Productivity and the Labor Market: Co-Movement over the Business Cycle[*]

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Abstract

The productivity-driven Mortensen-Pissarides model predicts that labor productivity, defined as the ratio of output to employment, is strongly correlated with employment, unemployment, vacancies and wages whereas these correlations were argued to be much weaker in the data, especially since the mid 1980s. We first document that the size of these discrepancies between the data and the model becomes substantially smaller if employment data from the Current Population Survey is used in measuring productivity instead of the commonly used employment data from the Current Employment Statistics. Second, we show that incorporating time to build and a stochastic value of home production helps reconcile the quantitative performance of the model with the data with stochastic productivity being the key determinant of the business cycle dynamics of the model.

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1 Introduction

There is a renewed interest in the literature on whether productivity driven models of the business cycle, e.g, the real business cycle model (Kydland and Prescott (1982), Long and Plosser (1983)) or the search and matching model (Mortensen and Pissarides (1994), Pissarides (1985, 2000)) are consistent with key business cycle facts. One critique of this class of models, articulated in, e.g., Hall (2007), is that while productivity shocks are the driving process of business cycles in the model, at least the 1990-1991 and 2001 U.S. recessions were not driven by a drop in productivity. Whereas these models imply that employment is closely linked to labor productivity, the observed employment reductions in these recessions are argued to have occurred without a decline in productivity. Similar patterns were also documented for the recession of 2008 (e.g., Mulligan (2009)).

The second set of criticisms is more specific to the quantitative performance of the search and matching model. The issue that received the most attention is whether the model can generate the volatility of labor market variables (e.g., vacancies, unemployment) in response to measured productivity shocks that is quantitatively consistent with the data. Shimer (2005) proposed a calibration of the model that implied that the model generates only a small volatility in the variables of interest. Hagedorn and Manovskii (2008) proposed a different calibration strategy and found that the model does generate a volatile labor market.[1]

However, it has been argued in the literature discussed below that the model has additional empirical shortcomings related to the co-movement of productivity and labor market variables, all of which occur regardless of which of the two calibration strategies is chosen.

   i) In the data the standard deviation of wages is higher than the elasticity of wages with respect to productivity. In the model they are virtually identical.[2]

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[1]The difference is driven by the way that the two central parameters of the Mortensen-Pissarides model – the worker's value of non-market activity and the worker's bargaining power – are identified. Shimer (2005) calibrates that value of non-market activity to the average replacement rate of unemployment insurance and sets the worker's bargaining power to ensure efficiency of the model. Hagedorn and Manovskii (2008) use the data on the costs of posting vacancies and the elasticity of wages with respect to productivity to identify the two parameters.

[2]Since Hagedorn and Manovskii (2008) target the elasticity in their calibration strategy, it delivers a standard deviation of wages that is too low compared to the data. This also implies that the correlation of wages and productivity is smaller in the data than in the model. This follows since the correlation of wages and productivity $corr(w, p)$ is equal to the product of the elasticity of wages with respect to productivity $\epsilon_{w,p}$ and the ratio of the standard deviations of productivity p and wages w, $\frac{\sigma_p}{\sigma_w}$: $corr(w, p) = \epsilon_{w,p} \frac{\sigma_p}{\sigma_w}$.

ii) In the data the correlation between current productivity and vacancies is maximized when vacancies one or two quarters ahead are considered. In the model this correlation is maximized for contemporaneously measured vacancies.

iii) The correlation between contemporaneously measured labor market tightness (the ratio of vacancies to unemployment) and productivity is close to 1 in the model but is as low as 0.39 in the data.

We emphasize that these shortcomings of the model do not depend on the calibration strategy employed.[3]

In this paper we tackle these issues both from an empirical and a theoretical perspective. We start by reassessing the key motivating facts. Traditionally, the quantitative search and matching literature has focused on the labor productivity series measured as the seasonally adjusted ratio of quarterly real non-farm business output constructed by the BLS from the National Income and Product Accounts to employment constructed by the BLS from the Current Employment Statistics (CES). We find, however, that the cyclical properties of the productivity process are extremely sensitive to the employment data used.[4]

Using the same output series but employment data from the Current Population Survey (CPS) we find, for example, that the correlation between labor market tightness and productivity is almost twice higher as compared to the usual estimates based on the CES data. In addition, the lag at which the maximum correlation between market tightness and productivity is achieved is only one quarter instead of the two quarters implied by the CES data. Finally, the cyclical properties of productivity itself depend on the employment series used. In particular, Hall's conclusions are based on the CES data, but do not follow from an investigation based on the CPS data. Since the high positive correlation between CPS-based productivity and employment series is stable and consistent over time, we think it is pre-

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[3]A further problem with the basic Mortensen-Pissarides model, specific to the calibration in Hagedorn and Manovskii (2008), is that the response of unemployment to changes in unemployment insurance or taxes is too strong compared to the data. However, Hagedorn, Manovskii, and Stetsenko (2009) show that this concern is alleviated once the simplifying assumption of exogenous productivity is relaxed. For the business cycle analysis in this paper the endogeneity of productivity is not relevant. Only its cyclical properties are.

[4]While we study the effects of the choice of employment data holding output data fixed we note that the degree of co-movement between productivity and the labor market variables is affected by the treatment of the government sector. If it is included in the measures of output and employment the extent of co-movement weakens.

mature to reject models driven by productivity shocks based on the CES-based series whose cyclical co-movement inexplicably flips sign in the mid 1980s. While there is a large amount of research that documents differing trends in employment in CES and CPS, we are not aware of any work documenting the strikingly different cyclical properties of productivity based on the employment measures from the two surveys.[5]

While using different measures of employment and productivity affects the size of the discrepancy between the data and the predictions of the search model, it is not sufficient to eliminate such differences. The inconsistencies between the model and the data remain. However, these failures are reminiscent of some of the critiques leveled against the early versions of the real business cycle model. The RBC literature has overcome those critiques by adding some realistic features to the basic model. In this paper, we investigate whether the same fixes solve similar problems faced by the basic search model. This leads us to modify the model in two ways. First, Benhabib, Rogerson, and Wright (1991), Hall (1997), McGrattan, Rogerson, and Wright (1997), and others, noted that the value of non-market activity includes, among other components, the stochastic value of home production. We incorporate this feature into the Mortensen-Pissarides (MP) model and show that allowing for stochastic non-market activity adds an additional (to fluctuations of productivity) source of wage fluctuations to the model. We find that, since the standard deviation of wages is higher than the elasticity, both of them can be matched in the extended model. [6] Importantly, stochastic productivity remains the key driver of employment, unemployment and vacancies in the model.

Second, we address the differences between the data and the standard search model in the correlation between productivity and vacancies. We show that these empirical shortcomings of the MP model can be corrected by incorporating another standard feature of the RBC model − time-to-build − into the model (Kydland and Prescott (1982)). Specifically, we add a lag in vacancy posting so that vacancies created by firms today enter the labor market with

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[5]Hall (2008) documented different employment volatility at cyclical frequencies in the CES and CPS.

[6]Whereas we only consider here a shock to the flow value of unemployment one may as plausibly think of other shocks, for example to the matching function or a combinations of shocks distinct from the shock to productivity, which would serve as a source of additional wage fluctuations. Gertler and Trigari (2009) modify the model by introducing staggered wage contracting. Since only a fraction of firms is allowed to adjust wages in a given month, wages are relatively non-responsive to contemporaneous productivity changes. Since workers are assumed to have a large bargaining weight, when a firm is able to adjust wages, the adjustment is large.

a short delay. Such a lag is natural if it takes firms some time to adjust productive capacity in response to a change in productivity. It may also arise if it takes firms time to infer that an aggregate productivity change has occurred.[7]

Having incorporated these features into the model, we must choose the calibration strategy to evaluate its quantitative performance. The ability of the modified model to remedy the shortcomings that we are focusing on does not depend on the calibration strategy used. Since the strategy in Hagedorn and Manovskii (2008) generates the right magnitude of the volatility in the labor market variables we see it as a convenient benchmark. It appears important to evaluate whether there is a specification of the model that is simultaneously quantitatively consistent with the cyclical volatility of unemployment, vacancies, and wages as well as their co-movement with labor productivity. Thus, we jointly calibrate all the parameters of the modified model, including the worker's value of non-market activity, the worker's bargaining power, as well as the length of the vacancy posting lag and the variance of the shocks to the flow value of being unemployed. We target the standard deviation of wages and the lag length at which the maximum correlation between productivity and vacancies is observed in addition to the calibration targets in Hagedorn and Manovskii (2008) that include the costs of posting vacancies and the elasticity of wages with respect to productivity.

We find that the calibrated model is simultaneously consistent with all the evidence on wages, vacancies and unemployment described above. In particular, the model generates as much volatility in the variables of interest as there is in the data. This was unclear *a priori* since on the one hand the (two central) parameters of the MP model had to be recalibrated and on the other hand the two new model features dampen the volatility of unemployment. The lag in vacancy posting dampens the incentives to post vacancies since the benefits of having a filled vacancy occur only with a lag. The increase in the volatility of wages lowers the volatility of firms' profits and thus can lower the incentives to post vacancies. Furthermore, it is unclear that the higher volatility of wages can be generated through allowing for a stochastic flow value of unemployment because the flow value of unemployment cannot

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[7]Although adding sunk cost in vacancy creation to the model leads to significantly more realistic dynamics of vacancies, the contemporaneous correlation between market tightness and productivity is still close to one (Fujita and Ramey (2005)). Thus, sunk costs and time to build are not observationally equivalent but rather seem to be complementary assumptions to better describe the behavior of market tightness.

substantially exceed the exogenous value of productivity in the standard MP model.[8]

We also find that the correlation between labor market tightness and productivity, although not targeted, is very close in the model and in the data. This is quite remarkable since the discrepancy of this correlation between the data (0.39 based on CES) and the standard model (≈ 1) led Hall (2005), Mortensen and Nagypal (2007), Shimer (2007), and Pissarides (2008), among others, to the conclusion that the "volatility puzzle" is less dramatic than stated in Shimer (2005). They argue that it is a success of the model to account for the elasticity of labor market tightness with respect to productivity and not for the full volatility of labor market tightness. Accounting for the elasticity amounts to replicating a substantially smaller volatility due to the discrepancy of the correlation of labor market tightness and productivity between the data and the model.[9] In contrast, we simultaneously account for the high volatility of labor market tightness and the low correlation of labor market tightness and productivity. Our result suggests that the volatility-puzzle for the standard calibration is indeed as large as suggested by Shimer (2005). Appealing to the low correlation of 0.39 between market tightness and productivity to "solve" this puzzle is also problematic from an empirical point of view. As we noted above, the size of this correlation depends on the employment series used to construct labor productivity. It equals 0.39 for the CES-based productivity series but is equal to 0.76 for the CPS-based one. These findings are relevant when assessing the model through its ability to match the elasticity of market tightness with respect to productivity. If one finds a modification of MP which delivers the right elasticity based on the CES data, it still fails by a factor of two if the CPS data are used. One may have thought that the CES data, because they are much larger, are less noisy and thus superior to the CPS data. This reasoning would imply lower correlations based on CPS data than on CES data. However, we find the opposite.

The paper is organized as follows. In Section 2 we document the key facts at the center of

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[8]Thus, allowing for a stochastic value of home activity is a larger challenge for a model where the difference between market and non-market productivity is small. Since this is the key implication of the calibration strategy in Hagedorn and Manovskii (2008), once we know that the model calibrated according to this strategy generates the right volatility of wages, we can be sure that it will also perform well if the calibration strategy in Shimer (2005) is used.

[9]It holds that $\sigma_\theta = \epsilon_{\theta,p} \frac{\sigma_p}{corr(\theta,p)}$, where σ_θ and σ_p are the standard deviations of labor market tightness and productivity, $\epsilon_{\theta,p}$ is the elasticity of labor market tightness with respect to productivity and $corr(\theta,p)$ is the correlation of labor market tightness and productivity. A lower $corr(\theta,p)$ in the data than in the model than implies a higher σ_θ in the data than in the model for the same values of $\epsilon_{\theta,p}$ and σ_p.

the discussion in the literature. In Section 3 we describe a discrete time stochastic version of the Pissarides (1985, 2000) model that incorporates a shock to the value of home production and the lag in vacancy creation. In Section 4 we develop our calibration strategy, perform a quantitative analysis and discuss the findings. Section 5 concludes.
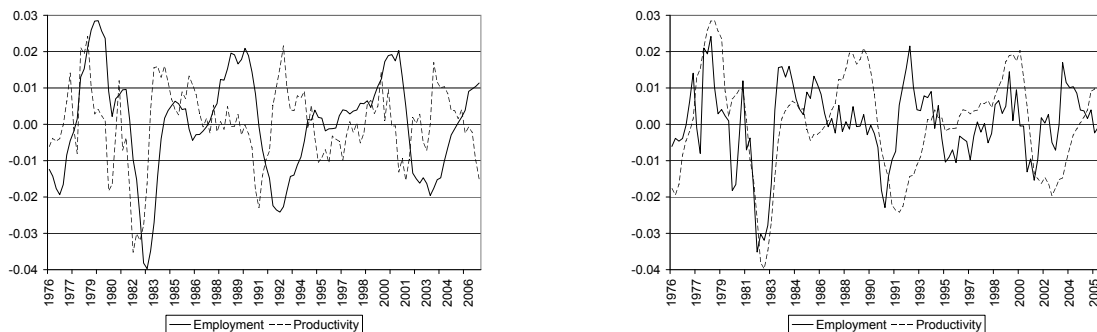
2   Facts

Consider the standard labor productivity measure used in the quantitative search and matching literature defined as the seasonally adjusted ratio of quarterly real non-farm business output (constructed by the BLS from NIPA) to employment constructed by the BLS from the Current Employment Statistics (CES).[10] The statistics of interest for 1951:1 to 2004:4 were computed using this measure of productivity in Hagedorn and Manovskii (2008) and are presented in Panel 1 of Table 1. As is well known, the table indicates that unemployment, vacancies and their ratio are considerably more volatile than productivity.

The numbers in the bottom row of Panel 1 in Table 1 imply that the labor market variables are only weakly correlated with productivity. For example, the correlation between labor market tightness and productivity is only 0.393. It was this low correlation that lead several authors cited in the Introduction to the conclusion that the "volatility puzzle" is less dramatic than stated in Shimer (2005).

Because the alternative employment series that we will be using are available only starting in 1976 we now compute similar statistics for 1976:1 to 2006:4. The results, summarized in Panel 2 of Table 1, show that over the latter time period BLS's measure of productivity became less volatile. Relative to the volatility of productivity, other labor market variables remain similarly volatile. The correlations of productivity with vacancies, unemployment, and their ratio, labor market tightness, become even smaller. Regardless of the time period, the maximum correlation between productivity and labor market tightness is achieved with a lag of two quarters.

Until this point, the labor series used was based on the CES. In contrast, the unemployment series was constructed using the Current Population Survey (CPS) data. We now

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[10]Although the CES is the main source of information on employment in this measure of productivity, BLS supplements it with the data from CPS on numbers of proprietors and unpaid family workers (and farm employment when output measure does not exclude farm output).

(a) CES Based Productivity and Employment

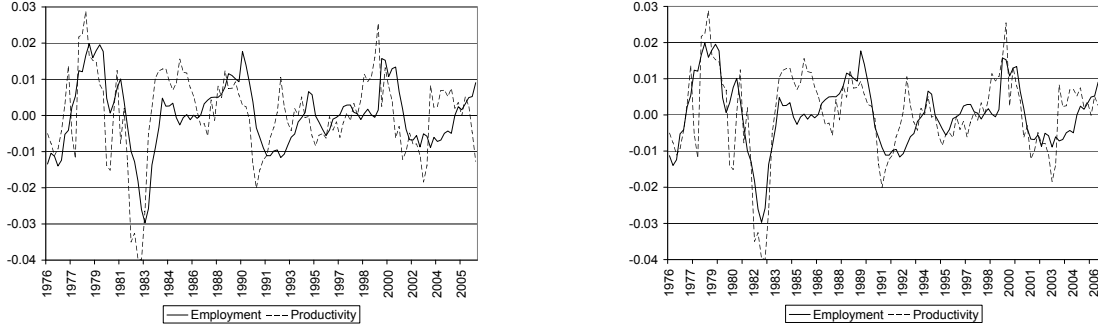(b) CES Based Productivity and Employment Lagged Two Quarters

Figure 1: CES Employment and Output per Worker (labor productivity) based on CES, 1976-2006.

compute the same statistics but use the employment series from the CPS when constructing the measure of productivity. The results in Panel 3 of Table 1 indicate that this series implies a dramatically higher correlation between productivity and other labor market variables. The correlation between vacancies or labor market tightness and productivity almost doubles, while the correlation between unemployment and productivity almost triples. In addition, the maximum correlation between productivity and labor market tightness is achieved with a lag of only one quarter.[11]

Next, we reconsider the evidence in Hall (2007) that the U.S. recessions of 1990-1991 and 2001 were not accompanied by a decline in productivity. The evidence is summarized in Figure 1(a) that plots HP-filtered (1600) productivity and employment. Both series are based on the CES data. The series are visibly negatively correlated since the early 1980 (the correlation is equal to 0.08 on the full sample and -0.3 after 1984). Figure 1(b) plots the same productivity series and employment lagged by two quarters. There is still no strong positive relationship between the series during the last two recessions (with a correlation of 0.42 on the full sample and 0.06 after 1984).

Figure 2 plots the corresponding series based on CPS employment. Although the correlation between the series has declined since the early 1980 it is strong and positive. The

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[11]Interestingly, we do not find clear evidence of a phase shift between the two employment series.

(a) CPS Based Productivity and Employment

(b) CPS Based Productivity and Employment Lagged Two Quarters

Figure 2: CPS Employment and Output per Worker (labor productivity) based on CPS, 1976-2006.

correlation between contemporaneously measured variables equals 0.53 on the full sample and 0.26 after 1984. When employment is lagged by two quarters the correlation rises to 0.73 on the full sample and to 0.59 after 1984.

The difference between the results in Figures 1 and 2 is striking. While the observer of the CES-based series would be tempted to conclude that productivity is unlikely to be an important driving force of the business cycle, at least after 1984, the observer of the CPS-based series would likely disagree.

It is not entirely clear what accounts for this difference.[12] Both surveys are conducted by the BLS but are distinct in their coverage, definitions, and size. CES is a monthly survey of approximately 160,000 business establishments and government agencies. CPS is a monthly survey of approximately 60,000 households. For each member of these households the employment and unemployment status is recorded. The CES sample is drawn from the universe of establishments with Unemployment Insurance (UI) tax records. This implies several limitations. First, there is a time lag before a newly created establishment appears in the UI tax records. Similarly, CES is not able to capture business death in a timely manner because it cannot distinguish exiting establishments from the ones that fail to respond to the survey.

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[12]Bowler and Merisi (2006) discuss a large number of explanations offered for the different behavior of employment series in the CPS and CES but conclude that no compelling explanation has been documented.

Although CES attempts to correct for the average level of this bias, until 1983 the correction procedure did not account for the cyclical properties of business birth/death at all. Since 1983 a regression procedure was used in an attempt to correct for the cyclical employment changes in the newly created and exiting establishments. Since 2000 the CES began to sample more frequently - twice a year - in an attempt to reduce the extent of this bias. Thus, it is possible that the failure to timely measure the changes in employment due to business entry and exit tends to reduce the correlation between measured employment and, say, output.[13]

Second, our CPS sample includes government workers, unincorporated self employed, unpaid family workers, agriculture and related workers, private household workers, and workers absent without pay. All these workers are excluded from the CES. We have excluded all these workers from the CPS sample and found that this does not measurably affect the results. Finally, CES counts the number of jobs (multiple jobholders are counted in each job) while CPS counts the number of employed workers regardless of the number of businesses they are on the payroll of. While it is unclear which measure is more consistent with the standard search model, counting workers on payroll presents a potential problem. CES considers a worker employed in a particular job if his/her pay period (could be weekly, monthly, or other) includes the 12th of the month. Thus, if a monthly paid worker switches jobs within a month, he will be counted twice (once in each job). Since such job-to-job moves are strongly procyclical, this will induce spurious procyclicality into the CES employment series. This maybe part of the reason for a higher cyclical volatility of CES employment leading to less volatile productivity.[14]

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[13]Interestingly, the relationship between the cyclical components of employment and productivity changes right after the introduction of the imputation procedure for firm birth/death in 1983. Unfortunately, we do not have access to the unadjusted data after 1983 to verify whether this is just a coincidence.

[14]While our major concern is with the correlation of the productivity with other labor market variables depending on the employment series used, Abraham, Haltiwanger, Snadusky, and Spletzer (2009) provide some evidence that helps to further account for the different volatility of two employment series. They use the Social Security numbers of CPS respondents to link them to the Unemployment Insurance (UI) system records. They find that the number of people who report to be employed in the CPS is about 10 percent larger than the number of these workers who have a record of employment in the UI data. A likely important reason for this is that employers classify many workers as independent contractors (perhaps to avoid paying employment taxes) and thus do not count them on payroll and do not report them as being employed to the CES. In addition, some workers are simply paid off-the-books. When asked asked by the CPS, however, these workers often consider themselves to be employed. This increases the cyclicality of the CES employment series because employers are more likely to classify such employees as regular employment in booms than in recessions but has little effect on the cyclicality of the CPS employment. There is a clear possibility of misclassification in the CPS as well. Some workers in "marginal" jobs that they take temporarily may report

To summarize, we cannot conclusively say which survey is more appropriate for measuring the cyclical properties of productivity. CES is larger than the CPS, leading in general to more precise estimates. CPS, however, is considered large enough to be the source of the official unemployment statistics. Moreover, we take quarterly averages of the monthly data, which tends to reduce the influence of the measurement error. Finally, but perhaps most importantly, one would expect larger sampling error in CPS to *lower* rather than increase the correlations of productivity with other labor market variables. Since CPS avoids several problems induced by the design of the CES, it would appear that it might provide the preferred measure of employment for a business cycle analysis.[15]

Notice that if the CPS-based productivity is indeed preferred, the performance of the standard search and matching model is much closer to the data than previously thought. Indeed, the strong co-movement between productivity and the labor market variables implied by the model is not as counterfactual as the evidence from the CES-based productivity suggested. Nevertheless, the co-movement implied by the model is still too strong. Thus, in the next section we will modify the standard model by incorporating time-to-build and a stochastic value of home production − the two classic features of the RBC model. Given the uncertainty about the appropriate productivity series we will calibrate the model twice to match targets derived from both CPS and CES surveys. It would be a desirable feature of the modifications of the model that we use if they could bring the model in line with the data regardless of the productivity series used to calibrate the model.

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to the CPS that they are not employed but have a record of employment in the UI system. To the extent that the fraction of such workers is countercyclical (if more workers take up such jobs in recessions), it tends to increase the procyclicality of the CPS employment. On the contrary, if the fraction of such workers is procyclical (more employers hire short term help in booms) the cyclicality of the CPS employment would be spuriously low compared to that in the CES.

[15]This is also the conclusion reached by Perry (2005) who argues that the CPS employment data might be preferred because its growth rate is more correlated with the growth rate of output compared to the CES employment. After reviewing various data sources for the U.S. economy, Hall (2008) also concluded that "the household survey is the only source of data that supports a clean set of measures of hours and employment."

3 The Model

3.1 Workers and Firms

There is a measure one of infinitely lived workers and a continuum of infinitely lived firms. Workers maximize their expected lifetime utility:

$$\mathbb{E} \sum_{t=0}^{\infty} \delta^t y_t, \tag{1}$$

where y_t represents income in period t and $\delta \in (0,1)$ is workers' and firms' common discount factor. Output of each unit of labor is denoted by p_t. Aggregate labor productivity p_t follows a first order Markov process in discrete time, according to some distribution $G(p',p) = Pr(p_{t+1} \leq p' \mid p_t = p)$. There is free entry of firms. Firms attract unemployed workers by posting a vacancy at the flow cost c. There is a k-period planning lag in posting vacancies such that a vacancy planned in period t becomes active in period $t+k$ only. All unemployed workers obtain the same flow utility $z_t = z + \nu_t$ from leisure/non-market activity, where the aggregate shock ν_t is i.i.d. and is drawn from a normal distribution, $\nu_t \sim \mathcal{N}(0, \sigma_\nu^2)$, truncated at two standard deviations around its mean. Throughout the paper the notation X_p (or $X_{p,\nu}$) indicates that a variable X is a function of the aggregate productivity level p (or of the aggregate productivity level p and the flow value of unemployment shock ν). Once matched, workers and firms separate exogenously with probability s per period. Employed workers are paid a wage $w_{p,\nu}$, and firms make accounting profits of $p - w_{p,\nu}$ per worker each period in which they operate.

3.2 Matching

Let u_t denote the unemployment rate (or the number of unemployed people) and $n_t = 1 - u_t$ the employment rate. Let v_{t-k} be the number of vacancies posted (planned and paid for) in period $t-k$. These vacancies become ready to be matched with workers in period t. We refer to $\theta_t = v_{t-k}/u_t$ as the market tightness at time t.

The number of new matches (starting to produce output at $t+1$) is given by a constant returns to scale matching function $m(u_t, v_{t-k})$. To ensure that the probability of finding a job and of filling a vacancy lies between 0 and 1 we follow den Haan, Ramey, and Watson (2000)

and choose

$$m(u_t, v_{t-k}) = \frac{u_t \cdot v_{t-k}}{(u_t^l + v_{t-k}^l)^{1/l}}, \quad l > 0.$$

Employment evolves according to the following law of motion:

$$n_{t+1} = (1-s)n_t + m(u_t, v_{t-k}). \tag{2}$$

The probability for an unemployed worker to be matched with a vacancy next period equals $f(\theta_t) = m(u_t, v_{t-k})/u_t = m(1, \theta_t)$. The probability for a vacancy to be filled next period equals $q(\theta_t) = m(u_t, v_{t-k})/v_{t-k} = m(1/\theta_t, 1) = f(\theta_t)/\theta_t$. The information set of a firm posting a vacancy at period t includes aggregate shocks up to period t.

3.3 Equilibrium

Denote the firm's value of a job (a filled vacancy) by J, the firm's value of an unfilled vacancy by V, the worker's value of having a job by W, and the worker's value of being unemployed by U. The following Bellman equations describe an equilibrium of the model where J, W, U and V depend on the current shocks to market productivity p_t and non-market activity ν_t and all shocks between period $t - k$ and period $t - 1$, $p_{t-k}, \ldots p_{t-1}$ and $\nu_{t-k}, \ldots \nu_{t-1}$. Let $x_t = (p_t, \ldots, p_{t-k}, \nu_t, \ldots, \nu_{t-k})$ be today's state vector and $x_{t+1} = (p_{t+1}, \ldots, p_{t-k+1}, \nu_{t+1}, \ldots, \nu_{t-k+1})$ be next period's state vector. The k-period lagged shocks have to be included into the state vector since vacancies are posted with a k-period lag.[16]

$$J_{x_t} = p_t - w_{x_t} + \delta(1-s)E_{x_t}J_{x_{t+1}} \tag{3}$$

$$V_{x_t} = -c + \delta^{k+1}E_{x_t}q(\theta_{x_{t+k}})J_{x_{t+k+1}} \tag{4}$$

$$U_{x_t} = z_t + \delta\{f(\theta_{x_t})E_{x_t}W_{x_{t+1}} + (1 - f(\theta_{x_t}))E_{x_t}U_{x_{t+1}}\} \tag{5}$$

$$W_{x_t} = w_{x_t} + \delta\{(1-s)E_{x_t}W_{x_{t+1}} + sE_{x_t}U_{x_{t+1}}\}. \tag{6}$$

The interpretation is straightforward. Operating firms earn profits $p_t - w_{x_t}$ and the matches are exogenously destroyed with probability s. A vacancy costs c and is matched with a

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[16]In the standard model without a lag in vacancy posting, period t shocks are sufficient to determine outcomes in period t. In this model, however, the period t probability of finding a job depends on the number of vacancies posted in period $t - k$, which depends on the shocks realized in period $t - k$. Therefore, these lagged shocks have to be included in the state vector in period t. Finally, to be able to update the state vector, all shocks from intermediate periods have to be included as well (x_{t+1} includes p_{t-k+1}, a shock already known in period t).

worker (becomes productive in period $t + k + 1$) with probability $q(\theta_{x_{t+k}})$. Here we assume for simplicity that firms pay the vacancy costs only once. This is equivalent, of course, to assuming that firms make a sequence of payments c_{t+i} in periods $t + i$ ($i = 0 \ldots k$) with the same discounted present value $c = c_t + \delta c_{t+1} + \ldots + \delta^k c_{t+k}$. An unemployed worker derives utility z_t and finds a job next period with probability $f(\theta_{x_t})$. An employed worker earns wage w_{x_t} but may lose her job with probability s and become unemployed next period.

Since the firm and the worker bargain after they met, the existence of a planning lag does not affect bargaining. Nash bargaining then implies that a worker and a firm split the surplus $S_{x_t} = J_{x_t} + W_{x_t} - U_{x_t}$ such that

$$J_{x_t} = (1 - \beta)S_{x_t}, \tag{7}$$

$$W_{x_t} - U_{x_t} = \beta S_{x_t}. \tag{8}$$

Free entry implies that the value of posting a vacancy is zero: $V_{x_t} = 0$ for all t and, therefore,

$$
\begin{aligned}
c &= \delta^{k+1} E_{x_t} q(\theta_{x_{t+k}}) J_{x_{t+k+1}} \\
&= \delta^{k+1}(1 - \beta) E_{x_t} q(\theta_{x_{t+k}}) S_{x_{t+k+1}}.
\end{aligned}
\tag{9}
$$

The Bellman equation for the surplus is:

$$\tag{10}$$

$$
\begin{aligned}
S_{x_t} &= p_t - z_t + \delta(1 - s)E_{x_t}(W_{x_{t+1}} + J_{x_{t+1}}) + \delta E_{x_t}(sU_{x_{t+1}} - f(\theta_{x_t})W_{x_{t+1}} - (1 - f(\theta_{x_t}))U_{x_{t+1}}) \\
&= p_t - z_t + \delta(1 - s)E_{x_t}(W_{x_{t+1}} + J_{x_{t+1}} - U_{x_{t+1}}) - \delta f(\theta_{x_t})E_{x_t}(W_{x_{t+1}} - U_{x_{t+1}}) \\
&= p_t - z_t - \delta f(\theta_{x_t})\beta E_{x_t} S_{x_{t+1}} + \delta(1 - s)E_{x_t}(W_{x_{t+1}} + J_{x_{t+1}} - U_{x_{t+1}}) \\
&= p_t - (z_t + \delta f(\theta_{x_t})\beta E_{x_t} S_{x_{t+1}}) + \delta(1 - s)E_{x_t} S_{x_{t+1}}.
\end{aligned}
$$

An existing match generates p_t units of output in period t. It is destroyed next period with probability s. In this case, the value of the firm drops to zero, the value of a vacancy. The worker, on the other hand, becomes unemployed and gets utility z_t every period t until becoming employed again with probability $f(\theta_{x_t})$ per period. An employed worker keeps a share β of the match surplus. With probability $1 - s$, the match exists next period and generates surplus depending on the realizations of p_{t+1} and ν_{t+1}.

14

We now derive the expressions for equilibrium wages and profits. Using equation (10) and the flow equation (3) for J we find that:

$$w_{x_t} = \beta p_t + (1 - \beta) z_t + \delta f(\theta_{x_t}) \beta E_{x_t} J_{x_{t+1}}. \tag{11}$$

Accounting profits are then given by

$$\Pi_{x_t} = p_t - w_{x_t} = (1 - \beta)(p_t - z_t) - \delta f(\theta_{x_t}) \beta E_{x_t} J_{x_{t+1}}. \tag{12}$$

Since the standard deviation of z, σ_ν, is a calibrated parameter, it is conceivable that the value of home activity z is so high relative to market productivity p that everyone decides to stay home. In our calibration we find, however, that this is never the case. Although the value of z is higher than p in some states of the world, search frictions imply that the value of being unemployed U is never higher than the value of having a job W. All separations are thus exogenous. In particular, nobody leaves employment to stay home due to a high z value so that the unemployment rate is known once the number of vacancies is known. Note that the planning lag of length k then implies that $q(\theta_{x_{t+k}})$ is known at period t.

4 Cyclical Behavior of Unemployment, Vacancies, and Wages

4.1 Calibration

In this section we calibrate the model to match U.S. labor market facts. Given the uncertainty about the quality of the productivity series, we calibrate the model twice. In our benchmark calibration we use productivity based on the CPS employment data. In Section 4.3 we recalibrate the model using the productivity series implied by the CES data. The following twelve parameters have to be determined: average productivity $\bar{p}$, the persistence ρ and the standard deviation σ_ϵ governing the stochastic evolution of p, the average value of non-market activity $\bar{z}$, the standard deviation σ_ν of ν, the discount factor δ, the separation rate s, the bargaining power of workers β, the vacancy cost c, the length of the vacancy posting lag k, and the matching function parameter l.

Basics. We choose the model period to be two weeks. This is longer than the frequency of one week used in Hagedorn and Manovskii (2008). Since we need to keep track of the shock histories, we make this choice to limit the dimensionality of the state space. The data used to compute some of the targets have monthly, quarterly or annual frequency, and we aggregate the model-generated data appropriately when matching those targets. We set $\delta = 0.9983$. As in Hagedorn and Manovskii (2008) we target the average monthly job finding rate of 0.45, the average value for labor market tightness $\theta = 0.634$, and the separation rate (not adjusted for time aggregation) of 0.026. At a bi-weekly frequency these estimates imply a job finding rate $f = 0.2584$ and a job separation rate $s = 0.015$.[17] Following the procedure in Hagedorn and Manovskii (2008) we find that the average flow cost of posting a vacancy equals 57.7 percent of the average monthly labor productivity, i.e., $c = 0.577$.[18]

Productivity. In our benchmark calibration we measure labor productivity, p_t, as the ratio of seasonally adjusted quarterly real non-farm business output constructed by the BLS from the NIPA divided by quarterly averages of monthly employment series obtained from the CPS. The stochastic process for labor productivity is chosen as follows. We approximate through a discrete Markov chain the continuous-valued AR(1) process (truncated at two standard deviations),

$$logp_{t+1} = \rho \cdot logp_t + \epsilon_{t+1}, \tag{13}$$

where $\rho \in (0,1)$ and $\epsilon \sim N(0, \sigma_\epsilon^2)$. To calibrate ρ and σ_ϵ^2, we consider quarterly averages of bi-weekly productivity and HP-filter this process with a smoothing parameter of 1600. In the data we find an autocorrelation of 0.762 and an unconditional standard deviation of

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[17]The probability of not finding a job within a month is 0.55. The probability of not finding a job within two weeks then equals $0.55^{1/2} = 0.7416$ and the probability of finding a job equals $1 - 0.7416 = 0.2584$. The probability of observing someone not having a job who had a job one month ago equals (counting paths in a probability tree): $s(1-f) + (1-s)s = 0.026$. Solving for s, we obtain $s = 0.015$.

[18]Hagedorn and Manovskii (2008) measured the costs of posting vacancies in the data, which include the labor costs of time spent on hiring and costs of non-operating capital. To account for the capital costs of hiring, they added capital to that model. Here we use the cost of posting vacancies found in Hagedorn and Manovskii (2008) without explicitly modeling capital. Since the only effect of capital is on the vacancy posting costs, adding capital to the model in this paper would have been inconsequential once the level of the vacancy posting costs is accounted for. In difference to Hagedorn and Manovskii (2008), we assume that vacancy posting costs are acyclical. Modeling vacancy costs as being cyclical would complicate the model substantially but is unlikely to change our conclusions. The reason for the complication is that the cyclicality of costs in Hagedorn and Manovskii (2008) depends on the cyclicality of wages of those who do the hiring. Thus, the decision to post a vacancy today depends on the expected wages at the time that the vacancy becomes ready to be filled, which in turn depend on the number of vacancies created today.

0.013 for the HP-filtered productivity process. At a bi-weekly frequency this requires setting $\rho = 0.9809$ and $\sigma_\epsilon = 0.0046$ in the model. The mean of p is normalized to one.

Remaining Parameters. Five parameters remain to be determined: the average value of non-market activity $\bar{z}$, worker's bargaining weight, β, the matching function parameter, l, the standard deviation of the ν-shock, σ_ν, and the length of the vacancy posting lag, k. We choose the values for these parameters to match the average values for $\theta = 0.634$, $f = 0.2584$, the productivity elasticity of wages (measured as labor share times labor productivity) $\epsilon_{w,p} = 0.639$, the standard deviations of wages $\sigma_w = 0.012$, and the fact that the correlation of θ_{t+k} and p_t is maximized when k equals 1 quarter (3 months).[19] Thus, there are five targets to pin down five parameters.

Computation. We first use the free entry condition (9) and the flow equation for the surplus (10) to derive the following difference equation in θ:

$$(14)$$

$$
\begin{aligned}
&\frac{c}{\delta^{k+1} q(\theta_{x_{t+k}})} \\
={}& (1-\beta) E_{x_t} S_{x_{t+k+1}} \\
={}& (1-\beta) E_{x_t}\{p_{t+k+1} - (z_{t+k+1} + \delta f(\theta_{x_{t+k+1}})\beta E_{x_{t+k+1}} S_{x_{t+k+2}}) + \delta(1-s) E_{x_{t+k+1}} S_{x_{t+k+2}}\} \\
={}& E_{x_t}(1-\beta)(p_{t+k+1} - z_{t+k+1}) \\
+{}& E_{x_t} E_{x_{t+1}}\{-\delta f(\theta_{x_{t+k+1}})\beta E_{x_{t+k+1}} J_{x_{t+k+2}}) + \delta(1-s) E_{x_{t+k+1}} J_{x_{t+k+2}}\} \\
={}& E_{x_t}(1-\beta)(p_{t+k+1} - z_{t+k+1}) + \delta E_{x_t}\{((1-s) - f(\theta_{x_{t+k+1}})) E_{x_{t+1}} J_{x_{t+k+2}})\} \\
={}& E_{x_t}(1-\beta)(p_{t+k+1} - z_{t+k+1}) + \delta E_{x_t}\{((1-s) - f(\theta_{x_{t+k+1}}))\frac{c}{\delta^{k+1} q(\theta_{x_{t+k+1}})}\} \\
={}& E_{x_t}(1-\beta)(p_{t+k+1} - z_{t+k+1}) + E_{x_t}\{\frac{c(1-s)}{\delta^k q(\theta_{x_{t+k+1}})} - \frac{c\beta\theta_{x_{t+k+1}}}{\delta^k}\}.
\end{aligned}
$$

We solve this difference equation to find θ as a function of productivity p_{t-k} only. Such an equilibrium, where θ does not depend on all variables in x, exists and is the one we consider.

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[19]To gain precision, we confirmed the latter target on the monthly data as follows. CPS employment data is available monthly. The output series is available quarterly. We interpolate the quarterly output series into a monthly series using the proportional Denton method using the Industrial Production Index, available monthly, as an indicator series. The Denton method is a standard interpolation procedure. Using the interpolated monthly series we find that the maximum correlation between market tightness and productivity occurs with a lag of three months. The monthly data was filtered through the band-pass filter restricted to the standard business-cycle frequencies of 15 to 96 months.

Note that p_{t-k} is the only relevant information in period $t-k$ since the z-shock is i.i.d. and, thus, uninformative about future shock realizations.

Next we solve for wages. Because of the planning lag in vacancies, we need to know the value function J or, equivalently, S to compute wages (see equation 11). To compute S we solve the difference equation (10) for S. This gives S and $J = (1 - \beta)S$ as a function of $p_{t-k}, \ldots p_t$ and ν_t.[20] We can then use equation (11) to compute w_{x_t}. Finally, we simulate the model to generate artificial time series for productivity, unemployment, vacancies, and wages. To do so, we start in period k with an initial value for unemployment u_k, a productivity level p_0 at time 0 and a z-shock ν_0. We draw a new productivity shock and a new z-shock according to the stochastic processes described above. We then know θ and, thus, the job finding rate and the new unemployment rate. Iterating this procedure generates the time series of productivity, unemployment, vacancies and wages.

The performance of the model in matching calibration targets is described in Panel 1 of Table 2. Calibrated parameter values can be found in Panel 1 of Table 3.

4.2   Findings

We use the calibrated parameter values to simulate the model to create artificial time series and compute their relevant moments. Panel 1 of Table 4 describes the results. A comparison with the corresponding statistics in the data (Panel 3 of Table 1) reveals that the model matches the key business cycle facts quite well. In particular, the volatility of labor market tightness, unemployment, and vacancies is close to that in the data. This result was unclear a priori because the lag in vacancy posting dampens the incentives to create vacancies. This effect is due to the fact that a given level of productivity today will partially revert to the mean by the time the vacancy becomes active. We find however that this effect is not large and the incentives to create vacancies are still very responsive to changes in the current level of productivity.

In terms of wages, we not only match the productivity elasticity of wages but also the standard deviation of wages. The reason why we are able to match both wage targets is that we can choose two parameters, the worker's bargaining power and the variance of the

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[20]The value functions J_t and S_t do not depend on $\nu_{t-k}, \ldots \nu_{t-1}$ since ν_t is i.i.d.

ν-shock. To see this, consider (for illustration purposes) the wage in a model without lags in vacancy posting, $w_p = \beta p + (1 - \beta)z + c\beta\theta_p$. Choosing β then controls the response of wages w_p to changes in productivity p (note that θ_p also changes with p). It is quite evident from the above equation and it also holds in the model with lags that changing the variance of z changes the standard deviation of wages. Thus, one can adjust the standard deviation of the ν-shock to match the standard deviation of wages. Of course, all parameters have to be chosen simultaneously since, for example, the elasticity of wages also depends on the standard deviation of the ν-shock. Table 4 shows that our model is successful.

As we documented above, the correlation between $logp_t$ and $log\theta_{t+k}$, where k can be any positive or negative number of months, is maximized when $k = 3$. The calibrated model is able to generate this relationship through the appropriate choice of the lag length in vacancy posting.

The model is also successful in matching the contemporaneous correlations of θ, u and v with p without targeting them. The correlation between θ and p is 0.7 in the CPS-based data whereas it is close to one in Shimer (2005) and Hagedorn and Manovskii (2008). In our benchmark calibration this correlation equals 0.76. Whereas Shimer (2005) and Hagedorn and Manovskii (2008) generate a correlation between p and $u(v)$ of close to $-1(1)$, our model is much closer to the data. In the data, the correlation of u with p is -0.633 and the correlation of v with p is 0.719. In the model these numbers equal -0.612 and 0.790, respectively.

The model also generates a strong Beveridge curve relationship. The correlation between vacancies and unemployment in the model is only slightly lower (in absolute value) than in the data (-0.72 vs. -0.92). The performance of the model along this dimension can be improved by considering a shorter model period to alleviate the time-aggregation issues in our discrete time model. Since the state of the model is given by $(k + 1)$-period long histories of the aggregate shocks, decreasing the length of the model period would dramatically increase the dimensionality of the problem, rendering such an experiment computationally infeasible. We therefore replicate the analysis in the simpler to compute model of Hagedorn and Manovskii (2008) with a model period of one and two weeks. We find that the length of the model period accounts for most of the discrepancy between the data and the model.

Despite the success in matching the volatility of unemployment, vacancies and wages as

well as the correlation between these variables and productivity, the model inherits one short-coming of its predecessors. The autocorrelation of vacancies and wages is lower in the model than in the data. This is the standard problem for matching models where unemployment is a state variable and vacancies are a jump variable and can be fixed, as argued in Shimer (2005), by introducing adjustment costs in vacancy posting that generate a more persistent response of vacancies.

4.3 Sensitivity to Using the Standard Productivity Measure

We now re-calibrate the model to the targets implied by the standard productivity series based on CES employment. We follow exactly the same calibration strategy. Thus, we discuss here only the targets that change as compared to the benchmark calibration.

Using the productivity series based on the CES employment data implies that the correlation of θ_{t+k} and p_t is maximized when k equals 2 quarters (6 months). Since we have to keep track of histories with the length equal to the number of lags, it becomes exceedingly hard computationally to maintain a two week model period. To alleviate this problem we set the model period to one month in this re-calibration. Consistent with this choice, we set $\delta = 0.9966$, $f = 0.45$, and $s = 0.034$ (adjusted for time aggregation as in Shimer (2005) because with the longer model period we can no longer do this adjustment within the model). The CES-based productivity series also implies a lower productivity elasticity of wages $\epsilon_{w,p} = 0.449$ and the standard deviations of wages $\sigma_w = 0.010$.

As in Shimer (2005), labor productivity, p_t, is measured in the data as seasonally adjusted quarterly real average output per person in the non-farm business sector constructed by the BLS from the NIPA and the CES. To calibrate ρ and σ_ϵ^2 – the parameters of the AR(1) process for labor productivity – we consider quarterly averages of monthly productivity and HP-filter this process with a smoothing parameter of 1600. In the data we find an autocorrelation of 0.765 and an unconditional standard deviation of 0.013 for the HP-filtered productivity process. At a monthly frequency this requires setting $\rho = 0.97$ and $\sigma_\epsilon = 0.006$ in the model.

In Panel 2 of Table 2 we show that the re-calibrated model closely matches the targets with the values of calibrated parameters reported in Panel 2 of Table 3. Comparing the calibrated parameters with those obtained in the benchmark calibration, we note that the average value

of non-market activity, z, has increased from 0.925 to 0.936 while workers' bargaining power, β has declined from 0.117 to 0.078. This happened because wages are substantially more responsive in the benchmark calibration (elasticity of 0.635 vs 0.449). To match the lower productivity elasticity of wages, β has to be lowered. The measure of vacancy posting costs pins down the size of accounting profits in the model. Thus, to match the size of these profits with a lower β, the level of z had to be increased.

We use the calibrated parameter values to simulate the model and compute the relevant moments. The results are reported in Panel 2 of Table 4. A comparison with the corresponding statistics in the data (Panel 1 of Table 1) reveals that the model matches the key business cycle facts quite well. In particular, the volatility of labor market tightness, unemployment, and vacancies is close to that in the data. As in the benchmark calibration, the model matches well the cyclical properties of wages. In addition, the model is again quite successful in matching the contemporaneous correlation between θ and p without targeting it. The contemporaneous correlation between θ and p is 0.393 in the data based on the CES employment and is equal to 0.449 in the re-calibrated model. The same conclusion is reached for the correlations of unemployment and vacancies with productivity. The correlation between u and p equals -0.302 in the data (based on CES employment) and -0.298 in the model and the correlation between v and p is 0.460 in the data (based on CES employment) and 0.468 in the model.

5   Conclusion

In this paper we consider several shortcomings of the Mortensen-Pissarides search and matching model both from an empirical and a theoretical perspective. The productivity-driven model predicts that labor productivity is strongly correlated with employment, unemployment, vacancies, wages and labor market market tightness whereas these correlations are much weaker in the data. This also implies that the elasticities of these variables with respect to productivity and their standard deviations cannot be consistent with the data at the same time. These shortcomings concern correlations and arise independently of the volatility of labor market statistics generated by the model (which differ depending on the calibration strategy used).

We found strikingly different cyclical properties of the labor productivity series based on

employment data from the CES and CPS. The correlations of productivity with labor market variables strongly depend on the employment data used to measure productivity. Identifying the right productivity measure is thus important for understanding the co-movement of productivity and labor market variables and for evaluating the quantitative performance of the model. For example, the discrepancy between the predictions of the standard model and the data are substantially smaller when productivity is based on CPS employment data. More generally, identifying the right productivity measure seems critically important for measuring the contribution of productivity as a driving force of business cycles. As we documented, different conclusions are reached depending on the employment data used to construct productivity.

While using different measures of employment and productivity affects the size of the discrepancy between the data and the predictions of the model, it is not sufficient to eliminate such differences. The model has to be modified. We incorporate time to build and a stochastic value of home production into the model and evaluate the quantitative performance of the modified model using an extension of the calibration strategy in Hagedorn and Manovskii (2008). We find that the calibrated extended model accounts very well for the data. In particular, the model still accounts for the volatility of vacancies and unemployment. It also generates the standard deviation of wages and the productivity elasticity of wages that are consistent with the data. Importantly, the only shock of structural importance in the model is the shock to productivity. The shock to the value of home production is white noise and its only role is to increase the volatility of wages. In addition, the contemporaneous correlations of unemployment, vacancies, and market tightness with productivity in the model are close to their values in the data despite not being targeted. We found that the modifications of the model that we use substantially improve the performance of the model regardless of whether it is calibrated to match targets constructed from the CPS- or CES-based productivity.

Table 1: Summary Statistics, Quarterly U.S. data.

	u	v	v/u	w	p
Panel 1. CES-based productivity, 1951:1 to 2004:4					
Standard Deviation	0.125	0.139	0.259	0.010	0.013
Autocorrelation	0.870	0.904	0.896	0.841	0.765
Correlation with p	-0.302	0.460	0.393	0.594	1.000
Panel 2. CES-based productivity, 1976:1 to 2006:4					
Standard Deviation	0.093	0.124	0.213	0.010	0.011
Autocorrelation	0.924	0.923	0.931	0.803	0.749
Correlation with p	-0.219	0.421	0.341	0.562	1.000
Panel 3. CPS-based productivity, 1976:1 to 2006:4					
Standard Deviation	0.093	0.124	0.213	0.012	0.013
Autocorrelation	0.924	0.923	0.931	0.801	0.762
Correlation with p	-0.633	0.719	0.703	0.710	1.000

Note - Seasonally adjusted unemployment, u, is constructed from the Current Population Survey. The seasonally adjusted help-wanted advertising index, v, is constructed by the Conference Board. Both u and v are quarterly averages of monthly series. In Panels 1 and 2 average labor productivity p is seasonally adjusted real non-farm business output constructed by the BLS from the NIPA divided by employment from the the Current Employment Statistics constructed by the BLS. In Panel 3 average labor productivity p is seasonally adjusted real non-farm business output constructed by the BLS from the NIPA divided by employment form the Monthly Current Population Survey. Wages, w, are measured as labor share times labor productivity from BLS data. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

Table 2: Matching the Calibration Targets.

	Target	Value			
		Panel 1		*Panel 2*	
		CPS-based productivity		*CES-based productivity*	
		Data	Model	Data	Model
1.	Prod. elasticity of wages, $\epsilon_{w,p}$	0.639	0.635	0.449	0.448
2.	Average job finding rate, f	0.258	0.252	0.450	0.451
3.	Average market tightness, θ	0.634	0.635	0.634	0.630
4.	Standard deviation of wages	0.012	0.012	0.010	0.010
5.	Max. $corr(p_t, \theta_{t+k})$ at k	3 months	3 months	6 months	6 months

Note - The table describes the performance of the model in matching the calibration targets. Panel 1 refers to the calibration based on CPS productivity series described in Section 4.1. Panel 2 refers to the calibration based on CES productivity series described in Section 4.3.

Table 3: Calibrated Parameter Values.

		Panel 1	Panel 2
		CPS-based productivity	CES-based productivity
$\bar{z}$	av. value of non-market activity	0.925	0.936
β	workers' bargaining power	0.117	0.078
l	matching parameter	0.618	1.449
c	cost of vacancy	0.577	0.584
δ	discount rate	0.9983	0.9966
s	separation rate	0.015	0.034
ρ	persistence of productivity	0.981	0.970
σ_ϵ^2	st. dev. of prod. innovations	0.0046	0.006
σ_ν^2	st. dev. of innovations to z	0.026	0.014
k	planning lag	3 months	6 months

Note - The table contains the calibrated parameter values in the two calibrations. Panel 1 to the calibration based on CPS productivity series described in Section 4.1. Panel 2 refers to the calibration based on CES productivity series described in Section 4.3. Note that the values of δ, s and c are not the same because the calibration in Panel 1 is based on a two week model period, while calibration in Panel 2 is based on model period of one month.

Table 4: Results from the Calibrated Model.

	u	v	v/u	w	p
Panel 1. CPS-based productivity, 1976:1 to 2006:4					
Standard Deviation	0.093	0.101	0.179	0.012	0.013
Autocorrelation	0.845	0.589	0.776	0.427	0.762
Correlation with p	-0.612	0.790	0.762	0.700	1.000
Panel 2. CES-based productivity, 1951:1 to 2004:4					
Standard Deviation	0.169	0.158	0.277	0.010	0.013
Quarterly Autocorrelation	0.844	0.456	0.753	0.413	0.765
Correlation with p	-0.298	0.468	0.449	0.610	1.000

Note - All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600. Calibrated parameter values are described in corresponding Panels of Table 3. The results in Panel 1 of this table should be compared to corresponding values in the data reported in Panel 3 of Table 1. The results in Panel 2 of this table should be compared to corresponding values in the data reported in Panel 1 of Table 1.

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