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Labor and investment frictions in a real business cycle model

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Abstract

This paper develops a prototype real business cycle model in which labor and investment frictions may compete directly with technology shocks in accounting for fluctuations in the postwar US economy. Using Ireland's [2004a. A method for taking models to the data. Journal of Economic Dynamics and Control 28, 1205–1226] methodology, we establish that both types of friction are quantitatively important. Technology shocks still explain a substantial fraction of the fluctuations in aggregate output, as the baseline real business cycle model predicts. Formal hypothesis tests suggest that changes in the recurrence of shocks, frictions, and structural parameters all play a role in accounting for the shift in the time series properties of the data between the periods before and after 1980.

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1. Introduction

In its original formulation, the RBC theory postulates that technology shocks play the dominant role in driving economic fluctuations.[1] Other shocks either have minimal effects

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[1]See, for instance, King and Rebelo (2000), the The Royal Swedish Academy of Sciences (2004), and McGrattan (2008).

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on the cyclical behavior of the economy or are absent altogether. Researchers have extended the basic RBC setting by adding market frictions that modify the transmission mechanism, or by incorporating exogenous shocks capable of driving business cycle fluctuations.[2] A recent paper by Chari et al. (2007) brings these extensions together and demonstrates that market frictions can be represented by 'wedges' that distort the relation between various marginal conditions dictated by the prototype RBC model. These wedges, in their general specification, are time-varying and stochastic. Therefore, frictions in their most primitive form can be interpreted as stochastic wedges that enter the structure of the prototype RBC model, and can be approximated by stochastic processes that help the model to match the complex dynamics in the data.

In this paper, we take this intuition forward and investigate the role of labor and investment frictions in the postwar US economy. More specifically, we examine quantitatively, by applying Ireland's (2004a) methodology, the interactions between these frictions and the original technology shocks, using a prototype RBC model.

Towards that end, Section 2 of this paper develops a dynamic, stochastic, general equilibrium (DSGE) model that allows for, but does not require, labor market frictions to introduce a stochastic time-varying wedge in the agents' optimal employment rules, and, hence, to affect aggregate fluctuations. The same model also allows for, but again does not require, investment frictions to introduce a stochastic time-varying wedge into the marginal efficiency of investments and, hence, again, to affect aggregate fluctuations. The model can therefore distinguish between labor market frictions, investment frictions, and technology shocks when accounting for macroeconomic fluctuations. In essence, this extended model nests, as a special case, the prototype RBC model in which technology shocks alone play the dominant role. It therefore provides a useful framework in which a technology shock-driven specification can be compared to more general alternatives. Section 3 takes this framework to the data via maximum likelihood estimation, using postwar US data. Two constrained versions of the model, first without labor frictions and then without investment frictions, are compared and formally tested against the unconstrained alternative that allows for both frictions. The results of this econometric exercise indicate whether one, or a combination of both, of these frictions is needed to improve the ability of the prototype RBC model to mimic the dynamics in the data. Maximum likelihood estimation prefers a version of the model in which both frictions are present, pointing out that the presence of these frictions together is quantitatively important in explaining fluctuations in the postwar US economy. The out-of-sample forecasts of the model with both frictions are more accurate than those from the competing specifications. The estimated model is then used to address a number of key issues concerning the ability of these frictions to explain movements in output, consumption, investment and hours worked in the postwar US data. The analysis shows that, even in a model incorporating these frictions, technology shocks still explain a substantial fraction of the fluctuations in aggregate output, as the baseline real business cycle model predicts. Moreover, forecast error variance decomposition supports the estimation exercise in showing that technology shocks, labor and investment frictions together account for nearly all the observed movement in output, consumption, investment, and hours worked. In addition, formal hypothesis tests suggest instability between the periods before and after 1980 in the estimated parameters for the technology shock, investment frictions and, also,

[2] See King and Rebelo (2000) and, for a more recent review, Rebelo (2005) and references therein.

for the more structural parameter of the capital share of output. Finally, Section 4 concludes.

Before proceeding, we discuss the context provided by previous studies. This paper is related to the literature that examines the role of market frictions in a DSGE setting. The role of labor market frictions has been extensively studied by, for example, Parkin (1988), Hall (1997), Holland and Scott (1998), Mulligan (2002), and Gali et al. (2007), in the context of a wedge between the household's marginal rate of substitution and the marginal product of labor. The role of investment frictions has been extensively studied by McGrattan (1994) in the form of distortionary taxation, and by Carlstrom and Fuerst (1997) and Cooper and Ejarque (2000) in the form of agency costs for the financing of investment. All these works show that labor and investment frictions, considered on their own, are important features in explaining aggregate fluctuations of the US economy. In this paper, we consider these frictions in a unified, full-blown, general equilibrium framework and, unlike any of these previous works, we estimate and formally test their importance.

As mentioned, this paper is closely related to Chari et al. (2007), as it shares the same underlying framework and conducts the analysis over the same time period. Despite these similarities, these authors find that the efficiency wedge – or, more generally, technology shocks – and the labor wedge are the most important frictions and that the investment wedge plays a negligible role in explaining fluctuations in the postwar US economy. This paper instead finds that technology shocks, together with both labor and investment frictions, are statistically important. As detailed below, one important difference is that while Chari et al. (2007) use the data to solely estimate the structural form of the wedges, we instead allow the structure of the model to interact with technology shocks and frictions in explaining fluctuations in the postwar US economy. Hence, the approach used here is broader as it does not force technology shocks and labor and investment frictions alone to match complex dynamics in the data, since structural parameters of the model also play a role in explaining the observed variables. This, as shown below, has non-trivial influence on the results. Furthermore, it also enables us to test the significance and the stability of technology shocks, frictions and, moreover, of some structural parameters of the model over the sample period, in order to establish how their significance and explanatory role varied over time.

This paper is also related to Greenwood et al. (2000), DeJong et al. (2000), Pakko (2002, 2005), and Fisher (2006) who investigate the role of investment-specific technology shocks in explaining macroeconomic fluctuations using a prototype RBC model. Greenwood et al. (2000), using a calibrated RBC model, find that investment-specific technology shocks are important in explaining long-run economic growth. Pakko (2002, 2005) enriches this setting to show that shocks to both the level and the growth rates of neutral and investment-specific technology are important in accounting for observed fluctuations. Fisher (2006) extends the analysis by using a calibrated RBC model, enriched with investment-specific shocks, to identify the long-run restrictions to impose in the VAR estimation, so as to use the empirical model to quantify the impact of investment-specific shocks on short-run fluctuations of observed macroeconomic variables. His estimation supports the importance of investment-specific technology shocks in explaining fluctuations in the postwar US economy. DeJong et al. (2000) estimate a RBC model enriched with investment shocks and show that these play an important role in driving cyclical activity. Our conclusions are similar to these, since investment frictions are found to be statistically significant in accounting for fluctuations in the postwar US economy. Nonetheless, we find that, although investment frictions contribute significantly to short-run fluctuations in output, they play a minor role in accounting for long-run fluctuations. Our approach is different in two key aspects. First, the theoretical framework embeds investment frictions with labor frictions, and therefore these also compete in explaining fluctuations in the data. Second, we estimate the structural equations of the model using maximum likelihood and we then use this coherent, empirically grounded, framework to draw conclusions. These authors, with the exception of DeJong et al. (2000), either use a calibrated model or they use an empirical VAR model validated by the underlying theoretical framework. We think that the advantage of our approach is that it develops the analysis using a unified, empirically grounded, general equilibrium framework.

This paper also relates to Justiniano and Primiceri (2007), who study the sources of shifts in the volatility of macroeconomic variables in the postwar US economy. They use a large-scale model in which a variety of real and nominal shocks, whose volatility is allowed to change over time, compete in accounting for macroeconomic fluctuations. They find that the volatility of several shocks has changed dramatically over the postwar period, and that the reduction in the standard deviation of output growth is mainly due to the decline in the volatility of investment-specific technology shocks. Similarly, in our analysis, formal hypothesis tests suggest instability of the technology shocks, frictions, and structural parameters between two sample periods. Moreover, as in Justiniano and Primiceri (2007), the estimated volatilities of technology shocks and labor and investment frictions decline over the sample period. In contrast to them, though, we cannot attribute the reduction in output growth volatility to only one shock. Our approach is radically different since, in order to keep the simplest theoretical model and the closest coherence to the RBC paradigm, we reach our conclusions using a theoretical framework in which nominal shocks do not play a role in driving macroeconomic fluctuations, and in which the effects of monetary and fiscal policies are not considered.

Of course this is not the first paper that estimates a prototype RBC model. Altug (1989), Bencivenga (1992), McGrattan (1994), and McGrattan et al. (1997), represent early attempts to estimate, using maximum likelihood, a RBC model augmented with various stochastic shocks and interpret these as measurement errors to the underlying RBC model. Subsequently, Ireland (2001b) estimates, again using maximum likelihood, as described in Ireland (2004a), a prototype RBC model and shows that the data prefers technology shocks that are trend stationary over random-walk processes. This author, similarly to these previous studies, limits the analysis to consider technology shocks only, and interprets the other stochastic components as measurement errors to the underlying RBC model. Instead, this paper enriches the model with additional stochastic components, which have the structural interpretation of labor and investment frictions, and which compete directly with technology shocks in accounting for the dynamics of the data. Recent attempts to estimate a RBC model are those by Chang and Schorfheide (2003) and Chang et al. (2007), who enrich a baseline RBC model with home production technology shocks and permanent labor supply shocks, respectively. These authors, using Bayesian methods, show that these enriched models fit the labor market data better. Their focus is exclusively on labor shocks, while this paper, again, in a unified framework, also considers investment shocks as an important element to account for fluctuations in the data. Another recent paper on this topic is Ireland and Schuh (2007), who estimate a two-sector real business cycle model and show that technology shocks in consumption- and investment-goods producing sectors and labor supply shocks are important in explaining postwar US fluctuations. These authors focus mainly on issues relating the persistence of different shocks and in using the model to interpret the productivity slowdown of the 1970s and the revival of the 1990s, whereas this paper links the results more directly to Chari et al. (2007) and those in Ireland (2004a). Overall, although the framework of this paper shares certain common features, and in some cases also the methodology, with each of the mentioned works, it is the first to estimate, through maximum likelihood, and test the importance of labor and investment frictions in accounting for fluctuations in the postwar US economy using a prototype RBC model.

2. Model

The model resembles Hansen (1985), with the additional feature of labor and investment frictions. This takes the form of adding stochastic time-varying wedges to their respective marginal conditions. The economic environment consists of a representative household and a representative firm.

The representative household enters each period $t = 0, 1, 2, \ldots$ with capital K_t, and supplies H_t units of labor at the nominal wage rate W_t, and K_t units of capital at the nominal rental rate Q_t to the firm. The household also consumes C_t units of finished goods, purchased at the nominal price P_t from the representative firm. 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

$$K_{t+1} = (1-\delta)K_t + x_t I_t, \tag{1}$$

where the depreciation rate satisfies $1<\delta<0$, and the disturbance x_t is, in equilibrium, the Greenwood et al. (1988) shock to the marginal efficiency of investment; it follows the autoregressive process

$$\ln(x_t) = (1-\rho_x)\ln(x) + \rho_x \ln(x_{t-1}) + \varepsilon_{xt}, \tag{2}$$

with $1<\rho_x<0$, and where the zero-mean, serially uncorrelated innovation ε_{xt} is normally distributed with standard deviation σ_x. Thus the household chooses consumption C_t, units of labor H_t, and units of capital K_{t+1} to maximize the expected utility function

$$\mathrm{E}\sum_{t=0}^{\infty} \beta^t [\ln(C_t) - \gamma e_t H_t]$$

subject to the budget constraint

$$Y_t = C_t + I_t \tag{3}$$

for all $t = 0, 1, 2, \ldots$. The discount factor satisfies $1<\beta<0$ and $\gamma>0$. The preference shock e_t translates, in equilibrium, as shown below, into the Parkin (1988) shock to the equality between the household's marginal rate of substitution and the firm's marginal product of labor; it follows the autoregressive process

$$\ln(e_t) = (1-\rho_e)\ln(e) + \rho_e \ln(e_{t-1}) + \varepsilon_{et} \tag{4}$$

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

The representative firm hires H_t units of labor and K_t units of capital from the representative household during each period $t = 0, 1, 2, \ldots$ to manufacture Y_t units of goods using the technology

$$Y_t = A_t K_t^{\theta} (\eta^t H_t)^{1-\theta}, \tag{5}$$

where $1 < \theta < 0$ represents the capital share of production. The technology shock follows the autoregressive process

$$\ln(A_t) = (1 - \rho_a)\ln(A) + \rho_a \ln(A_{t-1}) + \varepsilon_{at} \tag{6}$$

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

The equilibrium conditions are derived by equating the household and firm's first-order conditions on labor and capital, which produce

$$\gamma e_t C_t = (1 - \theta) Y_t / H_t \tag{7}$$

and

$$1/x_t C_t = \beta \mathrm{E}_t \{(1/x_{t+1} C_{t+1})[\theta Y_{t+1}/K_{t+1} + 1 - \delta]\} \tag{8}$$

and by Eqs. (1)–(6). Eq. (7) confirms that, as suggested earlier, the preference shock e_t enters as a time-varying wedge to the agents' optimal labor decisions.

3. Estimation and results

In equilibrium, the variables of the model, except hours worked, grow at the same rate η^t. To make them stationary, we de-trend them, by dividing each of them by η, so that in absence of disturbances the model converges to a balanced growth path, along which all variables are constant. Before estimating the model, we need to make the variables in the model consistent with their measures in the data. For this reason, we define a new variable $I_t^* = x_t I_t$ and re-write Eqs. (1) and (3) as

$$K_{t+1} = (1 - \delta) K_t + I_t^* \tag{9}$$

and

$$Y_t = C_t + I_t^* / x_t. \tag{10}$$

Eqs. (9) and (10) are fully equivalent to (1) and (3) in terms of their implications for the model, but I_t^* is expressed in units of investment goods, and C_t and Y_t are expressed in units of consumption goods, consistently with the data, so that $(1/x_t)$ appears as the relative price of investment compared to consumption. To convert the model into a suitable form for the estimation, the system of equations (2), (4)–(10) is log-linearized around the steady-state and solved using the method developed by Klein (2000), which is a modification of Blanchard and Kahn (1980). In this way, the equilibrium conditions take the form of a state-space econometric model, with the observation equation

$$f_t = F s_t \tag{11}$$

and the state equation

$$s_{t+1} = \Pi s_t + W \varepsilon_t, \tag{12}$$

where $f_t = (y_t, i_t^*, h_t, c_t)$, $s_t = (k_t, a_t, e_t, x_t)$, $\varepsilon_t = (0, \varepsilon_{at}, \varepsilon_{et}, \varepsilon_{xt})$, and the matrices F, Π, and W depend upon parameters expressing agents' tastes and technologies. Hence, the Kalman filter techniques, described by Hamilton (1994, Chapter 3) and Hansen and Sargent (2002), can be applied to estimate the model parameters via maximum likelihood.

To implement the estimation, we use US data to measure C_t, H_t, and I_t^* in the model. We use quarterly US data on consumption, defined as real personal consumption expenditures in chained 1996 dollars, and investment, defined as real gross private domestic investment in chained 1996 dollars, taken from the Federal Reserve Bank of St. Louis's FRED database. Data for hours worked, defined as hours of wage and salary workers on private, non-farm payrolls, are from the Establishment Survey of the Bureau of Labor Statistics. The sample is from 1948:Q1 to 2002:Q2. All series are seasonally adjusted and are expressed in per-capita units, by dividing each variable by population,[3] so to make the data comparable with the model. The RBC model assumes that investment and consumption grow at the rate η in steady-state. For this reason, log levels of investment and consumption are linearly de-trended, so that they are expressed in percentage deviations from the trend, consistent with the theoretical model, as part of the estimation process.[4] The data are not filtered in any other way.

To estimate the model we apply the methodology described in Bouakez (2005), Bouakez et al. (2005), and Lippi and Neri (2007), and originally developed by Sargent (1989) and Ireland (2004a), where the vector of observable variables $f_t = (i_t^*, h_t, c_t)$ is enriched by some measurement errors u_t, which follow an autoregressive process $u_t = Du_{t-1} + \xi_t$, where the zero-mean, serially uncorrelated vector ξ_t is normally distributed with covariance matrix V. As originally suggested by Altug (1989), Sargent (1989), McGrattan (1994), McGrattan et al. (1997), and then by Bouakez (2005), Bouakez et al. (2005), and Lippi and Neri (2007) we assume that the measurement errors are uncorrelated across variables so that V is diagonal, and that the real business framework enriched with labor and investment frictions accounts for all the co-movements between the observed variables so that D is diagonal. Ireland (2004a) considers a more general structure for the matrices V and D, where they are not constrained to be diagonal. In this way he can interpret the residuals serving as measurement errors and also capturing all the comovement in the data. Here instead, assuming the matrices D and V to be diagonal allows the residuals to be interpreted exclusively as measurement errors, while allowing the comovement of the data to be captured by technology shocks, labor and investment frictions. This assumption also implies that technology shocks and labor and investment frictions are independent of each other. It may not be satisfied if, for example, technology shocks have spill over effects on investment frictions due to the presence of monetary policy variables, which are not explicitly considered in the basic real business cycle model, that may alter the dynamics of investment frictions in response to technology shocks. The presumption is that this assumption holds as an approximation, so that the estimation provides informative results.

[3]Population is measured by the civilian, non-institutional population, aged 16 years and over and is taken from the Federal Reserve Bank of St. Louis's FRED database.

[4]Recent work by Greenwood et al. (1997) and Whelan (2003) suggests that the trend in real investment is different from the trend in real consumption, thereby requiring that the two series should be ideally de-trended using a different trend. Unfortunately, in the context of the one-sector model used here no easy way of correcting for this discrepancy exists; but extending the analysis using a two-sector model would be a useful extension for future research.

Here, the data do not contain enough information to estimate all the model parameters. Hence, as in other similar studies,[5] since the estimate of those is implausible, we use additional evidence about their magnitude to calibrate their values. We fix the household's discount factor β to 0.99, implying a steady-state gross real interest rate of approximately 1.01, and the depreciation rate δ to 0.025. These values were originally used in Hansen (1985), and similar values are commonly employed in the literature.

Table 1 presents maximum likelihood estimates of the model structural parameters γ, η, θ, A, e, x, ρ_a, ρ_e, ρ_x, σ_a, σ_e, and σ_x, along with the elements of the matrix D, d_i, d_c, d_h, and the elements of the matrix V, v_i^2, v_c^2, and v_h^2. The values in parenthesis are the standard errors, which are calculated as the square roots of the diagonal elements of minus one times the inverted matrix of second derivatives of the maximized log-likelihood function. Column 1 shows the estimates of the unconstrained model, where both labor and investment frictions are included. The point estimates of the parameters describing the agents' tastes and technologies appear quite plausible. The parameter of the disutility of hours worked, γ, is 0.0057. This value is in line with the point estimate in Ireland (2001b, 2004a). The estimate of the capital share parameter, θ, equals 0.18, which, considering the associated low standard error, is lower than the value of 0.3 commonly used in the literature, but not that much lower than the estimate of 0.23 in Ireland (2004a). The estimate of the trend growth term in the production function, η, equals 1.0051. This value implies a steady-state annual growth of output of 2.04%, which is consistent with the US average growth of output over the sample period. To make the model closer to the RBC literature and the approach similar to Chari et al. (2007), we could have calibrated these structural parameters of the model, so to force technology shocks and labor and investment frictions alone to match complex dynamics in the data. By leaving the data to also establish the values for some structural parameters, the model has more degrees of freedom in explaining the data and, moreover, as detailed below, we can formally test the significance and stability of technology shocks, frictions, and structural parameters of the model over the sample period so to establish how their significance and explanatory role varied over time.

We now turn to the analysis of the model's stochastic components. The estimate of the level of productivity, A, equals 7.25. Ireland (2001b, 2004a) find similar point estimates for this parameter. The estimate for the parameter that represents the magnitude of the steady-state labor frictions, e, is 0.89. The estimate for the steady-state investment frictions, x, is 0.83. The standard errors associated with these estimates are small. In general, all the three model's stochastic components are highly persistent. The estimate of the persistence of technology shocks, ρ_a, is 0.99. Though it is higher than the 0.95 value assumed in the original RBC literature, it is in line with more recent estimates and a similar value is commonly used in calibrated models. The estimate of the persistence of the labor wedge, ρ_e, is 0.99, identical to that of the technology shock, while the estimate of the persistence of the investment wedge, ρ_x, is 0.97, pointing out that investment frictions are substantially less persistent than technology shocks and labor frictions. Note that the estimates for the autoregressive component of technology shocks and labor frictions are highly persistent. On this basis, the theoretical model may have allowed for a random-walk process for these processes instead of a first order specification. We impose a persistent, but trend stationary, process for the technology shocks based on the findings in Ireland (2001b).

[5]See, among others, Ireland (2001b, 2004a).

Table 1
Maximum likelihood estimates and standard errors[a]

Parameter	Labor frictions/investment frictions			
	(1) Yes/Yes	(2) Yes/No	(3) No/Yes	(4) No/No
γ	0.0057	0.0053	0.0044	0.0043
	(0.0003)	(0.0006)	(0.0002)	(0.0001)
θ	0.1834	0.2464	0.1965	0.2353
	(0.0232)	(0.0039)	(0.0031)	(0.0022)
η	1.0051	1.0053	1.0053	1.0053
	(0.0007)	(0.0023)	(0.0032)	(0.0052)
A	7.2547	5.2843	6.8492	5.3847
	(1.4738)	(0.8465)	(0.6654)	(0.0259)
ρ_a	0.9974	0.9934	0.9972	0.9801
	(0.0022)	(0.0006)	(0.0003)	(0.0003)
σ_a	0.0081	0.0075	0.0088	0.0082
	(0.0006)	(0.0004)	(0.0008)	(0.0007)
e	0.8954	0.8286	–	–
	(0.0164)	(0.1084)		
ρ_e	0.9953	0.9683	–	–
	(0.0056)	(0.0056)		
σ_e	0.0038	0.0039	–	–
	(0.0011)	(0.0296)		
x	0.8328	–	0.8893	–
	(0.2374)		(0.0683)	
ρ_x	0.9743	–	0.9743	–
	(0.0221)		(0.0016)	
σ_x	0.0412	–	0.0072	–
	(0.0053)		(0.0014)	
d_i	−0.8654	−0.8724	−0.8832	−0.8867
	(0.0371)	(0.0356)	(0.0165)	(0.0243)
d_c	−0.3543	0.8933	−0.3572	0.9235
	(0.1595)	(0.0186)	(0.0022)	(0.0065)
d_h	0.9932	0.9929	0.9950	0.9959
	(0.0203)	(0.0302)	(0.0082)	(0.0067)
v_i	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
v_c	0.0031	0.0062	0.0031	0.0061
	(0.0002)	(0.0004)	(0.0003)	(0.0006)
v_h	0.0058	0.0065	0.0062	0.0072
	(0.0006)	(0.0002)	(0.0003)	(0.0002)
Log-likelihood	2228.97	2207.17	2222.98	2202.73

[a]The standard error of each variable is in brackets.

He finds that a RBC model prefers highly persistent but still trend stationary shocks to a random walk. Moreover, his results point out that the estimates of the other structural parameters of the model are substantially invariant to the specification of the persistence of the shocks. We also impose a persistent but trend stationary component on labor and investment frictions, as suggested by the findings in Chari et al. (2007), whose estimates of the wedges are highly persistent but still trend stationary. As a robustness check, by estimating the model imposing a random-walk specification to labor and investment frictions, we find that the structural parameters of the model remain substantially unchanged. The estimate of the volatility of technology shocks, σ_a, of 0.0081 is in line with empirical evidence. Labor frictions have a volatility parameter, σ_e, of 0.0038, half the size of σ_a. The large point estimate of the volatility of investment frictions, σ_x, of 0.041 strongly suggests that, as expected, investment is a highly volatile component. The other estimates, those for the terms in the matrices D and V, suggest that the model is not able to fully explain all of the complex dynamics in the data. In particular, the estimate of the volatility of disturbances of hours worked, v_h, of 0.0058 shows that the model still has difficulties, as documented below, in explaining all of the volatility of hours worked.

To understand whether measurement errors are important to capture the dynamics in the data, Table 2 re-estimates the model for the full sample period without imposing measurement errors on the structure of the state-space econometric model. The estimates of the disutility of hours worked, γ, the capital share parameter, θ, and the steady-state investment frictions, x, are somewhat different from those from the baseline estimation. Moreover, the log-likelihood function of this constrained version of the model is 2188.22, which is substantially lower than the value of 2228.97 of the model specification enriched by measurement errors. A likelihood ratio test thus rejects the hypothesis that the data prefer a version of the model without measurement errors.

Table 2
Maximum likelihood estimates and standard errors, model without measurement errors[a]

Parameter	
γ	0.0079
	(0.0008)
θ	0.4956
	(0.0469)
η	1.0069
	(0.0022)
A	7.5642
	(1.1675)
ρ_a	0.9973
	(0.0173)
σ_a	0.0098
	(0.0027)
e	0.7345
	(0.1034)
ρ_e	0.9954
	(0.0223)
σ_e	0.0085
	(0.0014)
x	1.2369
	(0.1259)
ρ_x	0.3982
	(0.0234)
σ_x	0.1288
	(0.0518)
Log-likelihood	2188.22

[a]The standard error of each variable is in brackets.

We then look to determine whether the data prefer the version of the model with both frictions or a more general specification where only one of the two frictions, or neither of them, is present. Since labor and investment frictions compete directly with technology shocks in driving economic fluctuations, we test their importance by excluding them, in turn and all together, from the specification of the prototype RCB model. In Table 1, column 2 reports parameter estimates for the model without investment frictions that results when the shock x_t is absent; column 3 reports the parameter estimates for the model without labor frictions that results when the shock e_t is absent; and column 4 reports parameter estimates for the model without either labor or investment frictions, that results when both e_t and x_t are absent. The point estimates of the structural parameters for the different model specifications are reasonably close. This suggests that the underlying RBC model is consistently estimated across different model specifications. In order to establish whether these different versions of the model are statistically indistinguishable, we compare the log-likelihood function of the unconstrained model, in column 1, against each of the constrained specifications, columns 2–4, a likelihood ratio test rejects the null hypothesis that labor or investment frictions are not statistically significant to capture the dynamics in the data. In particular, the p-value for the likelihood ratio test of the model with both frictions against each of the constrained specifications is less than 0.02. Therefore, overall, these findings suggest that the data prefer a version of the model with both labor and investment frictions.

An additional exercise to gauge the relevance of labor and investment frictions, together with technology shocks in explaining the dynamics in the data is to compare the out-of-sample forecasts accuracy of versions of the model where both frictions, or only one of the two, or neither or them, interact with technology shocks. To produce out-of-sample forecasts we estimate the model with data from 1948:1 to 1984:4, and then produce out-of-sample forecasts one to four quarters ahead. Next, the sample is extended one quarter and forecasts are generated using the updated estimates. Continuing to extend the sample till 2002:2 produces one to four quarters ahead forecast series that can be compared to the data. Table 3 shows the root-mean-squared error (RMSE) from the different specifications of the model.[6] The figures indicate that, especially in the case of investment and hours worked, forecasts from the model with both labor and investment frictions in general outperform the specifications that exclude both or either one of them. Once more, this supports the idea that a model that incorporates both labor and investment frictions is more powerful than the other specifications in capturing the dynamics in the data.

Another exercise that can shed light on the relevance of labor and investment frictions, together with technology shocks, in explaining movements in output, consumption, investment, and hours worked is to decompose the k-step-ahead forecast error variances of these variables into the model's four orthogonal components: ε_{at}, ε_{et}, ε_{xt}, and ξ_t. This decomposition uses the estimated model to isolate the contribution of the primitive shocks to technology, labor and investment frictions, and measurement errors on the variables

[6] Note that consumption, investment and hours worked are the observable variables in the model, and so they can be compared against their measures in the data. In principle, an empirical measure of output could also be derived, using readings on investment and consumption and defining output by Eq. (10). However, the presence of the relative price of investment compared to consumption, $1/x_t$, makes the measure of output model dependent. For instance, in the version of the model without investment frictions, x_t is constant and so output would be constructed as a weighted sum of the observable series. For this reason, we cannot accurately compare out-of-sample forecasts for output from different versions of the model.

Table 3
Out-of-sample forecast accuracy, 1985:1–2002:2

Quarters ahead	1	2	3	4
Consumption				
Labor/investment frictions	0.4854	0.6972	0.8965	1.1468
No frictions	0.4723	0.6933	0.8654	1.1209
Labor frictions	0.6463	0.7335	0.9658	1.2104
Investment frictions	0.4702	0.6812	0.8754	1.1239
Investment				
Labor/investment frictions	3.2905	4.9633	6.5923	7.9948
No frictions	3.3265	5.2654	6.9395	8.3549
Labor frictions	4.0853	5.4456	7.1456	8.7822
Investment frictions	3.3843	5.3653	7.0194	8.7930
Hours worked				
Labor/investment frictions	0.6330	1.2194	1.6703	2.2065
No frictions	0.6583	1.2496	1.7836	2.2946
Labor frictions	0.6514	1.2499	1.8196	2.3061
Investment frictions	0.6924	1.3065	1.8792	2.4167

Root-mean-squared errors from different models.

variation in the model. Hence, using this methodology, the variation of each variable is entirely explained by shocks to technology, frictions, or measurement errors. Towards this objective, Table 4 measures the percentages of the forecast error variances due to technology shocks, labor and investment frictions. Both at long and short-run horizons, the technology shock contributes heavily to output and consumption fluctuations. It competes with investment frictions in accounting for the variance of investment in the short-run, but, in the long-run, accounts for only nearly 30% of it. On the other hand, labor and investment frictions together explain nearly 50% of the fluctuations of hours worked in the short-run, against roughly, on average, of 10% accounted by the technology shock. In the long-run, though, labor frictions account for nearly 50% of the variability of hours worked. Here, as in the seminal paper by Kydland and Prescott (1982), technology shocks still have a dominant role in accounting for fluctuations in output, and consumption. Moreover, the three disturbances together account for nearly all of the unconditional variance in these variables. Still perhaps disappointingly, in the long-run, 45% of the variation in hours worked is accounted by the residuals in u_t, which pick up the combined effect of disturbances, such as fiscal and monetary policy shocks, not included in this framework.

The next question we ask is: are these findings robust across different time periods? This is particularly important given the well-documented finding that a shift in the time series properties of output and other macroeconomic variables has occurred in the US data since the eighties. Such evidence is documented in papers by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Stock and Watson (2002), Justiniano and Primiceri (2007), and Sims and Zha (2006). Though there is no consensus on the precise point in time of the shift, these studies identify the early eighties as the relevant time period. Table 5, therefore, shows the point estimates when the model is re-estimated over two distinct samples: the

Table 4
Percentage of forecast error variance explained by exogenous components

Quarters ahead	Technology	Labor frictions	Investment frictions
Output			
1	49.4491	6.8625	43.6882
4	47.4480	6.5596	45.9921
8	45.4474	6.2528	48.2995
12	44.0833	6.0382	49.8780
20	42.6946	5.8019	51.5030
40	42.9849	5.7380	51.2763
∞	74.2195	5.1179	20.6621
Consumption			
1	72.7329	9.4315	3.2886
4	82.9796	10.7796	2.3249
8	85.6905	11.1296	1.4459
12	86.7188	11.2413	0.9857
20	87.5907	11.2803	0.5648
40	88.3526	11.1334	0.2601
∞	94.5471	5.4160	0.0187
Investment			
1	41.7234	5.8504	52.2250
4	38.3746	5.3696	56.1842
8	34.7959	4.8565	60.3006
12	32.1692	4.4804	63.3113
20	28.9390	4.0187	67.0090
40	26.1171	3.6135	70.2397
∞	28.7808	3.5058	67.6858
Hours worked			
1	19.3398	23.6954	26.1869
4	15.7873	24.1870	25.4156
8	12.4093	24.6228	24.1110
12	10.1333	24.9271	22.7114
20	7.4662	25.4318	20.0860
40	4.8406	26.8962	15.4051
∞	1.7814	48.7646	5.9890

first for the pre-1980 data and the second for the post-1980 data.[7] The point estimates differ across the two sub-samples; this may be further evidence that important structural changes, and a different mix and recurrence of shocks and frictions may have characterized the two time periods. At their face values, the most noticeable changes are the increase of

[7]In the literature there is not a clear consensus on the precise timing of the shift. Many authors have labeled this phenomenon as the 'Great Moderation' and they identify the date for the onset of this period to be 1984, which coincides with a shift in the conduct of monetary policy. Justiniano and Primiceri (2007) using an estimated DSGE model that allows for time variation in the volatility of structural innovation identifies 1980 as being the starting point of the shift in the time series properties of output. Similarly, Ireland (2001a, 2003), using formal statistical hypothesis tests on an estimated DSGE model, detects a shift in the conduct of monetary policy pre- and post-1979. Here, in line with these recent studies, and similarly to Ireland (2004b), we use 1980 as the onset date of the change. As a robustness check, we have also estimated the model using 1984 as the breakpoint date and this does not affect the main conclusions.

Table 5
Sub-samples maximum likelihood estimates and standard errors[a]

Parameter	Pre-1980	Post-1980	W
γ	0.0050	0.0052	0.0412
	(0.0004)	(0.0009)	
θ	0.1828	0.3596	7.8525**
	(0.0601)	(0.0192)	
η	1.0057	1.0051	0.1988
	(0.001)	(0.0009)	
A	6.0164	2.936	10.9938**
	(0.8365)	(0.4042)	
ρ_a	0.9982	0.9961	0.3724
	(0.0020)	(0.0028)	
σ_a	0.0088	0.0066	4.1367*
	(0.0009)	(0.0006)	
e	0.9829	0.8286	0.9792
	(0.0352)	(0.1519)	
ρ_e	0.9910	0.9991	0.1401
	(0.0149)	(0.0157)	
σ_e	0.0042	0.0009	0.2612
	(0.0018)	(0.0062)	
x	0.8367	1.4501	4.2164*
	(0.2915)	(0.0653)	
ρ_x	0.8946	0.9547	0.3139
	(0.0901)	(0.0582)	
σ_x	0.0501	0.0180	0.9568
	(0.0318)	(0.0081)	
d_i	−0.9998	−0.9491	0.2789
	(0.0948)	(0.0151)	
d_c	−0.5105	0.0891	1.2803
	(0.1723)	(0.5011)	
d_h	0.9812	0.9933	0.1569
	(0.0301)	(0.0052)	
v_i	0.0000	0.0000	0.0001
	(0.0003)	(0.0003)	
v_c	0.0027	0.0028	0.0085
	(0.0006)	(0.0009)	
v_h	0.0077	0.0049	5.4068*
	(0.0009)	(0.0008)	

[a]The standard error of each variable is in brackets. W denotes Wald statistics for the null hypothesis of parameter stability, and * and ** denote significance level of the 5% and 1% levels, respectively.

the capital share, θ, and the changes in the levels and volatilities of the stochastic disturbances. The level and volatility of the technology shock, A and σ_a, and labor frictions, e and σ_e, decline, while the level of investment frictions, x, increase though their volatility, σ_x, decreases. To formally test whether these changes in point estimates are statistically significant, the last column of Table 5 reports the Wald statistics for Andrews and Fair's (1988) test for parameter stability. This test statistic is asymptotically distributed as a *chi*-square random variable with one degree of freedom. The p-value for the test of the null hypothesis of parameter stability is less than 0.01 for the capital share, θ, and the level of productivity, A. Moreover, the p-value is less than 0.05 for the volatility of technology shocks, σ_a, for the steady-state investment frictions, x, and the variability of disturbances of hours worked, v_h. This is consistent with the first impression that the importance of technology shocks, and frictions has changed over time. But also instability appears in a more structural parameter: the Wald test rejects the null hypothesis of stability for the capital share parameter θ. Hence, while estimates from the two sub-samples attribute the shift of the time series properties of the data to changes to the level and volatility of technology shocks, and investment frictions, these estimates also suggest that other structural changes have played an important role.

Tables 6 and 7 report the percentages of the forecast error variances due to technology shocks, labor and investment frictions for the pre- and post-1980 sub-samples, respectively. The results for the pre-1980 sub-sample in Table 6 are similar to the full period analysis: technology shocks remain the major contributors to fluctuations in output and consumption, and labor frictions remain the main source of the variability of hours

Table 6
Percentage of forecast error variance explained by exogenous components, pre-1980 sub-sample

Quarters ahead	Technology	Labor frictions	Investment frictions
Output			
1	46.8653	8.7003	44.4344
4	47.3728	8.6094	44.0178
8	48.3416	8.5585	43.0998
12	49.4205	8.5491	42.0304
20	51.4307	8.5545	40.0148
40	55.1672	8.4565	36.3762
∞	85.0297	3.2276	11.7420
Consumption			
1	74.0183	9.7364	3.7863
4	82.6791	10.9657	2.6928
8	85.3659	11.2852	1.7124
12	86.5173	11.2961	1.1827
20	87.7398	11.0281	0.6860
40	89.4379	9.9891	0.3209
∞	98.3938	1.5670	0.0220
Investment			
1	39.4852	7.6850	52.6780
4	38.5106	7.4008	54.0235
8	37.7097	7.1404	55.1027
12	37.3279	6.9873	55.6422
20	37.1623	6.8584	55.9389
40	37.3537	6.8027	55.8038
∞	41.7340	6.3296	51.8966
Hours worked			
1	16.7301	24.9966	24.0015
4	14.1914	26.3900	21.7663
8	11.7957	28.0748	19.2117
12	10.2060	29.6042	17.2102
20	8.3991	32.3661	14.5597
40	6.7296	38.1545	11.7567
∞	5.0706	51.8419	8.8529

Table 7
Percentage of forecast error variance explained by exogenous components, post-1980 sub-sample

Quarters ahead	Technology	Labor frictions	Investment frictions
Output			
1	77.3308	0.5044	22.1647
4	78.5291	0.2126	21.2583
8	79.8328	0.1235	20.0436
12	81.0012	0.0934	18.9055
20	83.0092	0.0692	16.9216
40	86.4554	0.0499	13.4948
∞	95.6016	0.0160	4.3823
Consumption			
1	69.8693	0.0023	6.3916
4	88.3246	0.0012	5.5327
8	93.5577	0.0008	3.8235
12	95.7487	0.0005	2.7372
20	97.6726	0.0003	1.5906
40	99.0452	0.0001	0.6707
∞	99.8975	0.0000	0.0722
Investment			
1	65.7213	0.6060	32.7478
4	66.1900	0.2737	33.2579
8	66.1735	0.1701	33.4852
12	66.1466	0.1368	33.5791
20	66.2151	0.1133	33.5577
40	66.7074	0.1011	33.0899
∞	70.1991	0.0895	29.6215
Hours worked			
1	41.3369	3.7238	23.5413
4	39.5507	1.5474	23.1467
8	36.4052	0.9082	21.9841
12	33.4100	0.6857	20.7031
20	28.3552	0.5004	18.2347
40	20.4921	0.3399	13.6887
∞	8.7280	0.1436	5.8486

worked. The results for the post-1980 sub-sample in Table 7 show some differences. Productivity shocks become somewhat more important in the short-run and are the main driving source of fluctuations in output, consumption, as well as investment and hours worked. This change in the post-1980 sub-sample is not new in the literature, as documented in Gali et al. (2003) and Ireland (2004b), where they both attribute this shift to differences of monetary policy regimes between the two periods. Labor frictions no longer make a sizeable contribution to the variables' variability, and the three stochastic components together account for just approximately one-sixth of the variations in hours worked in the long-run. Evidently, fluctuations in hours worked after the eighties are mainly accounted for by factors not included in this model. As Prescott (2004) suggests, the inclusion of fiscal and monetary policy shocks is one of the possible explanations for the failure of the model to capture variations in hours worked, but also that a more

Table 8
Percentage of forecast error variance explained by exogenous components, full sample, model's structural parameters calibrated

Quarters ahead	Technology	Labor frictions	Investment frictions
Output			
1	62.5099	36.4930	0.9966
4	62.4584	36.3366	1.2042
8	62.4004	36.1556	1.4429
12	62.3617	36.0104	1.6265
20	62.3482	35.7989	1.8508
40	62.5758	35.4583	1.9629
∞	73.7009	25.5357	0.7616
Consumption			
1	48.4068	27.1360	0.0255
4	59.6366	33.4494	0.0167
8	62.1440	34.7980	0.0094
12	62.9704	35.1552	0.0062
20	63.6870	35.2832	0.0035
40	64.5336	34.9799	0.0017
∞	77.8991	22.0516	0.0002
Investment			
1	61.9554	36.3390	1.2790
4	61.9197	36.2341	1.6552
8	61.6986	36.0159	2.1310
12	61.4882	35.8346	2.5296
20	61.1787	35.5974	3.0784
40	60.8532	35.3606	3.6399
∞	61.4475	34.6685	3.7387
Hours worked			
1	8.1304	47.8497	0.1741
4	5.6755	46.1011	0.1590
8	3.8578	44.2052	0.1412
12	2.8807	42.8710	0.1265
20	1.9325	41.4618	0.1045
40	1.1339	41.2281	0.0731
∞	0.3393	62.0070	0.0231

complex structure of the model that lays out explicit microfoundations for labor and investment frictions might improve the performance of the model.

As mentioned, this paper shares a similar framework and the same sample period considered in Chari et al. (2007). Here, using formal hypothesis tests, the analysis suggests that both labor and investment frictions contribute with technology shocks in explaining fluctuations in the postwar US economy, while these authors find that investment frictions play, at best, a negligible role. To identify why the findings here are different, Table 8 shows the percentages of the forecast error variances due to technology shocks, labor and investment frictions for the full sample period, once all the model's structural parameters are calibrated, and solely the stochastic components are estimated. In this way, as in Chari et al. (2007), technology shocks, and labor and investment frictions alone support the theoretical model in matching the data. The calibrated parameters γ, θ, and η are set equal to 2.24, 0.35, and 1.004, respectively, as in Chari et al. (2007). Table 8 shows that ruling the estimation of the structural parameters out, technology shocks and labor frictions become the major contributors to fluctuations, while investment frictions play a minor role only, as in Chari et al. (2007). As a final exercise, in order to investigate the change in the importance of investment frictions from the benchmark case, Table 9 shows the percentages of the forecast error variances due to technology shocks, labor and investment frictions for the full sample period, once only the parameter θ is calibrated equal to 0.35, as in Chari et al. (2007). This would help to understand whether calibrating only the parameter θ, whose estimate seems problematic from the sub-sample estimations, would change the conclusion about the role of investment frictions. Table 9 shows that, once only θ is calibrated, investment frictions still play a minor role in explaining fluctuations in the postwar US economy. This suggests that allowing the model's structural parameters to interact with its stochastic components has a non-trivial influence to the extent to which

Table 9
Percentage of forecast error variance explained by exogenous components, full sample, parameter θ calibrated

Quarters ahead	Technology	Labor frictions	Investment frictions
Output			
1	68.7988	24.9195	6.2780
4	68.8669	24.8550	6.2741
8	69.0109	24.7899	6.1947
12	69.1988	24.7430	6.0534
20	69.6488	24.6808	5.6651
40	70.8399	24.5612	4.5932
∞	83.6167	15.5932	0.7886
Consumption			
1	50.1657	17.3251	1.0953
4	66.9831	23.1994	0.8592
8	71.1454	24.6577	0.5210
12	72.4818	25.0882	0.3423
20	73.4981	25.3013	0.1836
40	74.3961	25.1159	0.0767
∞	85.0394	14.9209	0.0063
Investment			
1	65.0828	23.7815	9.7063
4	65.2825	23.7911	10.4271
8	64.9606	23.5919	11.1289
12	64.6826	23.4131	11.6430
20	64.3932	23.1655	12.2230
40	64.6675	22.9426	12.2038
∞	78.5088	16.8789	4.5436
Hours worked			
1	10.3844	44.2536	2.1750
4	8.5159	43.8813	2.0343
8	6.7080	43.3702	1.8584
12	5.4519	42.9127	1.7004
20	3.9236	42.2753	1.4400
40	2.3896	42.1237	1.0319
∞	0.7420	61.9536	0.3376

technology shocks, labor and investment frictions contribute in accounting for fluctuations in the data.

4. Conclusion

This paper enriches the prototype real business cycle model with time-varying stochastic wedges that distort the optimal conditions of labor and investment derived from the theoretical model. It then takes this enriched framework to the data and estimates its parameters via maximum likelihood.

The estimation exercise strongly suggests that both labor and investment frictions play an important role in allowing the prototype real business cycle model to fit the postwar US data. Econometric hypothesis tests reject the constrained version of the model where one or both frictions are absent, supporting the more general framework characterized by both frictions. The out-of-sample forecasts of the model with both labor and investment frictions outperform those where only one of the two frictions, or neither of them, are present. Moreover, forecast error variance decompositions indicate that technology shocks, labor and investment frictions are able to account for nearly all the variations in output, consumption, and investment, and for approximately 50% of the variations in hours worked. Though labor and investment frictions compete directly with technology shocks in accounting for macroeconomic fluctuations, technology shocks still explain a substantial fraction of output variations, as in the seminal paper by Kydland and Prescott (1982).

Econometric hypothesis tests confirm that important changes in the level and volatility of the technology shock and the investment wedge have characterized both the periods before and after the early eighties. At the same time, though, other important changes have affected the more structural parameter of the capital share of output. Thus, while changes in the time series properties of key macroeconomic variables can be explained by a different mix and recurrence of technology shocks and frictions, other, more structural factors also play a role.

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