$	-0.240	-0.775	-0.832
$corr(\Delta y, \Delta y/n)$	0.764	0.979	0.972
$corr(\Delta y, \Delta w)$	-0.073	0.322	0.265

Furthermore, as Table 10 shows, results from our baseline calibrated model contain two important predictions. Regarding the labor market, the negative correlation of -0.82 between vacancies and unemployment is correctly matched, and the model is thus able

to reproduce the Beveridge curve. Regarding the macroeconomic scenario, the model is able to reproduce the sign of the relationship between GDP and the rest of variables (except wages) although most of the observed correlations are overestimated. This quantitative discrepancy, which is not large in most cases, is in part due to the absence of other relevant sources of shocks, such as investment-specific shocks. Consideration of these shocks, which are receiving growing attention in the literature but lie beyond the scope of this paper, would tend to reduce the simulated correlations.[14]

7   Conclusions

This paper brings several new and important results to the literature. First, shocks in real oil prices are a relevant driving force of labor market fluctuations. Second, the transmission mechanism of such shocks is essentially the job finding rate. And third, oil price shocks are complementary to the standard technological shocks and provide a new amplification mechanism of business cycle fluctuations in the context of the Pissarides' model.

To enhance our understanding of these new results, we have augmented Pissarides' (2000) search and matching model to incorporate energy consumption and endogenous capacity utilization, both depending on oil prices. Through this model we have been able to confirm and explain the relevance of real oil price shocks in generating labor market fluctuations. We have also uncovered and quantified the relevant role of the job finding rate as a key driving force of those shocks, and we have provided a satisfactory account of the facts in terms of their cumulative impact. On the less successful side, we have failed to match the gradual response of the different variables.

In a nutshell, our model yields two new important insights. On the one hand, it seems safe to conclude that shocks in oil prices cannot be neglected in explaining cyclical labor adjustments in the U.S. On the other hand, to provide a fully comprehensive account of the relationships at work, search and matching models *à la* Pissarides (2000) need to be further extended.

Along the lines of Polgreen and Silos (2009), one possibility would be to distinguish skilled from non skilled workers and focus on the interactions between the match quality/skill level of workers and oil as an input. Another natural extension could consider Kilian's (2009) claim that not all oil price shocks are alike and, thus, that demand and supply shocks need to be disentangled. This would give room to a full consideration of the nonlinear and asymmetric effects of such shocks, which has been constrained in

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[14]Toledo and Silva (2010), for example, show that investment-specific technological shocks (*i*-shocks) reduce the correlation coefficients between GDP and the rest of labor market and macroeconomic variables (for example, the correlation between GDP and unemployment falls from -0.95 to -0.82; see their Table 7 for details)

this paper. Following this claim, new research avenues should consider general equilibrium models where not only firm's decisions depend on oil prices, but also household's decisions are taken into account. We suspect such extension could deliver an extra propagation mechanism for the effects of the shocks in oil prices. If households react to such shocks, as it seems to be the case (Edelstein and Kilian, 2009), then firms will feel demand-side constraints, on top of supply-side constraints of the type considered in this paper. This will help to complete the important but still incomplete picture we have just presented.

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