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

Pedro S. Amaral and Murat Tasci



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The Cyclical Behavior of Equilibrium Unemployment and Vacancies across OECD Countries

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We show that the inability of a standardly calibrated labor search-and-matching model to account for observed levels of labor market volatility extends beyond the U.S. to a set of OECD countries. That is, the volatility puzzle is ubiquitous. We argue that 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) is rather fragile and fails for some countries in our sample. It delivers counterfactually low volatility for economies where the elasticity of wages with respect to productivity is sufficiently high and where productivity persistence and/or vacancy-filling rates are sufficiently low.

JEL Classification: E24, E32, J63, J64.

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

Suggested citation: Amaral, Pedro S., and Murat Tasci, 2015. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies across OECD Countries," Federal Reserve Bank of Cleveland, Working Paper, no. 12-36R.

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*The first version of this paper was posted in December 2012. A first revision was posted in November 2013.

1 Introduction

Labor market search models as pioneered by [Diamond \(1982\)](#), [Mortensen and Pissarides \(1994\)](#), and [Pissarides \(2000\)](#), henceforth DMP, have proven very useful in understanding equilibrium properties of labor market variables as well as their long-run relationships. However, when the model is extended to accommodate aggregate fluctuations, as in [Shimer \(2005\)](#), it fails to generate the observed volatility in key variables at business-cycle frequencies by an order of magnitude. In particular, the model requires implausibly large shocks to generate substantial variation in unemployment, vacancies, and market tightness (vacancy-to-unemployment ratio). This “volatility puzzle” has spurred a considerably large literature that, by-and-large, has either modified some aspect of the model to better reconcile its predictions with the data, or modified the mapping between the data and the model.¹

The availability of vacancy data from the OECD, as well as the work of [Elsby, Hobijn, and Sahin \(2013\)](#) in estimating job-finding and separation rates for a set of OECD countries, has created an opportunity to consistently 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 across countries.

In this paper we start by putting together a data set that should be of interest to the literature as it is the first to bring together data on vacancies, unemployment, and labor productivity 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.

Using this data set, we evaluate the DMP model’s ability to replicate some key business-cycle moments observed in the data. Simulations of the model, calibrated to country-specific parameter values in a standard way, as in [Shimer \(2005\)](#), fail to generate the observed degree of volatility in labor market variables. That is, the volatility puzzle is ubiquitous.² We also estimate country-specific aggregate matching functions and show that this result is quite robust to the variation in the matching elasticity parameter.

Finally, 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

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 \(2013\)](#).

²There are a significant number of country-specific studies: [Zhang \(2008\)](#) compares the U.S. to Canada; [Gartner, Merkl, and Rothe \(2009\)](#) look at Germany; [Miyamoto \(2011\)](#) and [Esteban-Pretel, Ryo, and Ryuichi \(2011\)](#) focus on Japan; [Obstbaum \(2011\)](#) on Finland; and [Cardullo and Guerrazzi \(2013\)](#) look at Italy.

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.

The fact that this strategy fails to work for some countries in our sample prompted us to investigate what are the regions of the parameter space where the HM strategy runs into problems (as far as being a solution to the volatility puzzle), and why. We find that the strategy is rather fragile in that it is very sensitive to (reasonable) parameter variations. There are a variety of potential pathologies, including cases where the model generates too much volatility.

First, for countries that exhibit small enough persistence in their estimated productivity process, the model delivers significantly smaller volatilities in labor market variables than seen in the data. Second, this strategy will also fail to deliver enough volatility for economies that exhibit a relatively high elasticity of wages to productivity. Finally, we also show that the model's ability to generate enough volatility substantially depends on the magnitude of the steady-state vacancy-filling rate a country exhibits.

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; [Pissarides \(2009\)](#) introduces a fixed component to vacancy posting costs; [Krause and Lubik \(2006\)](#), [Nagypál \(2006\)](#), and [Tasci \(2007\)](#) explore the role of job-to-job transitions; [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 the 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

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.

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 macro-labor search business-cycle 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 substantial value-added 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 use data for two purposes: to compute the data moments against which we measure the model’s performance and to calibrate the parameters that discipline the model. With the first purpose in mind we collect unbalanced data panels at a quarterly frequency on vacancies, unemployment, employment, and real GDP for a set of 16 OECD countries.⁴ To help us calibrate the model we use job-finding rates and separation rates from [Elsby, Hobijn, and Sahin \(2013\)](#) and [Hobijn and Şahin \(2009\)](#), we use data on replacement ratios for the unemployed from the OECD, and finally we collected panel data on labor income shares from a variety of national sources and use it in computing the elasticity of wages to productivity, a crucial object in the calibration of the model

⁴Our sample of OECD countries is: Australia, Austria, Canada, Czech Republic, Finland, France, Germany, Japan, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, U.K., and U.S.

in HM. We leave a more detailed description of this second set of data to the calibration section.

The data on unemployment correspond to the total number of people unemployed according to the ILO definition. The proximate source for the data is the OECD's Main Economic Indicators (MEI) Database and are based on each country's household labor force surveys except where unavailable where we use registered unemployment (Austria, Czech Republic, France, Germany, the Netherlands, Norway and Poland). The employment data is for total civilian employment also from the OECD's MEI database except for the Netherlands which we obtained from the IMF's International Financial Statistics. The data also originate on each country's household labor force surveys except for France (establishment survey) and Norway (register-based). The real GDP data is from the OECD's Quarterly National Accounts database.

We compute output per worker, our proxy for productivity, by dividing real GDP by the number of employed people, as this is the concept of productivity that more closely resembles its model counterpart to be introduced in the next section. We compute the labor force as the sum of employment and unemployment.

The vacancy data comes from a variety of national sources detailed in the online Appendix [Amaral and Tasci \(2015\)](#). While the proximate source for most of it is the OECD's Registered Unemployment and Job Vacancies dataset (a subset of the their Short-Term Labour Situation database), we also collected data directly from national sources, namely for Canada, Japan, U.K. and U.S. Unlike what happens with unemployment, in the case of vacancies there are no harmonized reporting procedures. As a result, the vacancy data are less reliable than the rest of the data we use. They differ in terms of their immediate source (some of the data come from vacancies filed by firms at employment centers, other come from business surveys, other still, like in the case of the U.S. is a composite of job advertising indices⁵); in terms of their originating source (some is establishment level data while other is firm level data); and in terms of reference period within the quarter.⁶

Despite this disparity in sources and concepts, to the extent that the majority of vacancy collection differences manifest themselves at low frequencies, the fact that we filter out a low frequency trend should help make the numbers more comparable across countries. Throughout the paper all variables are in quarterly levels, seasonally adjusted, and are reported as log deviations from an HP-trend with smoothing parameter ($\lambda = 1,600$).

⁵Our measure of vacancies for the U.S. is a composite job advertising index computed as in [Barnichon \(2010\)](#). This allows us to have a much longer series, going back to 1955, whereas the more frequently used number from the Job Opening and Labor Turnover Survey is only available since December 2000.

⁶Please see the online appendix for a detailed description of the sources used for each of the series. We also make available a database with the raw series, the treated series, and the treatment process for each of the variables we consider.

Since our panels are unbalanced across countries, and even across variables for the same country, we compute statistics pertaining to the period for which all variables are available for each country. 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 (because our employment and unemployment samples end then). 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.

Looking at the statistical properties of the cyclical component of our sample of labor market variables, summarized in Table 1, 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. The first one is that there is substantial variation in the degree of correlation between productivity and unemployment and between productivity and vacancies as shown in the top-left panel of 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. The first observation highlights the limitations of technology shocks as the sole driving mechanism in the DMP model. In countries like Norway and Australia, labor market variables do not co-move with productivity. Spain exhibits a robust positive correlation between productivity and unemployment. This suggests other mechanisms may be 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.

A word of caution is in order regarding the need not to overinterpret the magnitude of these correlations. As Hagedorn and Manovskii (2011) show for the US case, this correlation can vary considerably depending on the employment series used in the denominator of the productivity computation. Using employment from the BLSs Current Employment Statistics (CES) they obtain correlations between unemployment and productivity in the -0.2 to -0.3 range, while using employment from the monthly Current Population Survey (CPS) they obtain magnitudes in the order of -0.6. It is not clear which series is better suited to capture the "true" cyclical properties of productivity. Here, we opted for consistency across countries and our original national sources for employment are each country's household surveys when available. So, for instance, in the U.S. case we use the employment series from the CPS.

The second observation is that there is a fairly strong positive cross-country correlation between the volatility of productivity and that of both unemployment and vacancies as shown in the two bottom panels of Figure 1. In contrast to the first observation, this 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 same can be said for fact that both

vacancies and unemployment, just like productivity, are very persistent (as seen in the top-right panel of Figure 1).

Finally, while 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 2. This raises two unrelated sources of concern. The first one has to do with the possibility that these differences in correlations could be generated by some heterogeneity in vacancy data quality across countries; the second one is related to the fact that 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. The fact that this correlation is smaller for all other countries could therefore pose some difficulties for the model in the sense that the model would overpredict this correlation for other countries.

With regard to the first concern, while we cannot guarantee for sure that differences in vacancy data quality are not behind these differences in correlation we would like to note that countries that are usually regarded by the literature as having similar institutional features in their labor markets, line-up fairly close to each other in this metric. We have the U.S. and Canada with the highest correlations between unemployment and vacancies, followed by the Scandinavian countries and the U.K., and ending with countries like Portugal, Spain, and France with the smallest correlations. This may be spurious or not, but it does suggest that institutional features may play an important role in introducing frictions that drive such disparities in correlations between labor market variables. Regarding the second concern, it turns out the model does find it hard to replicate these data, 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.

3 Model

We use a stochastic, discrete time version of the DMP model. 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 , the opportunity cost of employment. 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 $m_t = Au_t^\alpha v_t^{1-\alpha}$. 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

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

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, substituting 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 discussed in the introduction, the model's ability to replicate the degree of volatility observed in US 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 call this the *standard calibration*.

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. To discipline the workers' bargaining power, β , we appeal to the Hosios condition, which guarantees match efficiency and in the context of the model means setting $\beta_i = \alpha_i$, the elasticity of the matching function with respect to unemployment.

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.

For the country specific separation and job-finding rates, s_i and f_i , we used the estimates of [Elsby, Hobijn, and Sahin \(2013\)](#) where available, and alternatively those in [Hobijn and Sahin \(2009\)](#). Estimates for Australia, Canada, Germany, Japan, Norway, Portugal, Spain, U.K., and U.S. are from the former, where we converted hazard rates, λ_f into probabilities $f = 1 - e^{-\lambda_f}$. For the remaining countries the estimates are taken from the latter.

The assumption of a constant and exogenous separation rate has been common in the literature, going back to [Shimer \(2005\)](#). In order to bring cross-country data scrutiny to bear on the relative merits of models that have gathered attention in the volatility puzzle literature, we opted for keeping

this standard assumption. In addition, the lack of high-frequency data on separations for all of the countries (or even a majority of them) in our sample, restricts any discipline on the extension of the model with endogenous separations.⁷

Although there are a wealth of studies estimating matching function elasticities 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.⁸ Ideally, we would like to have high frequency data on job-finding rates, unemployment and vacancies to estimate α_i as in [Shimer \(2005\)](#). In our data set, we lack the former. In the absence of other assumptions, this restricts what we can do.

We use instead annual estimates of the monthly job-finding rates from [Elsby, Hobijn, and Sahin \(2013\)](#). They rely on aggregate data on unemployment duration to estimate worker flow hazard rates for a set of OECD countries, between 1960 and 2010, depending on the specific case. Due to the absence of data, we cannot carry out this exercise for Austria, Czech Republic, Finland, the Netherlands and Poland.⁹ For the countries with data, we simply replicate [Shimer \(2005\)](#) using these annual estimates of the monthly job finding rates to estimate the matching function parameter, α_i , with OLS. In the end, this method provides estimates for 9 countries in our sample in a relatively compact range between 0.58 for Australia and 0.8 for France. Of course, to the extent that yearly data misrepresent the underlying labor market dynamism at a higher frequency in each country, we may be obtaining biased estimates of the true elasticity parameter.

As a robustness check, in addition to this benchmark, and because we recognize that cross-country differences in matching function elasticities may potentially be very important in driving the cyclical behavior of the job-finding rate, we also estimated country-specific α_i according to two other methods. We found that our conclusions are not affected by the alternative approaches.¹⁰

The opportunity cost of employment in this model, z_i , is mapped to the replacement rates unemployed workers receive. The data on replacement rates are from the OECD and capture average replacement rates net of income taxes over a period of 5 years of unemployment for an average of four family types (single no children; one-earner married couple no children; lone parent with two children aged four and six; and one earner married couple with 2 children aged four and

⁷[Elsby, Hobijn, and Sahin \(2013\)](#) report that while the contribution of variations in unemployment inflow rates to variations in the unemployment rate is relatively small for Anglo-Saxon economies, it is much larger, and roughly as important as the contribution of the variation in outflow rates, for Continental European economies. These findings imply that there are potential biases stemming from the constant rate assumption, at least for some countries where the model is precluding one channel (inflow rate variations) that has been shown to be important in the data, from contributing to unemployment rate fluctuations.

⁸A very comprehensive survey of where this literature stood at the start of the decade can be found in [Petrongolo and Pissarides \(2001\)](#).

⁹For these countries we use the median estimate found for the remaining countries.

¹⁰The detailed results for the two alternative estimation methods are presented in the appendix.

six) and two earnings levels (67 percent and 100 percent of average wages). It is assumed that the families qualify for cash housing assistance (housing costs assumed to be 20 percent of average wages) and social assistance, but not childcare benefits. We averaged these replacement rates from 2001 to 2011. Even though the OECD goes to great lengths in netting out taxes, accounting for different household situations and for the availability of housing and social assistance, comparisons across countries still suffer from the shortcomings laid out in [Whiteford \(1995\)](#).¹¹ One concern regarding the use of statutory levels has to do with actual take-up rates on unemployment benefits.¹² If the take-up rate is excessively low, then statutory levels overestimate effective replacement rates. Since we did not have data on take-up rates for the countries in our sample we proceeded with the use of the statutory averages.¹³

Recent work by [Chodorow-Reich and Karabarbounis \(2013\)](#) challenges the validity of a constant opportunity cost of employment for the U.S. and instead estimates it to be very procyclical and volatile. This finding has important implications for volatility in models that rely on a constant z_i to generate amplification (like the HM model we discuss below): if z_i moves proportionately to productivity, the incentives for firms to post vacancies do not change by much and labor market volatility is muted. Once again, we opted for keeping z_i constant in this paper in order to provide a direct comparison to the literature, including [Shimer \(2005\)](#). Moreover, replicating [Chodorow-Reich and Karabarbounis \(2013\)](#) is beyond the scope of this paper, if at all feasible.¹⁴

The parameters governing productivity’s law of motion, ρ_i and σ_{ε_i} , are set such that the first-order auto-correlation and the standard deviation of the log-deviations of productivity from the HP-trend in the model and the data are the same for each country. We approximate the AR(1) process described above with a discrete state-space Markov Chain as in [Tauchen \(1986\)](#). Detrending the simulated productivity data with the HP-filter removes a highly correlated (low frequency) trend. As a result, we are unable to match the first-order auto-correlation we measure in the data for the two countries in our sample that exhibit the highest ones: Czech Republic (0.885) and France (0.868). We dropped these countries from our simulated model sample, reducing the sample size to 14 countries.¹⁵

¹¹The original data was downloaded from <http://www.oecd.org/els/benefitsandwagesstatistics.htm>

¹²[Chodorow-Reich and Karabarbounis \(2013\)](#), for instance, find that U.S. take-up rates for UI benefits are rather low: on average, only about 40 percent of those unemployed actually receive UI.

¹³[Hernanz, Malherbet, and Pellizzari \(2004\)](#) survey some evidence on take-up rates for UI for Canada and the U.K. (in addition to the U.S.) and find somewhat higher rates, on the order of 60 to 80 percent.

¹⁴We discuss the potential implications of [Chodorow-Reich and Karabarbounis \(2013\)](#) in the appendix, in the context of the OECD countries in our sample with the limited data we have.

¹⁵Note, in particular, that this is not a consequence of the use of the [Tauchen \(1986\)](#) method, that has been shown to be more inaccurate than others in approximating highly persistent AR(1) processes. For instance, [Kopecky and Suen \(2010\)](#) shows [Rouwenhorst \(1995\)](#) to be a more accurate method for highly persistent AR(1) processes. We also experimented with this method but got similar results. It is instead a consequence of the use of the HP-filter and the AR(1) assumption. Instead of postulating a different productivity process and distancing ourselves from the

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.¹⁶ 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 2.

3.2 Results

Under the standard calibration we have just detailed, and for all countries without exception, the model is unable to replicate the volatility in labor market variables seen in the data by an order of magnitude. This is precisely what the charts on the left-hand column of Figure 3 illustrate for unemployment vacancies and market tightness, respectively, 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.¹⁷

Even though the overall performance of the model in this dimension is very poor, it is still very heterogeneous across countries. Take the volatility of unemployment (in the top left panel of Figure 3). Compared to how it performs for the U.S., the model performs 4 times better for Japan, but 6 times worse for Poland.

Mortensen and Nagypál (2007) argue that because productivity shocks are not the only driving force behind movements in labor market variables, instead of comparing relative volatilities of variable x , $\frac{\sigma_x}{\sigma_p}$, between data and model, one should instead compare the relative volatility in the model to the data moment $\text{corr}(x, p) \frac{\sigma_x}{\sigma_p}$, the coefficient obtained from regressing $(\log) x$ on $(\log) p$. This is what we do in the three plots on the right-hand column of Figure 3. To be clear, we are comparing $\frac{\sigma_x}{\sigma_p}$ in the model to $\text{corr}(x, p) \frac{\sigma_x}{\sigma_p}$ in the data.

To the extent that correlations are substantially lower than unity (as the top-left panel of Figure 1 shows), the model performance will be much improved under this metric. A word of caution is in order though. Take a country like Norway, whose labor market, at least from the point of view of unemployment and vacancies, seems very much impervious to the business cycle, with absolute correlations very close to zero. It is precisely in these countries where one would argue a model like this one, driven by productivity fluctuations, has very little to say, that the model's performance under this metric will look the best, everything else being the same. So much so as to overpredict

literature along this margin, we opted for dropping these countries from our simulated model sample, thus reducing it to 14 countries.

¹⁶The online appendix contains tables with business cycle statistics for all variables when adjusted by the labor force.

¹⁷In the online appendix we present the detailed statistics for each country.

volatility.¹⁸

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, the top-left panel of Figure 4 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 the top-right panel of Figure 4. In this instance, the model does slightly 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 the bottom-left panel of Figure 4 shows. In this case, by looking only at U.S. data, one would actually get a fair sense of how well the model does at a broader cross-country level.¹⁹

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 the bottom-right panel of Figure 4 shows, just like in Shimer (2005), the model does a very good 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.

4 Targeting small profits and the wage elasticity

Another way the cross-sectional data we have compiled 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.

¹⁸For some countries/labor market variable combinations, correlations in the data are the opposite sign of what the model predicts, so we opted for not including these countries in the right-hand column of Figure 3.

¹⁹The 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.

HM thinks 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.²⁰

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 2. To 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. As we show in Section 4.2, where we discuss the appropriateness of this numerical value and perform some sensitivity analysis, this is not an innocuous assumption. What should be clear is 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

²⁰For the exact form of c_k and c_w , please see HM.

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 elasticity of wages with respect to productivity we start by computing a quarterly series for the labor share of income in each country. We then multiply this share by labor productivity, obtaining wages per worker. We HP filter this series and compute its elasticity with respect to our measure of (HP filtered) productivity. In computing the labor share of income we used OECD data, as well as a variety of national sources, all detailed in the appendix.

Our preferred measure of the labor share of income apportions ambiguous income components to labor in the same proportion as unambiguous income components. More precisely, we take employee compensation and divide it by GDP net of mixed income (proprietors' income) and indirect taxes (less subsidies). We were able to do this for nine of the 16 countries in our sample. Unfortunately, we could not find quarterly data on mixed income for some countries, as it is either lumped with corporate profits or not available (in Austria, France, the Netherlands, and Spain). For these countries our measure of the labor income share is employee compensation divided by GDP net of indirect taxes (less subsidies). Finally, there were countries for which we could not find a quarterly series for either mixed income or indirect taxes and subsidies (Japan, Norway, and Poland), so for these countries our computed labor income share is employee compensation divided by GDP.²¹

The measured elasticity is positive and below one for all countries except for Norway where it is negative. While in Norway this elasticity was by no means constant over time, it was negative for all the sample horizon we have data for. Recall from Section 2 that Norwegian labor market variables appear to bear no cyclical relation to productivity at business-cycle frequencies. When we couple that with a negative wage elasticity we are left with facts that are very hard to square with the DMP paradigm.

For the remaining countries, wage elasticities vary between very inelastic for Canada (0.12) and unitary for Spain (0.99). The model cannot replicate negative wage elasticities and while it can replicate an elasticity of 0.99, it cannot do so while matching the two other targets for Spain at the same time. For that reason we leave Norway and Spain out of our sample of countries for the HM specification. The calibration is shown in Table 3 and it attains all targets exactly.

4.1 Results: volatility

As the left-hand column of Figure 5 shows, this calibration strategy does a much better job of accounting for the volatility of labor market variables than the standard strategy used in the

²¹We opted for a macro-estimate of the wage elasticity as there are not, to the best of our knowledge, cross-country surveys of micro-estimates. In Section 4.2 we review some existing evidence on wage elasticities.

previous section. After all, except for Poland, the volatility implied by the model is no longer off by an order of magnitude from the data, and there is a mild positive correlation between the model’s predictions for the volatility of vacancies and tightness and their data counterparts (0.44 and 0.35, respectively).

Unfortunately, this is where the good news ends. Under this calibration, the model runs into several problems. First, it continues to underpredict (albeit not by the same magnitudes) the volatility of labor market variables for some countries, like Poland, Germany, the U.S. and Portugal. Second, it can also be prone to overprediction, as in the case of Japan and the U.K., or that of Dutch vacancies.²² While one can argue that Japan is somewhat of a data outlier since it exhibits the smallest volatilities of all the countries in our sample, the same cannot be said of the U.K., or even of Dutch vacancies.²³ Third, this idea that the model can be "all over the place" is corroborated by the fact that the correlation between the volatility of unemployment in the model and in the data is essentially zero.

Under the metric [Mortensen and Nagypál \(2007\)](#) propose, shown on the right-hand column of [Figure 5](#), the model substantially overpredicts the volatility in the data for more than half the countries in our sample. This is something to be expected for countries with low correlation between productivity and labor market variables, but also a result of the calibration strategy. By matching the elasticity of wages we are essentially forcing the model to account for the cyclicalities of wages with productivity shocks alone. What the right-hand column of the figure shows is that for most countries, from the perspective of the cyclicalities of the other labor market variables, this exaggerates the effects of productivity shocks.

Going back to the more standard measures of volatility, on the left-hand column of [Figure 5](#), note that volatility in our simulated U.S. economy is substantially smaller (although not by an order of magnitude) than what we see in the data and what HM obtain in their calibration. [Table 3](#) shows that our calibrated parameters for the U.S. feature both a lower replacement rate, $z = 0.87$ (0.955 in HM), as well as a higher worker’s bargaining power, $\beta = 0.208$ (0.052 in HM).

The explanation lies in the fact that our estimate of the wage elasticity, 0.72, is larger than the one HM use (0.45) and that we are setting ρ , the parameter governing the persistence of the productivity process, to match a first-order autocorrelation of 0.72 (the same as the wage elasticity but by sheer coincidence), while HM are matching a higher persistence: 0.765. In this section we will explain where these differences in data come from and in the next section we explain how

²²The country-by-country business-cycle statistics and their model counterparts can be found in the online appendix.

²³While the model seems to severely underpredict German unemployment volatility, this finding is not robust to considering post-reunification data only. As the online appendix shows, if one looks at data from 1989 on only, the relative volatility of unemployment declines by more than half.

seemingly small differences in data give rise to such different outcomes.

The differences in data owe to the use of different sources for the productivity data: HM use output in the non-farm business sector divided by employment from the CES, while we use total GDP divided by total employment from the CPS for cross-country comparison purposes.²⁴ In a different paper, [Hagedorn and Manovskii \(2011\)](#), use CPS data and obtain estimates that are much closer to ours at 0.64, and 0.981 for the wage elasticity and the persistence of the productivity process, respectively. The fact that we obtain such differences for the U.S. for slightly different parameter values, as well as the large cross-country variability in predicted volatilities we obtain (a factor of ten in terms of unemployment between Japan and Poland) both serve to illustrate just how sensitive the model is, under this calibration strategy. A point we explore in detail below.

4.2 Results: how robust is the HM calibration strategy?

We are interested in understanding under what circumstances will the HM calibration strategy fail to deliver data-like volatility, like in the case of Poland or the UK. For this purpose we conduct a series of exercises that consist of generating a set of simulated economies highlighting different regions of the parameter space. For each exercise, the simulated economies only differ in two parameters at a time while the remaining parameters are set to the (cross-country) sample medians.²⁵ For each economy (β, z, l) are recalibrated to hit the parameter targets.

We find that model volatility is very sensitive to the wage elasticity, to the persistence of the productivity process and to the vacancy-filling rate; and to a less, but still important extent, to the job-finding rate.

4.2.1 The role of persistence in productivity

In the first exercise the economies differ only in their steady-state job-finding rates, and in their unconditional first-order auto-correlation of the productivity process.²⁶ The remaining parameters: the separation rate, the vacancy-filling rate, wage elasticity, and the productivity shock process' unconditional variance, are set to the (cross-country) sample medians.

The top two panels (A and B) in [Figure 6](#) report the resulting relative volatility in labor market variables for each of these economies. In an economy with low persistence, like Poland, productivity shocks are not amplified at all, regardless of job finding rates. They are, in fact, dampened just like in the standard calibration. In contrast, an economy with a very persistent shock process, like the U.K. in our sample, has no trouble generating data-like volatility – the median value for the relative

²⁴See [Section 2](#).

²⁵The sample medians are $\bar{\varepsilon}_{w,p} = 0.3766$, $\bar{f} = 0.1339$, $q = 0.71$, $\bar{s} = 0.01$, $\bar{\sigma} = 0.0038$, and $\bar{\rho} = 0.9746$

²⁶We vary both ρ and σ to generate different autocorrelations while keeping the unconditional variance constant.

standard deviation of unemployment in our data sample is roughly 10, while for vacancies it is 16. For processes that approach a unit root, labor market variables (vacancies, in particular) become extremely volatile and the model runs into the opposite problem: overprediction.²⁷ Variations in the job-finding rate matter less for volatility. As the steady-state job-finding rate falls, the volatility of unemployment drops but interestingly, this results in higher volatility for vacancies.

Together, variations in these two factors can account for a factor of 35 in the relative standard deviation of unemployment, showing just how sensitive the predicted volatility is, under this calibration, particularly to persistence.²⁸ Note that we are varying our parameter targets in a plausible way, from the minima to the maxima observed in our data sample.

These top two charts raise two important questions. The first is why do economies that exhibit less persistence in their productivity processes generate smaller volatility in labor market variables? The second is 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 changes in 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.²⁹

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, this means expected profits to vacancy creation will be smaller, therefore 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 this calibration, the former effect dominates, and this is more pronounced the smaller the job-finding rate is.

4.2.2 The role of the wage elasticity

The second experiment elucidates why, despite having a relatively high productivity persistence, the labor market volatility predicted by the model for the U.S. is much lower than in HM and in

²⁷The values indexing the autocorrelation axis correspond to the first-order autocorrelation of the HP-filtered labor productivity process, the U.S. for example is at 0.72 in this scale (see Table 1). The calibrated autocorrelation parameters ρ that corresponds to this appear on Table 3, and we can see that countries like the U.K. or the Netherlands are very close to a unit root.

²⁸At the median job-finding rate, varying persistence can generate up to a factor of 14 in unemployment volatility, while varying job-finding rates at the median persistence generates a factor of 2.

²⁹This mechanism is unrelated to others, also related to properties of the productivity process, that have been identified in the literature as possibly accounting for the volatility puzzle, like the endogeneity of productivity (Barnichon (2014)).

the data. In this experiment we vary the wage elasticity and the persistence of the productivity process. Again, all other parameters are set to the sample medians.

The results are in panels C and D of figure 6 and show just how sensitive the volatility of unemployment and vacancies are to elasticity, when persistency is relatively high, and to persistence when wage elasticity is relatively low. Going back to the U.S. case, recall that we are calibrating ρ to match a first-order auto-correlation of 0.72, while HM are matching 0.765, also, our measured wage elasticity at 0.72 is much larger than the one in HM (0.45), for the reasons we covered in Section 4.1. Looking at panel C in figure 6 these two changes by themselves imply a drop in the relative standard deviation of unemployment from 12 (very close to what we find in the data for the U.S.) to roughly 3.³⁰

With this degree of sensitivity it is thus perfectly possible to have a country like the U.K. where the model overpredicts the volatility data. First, in terms of the relative volatility of unemployment, the value for the U.K. at 7 is already below the median; second, the fact that it is the country with the highest degree of productivity persistence in our sample is more than enough to counter the effects of a moderately high elasticity. On the other hand, by looking at panels C and D it is very clear that there is a sweet spot in the parameter space where the model performs well in terms of volatility under this calibration, and that for elasticities above 0.7 and/or persistence below 0.6 this calibration will not be successful.

We already detailed the role of persistence in the context of the model; what is then the role of wage elasticity and why does it matter? Is it not the case that the model can generate data-like volatility despite having the bargaining parameter β calibrated to a high elasticity of wages as long as the replacement rate z is high enough, as HM argue (Section II.B)? Yes it can, but not while matching reasonable values of market tightness. In their experiment, they set the replacement rate to $z = 0.95$, then pick β to match a wage elasticity of $\varepsilon_{w,p} = 0.964$, and obtain a high volatility of market tightness, ($std(\theta) = 0.3$). But this is not a calibrated experiment since market tightness was not targeted. It is simply an experiment that serves the purpose of illustrating that the model can deliver data-like volatilities while matching high wage elasticities. In fact, to generate such high elasticities under replacement rates close to unity, one needs to push up β considerably, resulting in counterfactually low market tightness. In such an economy, market tightness is volatile because vacancies are extremely low, while unemployment by itself continues to exhibit volatility of the order of the one obtained under the standard calibration, with standard deviation below that of productivity.

Matching a higher elasticity, for a given replacement rate z , requires a higher bargaining weight

³⁰These are not the exact values for the U.S. as the other parameters are set to median sample values, not U.S. values.

β , but this lowers the equilibrium market tightness. To continue to match the same market tightness z must fall. As long as wages are only moderately procyclical the calibration strategy works because replacement rates are close to steady-state productivity and profits are small. But for countries that exhibit a wage elasticity closer to unit, the strategy (as means to solve the volatility puzzle) is doomed to fail. Values for the wage elasticity of 0.8 and above are entirely reasonable. As mentioned above, we estimate that the wage elasticity in Spain was 0.99 for the sample period we use. While this is the highest value we obtain, note that for sample reasons, we are using macro-estimates of the wage elasticity, and the only factor we are controlling for are long term trends which are removed by the HP-filter. In particular, by using the entire wage bill we are confounding the wages of stayers with those of new hires. [Pissarides \(2009\)](#) argues that the relevant wages are those of new hires and presents survey evidence from micro-studies that finds wage elasticities that are close to unitary, or even above that, for new hires.

4.2.3 The role of the vacancy-filling rate

Finally, in the third experiment we vary the vacancy-filling rate and the wage elasticity, again while keeping all other parameters constant at their sample median values. While we can actually use our sample to guide us in setting the boundaries for the wage elasticity as we did in the experiment above, that is not possible for the vacancy-filling rate.

In all the experiments so far, we have set a common monthly vacancy-filling rate for all countries at $q = 0.71$ following HM's value for the U.S. They, in turn, cite [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 complicated. 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.³¹ To get around this and other problems, in recent work, [Davis, Faberman, and Haltiwanger \(2013\)](#) develop a dynamic daily hiring 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

³¹See [Davis, Faberman, and Haltiwanger \(2013\)](#).

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. If there is a constant hazard rate over the quarter, the corresponding monthly value is $q = 1 - (1 - q_Q)^{1/3} \simeq 0.34$. Consequently in this experiment we let the monthly vacancy-filling rate vary between 0.71 and 0.34.

Economies with a low steady-state vacancy-filling rate have a harder time generating volatility in labor market variables, everything else being the same. As q decreases, so does the steady-state value of a vacancy, but free-entry means that in equilibrium, this has to be zero, implying that the steady-state value of a job increases. In turn, this means that steady-state wages are lower, and profits higher, which implies that, around steady-state, percentage changes in profits in response to changes in productivity are smaller, and so are incentives to post vacancies, reducing volatility. In quantitative terms, decreasing the monthly vacancy-filling rate reduces amplification by a factor of 3 both for unemployment and vacancies as the bottom two panels of [Figure 6](#) make clear. In fact, for monthly vacancy-filling rates below 0.6, regardless of the wage elasticity level, the volatility levels of both unemployment and vacancies are at least 50 percent below their median levels in the sample, so a relatively high vacancy-filling rate is indeed crucial for this strategy to be able to match observed labor market volatility.

4.3 Results: cross-country performance

Along dimensions other than labor market volatility, the HM calibration is less successful in improving over the standard calibration. [Figure 7](#) updates [Figure 4](#) with the country outcomes from the HM calibration. In terms of unemployment persistence and correlation with productivity (the two panels in the left column), the two calibrations are essentially identical, but when it comes to the behavior of vacancies, matters worsen considerably. ³²

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 the northeast panel in [Figure 7](#) shows. ³³ 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

³²The HM calibration improves modestly over the standard one when it comes to reducing the correlation between productivity and vacancies, but that is one dimension where the literature has already made some headway (see [Fujita and Ramey \(2007\)](#)).

³³The black dots represent the standard calibration while the red dots stand for the HM calibration.

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 the southeast panel of Figure 7. 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 and future work

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 limited set of countries. 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 in the context of a DMP-type model. 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. In some of the countries in our sample, labor market variables are largely acyclical, and in a few cases, of the opposite sign of what the model predicts. This suggests a need to explore alternative sources of shocks and frictions, while being mindful of what the standard model gets right.

We 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 the entire set of OECD countries we consider, establishing the pervasiveness of the volatility puzzle. This result holds even when controlling for differences in the matching process across countries by estimating country-specific matching functions. We believe that this approach can inform us about potential solutions to the puzzle. To illustrate the usefulness of this cross-country scrutiny, we modify the standard model as proposed by [Hagedorn and Manovskii \(2008\)](#) and show that while the model’s ability to match the observed labor market volatility improves for most countries, this improvement is not fully generalizable. This strategy turns out to be fragile under a variety of circumstances: when countries exhibit a sufficiently high elasticity of wages to productivity; when their productivity processes are not persistent enough; or when the steady-state vacancy-filling rates are not high enough. The regions of the parameter space for which these conditions are met are not remote and there are countries in our sample for

which they occur.

The extension proposed by [Hagedorn and Manovskii \(2008\)](#) 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 particular there are a set of contributions that propose wage rigidity as a potential resolution to the volatility puzzle. [Hall and Milgrom \(2008\)](#) replace the Nash bargaining assumption that results in wage flexibility with *credible* bargaining, where wages are the outcome of an alternating-offer bargaining game. Under Nash bargaining, wages are tightly connected to the opportunity cost of employment z , the outside option. Instead, under credible bargaining, this connection is lost as soon as the negotiation process starts and what matters is the parties' relative cost of delaying negotiations, the disagreement payoff. This results in stickier wages, and more volatile unemployment because in times of low productivity, the wage falls only partly in response; the burden of the rest of the decline falls on employers. Calibrating this model in a cross-country context is tricky. The model employs two additional parameters – one regulating the delay cost for the firm, and another the probability that the negotiations break down before a bargain is struck – for which there is no direct empirical evidence. Moreover these are off-equilibrium path values (but affect equilibrium outcomes), as the equilibrium has the worker accepting the first offer the employer makes. The authors choose to target the mean unemployment rate and the standard deviation of unemployment, but this is a course of action that we are not comfortable with in the context of what we aim to do. One of the metrics we are using to argue over the merits of alternative solutions is precisely how much (relative) unemployment volatility is accounted for by the model. In future work we would like to come up with an alternative calibration strategy to put this proposal through the cross-country scrutiny. We conjecture that as far as calibrating the delay cost for employers, firm liquidity could be an important factor, as more liquid, less constrained, firms would be able to better withstand delays.

There are another set of proposals that rely on changes to the costs firms incur in when they post vacancies and hire. In this set, [Pissarides \(2009\)](#) proposes a setting with fixed costs that are incurred after the two parties meet, but are sunk before the wage is bargained. As the hiring costs are shifted from the proportional to the fixed component, the volatility of job creation increases, and the same would happen for the countries in our sample. The challenge is, once again, disciplining the relative importance of such fixed costs in the absence of direct evidence for the OECD countries in our sample. We conjecture that these costs could be higher in countries where hiring takes place along more formal and bureaucratic channels. In future work, we would like to explore whether some of these fixed costs could be interpreted as institutional features that could potentially be measured for OECD countries.

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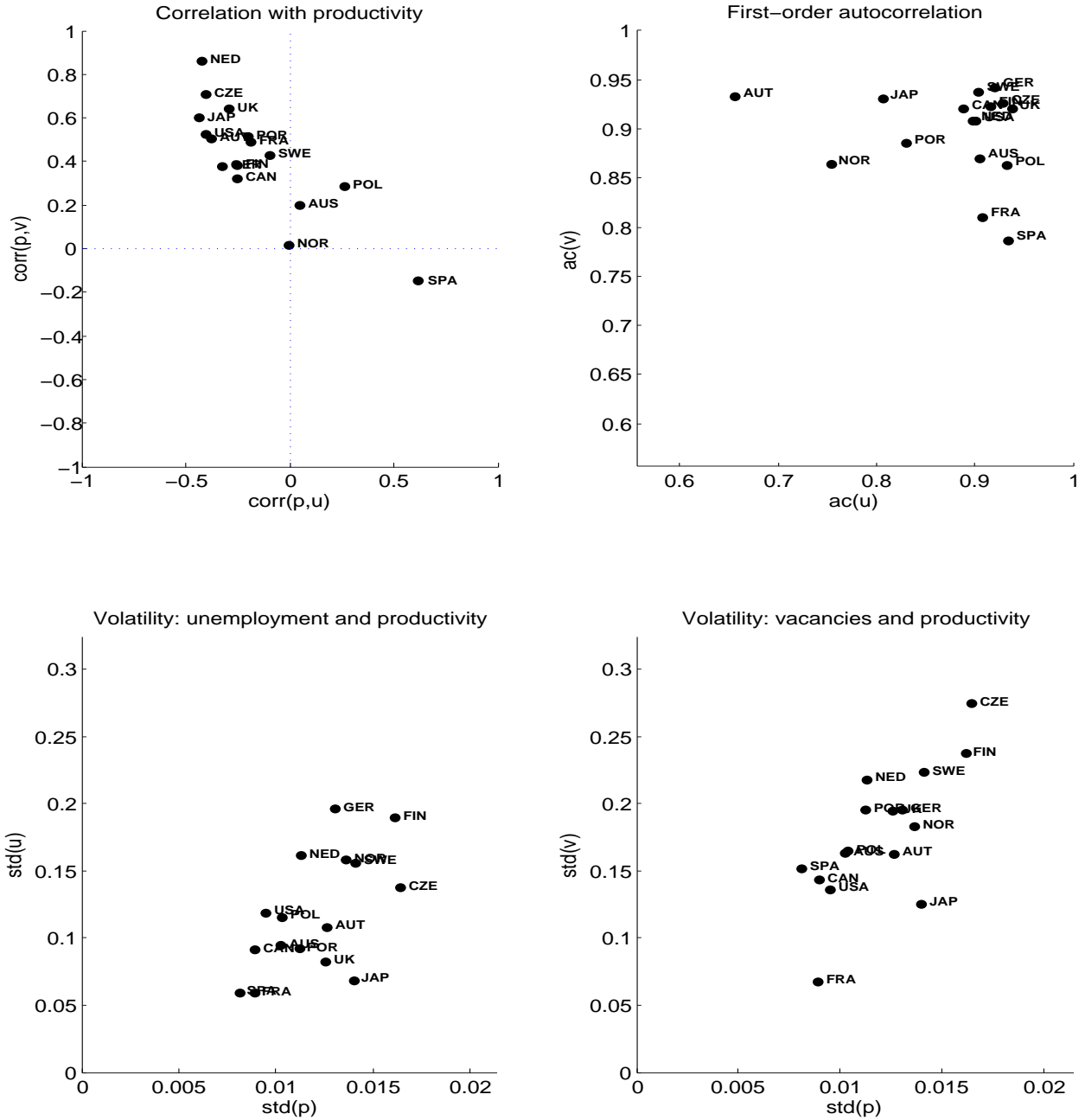
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Figure 1: Labor market moments



Note: All variables are quarterly, seasonally adjusted, and reported as log deviations from an HP trend with smoothing parameter $\lambda = 1600$.

Figure 2: Vacancies-unemployment correlation

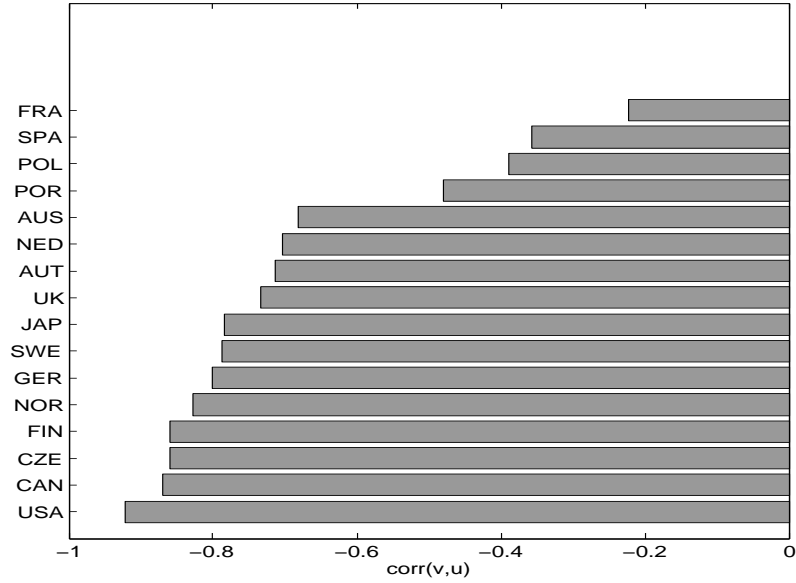


Table 1: Summary statistics

Countries	Productivity		Unemployment		Vacancies		V-U ratio	
	Auto corr.	Std. dev.	Auto corr.	Std. dev.	Auto corr.	Std. dev.	Auto corr.	Std. dev.
Australia	0.723	0.010	0.906	0.094	0.870	0.163	0.903	0.237
Austria	0.559	0.013	0.656	0.108	0.932	0.162	0.884	0.251
Canada	0.710	0.009	0.889	0.091	0.920	0.143	0.921	0.227
Czech Rep.	0.885	0.016	0.929	0.137	0.926	0.275	0.931	0.399
Finland	0.632	0.016	0.916	0.189	0.923	0.237	0.934	0.411
France	0.868	0.009	0.908	0.059	0.810	0.067	0.846	0.099
Germany	0.634	0.013	0.921	0.196	0.942	0.195	0.938	0.371
Japan	0.715	0.014	0.806	0.068	0.930	0.125	0.912	0.184
Netherlands	0.767	0.011	0.898	0.161	0.908	0.218	0.917	0.351
Norway	0.560	0.014	0.754	0.158	0.863	0.183	0.873	0.326
Poland	0.449	0.010	0.933	0.116	0.862	0.164	0.912	0.235
Portugal	0.598	0.011	0.831	0.092	0.885	0.195	0.894	0.252
Spain	0.672	0.008	0.935	0.059	0.786	0.152	0.832	0.182
Sweden	0.668	0.014	0.904	0.156	0.938	0.223	0.938	0.359
U.K.	0.770	0.013	0.938	0.082	0.920	0.195	0.929	0.261
U.S.	0.720	0.009	0.901	0.119	0.908	0.136	0.911	0.250

Note: All variables are quarterly, seasonally adjusted, and reported as log deviations from an HP trend with smoothing parameter $\lambda = 1600$.

Table 2: **Parameters: Standard calibration**

Countries	α	z	f_m	s_m	c	ρ	σ
Australia	0.5785	0.5560	0.2039	0.0169	0.3150	0.9833	0.0027
Austria	0.6932*	0.6442	0.1561	0.0080	0.1529	0.9541	0.0048
Canada	0.7433	0.5078	0.2297	0.0237	0.1669	0.9810	0.0025
Finland	0.6932*	0.7228	0.1336	0.0138	0.1185	0.9676	0.0053
Germany	0.7736	0.6561	0.0582	0.0050	0.0936	0.9680	0.0043
Japan	0.6932	0.7165	0.1722	0.0060	0.1222	0.9819	0.0038
Netherlands	0.6932*	0.7138	0.0468	0.0099	0.1146	0.9912	0.0026
Norway	0.7334	0.7337	0.3195	0.0159	0.0956	0.9544	0.0052
Poland	0.6932*	0.5489	0.0720	0.0099	0.1870	0.9308	0.0049
Portugal	0.6102	0.5971	0.0611	0.0040	0.2359	0.9615	0.0040
Spain	0.6875	0.4820	0.0611	0.0109	0.2179	0.9746	0.0025
Sweden	0.7374	0.7015	0.2532	0.0119	0.1045	0.9739	0.0043
U.K.	0.6919	0.6096	0.1298	0.0100	0.1677	0.9919	0.0028
U.S.	0.6427	0.3044	0.4316	0.0354	0.3828	0.9828	0.0025

Note: A * indicates data was not available for these countries. As an alternative we used the median from the remaining countries.

Table 3: **Parameters: HM calibration**

Country	Parameters							Targets		
	z	β	l	ρ	σ	c_k	c_w	f	θ	$\varepsilon_{w,p}$
Australia	0.9528	0.1432	0.3040	0.9833	0.0027	0.4815	0.0874	0.2039	0.2871	0.5124
Austria	0.9705	0.1260	0.2867	0.9540	0.0048	0.4910	0.0889	0.1561	0.2199	0.2783
Canada	0.9733	0.0209	0.3136	0.9811	0.0025	0.4743	0.0862	0.2297	0.3235	0.1158
Finland	0.9708	0.1095	0.2793	0.9677	0.0053	0.4847	0.0832	0.1336	0.1882	0.2724
Germany	0.9791	0.2015	0.2440	0.9679	0.0043	0.4944	0.0825	0.0582	0.0820	0.3343
Japan	0.9768	0.0940	0.2957	0.9821	0.0038	0.4933	0.0912	0.1722	0.2426	0.3766
Netherlands	0.9897	0.1488	0.2419	0.9912	0.0026	0.4889	0.0727	0.0468	0.0659	0.3252
Poland	0.9466	0.3791	0.2509	0.9307	0.0049	0.4889	0.0786	0.0720	0.1014	0.4704
Portugal	0.9732	0.2665	0.2452	0.9615	0.0040	0.4955	0.0844	0.0611	0.0860	0.4004
Sweden	0.9734	0.0592	0.3212	0.9739	0.0043	0.4868	0.0931	0.2532	0.3567	0.2643
U.K.	0.9652	0.1727	0.2825	0.9919	0.0028	0.4889	0.0855	0.1298	0.1828	0.6106
U.S.	0.8696	0.2080	0.3767	0.9827	0.0025	0.4627	0.0973	0.4316	0.6079	0.7207

Figure 3: Volatility: Standard calibration

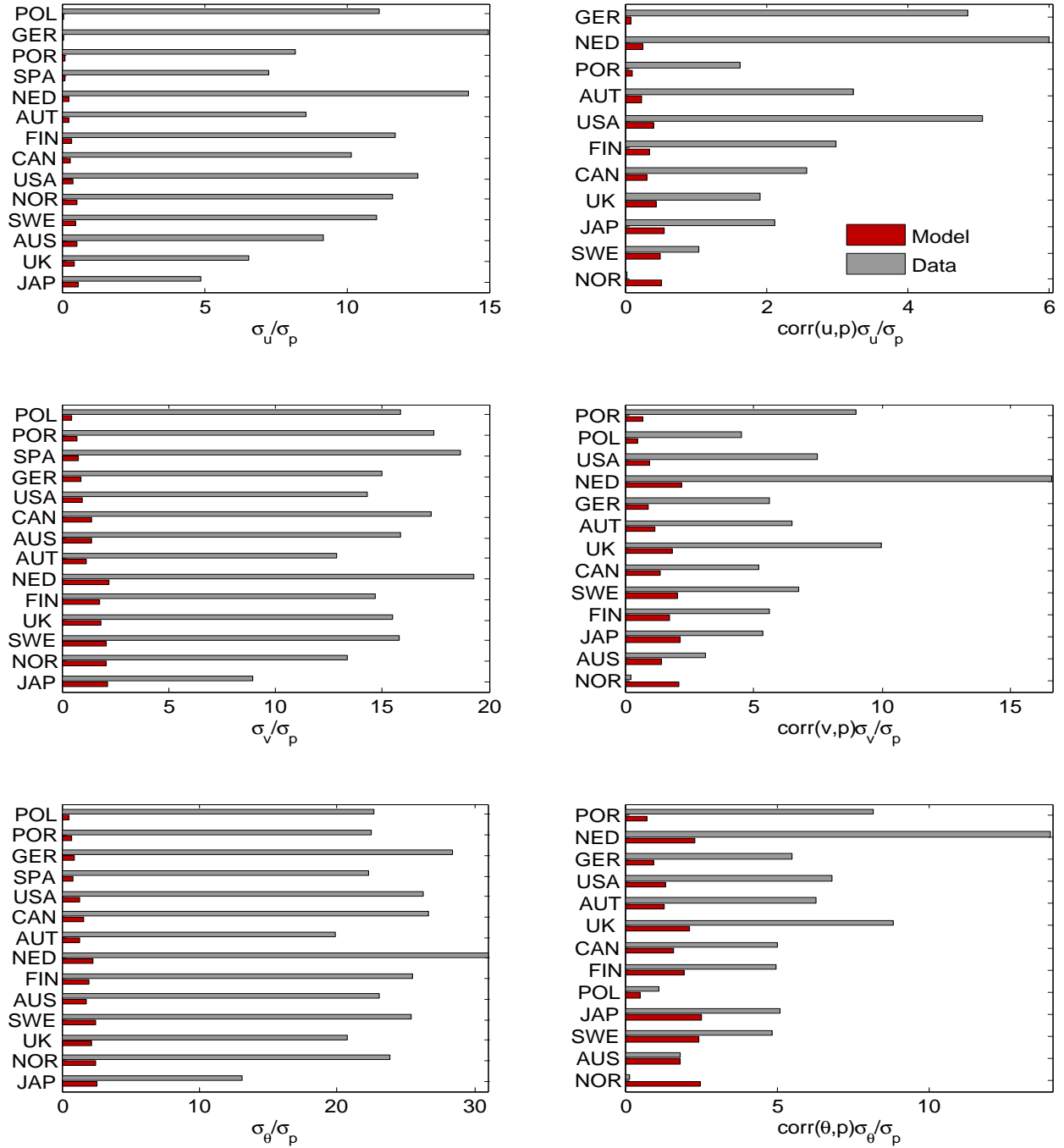


Figure 4: Labor market moments: standard calibration vs. data

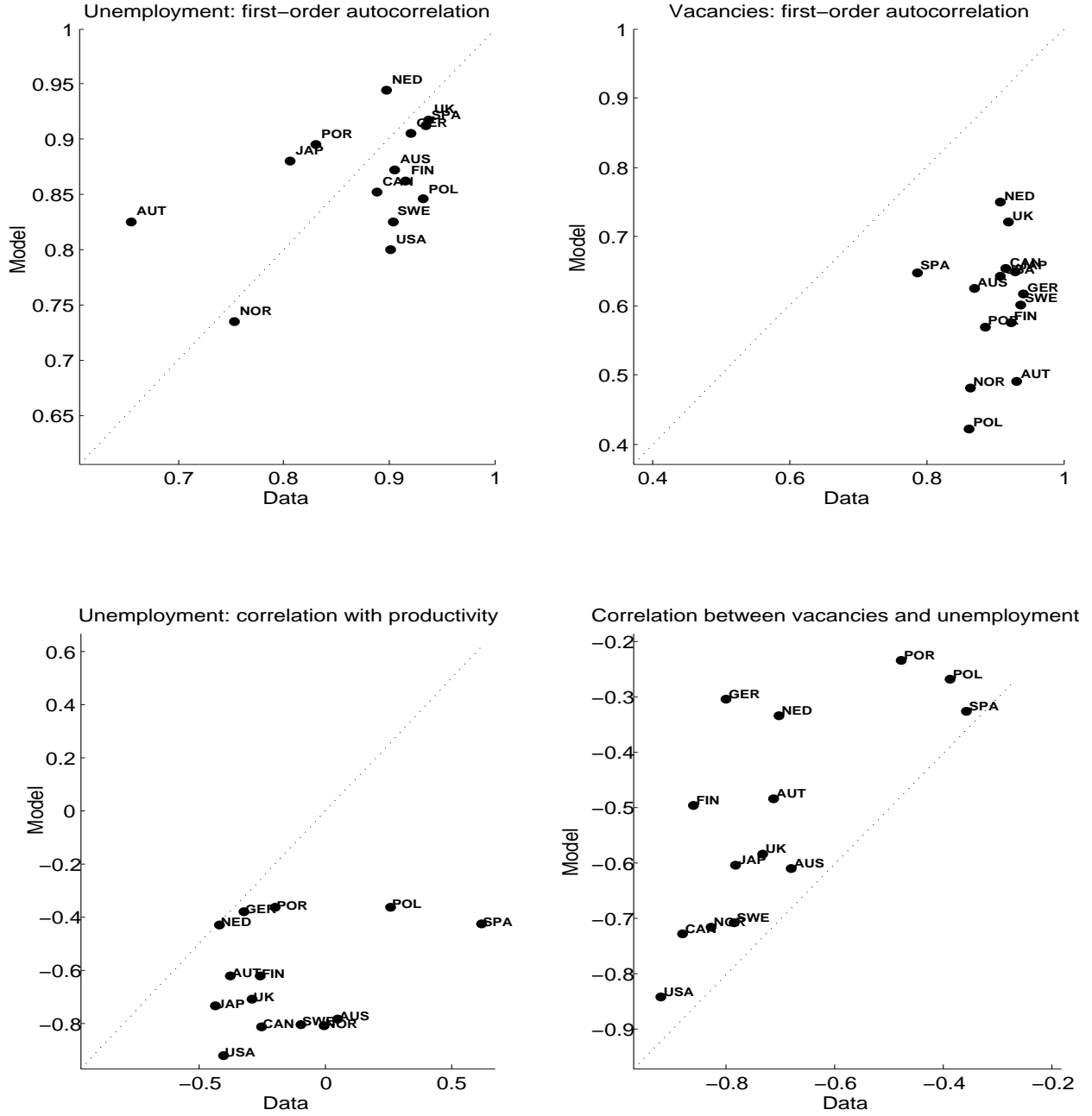


Figure 5: Volatility: HM calibration

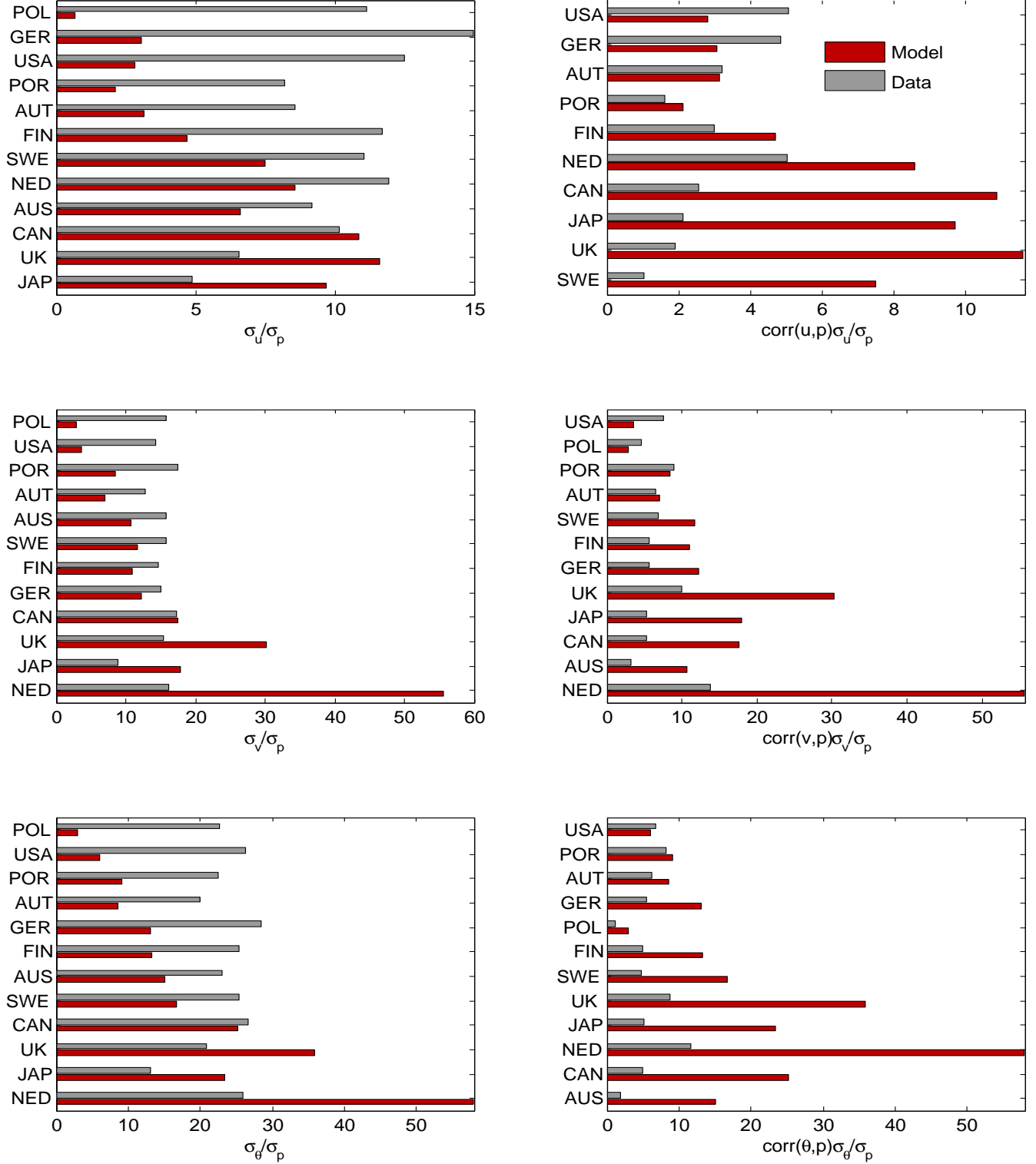


Figure 6: Robustness

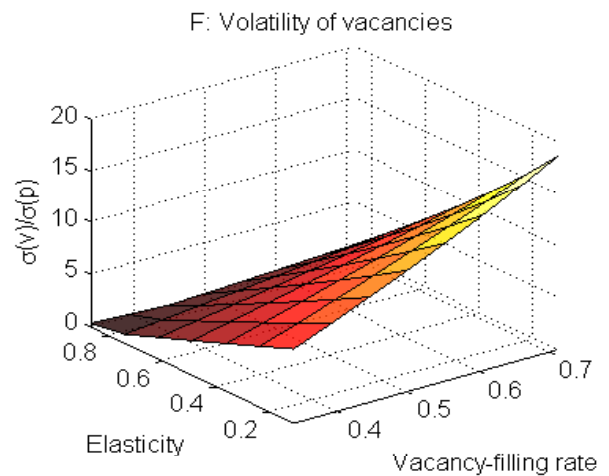
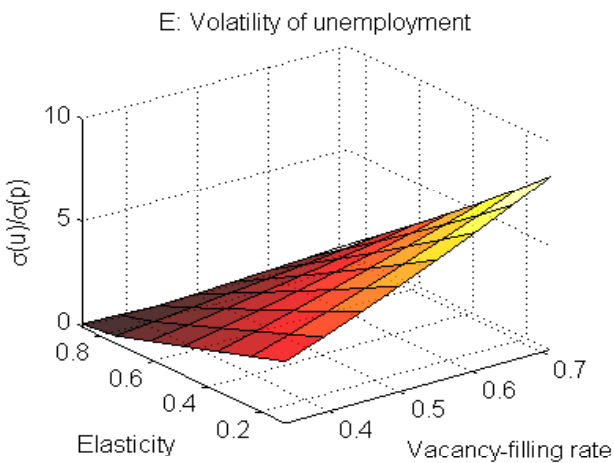
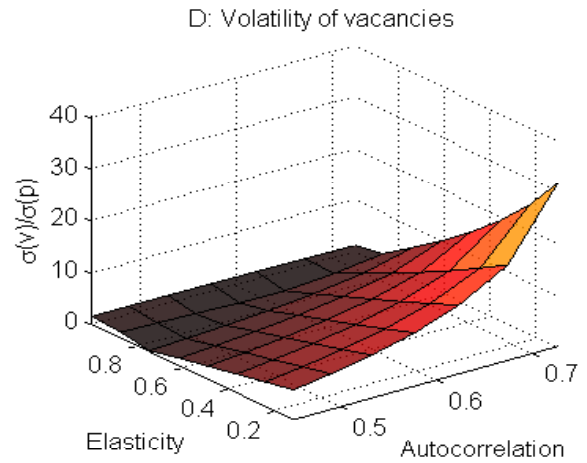
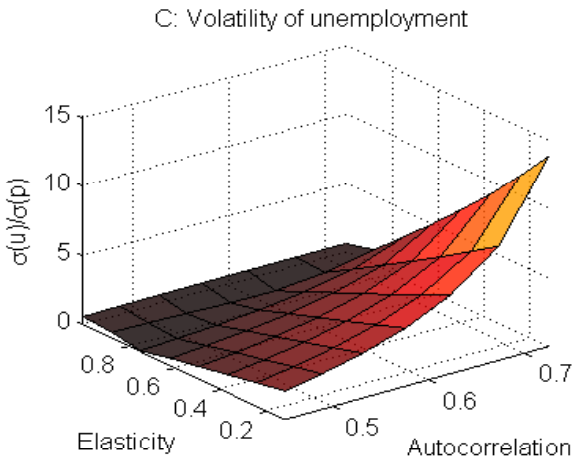
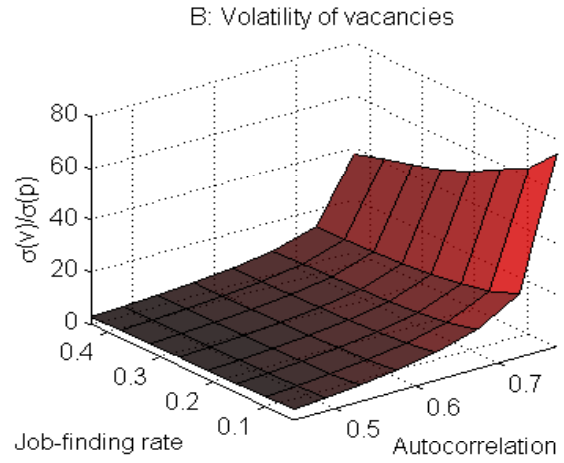
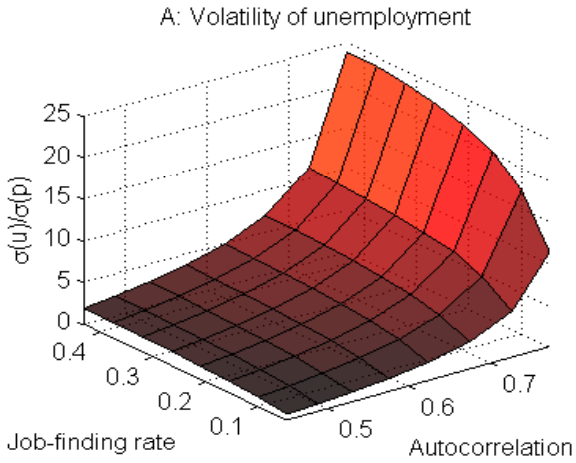


Figure 7: Comparing model moments (DMP: black; HM red)

