

w o r k i n g
p a p e r

12 36R

**The Cyclical Behavior of
Equilibrium Unemployment and
Vacancies across OECD Countries**

Pedro S. Amaral and Murat Tasci



FEDERAL RESERVE BANK OF CLEVELAND

Working papers of the Federal Reserve Bank of Cleveland are preliminary materials circulated to stimulate discussion and critical comment on research in progress. They may not have been subject to the formal editorial review accorded official Federal Reserve Bank of Cleveland publications. The views stated herein are those of the authors and are not necessarily those of the Federal Reserve Bank of Cleveland or of the Board of Governors of the Federal Reserve System.

Working papers are available at:

www.clevelandfed.org/research.

The Cyclical Behavior of Equilibrium Unemployment and Vacancies across OECD Countries

Pedro S. Amaral and Murat Tasci

We show that the inability of a standardly calibrated labor search-and-matching model to account for labor market volatility extends beyond the U.S. to a set of OECD countries. That is, the volatility puzzle is ubiquitous. We argue cross-country data is helpful in scrutinizing between potential solutions to this puzzle. To illustrate this, we show that the solution proposed in Hagedorn and Manovskii (2008) continues to deliver counterfactually low volatility in countries where labor-productivity persistence and/or steady-state job-finding rates are sufficiently low. Moreover, the model's ability to generate high enough volatility depends on vacancy-filling-rate levels that seem counterfactual outside the U.S.

JEL Classification: E24, E32, J63, J64.

Keywords: Labor Market, Vacancies, Unemployment, OECD countries.

*The first version of this paper was posted in December 2012.

Pedro S. Amaral is at the Federal Reserve Bank of Cleveland (pedro.amaral@clev.frb.org). Murat Tasci is at the Federal Reserve Bank of Cleveland (murat.tasci@clev.frb.org). The authors thank William Hawkins, Andrew Horowitz, Marios Karabarbounis, Aubhik Khan, Iourii Manovskii, Claudio Michelacci, Leonor Modesto, Jim Nason, Julia Thomas, and seminar and conference participants at various venues. They also thank Jim MacGee and Yahong Zhang for helping them with the Canadian vacancy data, and Hiroaki Miyamoto, who was kind enough to share his Japanese vacancy data. They thank John Lindner, Mary Zenker, and Kathryn Holston for expert research assistance.

1 Introduction

Labor market search models as pioneered by [Diamond \(1982\)](#), [Mortensen and Pissarides \(1994\)](#), and [Pissarides \(2000\)](#), henceforth DMP, have proved to be very useful in understanding equilibrium unemployment and vacancies, as well as the long-run relationship between the two. However, when the model is extended to accommodate aggregate fluctuations, as in [Shimer \(2005\)](#), it fails to generate the observed volatility at business-cycle frequencies by an order of magnitude. In particular, the model requires implausibly large shocks to generate substantial variation in key variables: unemployment, vacancies, and market tightness (vacancy-to-unemployment ratio). This “volatility puzzle” has spurred a considerably large literature on the subject and a scramble for a “solution.”¹

The availability of vacancy data from the OECD, as well as the work of [Elsby, Hobijn, and Sahin \(2011\)](#) in estimating job-finding and separation rates in a set of OECD countries has created an opportunity to analyze labor market fluctuations in the context of a search model across a fairly large set of countries beyond the U.S. Such an analysis is important because potential solutions to the volatility puzzle have been associated with features of the economic environment that might vary, at least to a degree, across countries.

In this paper, we accomplish three goals. First, we put together a data set that should be of interest to the literature as it is the first to bring together vacancies and unemployment data for a cross-section of OECD countries. We document a set of labor market facts at business-cycle frequencies that can be used as benchmarks for future work.

Second, we evaluate the DMP model’s ability to replicate business-cycle frequency moments observed in the data. Simulations of the model calibrated to country-specific parameter values in a standard, [Shimer \(2005\)](#)-like way fail to generate the observed degree of volatility in labor market variables. That is, the volatility puzzle is ubiquitous.²

Third, and most important, we show how the cross-country scrutiny this data allows can be helpful in evaluating the different solutions to the puzzle that are proposed in the literature. To illustrate this point we use the work of [Hagedorn and Manovskii \(2008\)](#), henceforth HM, that shows how calibrating a modified version of [Shimer \(2005\)](#) to target average market tightness and the elasticity of wages with respect to productivity enables the model to replicate the observed labor market fluctuation in the U.S. This strategy fails to work for some of the countries in our

¹For examples, see [Shimer \(2004\)](#), [Hall \(2005a\)](#), [Hall \(2005b\)](#), [Krause and Lubik \(2006\)](#), [Nagypál \(2006\)](#), [Mortensen and Nagypál \(2007\)](#), [Tasci \(2007\)](#), [Hagedorn and Manovskii \(2008\)](#), [Costain and Reiter \(2008\)](#), [Gertler and Trigari \(2009\)](#), [Silva and Toledo \(2009\)](#), [Kennan \(2010\)](#), and [Petrosky-Nadeau and Wasmer \(2013\)](#).

²[Zhang \(2008\)](#) compares the U.S. to Canada, while [Miyamoto \(2011\)](#) and [Esteban-Pretel, Ryo, and Ryuichi \(2011\)](#) focus on the Japanese labor market. Their findings are similar to ours for the respective countries.

sample. In some cases it leads to counterfactually low volatility in labor market variables, just like the standard calibration strategy, while in others it generates the precise opposite: volatility that far exceeds the magnitudes observed in the data.

There are three regions of the parameter space over which the HM calibration runs into problems. First, for countries that exhibit small enough persistence in their estimated productivity process, the model continues to deliver significantly smaller volatilities in labor market variables than seen in the data. The intuition is that faced with a positive productivity shock, everything else being the same, fewer vacancies will be created in an economy where the shock process exhibits relatively little persistence, as the expected gains from creating such vacancies are smaller. In turn, unemployment mechanically falls by less, as fewer vacancies are created.

Second, for countries with very low job-finding rates, the model generates lower volatility in unemployment. This happens because, conditional on existing vacancies, a positive productivity shock means unemployment will decrease by a lesser degree the smaller the job-finding rate is.

Finally, we show that the model's ability to generate data-like labor market volatility substantially depends on the magnitude of the vacancy-filling rate a country exhibits. The little evidence there exists on this seems to point to the fact that U.S vacancy-filling rates are substantially higher than mostly anywhere else (just like what happens for estimates of other rates capturing labor market dynamics like job-finding or separation rates.) In our baseline results we hold this rate constant across countries (at the U.S. level), but when we lower it to a level consistent with what has been observed in other OECD countries, and recalibrate the model to continue to hit the same targets, labor market volatility is substantially reduced.

Our paper is related to a large body of literature that emerged in response to [Shimer \(2005\)](#). In the standard stochastic version of the DMP model, firms respond to a positive productivity shock by creating more vacancies and therefore reducing unemployment duration. This puts upward pressure on wages, which absorb most of the productivity gains, resulting in insignificant changes in vacancies and unemployment. One of the responses in the literature was to propose wage rigidity as a potential resolution to the puzzle. [Shimer \(2004\)](#), [Hall \(2005b\)](#), [Hall and Milgrom \(2008\)](#), [Gertler and Trigari \(2009\)](#), and [Kennan \(2010\)](#) build on this diagnosis and introduce such a feature either by considering wage setting mechanisms that depart from the default generalized Nash bargaining, or by introducing asymmetric information.

Other studies provided alternative mechanisms that have the potential to amplify the effects of business cycles on vacancies and unemployment: [Silva and Toledo \(2009\)](#) introduce post-match labor turnover costs; [Krause and Lubik \(2006\)](#), [Nagypál \(2006\)](#), and [Tasci \(2007\)](#) explore post-match labor turnover costs; [Costain and Reiter \(2008\)](#) introduce the possibility that technology shocks may be cohort-specific; [Petrosky-Nadeau and Wasmer \(2013\)](#) explore financial frictions, working

together with labor market frictions; and finally, the aforementioned HM introduce procyclical vacancy posting costs and change mapping between the data and the model.³

Our paper provides a first step in the direction of testing the validity of these channels in a cross-country context. The ability of most, if not all, mechanisms described above to quantitatively match the volatility of labor market variables is predicated on particular calibrations designed to hit U.S. targets for the most part. We bring in an extra dimension of scrutiny that we hope will prove helpful in distinguishing between all these potential explanations. Recent work by [Justiniano and Michelacci \(2011\)](#) has proceeded in exactly this direction. They look at a real business cycle model with search and matching frictions driven by several possible shocks (neutral technology shocks, investment-specific shocks, discount factor shocks, search and matching technology shocks, job destruction shocks, and aggregate demand shocks) and estimate it on data from five European countries and the U.S. They find that while technology shocks are able to replicate the volatility of labor market variables in the U.S. quite well, matching shocks and job destruction shocks play a substantially more important role in European countries.

Our own examination of the cross-country data in [Section 2](#) reveals that there is a fairly robust positive correlation between the volatility of the estimated productivity shocks in each country and that of vacancies and unemployment. This suggests that such shocks should be seen as a prime candidate for the underlying source of uncertainty in any business-cycle labor macro model. On the other hand, some of the moments we find in the data stand in stark contrast to the DMP model's basic transmission mechanism: for some countries we find very little correlation between productivity shocks and labor market variables, or even correlations of the opposite sign of what the model predicts. While we value parsimony and stand firmly in the camp that sees models as rough approximations of reality, we also think there is high value to learning more about potentially different sources of shocks and frictions that may improve upon the model's ability to account for cross-country data.

2 Data

We have collected unbalanced data panels at a quarterly frequency on vacancies, unemployment, employment, labor force, and real GDP for a set OECD countries. The proximate sources are the OECD's Economic Outlook Database, the IMF's International Finance Statistics, [Ohanian and Raffo \(2012\)](#), as well as some direct national sources.⁴

³See [Cole and Rogerson \(1999\)](#), [Hornstein, Krusell, and Violante \(2005\)](#), [Mortensen and Nagypál \(2007\)](#), and [Pissarides \(2009\)](#) for additional criticism of the model's ability to fit the data and reviews of the various proposed alternatives.

⁴Please see the appendix for a detailed description of all the sources.

While the data collection process for unemployment, employment, labor force and real GDP is fairly standard across the set of OECD countries at which we look, the same cannot be said for the vacancy data. The OECD compiles its vacancy data from a variety of national sources with no harmonized reporting procedures. Nonetheless, to the extent that the majority of data collection differences manifest themselves at low frequencies, the fact that we detrend all variables using the HP-filter should help make the vacancy data more comparable across countries. A summary of the data appears in tables 8 to 13 in the appendix.⁵

Since our panels are unbalanced across countries, and even across variables for the same country, we had to make a decision regarding what period samples to use. For each country we have chosen to look at statistics pertaining to the period for which all variables are available. Thus, for instance, the sample for Australia extends from the second quarter of 1979 (before that vacancies were not available) to the second quarter of 2011. This means that we have different sample periods for different countries. In the appendix we show that the main data facts we look at remain unaltered when we use a shorter, common sample (from 1995 to 2011) for all countries.

A number of facts emerge, some new to the literature, some already known, that should provide useful benchmarks for business-cycle models of the labor market:

1. There is substantial variation in the degree of correlation between productivity and unemployment and between productivity and vacancies as shown in figure 1. While this correlation is mostly of the expected sign (negative for unemployment and positive for vacancies) there are exceptions lying outside the NW quadrant of the figure.
2. There is a fairly strong positive cross-country correlation between the volatility of productivity and that of both unemployment and vacancies as shown in figures 2 and 3.
3. Unlike what happens in the U.S., where vacancies and unemployment seem to be equally volatile, across countries, the former are much more volatile than the latter. Comparing figures 2 and 3 reveals that the median standard deviation of vacancies is over 60 percent higher than that of unemployment.
4. Vacancies and unemployment are both very persistent across countries, as seen in figure 4.
5. While virtually all countries show negative correlations between unemployment and vacancies, the strength of this relationship is, for all the countries in our sample, smaller than in the U.S., as seen in figure 5.

⁵Throughout the paper all the variables are in log levels and productivity is defined as output per worker.

6. Both vacancies and unemployment lag productivity, while unemployment lags vacancies by roughly a quarter, on average, as shown in tables 5 to 7 in the appendix.

The first observation highlights the limitations of technology shocks as the sole driving mechanism in the DMP model. In Spain, for example, it seems like productivity and vacancies do not co-move at all, while productivity and unemployment exhibit a puzzling positive correlation. In countries like Norway, Poland, and even Australia, it seems like the labor market is largely insulated from business cycle fluctuations. This suggests other mechanisms are at work. Moreover, the close linear relationship between the two sets of correlations suggests that whatever is driving a wedge between the behavior of productivity and labor market variables affects unemployment and vacancies equally.

In contrast to the first observation, the second one suggests the DMP model with neutral technological shocks as the main driver is, by and large, an appropriate modeling framework or, at the very least, one that is not rejected by these data.

The third point suggests vacancies are subject to extra amplification, at least if one is thinking about a common shock. This is something the DMP model delivers naturally, just like the fourth observation.

Regarding the fifth observation, one of the strengths of the DMP model, at least when compared to U.S. data, is that it is able to deliver a very high correlation between vacancies and unemployment. One might think that the fact that this correlation is smaller for all other countries could pose some difficulties for the model. It turns out it does, but for the opposite reason. As we will see in Section 3.2, the model ends up underpredicting the (absolute) correlation between unemployment and vacancies.

Finally, a look at tables 5 to 7 in the appendix detailing cross-correlations between variables across time confirms that some countries' business-cycles do not conform to the norm. This is the case for Spain, and to some extent, Norway. For the majority of countries though, a picture arises where unemployment reaches its trough roughly three quarters after productivity peaks, while vacancies peak roughly two quarters after productivity. As a consequence vacancies peak one to two quarters before unemployment reaches its trough.

In the next section we lay down the basic model and use the data to both discipline it, as well as to obtain benchmarks against which to judge its performance.

3 Model

We use a stochastic, discrete time version of the DMP model akin to the one used in Shimer (2005). Each country is a closed economy and even though the calibration below is country-specific, in

detailing the model, we abstract from country-indexing to make the notation easier to follow.

There is an underlying exogenous productivity process $\{p_t\}_{t=0}^{\infty}$ whose log evolves according to an AR(1) process $\log p_t = \rho \log p_{t-1} + \varepsilon_t$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$.

The economy is populated by two types of risk-neutral, infinitely-lived agents: a measure one of workers and a continuum of firms. Workers have preferences defined over stochastic streams of income $\{y_t\}_{t=0}^{\infty}$ and maximize their expected lifetime utility $E_0 \sum_{t=0}^{\infty} \delta^t y_t$, where the discount rate, $\delta \in (0, 1)$, is also the same rate at which firms discount profits.

At any point in time a worker is either matched with a firm or not. Unmatched workers are said to be unemployed and search for jobs while receiving a utility flow of z . Matched workers are said to be employed and while they are not allowed to search, they earn a period wage w_t . This wage rate is the outcome of a generalized Nash bargaining problem where firms and workers bargain over the match surplus. The worker's bargaining power is denoted by $\beta \in (0, 1)$. Firms and workers get separated with exogenous probability s . Firms are free to enter the market but have to pay a fixed vacancy posting cost of c to be able to obtain a match.

Let v_t denote the measure of vacancies posted, and n_t denote the measure of employed people. Then, $u_t = 1 - n_t$ denotes the unemployment rate. The vacancy-to-unemployment ratio, $\theta_t = \frac{v_t}{u_t}$, or market tightness, will turn out to be a key variable in the model, as it fully describes the state of the economy. We assume the flow of new matches is given by a Cobb-Douglas function $m_t = A u_t^\alpha v_t^{1-\alpha}$. The rate at which workers find a new job is

$$f_t = \frac{m_t}{u_t} = A \left(\frac{v_t}{u_t} \right)^{1-\alpha} = A \theta^{1-\alpha},$$

while the rate at which firms fill vacancies is

$$q_t = \frac{m_t}{v_t} = A \left(\frac{u_t}{v_t} \right)^\alpha = A (1/\theta)^\alpha = \frac{f_t}{\theta_t}.$$

Employment evolves according to $n_{t+1} = (1 - s)n_t + m(u_t, v_t)$, while unemployment's law of motion is $u_{t+1} = u_t + s(1 - u_t) - f_t u_t$. In this model, there is a unique equilibrium in which the vacancy-to-unemployment ratio, and consequently all other variables, depends exclusively on p and not on u , as shown in [Mortensen and Nagypál \(2007\)](#). This is the equilibrium on which we focus.

The value of a filled position for a firm is given by

$$J(p_t) = p_t - w(p_t) + \delta E_t \{ (1 - s)J(p_{t+1}) + sV(p_{t+1}) \},$$

where the value of an unfilled vacancy for the firm is given by:

$$V(p_t) = -c + \delta E_t \{q(p_t)J(p_{t+1}) + (1 - q(p_t))V(p_{t+1})\}.$$

The value of a job for a worker is

$$W(p_t) = w(p_t) + \delta E_t \{sU(p_t) + (1 - s)W(p_{t+1})\},$$

where the value of being unemployed is

$$U(p_t) = z + \delta E_t \{f(p_t)W(p_{t+1}) + (1 - f(p_t))U(p_{t+1})\}.$$

The firms' free entry condition implies that, in equilibrium, entry occurs until the value of a vacancy is driven all the way down to zero: $V(p_t) = 0$ for all p_t . This means the match surplus is given by $S(p_t) = W(p_t) + J(p_t) - U(p_t)$. Given the Nash bargaining weights, this means the firm gets $J(p_t) = (1 - \beta)S(p_t)$, and the worker gets $W(p_t) - U(p_t) = \beta S(p_t)$. Noting that the free entry condition implies $c = \delta q_t(p_t)E_t J(p_{t+1})$, this means that $w(p_t) = \beta p_t + (1 - \beta)z + \beta c\theta(p_t)$. Finally, replacing this and the free entry condition into the value of a filled position for a firm yields a first-order difference equation that can be used to compute the equilibrium:

$$\frac{c}{\delta q(p_t)} = E_t \left[(1 - \beta)(p_{t+1} - z) - \beta c\theta(p_{t+1}) + (1 - s)\frac{c}{q(p_{t+1})} \right]. \quad (1)$$

3.1 Standard calibration

As alluded to in the introduction, the model's ability to replicate the data ultimately depends on modeling extensions and on the calibration details. To establish a benchmark for each country against which to test potential solutions to the puzzle, we use the same calibration method as in [Shimer \(2005\)](#). We will call this the *standard calibration*.

While most of the parameters are country-specific, some are common across countries. In particular, we choose the model period to be a week and we set δ , the discount rate, such as to generate a yearly interest rate of 4 percent. The standard calibration uses the Hosios condition, which guarantees match efficiency and in the context of the model means $\alpha = \beta$. Although there are a wealth of studies estimating matching functions across different countries, not all the countries in our sample, as far as we could find, were the subject of such studies and, more importantly, different studies often use different underlying data and estimation methods, making it hard to compare across countries.⁶ As a result, we set $\alpha = \beta = 0.72$ for all countries, the value [Shimer](#)

⁶A very comprehensive survey of where this literature stood at the start of the decade can be found in [Petrongolo](#)

(2005) estimates for the U.S. using data for the job-finding rate and the vacancy-to-unemployment ratio based on the Current Population Survey.

The remaining parameters are set on a country-by-country basis. The data on replacement rates, z_i , are from the OECD and capture the average total benefit payable in a year of unemployment in 2009. Even though the OECD computes replacement rates net of taxes and tries to take into account housing and child support-related benefits, comparisons across countries still suffer from the shortcomings laid out in Whiteford (1995).

The separation and job-finding rates, s_i and f_i , are from Hobijn and Şahin (2009) who use data on job-tenure and unemployment duration to obtain their estimates.⁷ Since the level of the vacancy-to-unemployment ratio is meaningless in this particular calibration of the model we normalize its steady-state value to one, which means setting $A_i = f_i$. Normalizing the steady-state value of productivity $\bar{p}_i = 1$, we can recover the vacancy posting cost, c_i , from the analogue of (1) in steady-state.

The parameters governing productivity’s law of motion, ρ_i and σ_{ε_i} , are set such that the auto-correlation and the standard deviation of the HP-filtered residual productivity in the model and the data are the same for each country. We approximate the AR(1) process described above with a discrete Markov Chain. When we apply the HP filter (a low-pass filter) to the simulated productivity data, we are removing a highly autocorrelated trend. As a result we are unable to match the residual auto-correlation we measure in the data for some of the countries in our sample: France, the Netherlands, and Sweden. Instead of postulating a different productivity process and distancing ourselves from the literature along this margin, we opted for dropping these countries from our sample.

Finally, the model does not account for movements in and out of the labor force, as it assumes the labor force to be constant. When we adjust the raw data by the labor force, the statistics we obtain hardly change, as most labor force movements tend to be of relatively low frequency and are therefore filtered out.⁸ As a result, and for ease of comparison with most of the literature, we leave our data estimates unadjusted by the labor force. The calibrated parameters are summarized in table 1.

and Pissarides (2001).

⁷Since the estimate for the U.S. separation rate in Hobijn and Şahin (2009) is considerably below others in the literature, we use the estimates from HM for the U.S.’s separation and job-finding rates.

⁸The appendix contains tables with business cycle statistics for all variables when adjusted by the labor force.

3.2 Results

Under the standard calibration we just detailed, and for all countries without exception, the model is unable to replicate the volatility in labor market variables by an order of magnitude. This is exactly what figures 6 and 7 illustrate, where countries are ordered by the share of variation in the data that the model can account for. This extends the finding of Shimer (2005) from the U.S. to a broad set of OECD countries.⁹

We can also compare the model’s ability to replicate the whole set of cross-country data to its ability to replicate U.S. data only, along other margins in the data. Starting with serial correlation, figure 8 shows that the model does a better job of matching the persistence in unemployment for the median country than for the U.S., as most countries are closer to the 45 degree line than the U.S. This stands in contrast to the model’s ability to replicate the high degree of serial correlation in vacancies, as shown in figure 9. In this instance, the model does even worse on a cross-country perspective than for the U.S. alone. This well-known shortcoming can be addressed by considering extensions to the model that add mechanisms that slow the adjustment in vacancies, like in Fujita and Ramey (2007).

In terms of correlations, the DMP model’s transmission mechanism is such that when there is a positive productivity shock, vacancies go up (as the value of an unfilled position goes up with the expected match surplus) and the next period’s unemployment goes down, as more vacancies result in more matches. While most of the data conform to these correlation signs, there are some exceptions. As we already saw in Australia, Poland, and Spain, the correlation between productivity and unemployment is positive. More generally, the model systematically overpredicts the (absolute) correlation between productivity and unemployment for countries where this correlation is negative, as figure 10 shows. In this case, by looking only at U.S. data, one would be led to conclude that the model was doing a worse job than it is actually doing on a cross-country basis.¹⁰

One dimension along which the model’s ability to match the data may have been overstated in the literature (by virtue of the use of U.S. data) is along the unemployment-vacancies correlation margin. As figure 11 shows, just like in Shimer (2005), the model does a perfect job at matching this number for the U.S., while in a more general sense it tends to underpredict the (absolute) degree of correlation, as all countries without exception lie above the 45 degree line.

⁹Tables 14 to 26 in the appendix present the detailed statistics for each country.

¹⁰The corresponding figure for the correlation between productivity and vacancies is even more stark as the model basically predicts a 0.99 correlation for all countries.

4 Targeting small profits and the wage elasticity

Another way the cross-sectional data can be of use is in helping evaluate the relative plausibility of the different resolutions for the volatility puzzle that have been suggested in the literature. Here we subject one of the most prominent proposals in the literature, the one in HM, to this cross-country scrutiny.

HM think of the standard DMP model as an approximation to a more complex model economy with heterogeneous agents and curvature both in utility and in production. They suggest an alternative mapping between the data and a slightly modified version of the model above. Here we follow their work closely, and change the matching function to

$$m(u_t, v_t) = \frac{u_t v_t}{(u_t^l + v_t^l)^{1/l}},$$

in order to have job-filling rates and vacancy-filling rates that lie between zero and one.

In addition, the vacancy posting cost is no longer constant and is the sum of a capital cost component and a labor cost component that are both cyclical:

$$c_p = c_k p + c_w p^{\varepsilon_{w,p}},$$

where $\varepsilon_{w,p}$ is the elasticity of wages with respect to productivity, and c_k and c_w are endogenous objects that depend on the steady-state values of unemployment, vacancies, production, job-filling rates, and income factor shares.¹¹

The idea behind the calibration strategy is to generate large percentage changes in profits (and therefore, in the corresponding vacancy postings) in response to changes in productivity. This will be the case if steady-state productivity and the replacement rate are close enough, conditional on other parameter values. HM accomplish this in the context of U.S. data by targeting labor market tightness and the elasticity of wages to productivity.

While separation rates continue to be calibrated directly to their data counterpart, the same is not true of replacement rates. The idea being that the utility flow unemployed agents receive in the model, z , stands in for more than measured replacement rates and includes things like home production and leisure. The strategy is then to set values for parameters β_i , z_i , and l_i for each country, so as to match the steady-state job-finding rate, f_i , the steady-state labor market tightness, θ_i , and the elasticity of wages with respect to productivity in the data, $\varepsilon_{w,p}^i$.

The values for the average monthly job-finding rates in each country, f_i appear in table 1. To

¹¹For the exact form of c_k and c_w , please see HM.

compute average market tightness, we use the fact that $\theta_i = f_i/q_i$. We don't have country specific data for the monthly vacancy-filling rate q_i , so for comparison purposes we use the same value as in HM, $q_i = q = 0.71$ for all countries.¹² It should be clear that even though we have a common target for the vacancy-filling rate, q , and use it to compute market tightness for each country, it is still the case that we are jointly determining three parameters, (β_i, z_i, l_i) , to hit three targets $(\theta_i, q, \varepsilon_{w,p}^i)$, and therefore do not have an extra degree of freedom.

To compute the labor share of income, we use OECD data. For each country and quarter we take employee compensation and subtract indirect taxes and then divide the result by GDP also net of indirect taxes.¹³ We then multiply this share by labor productivity, obtaining total wages per worker. We HP filter this series and compute its elasticity with respect to productivity. The measure varies substantially across countries, from near acyclicity in Austria to a relatively strong procyclicality in Spain, as can be seen in table 2.¹⁴

4.1 Results: labor market volatility

The calibration is able to match all targets exactly and the parameter values that do so are in table 2. As figures 12 and 13 show, while this calibration strategy is able to account for the volatility of labor market variables in most countries, it can still run into problems. The model not only continues to underpredict the volatility of labor market variables for some countries, like Portugal and Spain, but it can also be prone to overprediction, as in the case of Japan and U.K. vacancies.¹⁵ While one can argue that Japan is a little bit of a data outlier in the sense that it exhibits volatilities for both unemployment and vacancies that are roughly half of the next lowest country values, the same cannot be said of Portugal and Spain, or even of U.K. vacancies. Finally, while the model seems to severely underpredict German unemployment volatility, this finding is not robust to considering post-reunification data only. As figure 18 in the appendix shows, if one looks at data from 1995 on only, the relative volatility of unemployment declines by more than half.

¹²A discussion of the appropriateness of this numerical value appears in section 4.1.3.

¹³A better measure would subtract other ambiguous components of income. Unfortunately, the OECD does not report proprietors' income separately from corporate profits, so our measure apportions the totality of proprietors' income to capital income.

¹⁴Data availability constrains our sample to nine countries. We opted to exclude Finland because it exhibits a slightly negative elasticity, a target the model cannot hit. Nonetheless, the fact that some countries exhibit negative elasticities should itself be seen as a challenge to the model.

¹⁵The country-by-country business-cycle statistics and their model counterparts are shown from tables 27 to 35 in the appendix.

4.1.1 Comparative statics

To better understand under what circumstances this calibration strategy may fail to generate data-like volatility, we conduct some comparative statics exercises where we vary selected parameters and compare the outcomes to the benchmark calibration. Table 3 summarizes the results. Each row shows the model’s resulting labor market volatility (the standard deviations of unemployment, vacancies, and tightness relative to the standard deviation of productivity), as well as a comparison of model moments and targets (steady-state job-finding rates, steady-state tightness, and wage elasticities.) Values are distinguished by the subscripts M for model and a T for target, and the shaded rows indicate the benchmark calibration, where model moments exactly match the targets.

We find that the model’s ability to deliver volatility magnitudes that are in the data’s ballpark depends crucially on the persistence of the underlying process and also, at least as far as the volatility of unemployment is concerned, on the average job-finding rate.

We start with Portugal, where the calibrated replacement rate, z , is higher than that of the U.S. for example, and yet it generates essentially no labor market volatility, seemingly contradicting the rationale in HM. In the first experiment, we take Portugal’s calibrated parameters and reduce steady-state (accounting) profits further by increasing the replacement rate z so as to match the relative volatility of vacancies observed in the data. Unemployment volatility fails to increase along with the volatility of vacancies because of the counterfactually low job-finding rate (it falls to practically zero) that results from the the replacement rate increase. To generate an increase in the volatility of unemployment, we need to decrease the workers’ bargaining power (we set $\beta = 0.01$), but this leads the elasticity to plunge away from its target, besides reducing the volatility of vacancies.

The first two experiments suggest that further pursuing the strategy of reducing profits to exaggerate percentage changes in response to productivity changes does not work in this instance. Why should this be the case? The next experiment, where we set $\rho = 0.99$, suggests that the answer may lie in the productivity process itself. In particular, its relatively lack of persistence when compared to other countries like the U.S. When we increase persistence (and change nothing else) the implied volatilities jump to realistic levels, although the elasticity of wages becomes counterfactually high. Nonetheless, this suggests that the productivity shock’s persistence may play an important role. At the same time, Portugal’s extremely low job-finding rate suggests that the volatility in productivity shocks may not necessarily translate into volatility in unemployment.

We run comparable experiments for Spain in table 3 that largely illustrate the same point. But the Spanish case adds a further, more subtle, refinement to our argument: what ultimately constitutes low persistence is dependent on how elastic wages are. The higher this elasticity is, the

more persistent the productivity process needs to be if the model is to generate high enough labor market volatility. To wit, Spain’s productivity process is as persistent as those of Germany and Austria, but because Spain has a much higher wage elasticity, the parameter that largely captures how much of the increase in surplus is captured by wages, β , needs to be higher. In turn, to continue matching the, roughly similar, accounting profits across countries (implied by free entry and vacancy costs), z needs to decrease to compensate for the increase in β , ultimately killing amplification.

From the point of view of the HM calibration strategy, the U.K. presents the opposite challenge from a country like Portugal: it has an extremely persistent estimated productivity process and a relatively low wage elasticity. The only way to match this low elasticity with such a persistent process is with an extremely high replacement rate, z , and a very low worker’s bargaining power, β . This leads to vacancy volatility overprediction. The reason this does not result in unemployment volatility overprediction is that the job-finding rate in the U.K. is low enough. This would be the case if it had, say, the U.S. job-finding rate. When we lower z to roughly match the vacancy volatility, the resulting elasticity and job-finding rates double above their targets. The final row shows that if the U.K.’s productivity process exhibited low enough persistency it would be possible to hit all targets with a smaller replacement rate than in the benchmark, while at the same time generating data-like volatilities.¹⁶

4.1.2 The importance of persistence and the job-finding rate

Without holding constant some of the targets these are just conjectures, though. To verify them more precisely, we generate a series of simulated economies that differ only in their steady-state job-finding rates, and in their unconditional first-order auto-correlation of the productivity process.¹⁷ Other than this, the parameters are calibrated to common targets, which we take from the U.S. economy: the separation rate, the vacancy-filling rate, wage elasticity, and the productivity shock’s unconditional variance.

The top two panels in figure 14 report the resulting relative volatility in labor market variables for each of these economies. The left panel shows that an economy with a monthly job-finding rate of 0.035 (Portugal is at 0.039)—at the very low end of the job-finding rate axis in the figure—and a first order auto-correlation of 0.5 (Portugal is at 0.46), actually experiences shock dampening as the standard deviation of unemployment is roughly a third of that of productivity. On the other hand, an economy with the U.S. job-finding rate, 0.48, and first order auto-correlation, 0.75, generates

¹⁶The reason we do not hit all targets precisely here is that we are not changing β and l . We simply want to illustrate the mechanism at work.

¹⁷We vary both ρ and σ_ε to generate different autocorrelations while keeping the unconditional variance constant.

substantial amplification. Together these two factors can account for a factor of 20 in the relative standard deviation of unemployment. The right panel in the first column shows that, as far as the relative volatility of vacancies goes, the persistence of the productivity process can account for roughly a factor of 6, while variations in the job-finding rate have non-monotonic effects and result in economies with lower job-finding rates actually exhibiting higher volatility in vacancies, although not by a large factor.

We need to answer two questions. The first: why do economies that exhibit less persistence in their productivity processes generate smaller volatility in labor market variables? The second: why do economies with lower job-finding rates exhibit lower volatility in unemployment but not in vacancies? The mechanism at work behind the first effect should be clear: conditional on a positive shock, expected firm profits are smaller in an economy where persistency is lower, so firms post less vacancies in response. At the same time, given the same job-finding and separation rates, unemployment decreases by less, because less vacancies result in less matches, and therefore also exhibits less volatility. This is exactly what we see in the impulse response functions (to a positive productivity shock) for vacancies and unemployment in the two bottom panels of figure 14.

The answer to the second question is that, conditional on a positive productivity shock and on a given number of posted vacancies, unemployment will decrease by less in an economy where the job-finding rate is smaller. In turn, because expected profits will be smaller, there is a negative wealth effect that leads firms to post more vacancies and a substitution effect that leads them to react in the opposite direction, conditional on everything else. Ultimately, for a low enough job-finding rate the former effect dominates.

4.1.3 The vacancy-filling rate: evidence and discussion

In the calibration above, we set the common monthly vacancy-filling rate to $q = 0.71$ following HM. This paper, in turn, cites [den Haan, Ramey, and Watson \(2000\)](#), henceforth HRW, as a source for this numerical value. There is a problem with simply transplanting this value: the models are different. In HRW, this value is generated by a model that includes, among other things, an endogenous separation decision—a margin that firms take into account when making vacancy-posting decisions, and therefore affects the vacancy-filling rate. Moreover, the HRW model is calibrated so that this is a quarterly value, not a monthly one.

Measuring vacancy-filling rates is particularly hard. In the U.S., the Job Openings and Labor Turnover Survey (JOLTS) has measures of the monthly stock of vacancies and subsequent month hirings, but it fails to take into account vacancies that are created and filled within the same month. As a result, as much as 42 percent of a month’s hiring come from establishments that reported

no vacancies in the previous month.¹⁸ To get around this and other problems, in recent work, [Davis, Faberman, and Haltiwanger \(2013\)](#) develop a daily hiring dynamics model and calibrate its monthly implications using JOLTS data (at the monthly frequency). They find an average daily vacancy-filling rate of 0.05, which suggests that $q = 0.71$ may be a roughly appropriate value for the monthly vacancy-filling rate in the U.S.

While this monthly value may be appropriate for the U.S.—a country with relatively high job turnover—the scant existing evidence suggests that this number may be too high for other countries. Using Dutch establishment survey data, [van Ours and Ridder \(1992\)](#) estimate the *quarterly* vacancy-filling rate to be 0.71, implying a substantially lower corresponding monthly value.

To better understand how much of the results depend on our assumption of this arguably high value for a monthly filling rate in countries other than the U.S., we conduct some sensitivity analysis where we take the stance that this is a quarterly value ($q_Q = 0.71$) and that there is a constant hazard rate over the quarter, so that the corresponding monthly value is $q = 1 - (1 - q_Q)^{1/3} \simeq 0.34$. We recalibrate every economy to hit the same targets under this new value for the vacancy-filling rate. As [table 4](#) shows, this results in unambiguously smaller replacement rates, z_i , and therefore reduces amplification by a factor as high as 3 in some instances.

While we judge the HM calibration to be largely successful in bringing the model closer to the data along the labor market volatility dimension, this sensitivity analysis reveals that our conclusion is very much predicated on values for q that are high enough. To get a clearer picture, a better sense of cross-country vacancy-filling rates is needed. Our own reading of the available data is that while a monthly vacancy-filling rate of 0.71 may be appropriate for the U.S., it might be too high for other countries in our sample that are characterized by less dynamic labor markets.¹⁹

4.2 Results: cross-country performance

Along dimensions other than labor market volatility, the HM calibration is less successful in improving over the standard calibration. In fairness, it was not designed to do this. Here we highlight

¹⁸See [Davis, Faberman, and Haltiwanger \(2013\)](#).

¹⁹One may be concerned that the particular matching function specification used may be constraining the model’s ability to fit certain dimensions of the data, particularly for countries where flows are small. With this in mind, we ran an experiment where we use a slightly generalized version of the matching function that allows us to weigh unemployment and vacancies differently and retains constant returns to scale (but no longer insures that f and q are between zero and one):

$$m(u_t, v_t) = \frac{u_t v_t}{[\gamma u_t^\gamma + (2 - \gamma) v_t^\gamma]^{1/\gamma}}$$

. In varying $\gamma \in (0, 2)$ and re-calibrating all other parameters to hit the same targets in the Portuguese economy we found no substantial changes in the volatility of labor market variables.

two such dimensions.²⁰

The standard calibration systematically underpredicts persistency in vacancies. Part of the HM calibration’s success in increasing the volatility of vacancies comes at the the expense of a move towards even less persistent vacancies, as figure 15 shows.²¹ Note that the productivity processes used are the same, so the changes in persistency are not inherited from changes to the underlying shock process. Because it results in higher replacement rates, the HM calibration increases the unconditional variance of vacancies by more than the covariance between v_t and v_{t-1} , therefore reducing first-order auto-correlation.

By lowering the persistency of vacancies, the HM calibration also leads to a deterioration in the model’s performance in terms of the contemporaneous correlation between unemployment and vacancies, as shown in figure 16. This follows because match formation (and unemployment) respond to vacancy posting with a one-period lag, so the model is designed to deliver a peak negative correlation between unemployment and vacancies at a one-period-lag: $\rho(v_{t-1}, u_t)$. By decreasing vacancy persistency, $\rho(v_{t-1}, v_t)$, this mechanically results in a fall in contemporaneous correlation between vacancies and unemployment: $\rho(v_t, u_t)$.

5 Conclusion

While the DMP framework, either on its own or embedded in larger models, has become widely used to study labor market fluctuations, this has been done largely on a country-by-country basis and for a very limited set of countries at that. We use cross-country OECD data to systematically discipline the model and evaluate its performance.

By-and-large, the data seems to support the use of technology shocks as the main driver. Nonetheless, the model has little hope of capturing the mechanics of labor markets in a fraction of countries where the correlations implied by its basic transmission mechanism are hard to square with the data. While in some countries labor market variables are largely acyclical, in others their correlation with technology shocks is the opposite of what the model would predict. This suggests a need to explore alternative sources of shocks and frictions, while being mindful of what the standard model gets right. We view the work of [Justiniano and Michelacci \(2011\)](#) along these lines as a very promising line of research.

We go on to show that the model’s inability to deliver the degree of labor market volatility present in the data extends beyond the U.S. and to a set of OECD countries, establishing the

²⁰The HM calibration improves modestly over the standard calibration in reducing the correlation between productivity and vacancies. Along other margins the two calibrations are essentially equivalent.

²¹The black dots represent the standard calibration while the red dots stand for the HM calibration.

pervasiveness of the volatility puzzle. To further illustrate the usefulness of the cross-country scrutiny, we modify the standard model as proposed by HM and show that while the model's ability to match labor market volatility improves for most countries, this improvement is not fully generalizable. In particular, it does not work for economies that have sufficiently small job-finding and vacancy-filling rates and/or productivity processes that are not persistent enough.

The extension proposed by HM is only one of many that have been put forward in the literature to try to reconcile the predictions of the DMP model with the data. In future work, data permitting, we plan to use this cross-country framework to examine other proposed solutions.

References

- COLE, H. L., AND R. ROGERSON (1999): “Can the Mortensen-Pissarides Matching Model Match the Business-Cycle Facts?,” *International Economic Review*, 40(4), 933–59.
- COSTAIN, J., AND M. REITER (2008): “Business Cycles, Unemployment Insurance, and the Calibration of Matching Models,” *Journal of Economic Dynamics and Control*, 32(4), 1120–55.
- DAVIS, S., J. FABERMAN, AND J. HALTIWANGER (2013): “The Establishment-Level Behavior of Vacancies and Hiring,” *Quarterly Journal of Economics*, 128(2), 581–622.
- DEN HAAN, W., G. RAMEY, AND J. WATSON (2000): “Job Destruction and Propagation of Shocks,” *American Economic Review*, 90(3), 482–98.
- DIAMOND, P. (1982): “Aggregate Demand Management in Search Equilibrium,” *Journal of Political Economy*, 90(5), 881–894.
- ELSBY, M. W., B. HOBIJN, AND A. SAHIN (2011): “Unemployment Dynamics in the OECD,” Tinbergen Institute Discussion Papers 11-159/3, Tinbergen Institute.
- ESTEBAN-PRETEL, J., N. RYO, AND T. RYUICHI (2011): “Japan’s Labor Market Cyclicity and the Volatility Puzzle,” Discussion papers 11040, Research Institute of Economy, Trade and Industry (RIETI).
- FUJITA, S., AND G. RAMEY (2007): “Job matching and propagation,” *Journal of Economic Dynamics and Control*, 31(11), 3671 – 3698.
- GERTLER, M., AND A. TRIGARI (2009): “Unemployment Fluctuations with Staggered Nash Wage Bargaining,” *Journal of Political Economy*, 117(1), 38–86.
- HAGEDORN, M., AND Y. MANOVSKII (2008): “The Cyclical Behavior of Cyclical Unemployment and Vacancies Revisited,” *American Economic Review*, 98(4), 1692–1706.
- HALL, R. (2005a): “Employment Efficiency and Sticky Wages: Evidence From Flows in the Labor Market,” *Review of Economics and Statistics*, 87(3), 397–405.
- (2005b): “Employment Fluctuations with Equilibrium Wage Stickiness,” *American Economic Review*, 95(1), 50–65.
- HALL, R., AND P. MILGROM (2008): “The Limited Influence of Unemployment on the Wage Bargaining,” *American Economic Review*, 98(4), 1653–74.

- HOBijn, B., AND A. ŞAHIN (2009): “Job-finding and Separation Rates in the OECD,” *Economics Letters*, 104, 107–111.
- HORNSTEIN, A., P. KRUSELL, AND G. L. VIOLANTE (2005): “Unemployment and Vacancy Fluctuations in the Matching Model: Inspecting the Mechanism,” *Federal Reserve Bank of Richmond Economic Quarterly*, 91(3), 19–50.
- JUSTINIANO, A., AND C. MICHELACCI (2011): “The Cyclical Behavior of Equilibrium Unemployment and Vacancies in the US and Europe,” NBER Working Papers 17429, National Bureau of Economic Research.
- KENNAN, J. (2010): “Private Information, Wage Bargaining and Employment Fluctuations,” *Review of Economic Studies*, 77(2), 633–664.
- KRAUSE, M., AND T. LUBIK (2006): “The Cyclical Upgrading of Labor and On-the-Job Search,” *Labour Economics*, 13(4), 459–77.
- MIYAMOTO, H. (2011): “Cyclical Behavior of Unemployment and Job Vacancies in Japan,” *Japan and the World Economy*, 23, 214–25.
- MORTENSEN, D., AND E. NAGYPÁL (2007): “More on Unemployment and Vacancy Fluctuations,” *Review of Economic Dynamics*, 10(3), 327–47.
- MORTENSEN, D., AND C. PISSARIDES (1994): “Job Creation and Job Destruction in the Theory of Unemployment,” *Review of Economic Studies*, 61(3), 397–415.
- NAGYPÁL, E. (2006): “Amplification of Productivity Shocks: Why Don't Vacancies Like to Hire the Unemployed?,” in *Structural Models of Wage and Employment Dynamics*, vol. 275 of “Contributions to Economic Analysis”, ed. by H. Bunzel, B. J. Christensen, G. R. Neumann, and J.-M. Robin, pp. 481–506. Elsevier, Amsterdam.
- OHANIAN, L., AND A. RAFFO (2011): “Aggregate Hours Worked in OECD Countries: New Measurement and Implications for Business Cycles,” *NBER Working Paper 17420*.
- OHANIAN, L. E., AND A. RAFFO (2012): “Aggregate hours worked in OECD countries: New measurement and implications for business cycles,” *Journal of Monetary Economics*, 59(1), 40–56.
- PETRONGOLO, B., AND C. A. PISSARIDES (2001): “Looking into the Black Box: A Survey of the Matching Function,” *Journal of Economic Literature*, 39(2), 390–431.

- PETROSKY-NADEAU, N., AND E. WASMER (2013): “The Cyclical Volatility of Labor Markets under Frictional Financial Markets,” *American Economic Journal: Macroeconomics*, 5(1), 193–221.
- PISSARIDES, C. (2000): *Equilibrium Unemployment Theory*. MIT Press.
- (2009): “The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?,” *Econometrica*, 77(5), 1339–69.
- SHIMER, R. (2004): “The Consequences of Rigid Wages in Search Models,” *Journal of the European Economic Association (Papers and Proceedings)*, 2, 469–79.
- (2005): “The Cyclical Behavior of Equilibrium Unemployment and Vacancies,” *American Economic Review*, 95(1), 25–49.
- SILVA, J., AND M. TOLEDO (2009): “Labor Turnover Costs and the Cyclical Behavior of Vacancies and Unemployment,” *Macroeconomic Dynamics*, 13(1), 76–96.
- TASCI, M. (2007): “On-the-Job Search and Labor Market Reallocation,” *Federal Reserve Bank of Cleveland Working Paper*, 07-25.
- VAN OURS, J., AND G. RIDDER (1992): “Vacancies and the Recruitment of New Employees,” *Journal of Labor Economics*, 10(2), 138–55.
- WHITEFORD, P. (1995): “The Use of Replacement Rates in International Comparisons of Benefit Systems,” Discussion Papers 0054, University of New South Wales, Social Policy Research Centre.
- ZHANG, M. (2008): “Cyclical Behavior of Unemployment and Job Vacancies: A Comparison between Canada and the United States,” *The B.E. Journal of Macroeconomics*, 8(1), 27.

Figure 1: Correlation between productivity and labor market variables

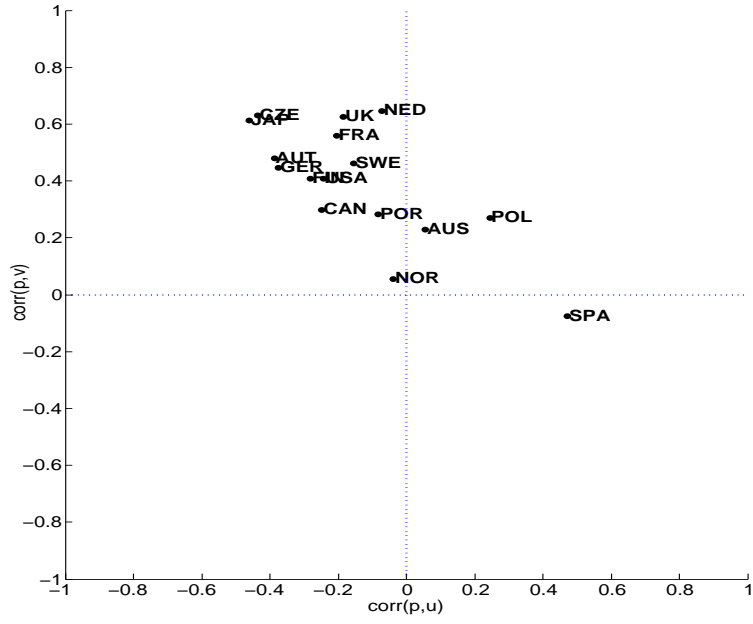


Figure 2: Productivity and unemployment

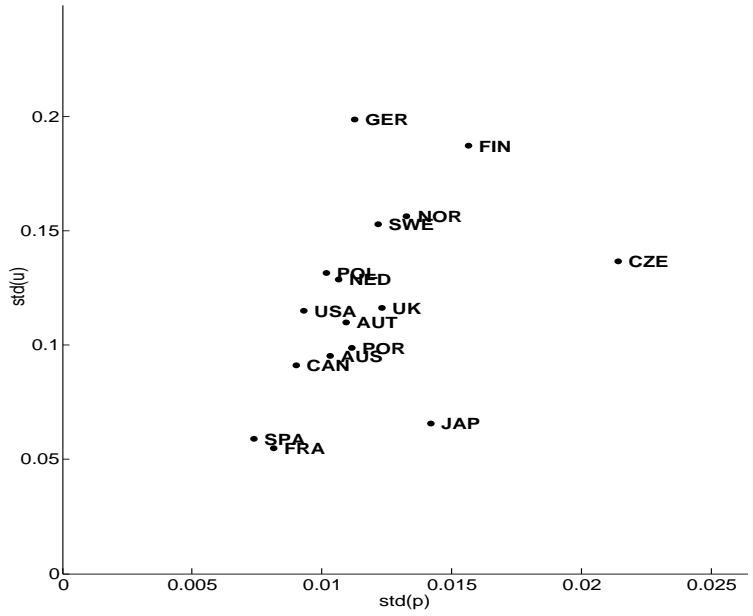


Figure 3: Productivity and vacancies

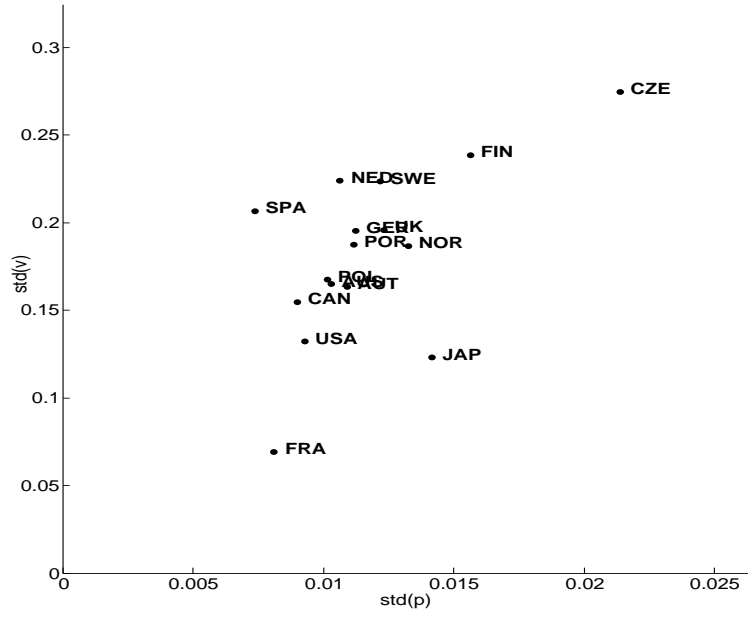


Figure 4: Persistence of labor market variables

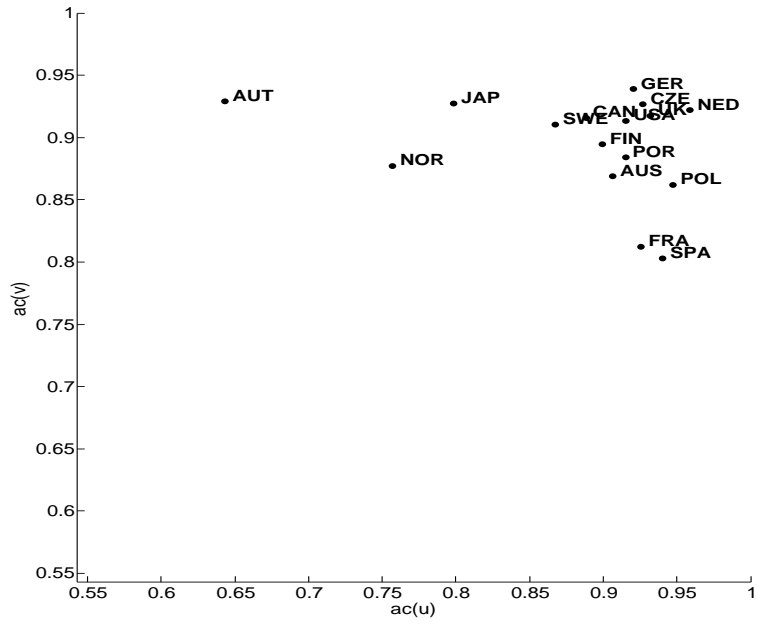


Figure 5: Vacancies-unemployment correlation

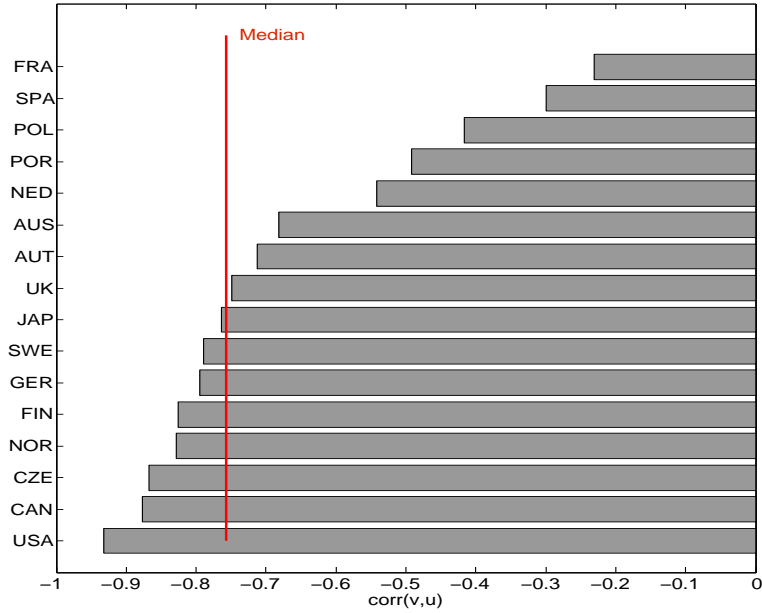


Table 1: Parameters (standard calibration)

	z	f_m	f_w	s_m	s_w	c	ρ	σ
Australia	0.5353	0.1705	0.0422	0.0175	0.0047	0.1761	0.9834	0.0027
Austria	0.6182	0.1561	0.0384	0.0106	0.0028	0.1443	0.9697	0.0035
Canada	0.5535	0.2890	0.0757	0.0178	0.0050	0.1711	0.9831	0.0024
Czech Rep.	0.5535	0.0806	0.0192	0.0094	0.0024	0.1641	0.9850	0.0055
Finland	0.6984	0.1336	0.0326	0.0138	0.0036	0.1134	0.9743	0.0048
Germany	0.6375	0.0698	0.0166	0.0106	0.0027	0.1321	0.9610	0.0040
Japan	0.7459	0.1907	0.0477	0.0060	0.0016	0.0965	0.9868	0.0036
Norway	0.7068	0.3053	0.0806	0.0134	0.0038	0.1125	0.9434	0.0057
Poland	0.4617	0.0720	0.0171	0.0099	0.0025	0.1966	0.9322	0.0047
Portugal	0.6042	0.0388	0.0091	0.0096	0.0024	0.1371	0.9358	0.0051
Spain	0.4726	0.0398	0.0093	0.0203	0.0052	0.1832	0.9637	0.0026
U.K.	0.6142	0.1127	0.0272	0.0153	0.0040	0.1441	0.9924	0.0028
U.S.	0.3346	0.4772	0.1390	0.0260	0.0081	0.2567	0.9897	0.0022

An m subscript represents a monthly rate, while a w stands for a weekly one.

Figure 6: Unemployment volatility: model vs. data

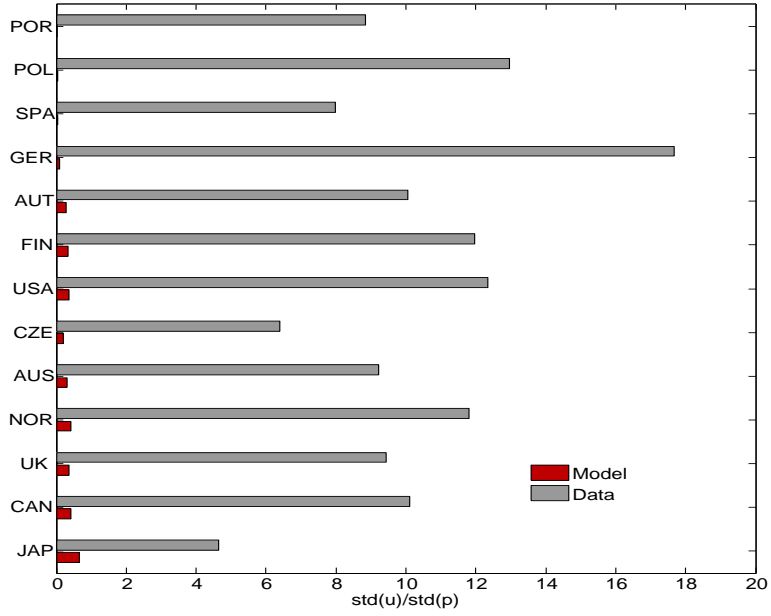


Figure 7: Vacancies volatility: model vs. data

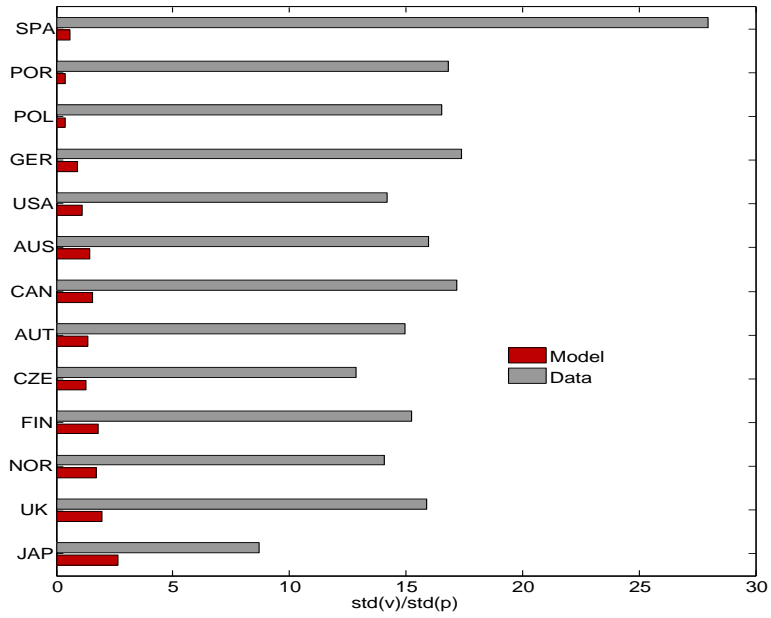


Figure 8: Unemployment auto-correlation

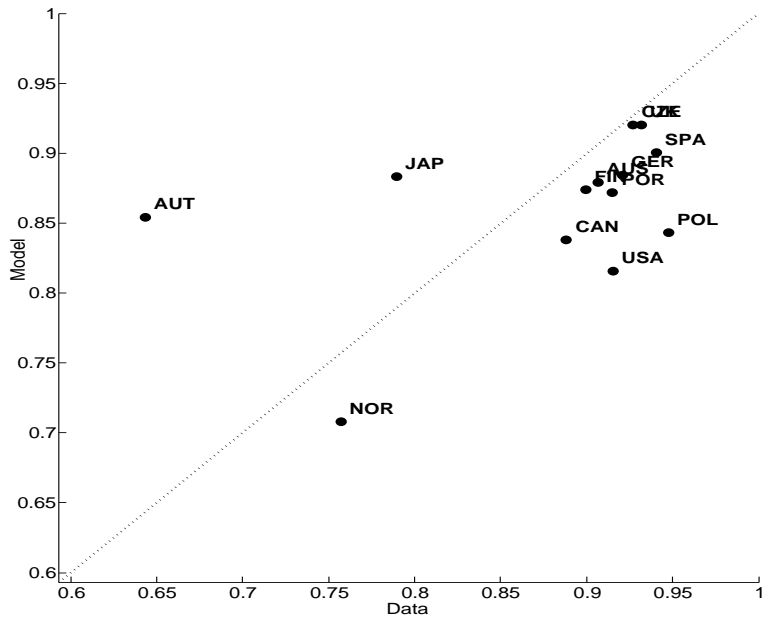


Figure 9: Vacancies auto-correlation

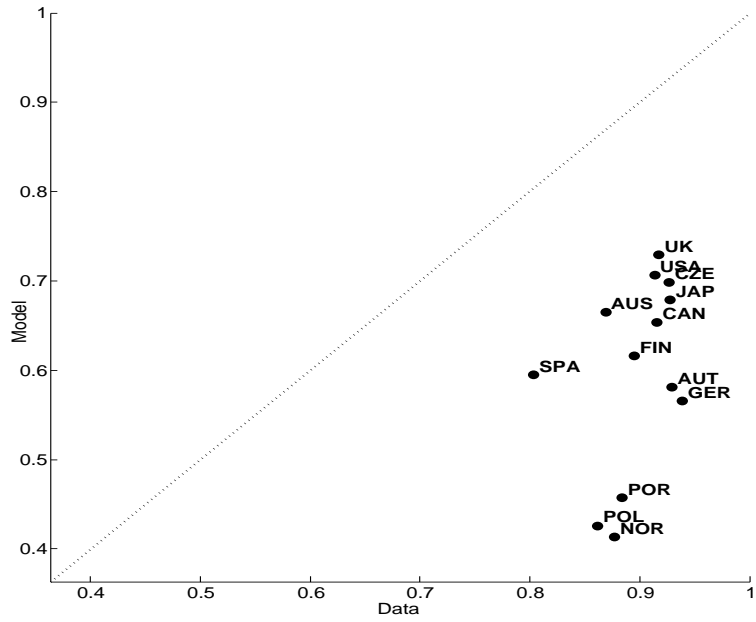


Figure 10: Unemployment-productivity correlation

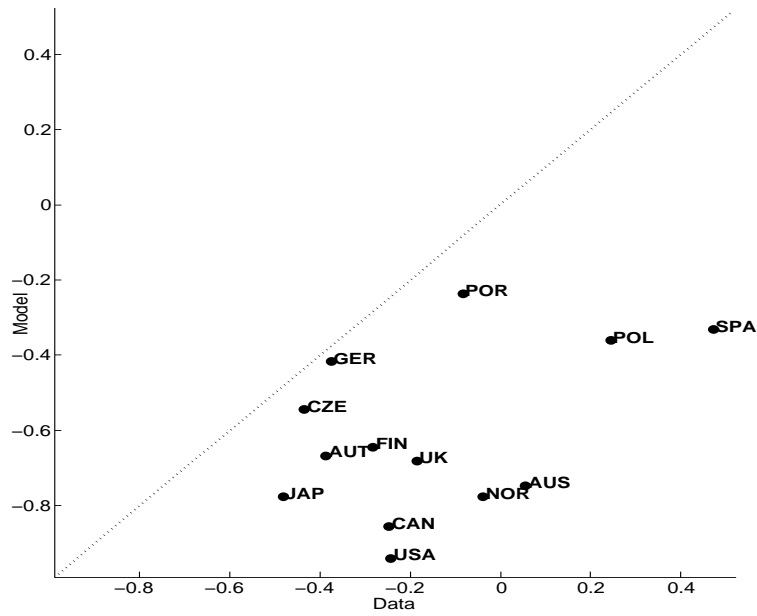


Figure 11: Unemployment-vacancies correlation

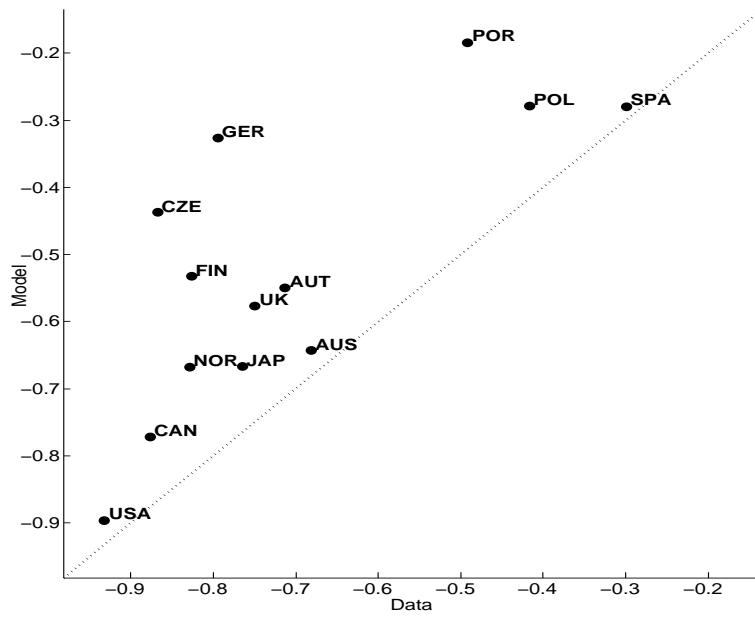


Table 2: **Parameters (HM calibration)**

	Parameters							Targets		
	z	β	l	ρ	σ	c_k	c_w	f	θ	$\varepsilon_{w,p}$
Australia	0.9733	0.0590	0.2942	0.9834	0.0027	0.4807	0.0843	0.1705	0.2401	0.2576
Austria	0.9846	0.0258	0.2877	0.9697	0.0035	0.4882	0.0872	0.1561	0.2199	0.0874
Canada	0.9721	0.0394	0.3328	0.9831	0.0024	0.4805	0.0929	0.2890	0.4070	0.2565
Germany	0.9817	0.0877	0.2501	0.9610	0.0040	0.4881	0.0775	0.0698	0.0983	0.1579
Japan	0.9732	0.1049	0.3043	0.9868	0.0036	0.4933	0.0923	0.1907	0.2686	0.4821
Portugal	0.9512	0.4766	0.2305	0.9358	0.0051	0.4892	0.0703	0.0388	0.0546	0.5378
Spain	0.9097	0.5901	0.2312	0.9637	0.0026	0.4777	0.0569	0.0398	0.0561	0.6887
U.K.	0.9916	0.0647	0.2769	0.9924	0.0028	0.4831	0.0798	0.1127	0.1587	0.2207
U.S.	0.9395	0.0803	0.3945	0.9897	0.0022	0.4722	0.1036	0.4772	0.6721	0.5863

Figure 12: Unemployment volatility: model(HM) vs. data

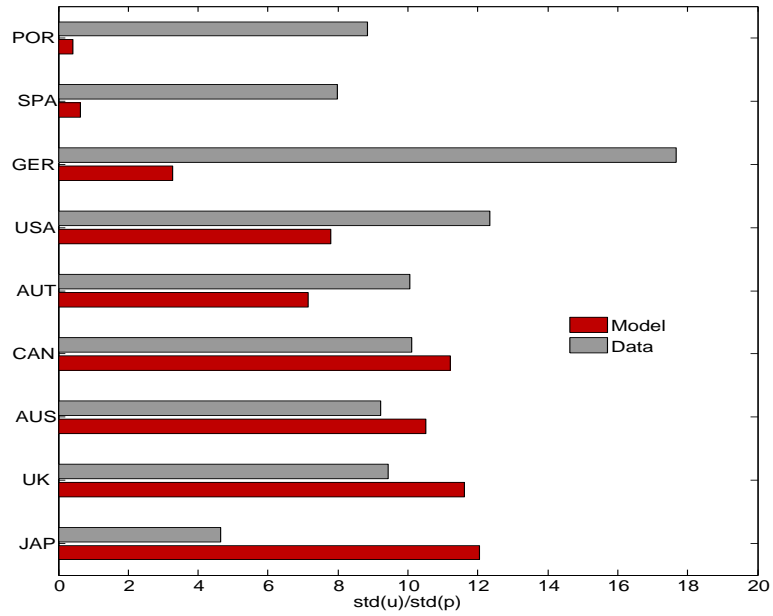


Figure 13: Vacancies volatility: model(HM) vs. data

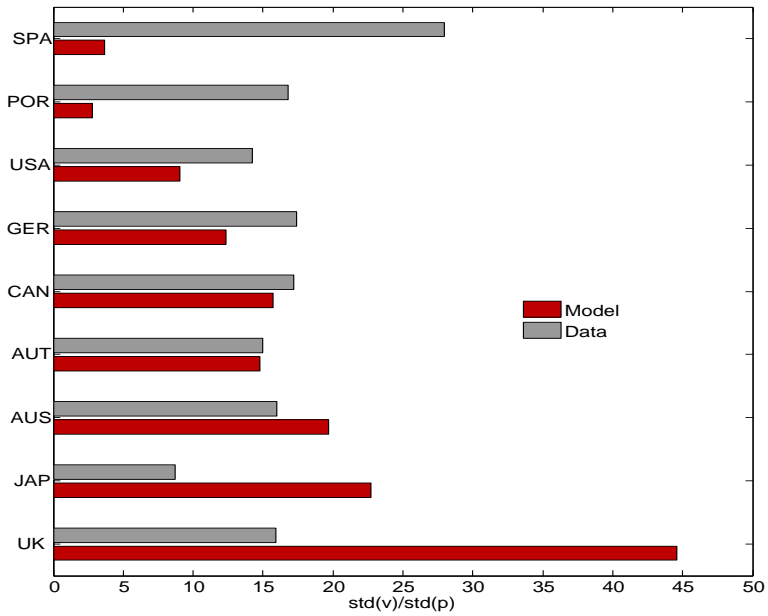


Table 3: Comparative statics

Experiment	Model outcomes			Calibration targets					
	$\frac{std(u)}{std(p)}$	$\frac{std(v)}{std(p)}$	$\frac{std(v/u)}{std(p)}$	f_M	f_T	θ_M	θ_T	ε_M	ε_T
POR	0.404	2.783	2.858	0.039	0.039	0.055	0.055	0.538	0.538
POR ($z = 0.989$)	0.391	17.621	17.646	0.005	0.039	0.003	0.055	0.493	0.538
POR ($z = 0.989; \beta = 0.01$)	1.299	9.400	9.631	0.037	0.039	0.050	0.055	0.013	0.538
POR ($\rho = 0.99$)	3.306	20.456	21.315	0.037	0.039	0.056	0.055	0.713	0.538
SPA	0.620	3.688	3.868	0.040	0.040	0.056	0.056	0.689	0.689
SPA ($z = 0.978$)	0.588	27.663	27.757	0.004	0.040	0.002	0.056	0.616	0.689
SPA ($z = 0.978; \beta = 0.01$)	2.707	14.095	14.949	0.048	0.040	0.076	0.056	0.017	0.689
SPA ($\rho = 0.99$)	1.947	9.119	9.855	0.040	0.040	0.056	0.056	0.791	0.689
U.K.	11.621	45.512	50.044	0.113	0.113	0.158	0.159	0.221	0.221
U.K. ($z = 0.955$)	9.197	15.863	22.154	0.220	0.113	0.510	0.159	0.421	0.221
U.K. ($z = 0.973; \rho = 0.983$)	8.707	17.836	22.808	0.145	0.113	0.227	0.159	0.250	0.221

Table 4: Sensitivity analysis: vacancy-filling rate

Country	Outcomes				Calibration					
	$std(u)/std(p)$		$std(v)/std(p)$		z		β		l	
	$q = 0.71$	$q = 0.34$	$q = 0.71$	$q = 0.34$	$q = 0.71$	$q = 0.34$	$q = 0.71$	$q = 0.34$	$q = 0.71$	$q = 0.34$
AUS	10.523	3.747	19.658	7.577	0.973	0.946	0.059	0.069	0.294	0.247
AUT	7.133	2.509	14.766	5.748	0.985	0.969	0.026	0.030	0.288	0.243
CAN	11.211	4.023	15.680	6.496	0.972	0.944	0.039	0.047	0.333	0.277
GER	3.268	1.083	12.368	4.458	0.982	0.963	0.088	0.098	0.250	0.214
JAP	12.036	3.797	22.734	6.787	0.973	0.941	0.105	0.122	0.304	0.253
POR	0.404	0.005	2.783	0.038	0.951	0.897	0.477	0.508	0.230	0.198
SPA	0.619	0.063	3.688	0.414	0.910	0.799	0.590	0.638	0.231	0.198
UK	11.612	8.244	44.574	22.097	0.992	0.962	0.065	0.048	0.277	0.233
USA	7.806	2.633	9.051	3.812	0.939	0.874	0.080	0.099	0.394	0.324

Figure 14: The importance of persistence and the job-finding rate

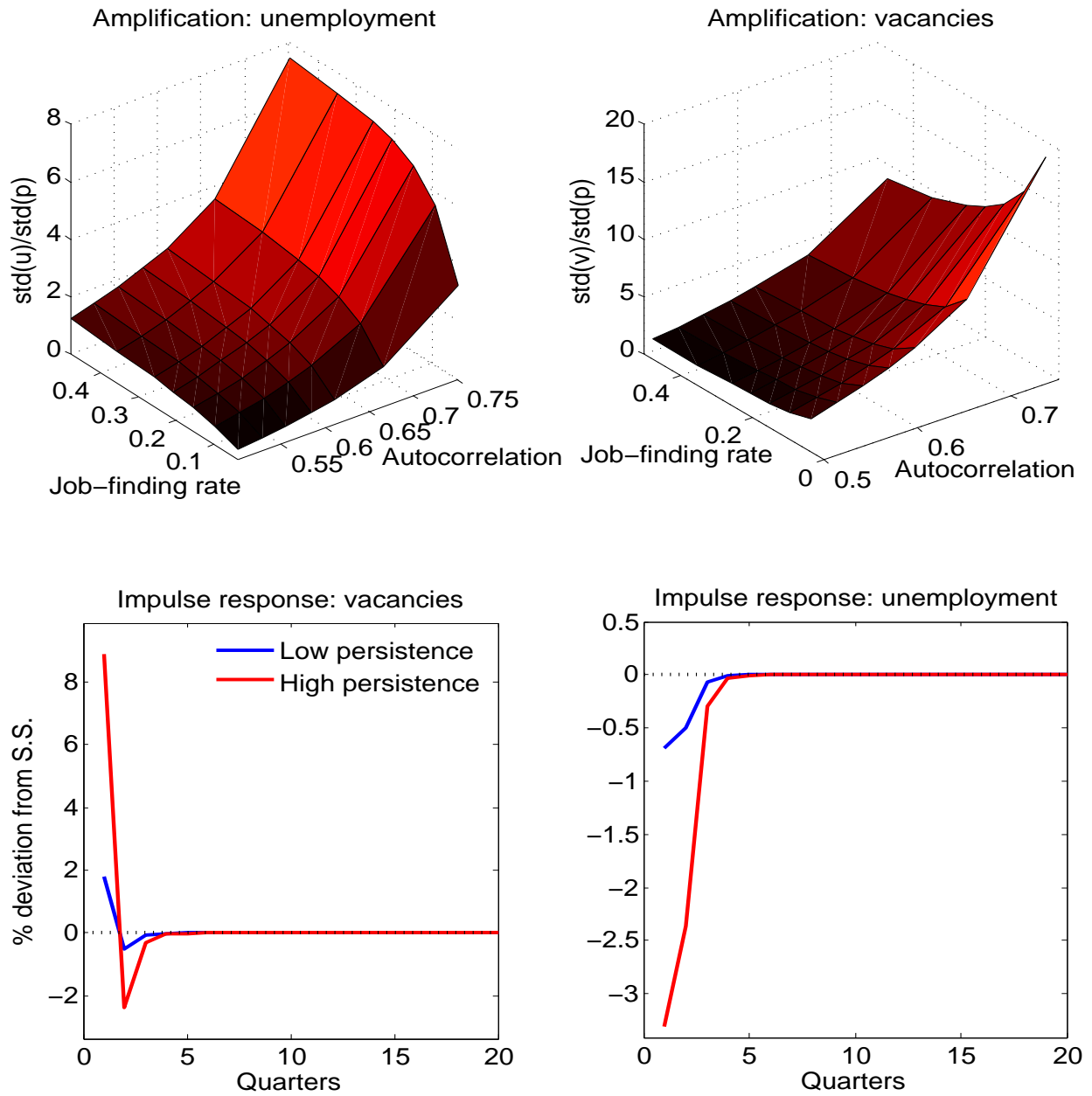


Figure 15: Vacancies auto-correlation (HM calibration)

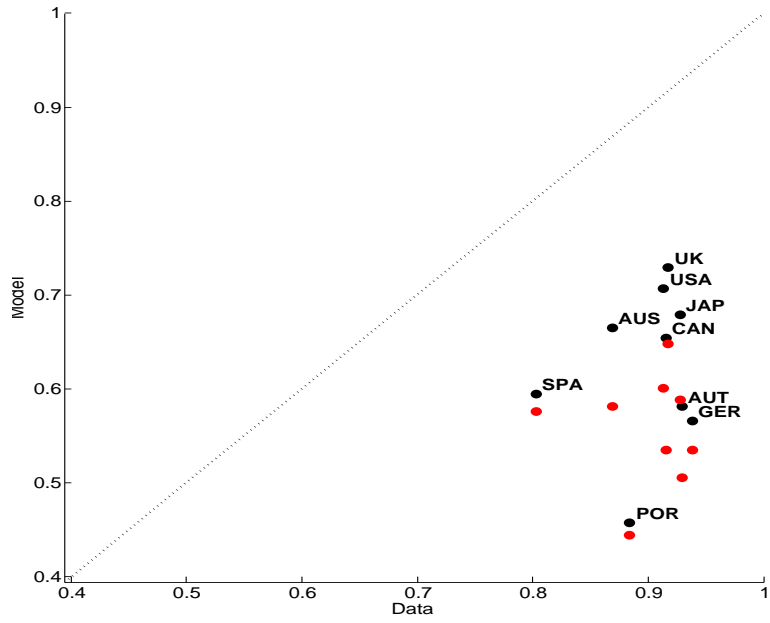


Figure 16: Unemployment-vacancies correlation (HM calibration)

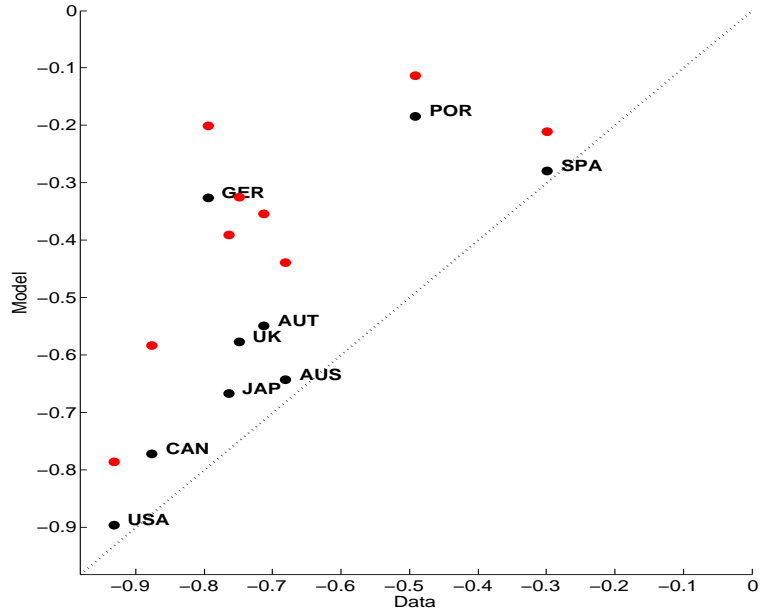


Table 5: Unemployment-Productivity cross-correlations

Countries	$x(-5)$	$x(-4)$	$x(-3)$	$x(-2)$	$x(-1)$	x	$x(+1)$	$x(+2)$	$x(+3)$	$x(+4)$	$x(+5)$
Australia	0.559	0.567	0.536	0.423	0.249	0.056	-0.153	-0.294	-0.378	-0.399	-0.364
<i>Std.</i>	0.278	0.206	0.083	-0.107	-0.385	-0.747	-0.938	-0.832	-0.602	-0.355	-0.138
<i>HM</i>	0.273	0.202	0.080	-0.108	-0.382	-0.740	-0.928	-0.823	-0.597	-0.355	-0.142
Austria	0.244	0.228	0.189	-0.019	-0.123	-0.387	-0.480	-0.424	-0.414	-0.322	-0.148
<i>Std.</i>	0.295	0.267	0.190	0.034	-0.243	-0.667	-0.910	-0.792	-0.538	-0.280	-0.069
<i>HM</i>	0.292	0.266	0.189	0.034	-0.244	-0.668	-0.909	-0.787	-0.531	-0.274	-0.064
Canada	0.456	0.347	0.209	0.041	-0.102	-0.247	-0.358	-0.431	-0.446	-0.431	-0.383
<i>Std.</i>	0.228	0.144	0.008	-0.197	-0.489	-0.856	-0.957	-0.724	-0.428	-0.175	0.015
<i>HM</i>	0.225	0.142	0.007	-0.194	-0.482	-0.844	-0.945	-0.718	-0.429	-0.180	0.007
Czech Rep.	0.500	0.402	0.204	0.019	-0.230	-0.435	-0.592	-0.671	-0.675	-0.612	-0.492
<i>Std.</i>	0.365	0.313	0.212	0.045	-0.205	-0.544	-0.802	-0.850	-0.762	-0.606	-0.425
Finland	0.440	0.367	0.222	0.062	-0.101	-0.282	-0.435	-0.522	-0.560	-0.584	-0.558
<i>Std.</i>	0.312	0.277	0.190	0.028	-0.245	-0.645	-0.894	-0.823	-0.608	-0.366	-0.149
Germany	0.179	0.097	-0.007	-0.125	-0.257	-0.376	-0.439	-0.434	-0.392	-0.297	-0.194
<i>Std.</i>	0.337	0.352	0.326	0.227	-0.002	-0.417	-0.748	-0.772	-0.638	-0.453	-0.269
<i>HM</i>	0.331	0.346	0.320	0.220	-0.010	-0.429	-0.758	-0.775	-0.632	-0.440	-0.253
Japan	0.241	0.166	0.029	-0.106	-0.293	-0.461	-0.571	-0.630	-0.611	-0.508	-0.337
<i>Std.</i>	0.253	0.169	0.036	-0.160	-0.433	-0.776	-0.947	-0.836	-0.608	-0.365	-0.151
<i>HM</i>	0.257	0.180	0.054	-0.133	-0.397	-0.730	-0.907	-0.817	-0.612	-0.385	-0.180
Norway	0.433	0.378	0.303	0.237	0.075	-0.038	-0.176	-0.293	-0.342	-0.347	-0.388
<i>Std.</i>	0.210	0.212	0.179	0.067	-0.219	-0.777	-0.906	-0.497	-0.136	0.072	0.169
Poland	0.197	0.279	0.350	0.352	0.312	0.244	0.125	0.049	-0.007	-0.032	-0.007
<i>Std.</i>	0.259	0.295	0.313	0.278	0.102	-0.363	-0.735	-0.696	-0.513	-0.319	-0.156
Portugal	0.205	0.170	0.148	0.080	-0.028	-0.082	-0.168	-0.213	-0.260	-0.246	-0.256
<i>Std.</i>	0.290	0.338	0.368	0.346	0.189	-0.237	-0.619	-0.659	-0.550	-0.403	-0.263
<i>HM</i>	0.286	0.332	0.361	0.337	0.178	-0.251	-0.633	-0.665	-0.549	-0.397	-0.254
Spain	0.313	0.399	0.433	0.477	0.477	0.472	0.420	0.369	0.323	0.261	0.203
<i>Std.</i>	0.367	0.388	0.368	0.276	0.060	-0.332	-0.669	-0.743	-0.663	-0.519	-0.359
<i>HM</i>	0.361	0.378	0.354	0.258	0.037	-0.360	-0.694	-0.755	-0.662	-0.507	-0.339
U.K.	0.711	0.647	0.487	0.283	0.046	-0.185	-0.392	-0.521	-0.584	-0.567	-0.508
<i>Std.</i>	0.282	0.195	0.063	-0.122	-0.373	-0.683	-0.889	-0.887	-0.760	-0.578	-0.383
<i>HM</i>	0.287	0.204	0.077	-0.105	-0.350	-0.655	-0.859	-0.861	-0.743	-0.572	-0.389
U.S.	0.569	0.550	0.460	0.284	0.041	-0.242	-0.425	-0.536	-0.544	-0.485	-0.393
<i>Std.</i>	0.150	0.040	-0.119	-0.335	-0.621	-0.940	-0.923	-0.630	-0.349	-0.130	0.031
<i>HM</i>	0.149	0.040	-0.116	-0.329	-0.609	-0.923	-0.909	-0.623	-0.348	-0.132	0.028

Note: Shaded rows: data; *Std.*: standard calibration; *HM*: Hagedorn-Manovskii (2008) calibration.

Table 6: **Vacancies-Productivity cross-correlations**

Countries	$x(-5)$	$x(-4)$	$x(-3)$	$x(-2)$	$x(-1)$	x	$x(+1)$	$x(+2)$	$x(+3)$	$x(+4)$	$x(+5)$
Australia	-0.536	-0.455	-0.287	-0.138	0.078	0.230	0.376	0.490	0.505	0.521	0.481
<i>Std.</i>	-0.103	0.011	0.180	0.418	0.745	0.989	0.624	0.259	0.029	-0.113	-0.196
<i>HM</i>	-0.035	0.073	0.228	0.441	0.730	0.905	0.440	0.060	-0.134	-0.226	-0.259
Austria	-0.158	-0.079	0.029	0.169	0.333	0.480	0.539	0.538	0.471	0.369	0.248
<i>Std.</i>	-0.151	-0.075	0.062	0.293	0.669	0.989	0.536	0.129	-0.083	-0.185	-0.224
<i>HM</i>	-0.092	-0.016	0.115	0.332	0.678	0.923	0.359	-0.062	-0.232	-0.277	-0.266
Canada	-0.381	-0.267	-0.139	0.014	0.167	0.299	0.394	0.457	0.468	0.455	0.411
<i>Std.</i>	-0.113	0.001	0.172	0.414	0.745	0.989	0.615	0.267	0.050	-0.088	-0.173
<i>HM</i>	-0.052	0.058	0.216	0.438	0.739	0.907	0.411	0.065	-0.095	-0.173	-0.209
Czech Rep.	-0.381	-0.250	-0.001	0.219	0.457	0.631	0.714	0.717	0.672	0.581	0.449
<i>Std.</i>	-0.088	0.030	0.200	0.434	0.751	0.992	0.663	0.303	0.056	-0.105	-0.205
Finland	-0.407	-0.299	-0.124	0.042	0.224	0.408	0.496	0.572	0.583	0.601	0.546
<i>Std.</i>	-0.142	-0.053	0.096	0.332	0.693	0.990	0.574	0.176	-0.051	-0.172	-0.228
Germany	-0.093	0.021	0.147	0.258	0.359	0.445	0.482	0.441	0.342	0.244	0.140
<i>Std.</i>	-0.165	-0.112	0.002	0.219	0.614	0.995	0.535	0.112	-0.102	-0.199	-0.231
<i>HM</i>	-0.122	-0.066	0.047	0.258	0.634	0.967	0.438	-0.003	-0.204	-0.275	-0.279
Japan	-0.169	-0.061	0.086	0.264	0.457	0.612	0.695	0.681	0.561	0.365	0.139
<i>Std.</i>	-0.075	0.047	0.219	0.454	0.764	0.987	0.635	0.284	0.057	-0.088	-0.178
<i>HM</i>	-0.007	0.097	0.241	0.435	0.688	0.832	0.413	0.067	-0.118	-0.209	-0.244
Norway	-0.514	-0.477	-0.375	-0.205	-0.078	0.056	0.171	0.269	0.327	0.394	0.430
<i>Std.</i>	-0.156	-0.136	-0.066	0.116	0.539	0.987	0.366	-0.026	-0.146	-0.172	-0.167
Poland	-0.368	-0.279	-0.141	-0.025	0.113	0.271	0.264	0.214	0.137	0.041	-0.060
<i>Std.</i>	-0.143	-0.134	-0.086	0.063	0.476	0.996	0.396	-0.030	-0.166	-0.194	-0.184
Portugal	-0.135	-0.043	0.042	0.119	0.268	0.282	0.260	0.219	0.161	0.146	0.169
<i>Std.</i>	-0.153	-0.144	-0.089	0.070	0.484	0.998	0.439	0.014	-0.141	-0.186	-0.185
<i>HM</i>	-0.129	-0.116	-0.060	0.099	0.505	0.990	0.388	-0.046	-0.192	-0.223	-0.209
Spain	-0.221	-0.214	-0.154	-0.143	-0.114	-0.076	-0.090	0.001	0.076	0.109	0.146
<i>Std.</i>	-0.175	-0.117	0.004	0.228	0.620	0.998	0.577	0.167	-0.058	-0.172	-0.219
<i>HM</i>	-0.141	-0.080	0.041	0.260	0.640	0.987	0.519	0.092	-0.129	-0.229	-0.260
U.K.	-0.412	-0.270	-0.060	0.181	0.418	0.625	0.741	0.747	0.661	0.551	0.406
<i>Std.</i>	-0.026	0.105	0.280	0.505	0.788	0.990	0.692	0.362	0.125	-0.040	-0.152
<i>HM</i>	0.017	0.121	0.258	0.433	0.654	0.792	0.485	0.184	-0.011	-0.132	-0.203
U.S.	-0.533	-0.465	-0.329	-0.107	0.157	0.408	0.555	0.608	0.576	0.497	0.404
<i>Std.</i>	-0.076	0.053	0.231	0.470	0.778	0.994	0.679	0.374	0.156	-0.003	-0.115
<i>HM</i>	-0.038	0.089	0.262	0.491	0.783	0.939	0.527	0.239	0.063	-0.059	-0.142

Note: Shaded rows: data; *Std.*: standard calibration; *HM*: Hagedorn-Manovskii (2008) calibration.

Table 7: Vacancies-Unemployment cross-correlations

Countries	$x(-5)$	$x(-4)$	$x(-3)$	$x(-2)$	$x(-1)$	x	$x(+1)$	$x(+2)$	$x(+3)$	$x(+4)$	$x(+5)$
Australia	-0.406	-0.569	-0.697	-0.780	-0.763	-0.681	-0.536	-0.336	-0.103	0.135	0.331
<i>Std.</i>	-0.182	-0.390	-0.621	-0.824	-0.889	-0.642	-0.252	0.011	0.170	0.258	0.300
<i>HM</i>	-0.246	-0.429	-0.620	-0.767	-0.761	-0.440	-0.028	0.197	0.297	0.327	0.319
Austria	-0.121	-0.304	-0.461	-0.592	-0.689	-0.713	-0.647	-0.551	-0.370	-0.185	-0.041
<i>Std.</i>	-0.112	-0.315	-0.555	-0.778	-0.851	-0.550	-0.103	0.148	0.263	0.301	0.297
<i>HM</i>	-0.166	-0.347	-0.551	-0.724	-0.728	-0.354	0.107	0.309	0.357	0.335	0.286
Canada	-0.166	-0.337	-0.533	-0.714	-0.843	-0.876	-0.793	-0.642	-0.461	-0.276	-0.108
<i>Std.</i>	-0.022	-0.212	-0.460	-0.742	-0.942	-0.772	-0.368	-0.095	0.076	0.181	0.241
<i>HM</i>	-0.090	-0.269	-0.495	-0.735	-0.862	-0.584	-0.137	0.088	0.191	0.237	0.251
Czech Rep.	-0.269	-0.489	-0.687	-0.835	-0.905	-0.867	-0.720	-0.495	-0.236	0.031	0.269
<i>Std.</i>	-0.450	-0.612	-0.745	-0.805	-0.725	-0.437	-0.085	0.155	0.300	0.374	0.399
Finland	-0.264	-0.455	-0.625	-0.746	-0.821	-0.826	-0.733	-0.585	-0.424	-0.238	-0.052
<i>Std.</i>	-0.190	-0.395	-0.618	-0.802	-0.832	-0.532	-0.112	0.141	0.268	0.318	0.323
Germany	-0.273	-0.448	-0.617	-0.747	-0.809	-0.794	-0.698	-0.540	-0.349	-0.155	0.011
<i>Std.</i>	-0.289	-0.460	-0.626	-0.735	-0.683	-0.326	0.093	0.303	0.377	0.377	0.341
<i>HM</i>	-0.301	-0.452	-0.594	-0.674	-0.588	-0.200	0.221	0.402	0.438	0.401	0.334
Japan	-0.293	-0.502	-0.700	-0.813	-0.836	-0.764	-0.579	-0.348	-0.116	0.093	0.261
<i>Std.</i>	-0.197	-0.403	-0.630	-0.830	-0.899	-0.667	-0.290	-0.030	0.133	0.230	0.282
<i>HM</i>	-0.289	-0.459	-0.625	-0.738	-0.703	-0.391	-0.005	0.207	0.302	0.329	0.319
Norway	-0.074	-0.248	-0.446	-0.628	-0.776	-0.828	-0.787	-0.660	-0.501	-0.323	-0.154
<i>Std.</i>	0.140	0.039	-0.170	-0.522	-0.893	-0.668	-0.082	0.145	0.204	0.206	0.188
Poland	-0.731	-0.804	-0.799	-0.726	-0.611	-0.416	-0.218	-0.018	0.160	0.307	0.406
<i>Std.</i>	-0.174	-0.327	-0.505	-0.666	-0.677	-0.278	0.186	0.338	0.346	0.307	0.253
Portugal	-0.501	-0.551	-0.573	-0.567	-0.538	-0.491	-0.382	-0.229	-0.090	0.038	0.147
<i>Std.</i>	-0.270	-0.402	-0.537	-0.632	-0.578	-0.184	0.240	0.384	0.392	0.348	0.290
<i>HM</i>	-0.272	-0.393	-0.515	-0.595	-0.523	-0.113	0.309	0.433	0.419	0.357	0.283
Spain	-0.369	-0.381	-0.382	-0.379	-0.353	-0.299	-0.213	-0.124	-0.068	-0.010	0.040
<i>Std.</i>	-0.367	-0.518	-0.651	-0.716	-0.627	-0.279	0.115	0.322	0.400	0.406	0.373
<i>HM</i>	-0.363	-0.505	-0.627	-0.680	-0.577	-0.211	0.188	0.381	0.439	0.424	0.372
U.K.	-0.423	-0.605	-0.754	-0.848	-0.850	-0.749	-0.547	-0.288	-0.002	0.272	0.499
<i>Std.</i>	-0.417	-0.596	-0.757	-0.856	-0.823	-0.577	-0.245	-0.001	0.164	0.269	0.328
<i>HM</i>	-0.421	-0.543	-0.636	-0.666	-0.581	-0.326	-0.028	0.168	0.279	0.333	0.347
U.S.	-0.224	-0.420	-0.625	-0.808	-0.927	-0.932	-0.798	-0.587	-0.354	-0.127	0.066
<i>Std.</i>	0.009	-0.155	-0.375	-0.654	-0.935	-0.897	-0.542	-0.271	-0.075	0.067	0.164
<i>HM</i>	-0.032	-0.195	-0.412	-0.680	-0.925	-0.786	-0.380	-0.142	0.011	0.116	0.185

Note: Shaded rows: data; *Std.*: standard calibration; *HM*: Hagedorn-Manovskii (2008) calibration.

A Appendix

Our data is mostly from the OECD's Outlook Economic Database (OECD), or from [Ohanian and Raffo \(2011\)](#) (OR) which draws on OECD data itself. For selected countries we used a variety of national sources. A detailed list follows. The dates available for each country/series pair are in the tables below.

Australia Vacancies: OECD; Unemployment: OECD ; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

Austria Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: IMF's International Financial Statistics (IFS).

Canada Vacancies: Conference Board and Help Wanted Index; Unemployment: OECD; GDP: OR and OECD; Employment: OECD; Labor Force: OECD.

Czech Republic Vacancies: OECD; Unemployment: OECD; GDP: IFS and OECD; Employment: OECD; Labor Force: OECD.

Finland Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR; Labor Force: OECD.

France Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD and IFS.

Germany Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

Japan Vacancies: Japanese Ministry of Health and Labor; Unemployment: OECD; GDP: OR and OECD; Employment: OECD; Labor Force: OECD.

Netherlands Vacancies: OECD; Unemployment: OECD; GDP: IFS and OECD; Employment: OECD and IFS; Labor Force: OECD.

Norway Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

Poland Vacancies: OECD; Unemployment: OECD; GDP: OECD; Employment: OECD; Labor Force: OECD.

Portugal Vacancies: OECD; Unemployment: OECD; GDP: IFS and OECD; Employment: OECD; Labor Force: OECD.

Spain Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

Sweden Vacancies: OECD; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

U.K. Vacancies: OECD and Office for National Statistics; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

U.S. Vacancies: Conference Board's Help-Wanted Index and Job Openings and Labor Turnover Survey; Unemployment: OECD; GDP: OR and OECD; Employment: OR and OECD; Labor Force: OECD.

Table 8: **Vacancies**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q2-1979	Q3-2011	0.1642	0.8689
Austria	Q1-1955	Q3-2011	0.1577	0.9251
Canada	Q1-1962	Q3-2011	0.1545	0.9155
Czech Rep.	Q1-1991	Q2-2011	0.2649	0.9132
Finland	Q1-1961	Q2-2010	0.2385	0.8948
France	Q1-1989	Q2-2011	0.0692	0.8124
Germany	Q1-1962	Q2-2010	0.1954	0.9387
Japan	Q2-1967	Q4-2011	0.1254	0.9303
Netherlands	Q1-1988	Q4-2009	0.2239	0.9219
Norway	Q1-1955	Q3-2011	0.1874	0.8803
Poland	Q1-1990	Q2-2011	0.1824	0.8524
Portugal	Q1-1974	Q3-2011	0.2588	0.8927
Spain	Q1-1977	Q1-2005	0.2065	0.8031
Sweden	Q3-1961	Q2-2011	0.2234	0.9104
U.K.	Q3-1958	Q3-2011	0.1991	0.9205
U.S.	Q1-1955	Q3-2011	0.1353	0.9036

Table 9: **Vacancies adjusted by labor force**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q2-1979	Q2-2011	0.1640	0.8680
Austria	Q1-1958	Q4-2010	0.1587	0.9254
Canada	Q1-1962	Q3-2011	0.1531	0.9151
Czech Rep.	Q1-1993	Q2-2011	0.2705	0.9264
Finland	Q1-1964	Q2-2010	0.2351	0.9153
France	Q1-1993	Q2-2011	0.0593	0.8270
Germany	Q1-1962	Q2-2010	0.1936	0.9381
Japan	Q2-1967	Q2-2011	0.1225	0.9268
Netherlands	Q2-1998	Q4-2009	0.2270	0.9147
Norway	Q1-1972	Q2-2011	0.1840	0.8734
Poland	Q2-1992	Q2-2011	0.1786	0.8846
Portugal	Q2-1983	Q2-2011	0.1872	0.8844
Spain	Q1-1977	Q1-2005	0.2071	0.8036
Sweden	Q1-1970	Q2-2011	0.2280	0.9067
U.K.	Q2-1971	Q2-2011	0.1960	0.9201
U.S.	Q1-1955	Q3-2011	0.1340	0.9026

Table 10: **Unemployment**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q1-1964	Q2-2011	0.1100	0.8424
Austria	Q1-1969	Q2-2011	0.1098	0.6433
Canada	Q1-1955	Q3-2011	0.1069	0.8785
Czech Rep.	Q1-1990	Q2-2011	0.2535	0.6704
Finland	Q1-1958	Q4-2010	0.1872	0.8856
France	Q1-1978	Q2-2011	0.0526	0.9284
Germany	Q1-1956	Q2-2011	0.1985	0.9188
Japan	Q1-1955	Q2-2011	0.0699	0.7993
Netherlands	Q1-1970	Q2-2011	0.1351	0.9151
Norway	Q1-1972	Q2-2011	0.1564	0.7573
Poland	Q4-1991	Q2-2011	0.1223	0.9352
Portugal	Q1-1983	Q2-2011	0.0994	0.9155
Spain	Q1-1977	Q2-2011	0.0842	0.9405
Sweden	Q2-1961	Q3-2011	0.1522	0.8674
U.K.	Q1-1971	Q2-2011	0.1163	0.9320
U.S.	Q1-1955	Q3-2011	0.1177	0.8994

Table 11: **Unemployment adjusted by labor force**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q1-1964	Q2-2011	0.1118	0.8494
Austria	Q1-1969	Q4-2010	0.1108	0.6470
Canada	Q1-1956	Q3-2011	0.1030	0.8768
Czech Rep.	Q1-1993	Q2-2011	0.1327	0.9284
Finland	Q1-1964	Q4-2010	0.1915	0.9176
France	Q1-1993	Q2-2011	0.0552	0.9223
Germany	Q1-1962	Q2-2011	0.1994	0.9208
Japan	Q1-1955	Q2-2011	0.0711	0.8006
Netherlands	Q2-1998	Q2-2011	0.1562	0.9553
Norway	Q1-1972	Q2-2011	0.1593	0.7675
Poland	Q2-1992	Q2-2011	0.1195	0.9371
Portugal	Q2-1983	Q2-2011	0.1015	0.9153
Spain	Q1-1977	Q2-2011	0.0845	0.9437
Sweden	Q1-1970	Q3-2011	0.1606	0.9079
U.K.	Q2-1971	Q2-2011	0.1180	0.9358
U.S.	Q1-1955	Q3-2011	0.1191	0.9021

Table 12: **Productivity**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q1-1964	Q2-2011	0.0118	0.5541
Austria	Q1-1960	Q2-2011	0.0104	0.6239
Canada	Q1-1960	Q2-2011	0.0090	0.7111
Czech Rep.	Q1-1994	Q2-2011	0.0214	0.7282
Finland	Q1-1960	Q2-2011	0.0159	0.6774
France	Q1-1960	Q2-2011	0.0094	0.5165
Germany	Q1-1960	Q2-2011	0.0112	0.5918
Japan	Q1-1960	Q2-2011	0.0143	0.7385
Netherlands	Q1-1984	Q2-2011	0.0108	0.8132
Norway	Q1-1960	Q2-2011	0.0124	0.5472
Poland	Q1-1995	Q2-2011	0.0102	0.4515
Portugal	Q2-1983	Q2-2011	0.0112	0.4684
Spain	Q3-1972	Q2-2011	0.0078	0.6428
Sweden	Q1-1960	Q2-2011	0.0120	0.8650
U.K.	Q1-1960	Q2-2011	0.0119	0.7322
U.S.	Q1-1960	Q2-2011	0.0093	0.7544

Table 13: **Productivity adjusted by labor force**

Countries	Start date	End date	Std. dev.	Autocorr.
Australia	Q1-1964	Q2-2011	0.0099	0.4652
Austria	Q1-1960	Q4-2010	0.0107	0.6634
Canada	Q1-1960	Q2-2011	0.0084	0.6844
Czech Rep.	Q1-1994	Q2-2011	0.0214	0.7309
Finland	Q1-1964	Q2-2011	0.0164	0.6757
France	Q1-1993	Q2-2011	0.0075	0.8744
Germany	Q1-1962	Q2-2011	0.0128	0.6418
Japan	Q1-1960	Q2-2011	0.0153	0.7485
Netherlands	Q2-1998	Q2-2011	0.0118	0.8792
Norway	Q1-1972	Q2-2011	0.0120	0.4524
Poland	Q1-1995	Q2-2011	0.0108	0.4895
Portugal	Q2-1983	Q2-2011	0.0110	0.5460
Spain	Q3-1972	Q2-2011	0.0093	0.6940
Sweden	Q1-1970	Q2-2011	0.0120	0.8435
U.K.	Q2-1971	Q2-2011	0.0117	0.7490
U.S.	Q1-1960	Q2-2011	0.0093	0.7481

Table 14: **Australia**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.095	0.165	0.240	0.010	0.003	0.015	0.017	0.010
Autocorr.		0.907	0.869	0.903	0.719	0.879	0.664	0.719	0.719
Correlation	u	1	-0.681	-0.864	0.056	1	-0.642	-0.747	-0.747
	v	-	1	0.957	0.230	-	1	0.989	0.989
	v/u	-	-	1	0.136	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q2-1979 : Q2-2011								

Table 15: **Austria**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.110	0.163	0.254	0.011	0.003	0.015	0.017	0.011
Autocorr.		0.643	0.929	0.879	0.639	0.854	0.582	0.640	0.640
Correlation	u	1	-0.713	-0.892	-0.387	1	-0.550	-0.667	-0.667
	v	-	1	0.953	0.480	-	1	0.989	0.989
	v/u	-	-	1	0.477	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1969 : Q2-2011								

Table 16: **Canada**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.091	0.155	0.239	0.009	0.004	0.014	0.017	0.009
Autocorr.		0.888	0.916	0.919	0.717	0.838	0.653	0.718	0.718
Correlation	u	1	-0.876	-0.950	-0.247	1	-0.772	-0.856	-0.856
	v	-	1	0.983	0.299	-	1	0.990	0.989
	v/u	-	-	1	0.288	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1962 : Q2-2011								

Table 17: **Czech Republic**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.137	0.275	0.399	0.021	0.004	0.027	0.029	0.021
Autocorr.		0.927	0.927	0.931	0.728	0.920	0.700	0.729	0.729
Correlation	u	1	-0.867	-0.939	-0.435	1	-0.437	-0.545	-0.544
	v	-	1	0.985	0.631	-	1	0.992	0.992
	v/u	-	-	1	0.583	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1994 : Q2-2011								

Table 18: **Finland**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.187	0.238	0.407	0.016	0.005	0.028	0.031	0.016
Autocorr.		0.899	0.895	0.915	0.665	0.874	0.615	0.665	0.665
Correlation	u	1	-0.826	-0.944	-0.282	1	-0.532	-0.645	-0.645
	v	-	1	0.966	0.408	-	1	0.990	0.990
	v/u	-	-	1	0.369	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1961 : Q2-2010								

Table 19: **Germany**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.199	0.195	0.373	0.011	0.001	0.010	0.011	0.011
Autocorr.		0.921	0.939	0.938	0.591	0.884	0.566	0.591	0.591
Correlation	u	1	-0.794	-0.948	-0.376	1	-0.327	-0.417	-0.417
	v	-	1	0.946	0.445	-	1	0.995	0.995
	v/u	-	-	1	0.433	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1962 : Q2-2010								

Table 20: **Japan**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.066	0.123	0.179	0.014	0.010	0.038	0.045	0.014
Autocorr.		0.799	0.928	0.909	0.727	0.883	0.679	0.739	0.739
Correlation	u	1	-0.764	-0.896	-0.461	1	-0.667	-0.776	-0.776
	v	-	1	0.971	0.612	-	1	0.987	0.987
	v/u	-	-	1	0.592	-	-	1	0.999
	p	-	-	-	1	-	-	-	1
Dates:	Q2-1967 : Q2-2011								

Table 21: **Norway**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.156	0.187	0.328	0.013	0.006	0.023	0.027	0.013
Autocorr.		0.757	0.877	0.879	0.501	0.708	0.413	0.502	0.502
Correlation	u	1	-0.828	-0.948	-0.038	1	-0.668	-0.777	-0.777
	v	-	1	0.964	0.056	-	1	0.987	0.987
	v/u	-	-	1	0.050	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1972 : Q2-2011								

Table 22: **Poland**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.132	0.168	0.253	0.010	0.000	0.004	0.004	0.010
Autocorr.		0.948	0.862	0.925	0.451	0.843	0.425	0.451	0.451
Correlation	u	1	-0.416	-0.797	0.244	1	-0.277	-0.362	-0.362
	v	-	1	0.881	0.271	-	1	0.996	0.996
	v/u	-	-	1	0.052	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1995 : Q2-2011								

Table 23: **Portugal**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.099	0.188	0.251	0.011	0.000	0.004	0.004	0.011
Autocorr.		0.915	0.884	0.908	0.468	0.872	0.456	0.467	0.467
Correlation	u	1	-0.491	-0.760	-0.082	1	-0.183	-0.236	-0.236
	v	-	1	0.940	0.282	-	1	0.999	0.998
	v/u	-	-	1	0.243	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q2-1983 : Q2-2011								

Table 24: **Spain**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.059	0.206	0.231	0.007	0.000	0.004	0.004	0.007
Autocorr.		0.941	0.803	0.831	0.605	0.900	0.594	0.606	0.605
Correlation	u	1	-0.299	-0.523	0.472	1	-0.279	-0.333	-0.332
	v	-	1	0.970	-0.076	-	1	0.998	0.998
	v/u	-	-	1	-0.188	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1977 : Q1-2005								

Table 25: **U.K.**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.116	0.196	0.293	0.012	0.005	0.024	0.027	0.012
Autocorr.		0.932	0.918	0.926	0.767	0.920	0.728	0.768	0.767
Correlation	u	1	-0.749	-0.897	-0.185	1	-0.577	-0.683	-0.683
	v	-	1	0.965	0.625	-	1	0.991	0.990
	v/u	-	-	1	0.491	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1971 : Q2-2011								

Table 26: **U.S.**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.115	0.132	0.243	0.009	0.003	0.010	0.013	0.009
Autocorr.		0.915	0.913	0.920	0.754	0.815	0.707	0.754	0.754
Correlation	u	1	-0.932	-0.980	-0.242	1	-0.897	-0.940	-0.940
	v	-	1	0.985	0.408	-	1	0.994	0.994
	v/u	-	-	1	0.337	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1960 : Q2-2011								

Table 27: **Australia (HM calibration)**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.095	0.165	0.240	0.010	0.108	0.202	0.268	0.010
Autocorr.		0.907	0.869	0.903	0.719	0.879	0.582	0.713	0.719
Correlation	u	1	-0.681	-0.864	0.056	1	-0.440	-0.734	-0.740
	v	-	1	0.957	0.230	-	1	0.932	0.905
	v/u	-	-	1	0.136	-	-	1	0.981
	p	-	-	-	1	-	-	-	1
Dates:	Q2-1979 : Q2-2011								

Table 28: **Austria (HM calibration)**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.110	0.163	0.254	0.011	0.078	0.161	0.202	0.011
Autocorr.		0.643	0.929	0.879	0.639	0.853	0.505	0.636	0.639
Correlation	u	1	-0.713	-0.892	-0.387	1	-0.354	-0.665	-0.668
	v	-	1	0.953	0.480	-	1	0.933	0.923
	v/u	-	-	1	0.477	-	-	1	0.993
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1969 : Q2-2011								

Table 29: **Canada (HM calibration)**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.091	0.155	0.239	0.009	0.101	0.142	0.217	0.009
Autocorr.		0.888	0.916	0.919	0.717	0.838	0.535	0.713	0.717
Correlation	u	1	-0.876	-0.950	-0.247	1	-0.583	-0.846	-0.843
	v	-	1	0.983	0.299	-	1	0.926	0.907
	v/u	-	-	1	0.288	-	-	1	0.986
	p	-	-	-	1	-	-	-	1
Dates:		Q1-1962 : Q2-2011							

Table 30: **Germany (HM calibration)**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.199	0.195	0.373	0.011	0.037	0.139	0.151	0.011
Autocorr.		0.921	0.939	0.938	0.591	0.882	0.533	0.588	0.589
Correlation	u	1	-0.794	-0.948	-0.376	1	-0.201	-0.428	-0.429
	v	-	1	0.946	0.445	-	1	0.971	0.967
	v/u	-	-	1	0.433	-	-	1	0.997
	p	-	-	-	1	-	-	-	1
Dates:		Q1-1962 : Q2-2010							

Table 31: **Japan (HM calibration)**

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.066	0.123	0.179	0.014	0.172	0.325	0.422	0.014
Autocorr.		0.799	0.928	0.909	0.727	0.889	0.588	0.718	0.738
Correlation	u	1	-0.764	-0.896	-0.461	1	-0.391	-0.710	-0.731
	v	-	1	0.971	0.612	-	1	0.925	0.832
	v/u	-	-	1	0.592	-	-	1	0.936
	p	-	-	-	1	-	-	-	1
Dates:		Q2-1967 : Q2-2011							

Table 32: Portugal (HM calibration)

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.099	0.188	0.251	0.011	0.005	0.031	0.032	0.011
Autocorr.		0.915	0.884	0.908	0.468	0.869	0.441	0.465	0.465
Correlation	u	1	-0.491	-0.760	-0.082	1	-0.113	-0.251	-0.251
	v	-	1	0.940	0.282	-	1	0.990	0.990
	v/u	-	-	1	0.243	-	-	1	0.999
	p	-	-	-	1	-	-	-	1
Dates:		Q2-1983 : Q2-2011							

Table 33: Spain (HM calibration)

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.059	0.206	0.231	0.007	0.005	0.027	0.029	0.007
Autocorr.		0.941	0.803	0.831	0.605	0.897	0.576	0.606	0.606
Correlation	u	1	-0.299	-0.523	0.472	1	-0.211	-0.361	-0.361
	v	-	1	0.970	-0.076	-	1	0.988	0.987
	v/u	-	-	1	-0.188	-	-	1	1.000
	p	-	-	-	1	-	-	-	1
Dates:		Q1-1977 : Q1-2005							

Table 34: U.K. (HM calibration)

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.116	0.196	0.293	0.012	0.143	0.567	0.622	0.012
Autocorr.		0.932	0.918	0.926	0.767	0.922	0.647	0.715	0.768
Correlation	u	1	-0.749	-0.897	-0.185	1	-0.325	-0.563	-0.655
	v	-	1	0.965	0.625	-	1	0.962	0.791
	v/u	-	-	1	0.491	-	-	1	0.869
	p	-	-	-	1	-	-	-	1
Dates:		Q1-1971 : Q2-2011							

Table 35: U.S. (HM calibration)

		Data				Model			
		u	v	v/u	p	u	v	v/u	p
Std. Dev.		0.115	0.132	0.243	0.009	0.073	0.084	0.149	0.009
Autocorr.		0.915	0.913	0.920	0.754	0.817	0.602	0.752	0.755
Correlation	u	1	-0.932	-0.980	-0.242	1	-0.787	-0.936	-0.923
	v	-	1	0.985	0.408	-	1	0.954	0.939
	v/u	-	-	1	0.337	-	-	1	0.985
	p	-	-	-	1	-	-	-	1
Dates:	Q1-1960 : Q2-2011								

Figure 17: Correlation between productivity and labor market variables – short(red) vs. long sample

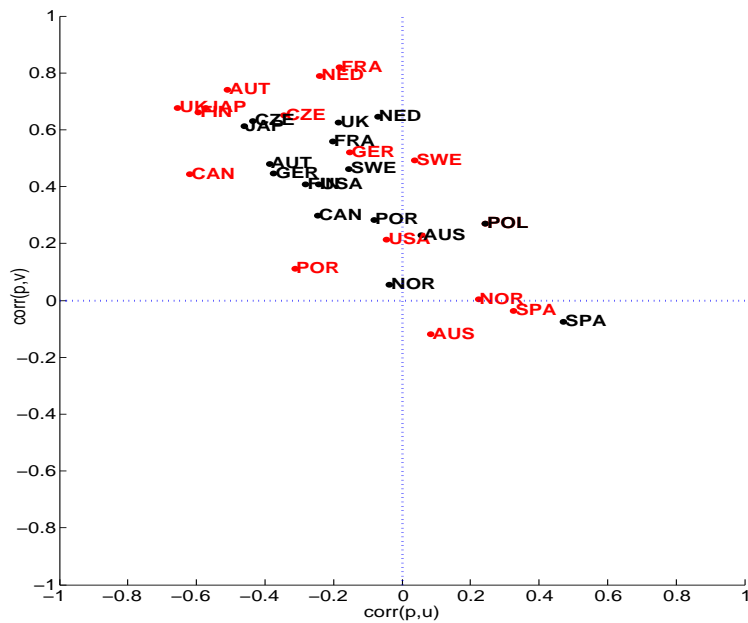


Figure 18: Productivity and unemployment – short(red) vs. long sample

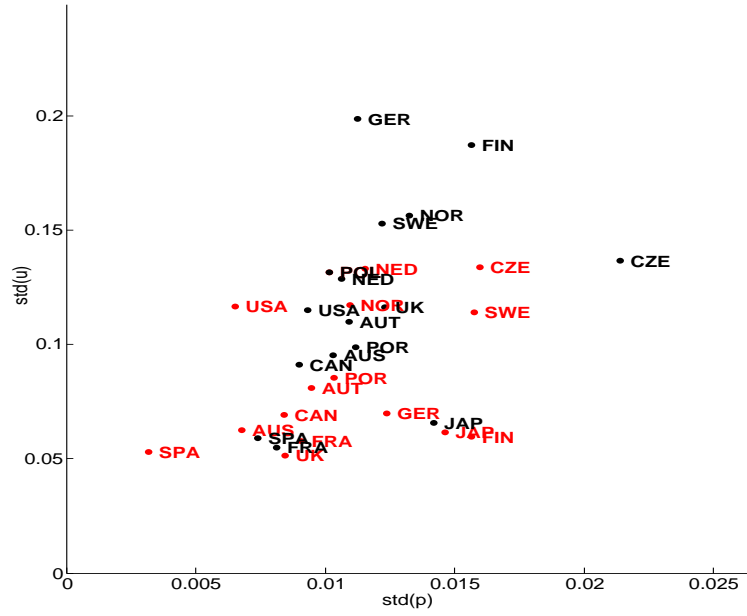


Figure 19: Productivity and vacancies – short(red) vs. long sample

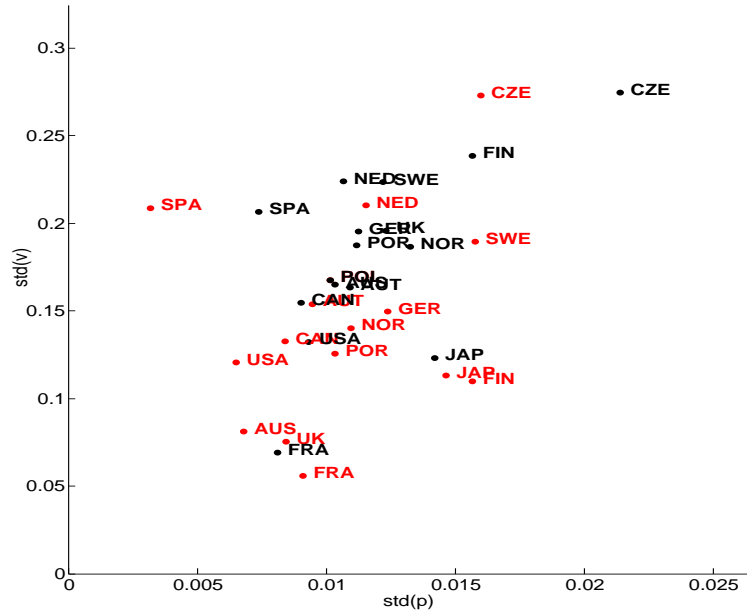


Figure 20: Persistence of labor market variables – short(red) vs. long sample

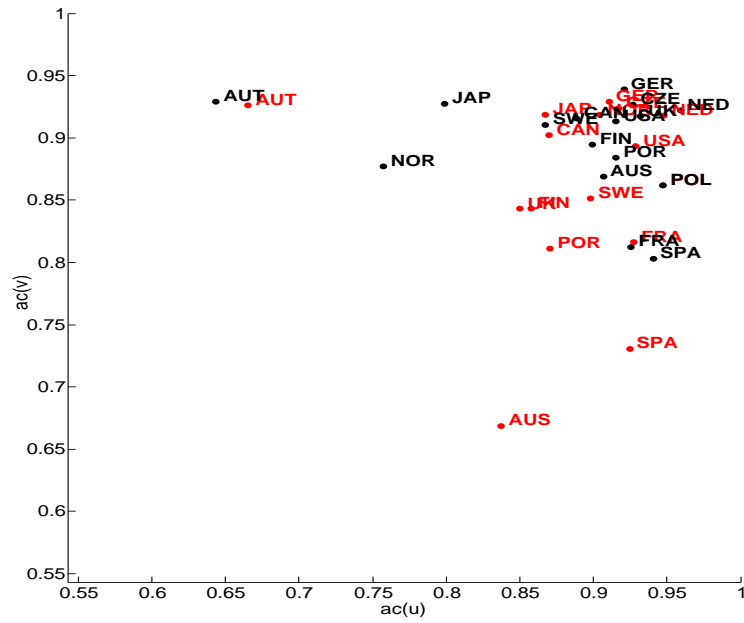


Figure 21: Vacancies-unemployment correlation – short vs. long sample

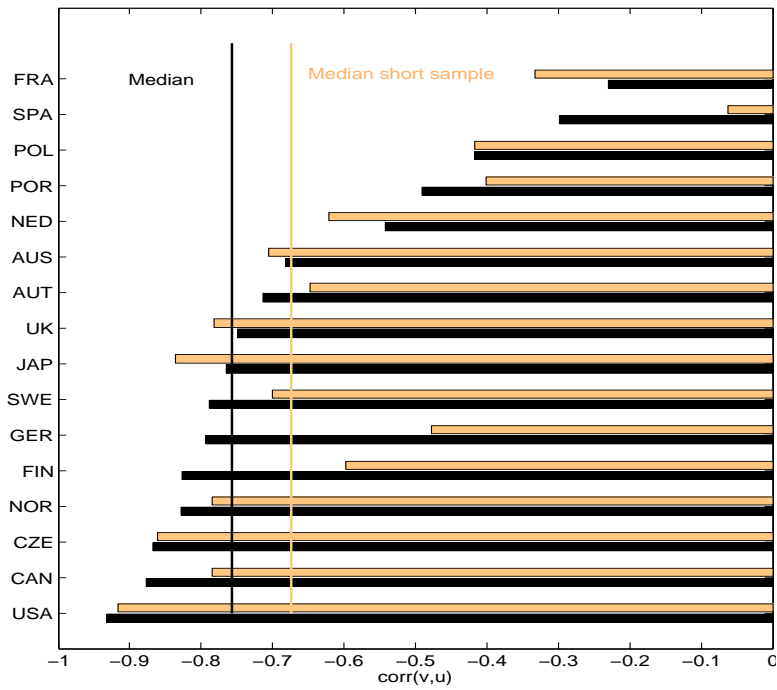


Table 36: Productivity auto-correlations

Countries	$x(-5)$	$x(-4)$	$x(-3)$	$x(-2)$	$x(-1)$	x	$x(+1)$	$x(+2)$	$x(+3)$	$x(+4)$	$x(+5)$
Australia	-0.120	-0.027	0.182	0.455	0.719	1.000	0.719	0.455	0.182	-0.027	-0.120
<i>Std.</i>	-0.143	-0.030	0.139	0.383	0.719	1.000	0.719	0.383	0.139	-0.030	-0.143
<i>HM</i>	-0.140	-0.028	0.141	0.383	0.719	1.000	0.719	0.383	0.141	-0.028	-0.140
Austria	-0.048	0.021	0.200	0.403	0.639	1.000	0.639	0.403	0.200	0.021	-0.048
<i>Std.</i>	-0.187	-0.115	0.021	0.255	0.639	1.000	0.639	0.255	0.021	-0.115	-0.187
<i>HM</i>	-0.188	-0.116	0.019	0.253	0.639	1.000	0.639	0.253	0.019	-0.116	-0.188
Canada	0.070	0.241	0.400	0.541	0.717	1.000	0.717	0.541	0.400	0.241	0.070
<i>Std.</i>	-0.144	-0.032	0.138	0.381	0.718	1.000	0.718	0.381	0.138	-0.032	-0.144
<i>HM</i>	-0.141	-0.029	0.140	0.382	0.718	1.000	0.718	0.382	0.140	-0.029	-0.141
Czech Rep.	0.006	0.170	0.352	0.645	0.728	1.000	0.728	0.645	0.352	0.170	0.006
<i>Std.</i>	-0.133	-0.015	0.157	0.399	0.728	1.000	0.728	0.399	0.157	-0.015	-0.133
Finland	-0.001	0.166	0.367	0.529	0.665	1.000	0.665	0.529	0.367	0.166	-0.001
<i>Std.</i>	-0.180	-0.094	0.054	0.294	0.665	1.000	0.665	0.294	0.054	-0.094	-0.180
Germany	-0.112	0.078	0.226	0.346	0.591	1.000	0.591	0.346	0.226	0.078	-0.112
<i>Std.</i>	-0.194	-0.144	-0.032	0.187	0.591	1.000	0.591	0.187	-0.032	-0.144	-0.194
<i>HM</i>	-0.195	-0.147	-0.035	0.185	0.590	1.000	0.590	0.185	-0.035	-0.147	-0.195
Japan	-0.126	0.011	0.274	0.497	0.727	1.000	0.727	0.497	0.274	0.011	-0.126
<i>Std.</i>	-0.118	0.003	0.177	0.418	0.738	1.000	0.738	0.418	0.177	0.003	-0.118
<i>HM</i>	-0.119	0.001	0.175	0.416	0.738	1.000	0.738	0.416	0.175	0.001	-0.119
Norway	0.188	0.160	0.235	0.403	0.501	1.000	0.501	0.403	0.235	0.160	0.188
<i>Std.</i>	-0.177	-0.160	-0.094	0.084	0.502	1.000	0.502	0.084	-0.094	-0.160	-0.177
Poland	-0.166	-0.138	-0.004	0.114	0.451	1.000	0.451	0.114	-0.004	-0.138	-0.166
<i>Std.</i>	-0.163	-0.158	-0.113	0.036	0.452	1.000	0.452	0.036	-0.113	-0.158	-0.163
Portugal	-0.177	0.010	0.150	0.207	0.468	1.000	0.468	0.207	0.150	0.010	-0.177
<i>Std.</i>	-0.167	-0.161	-0.109	0.050	0.468	1.000	0.468	0.050	-0.109	-0.161	-0.167
<i>HM</i>	-0.166	-0.160	-0.110	0.049	0.467	1.000	0.467	0.049	-0.110	-0.160	-0.166
Spain	0.065	0.079	0.281	0.491	0.605	1.000	0.605	0.491	0.281	0.079	0.065
<i>Std.</i>	-0.193	-0.138	-0.018	0.207	0.606	1.000	0.606	0.207	-0.018	-0.138	-0.193
<i>HM</i>	-0.193	-0.137	-0.018	0.207	0.605	1.000	0.605	0.207	-0.018	-0.137	-0.193
U.K.	-0.013	0.154	0.396	0.575	0.767	1.000	0.767	0.575	0.396	0.154	-0.013
<i>Std.</i>	-0.071	0.061	0.239	0.472	0.767	1.000	0.767	0.472	0.239	0.061	-0.071
<i>HM</i>	-0.072	0.060	0.238	0.472	0.768	1.000	0.768	0.472	0.238	0.060	-0.072
U.S.	-0.070	0.084	0.257	0.517	0.754	1.000	0.754	0.517	0.257	0.084	-0.070
<i>Std.</i>	-0.097	0.030	0.207	0.445	0.754	1.000	0.754	0.445	0.207	0.030	-0.097
<i>HM</i>	-0.096	0.031	0.209	0.446	0.755	1.000	0.755	0.446	0.209	0.031	-0.096

Note: Shaded rows: data; *Std.*: standard calibration; *HM*: Hagedorn-Manovskii (2008) calibration.