Comparative Advantage and Unemployment*

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Abstract

We model unemployment allowing workers to differ by comparative advantage in market work. Workers with comparative advantage are identified by who works more hours and earns more when employed. This enables us to test the model by grouping workers based on their long-term wages and hours from panel data. We calibrate the model so that its steady state exactly matches the average rates of separations, job findings, and employment for each group in the SIPP data. The model predicts, consistent with the data, that workers with weak comparative advantage will exhibit much more cyclical employment, with a big shift in separations during recessions toward low-hours workers, as in the SIPP. But, the model fails to generate the extent of fluctuations in separations for low-hours workers or the extent of fluctuations in finding rates for high-hours workers that we see in the data.

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1. Introduction

Does the Diamand-Mortensen-Pissarides (DMP) model capture fluctuations in unemployment? A number of authors, including Mortensen and Nagypal (2007) and Costain and Reiter (2008), point out that key to the answer are the rents to employment. If working yields a low flow of rents, then small shocks to the value of employment translate into large percentage shocks to the rents from employment that can yield large fluctuations in vacancies and unemployment. Establishing the size of these rents is difficult because they reflect hard-to-measure individual valuations of leisure and home production. But given workers differ markedly in both their hours and earnings when working, we expect them to differ markedly in their rents from employment–that is, in their comparative advantage in employment. Our approach is to ask how well the DMP predictions match what we see empirically across workers with high versus low comparative advantage.

We report employment, hours, and turnover patterns from the Survey of Income and Program Participation (SIPP). To get at high versus low market comparative advantage, we stratify men by their usual hours worked and wage rates when employed. Not surprisingly, lower-earnings workers show significantly higher rates of job separation and nonemployment. These workers also show much greater cyclicality in employment. There has been considerable discussion of the importance of cyclicality in separations versus finding rates (e.g., Shimer, 2005, Fujita, Nekarda, and Ramey, 2007). We find results differ drastically by comparative advantage–for low-hours workers separations largely drive cyclicality of employment, whereas for high-hours workers fluctuations in the finding rate are clearly the dominant factor.

To address these data we examine a Mortensen-Pissarides (1994) model of unemployment, with endogenous job separations and vacancies, but allow for workers to differ in their comparative advantage in market work. To generate dispersion in employment rents across workers we let workers differ in market human capital and in the value of their non-market time. We introduce enough dispersion in workers' market human capital to match the cross-sectional distribution of long-term wage rates in the data. Similarly, we introduce enough dispersion in workers' values of non-market time to capture the cross-sectional distribution of long-term hours worked conditional on being employed. To achieve this latter mapping to data, we introduce an intensive margin for labor supply. Workers with a high value of market human capital relative to non-market predictably work more hours. This identifies these workers as those with strong comparative advantage in the workforce—that is, high rents from employment.[1]

The paper proceeds as follows. We present the model of hours worked, separations, and vacancy creation in Section 2. In Section 3 we describe the SIPP data and present average patterns in employment, hours and turnover rates for four distinct groups of workers, stratifying both on workers' long-term wage rates and hours worked. In Section 4 we calibrate the model to four distinct groups in order to capture the dispersion in wage rates and hours worked observed in grouping the SIPP data. We calibrate the model so that it matches the average rates of separations, job-findings, and employment for each group in the SIPP data. In Section 5 we examine the model's cyclical predictions for our four groups, comparing to the patterns observed in the SIPP data. The model predicts that workers with low comparative advantage, that is low hours and wages, will exhibit more cyclical separations, more cyclical finding rates, and more cyclical employment. The data do clearly show more cyclical separations and employment for these workers. In fact, separations in the data are even more skewed toward low-hours workers during recessions than predicted. On finding rates the model does less well–in the data finding rates are actually more cyclical for high-hours workers, counter what we expect.

Hagedorn and Manovskii (2008) illustrate that it is possible for a flexible wage DMP model to generate employment cyclicality comparable to the data provided the replacement rate is sufficiently high. Our approach yields further discipline here. We allow high replacement rates for those workers with little comparative advantage; much higher replacement rates for these workers would predict falsely employment rates close to zero. Yet the large dispersion in hours and earnings across workers dictates a number of workers with nontrivial rents to being employed. As a result, we find that the model is unable to generate observed cyclicality of employment. The model under predicts cyclicality of separations for low-hours workers and, most strikingly, under predicts cyclicality of finding rates for workers with high hours, i.e., with high comparative advantage.

2. Model

We model unemployment determination with endogenous separations and vacancy creation, as in Mortensen and Pissarides (1994), while allowing for heterogeneity in workers' market skills and values of non-market time (differences in labor supply). We further depart by allowing for an intensive margin of labor supply, which we exploit for matching heterogeneity in labor supply

[1] Our setting shares features with Rogerson and Wallenius (2008), who allow both an extensive and intensive margins in modeling the response of total labor hours to tax changes. They model those workers at the beginning or end of the working life cycle as those with low market comparative advantage.

from the model to what we see in the SIPP data.

2.1. Environment

There is a continuum of infinitely-lived workers. Each worker has preferences defined by:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ c_{mt} + c_{nt} \right\} ,$$

where c_{mt} and c_{nt} are respectively consumption of a traded, market-produced good and a non-traded, home-produced good. We introduce consumption of the non-traded home produced goods in order to incorporate labor supply heterogeneity into the model. We follow Mortensen and Pissarides, and the rest of the literature cited above, by assuming linear utility from consumption.[2] The time discount factor is denoted by β. We assume that the market equates $(\frac{1}{1+r})$, where r is the rate of return on consumption loans, to this discount factor; so consumers are indifferent to consuming or saving their wage earnings.

Workers differ in terms of working ability in the market and productivity at home activities. We denote market ability by a. A worker's productivity at home is given by ab. So *relative* productivity at home, that is relative to market productivity, is b. A worker with a low value for b will have comparative advantage in the market (i.e., high rents to market work.) The cross-sectional distribution of workers in the economy is denoted by $\mu(a, b)$. In calibrating we consider two values for a and two values for b. In the introduction we referred to high versus low-wage workers and high versus low-hours workers. The model will map high-wage workers to high values of a and high-hours workers to low values for b. The correlation between a and b will reflect the cross-sectional distribution of wages and hours in the SIPP data.

Turning to the home activity, we relate the value of home production to time at home according to

$$c_{nt} = ab \cdot \frac{(1 - h_t)^{1-\frac{1}{\gamma}} - 1}{1 - \frac{1}{\gamma}} ,$$

where h_t are market hours. We assume γ is finite, implying diminishing returns to non-market time, $1 - h_t$, for the home activity. Our specification will yield a Frisch elasticity of labor supply

[2] A number of papers have allowed for diminishing returns to consumption in search and matching models of unemployment. (Recent examples include Bils, Chang, and Kim, 2008, Krusell, Mukuyama, and Sahin, 2008, Nakajima, 2007, and Shao and Silos, 2007.) Based on that work, we anticipate that the qualitative conclusions drawn here would survive allowing reasonable diminishing marginal returns to consumption.

for market hours h_t (the intensive margin) of $\gamma(\frac{1-h_t}{h_t})$.[3]

There is also a continuum of identical agents we refer to as entrepreneurs (or firms). Entrepreneurs have the ability to create job vacancies with a cost κ per vacancy. In calibrating we allow this cost to differ by skill and hours of the employment position, making it a function $\kappa(a,b)$. Entrepreneurs maximize the discounted present value of profits

$$E_0 \sum_{t=0}^{\infty} \beta^t \pi_t \ .$$

A worker is either matched with an entrepreneur and works (employed) or unmatched (unemployed) and available for a new match. A worker, when working, earns wages w_t. Note that w_t refers to the wage payment per period of employment, not the rate per hour. (The hourly wage rate is w_t/h_t.) This wage will differ across the workers, reflecting differences in a, b, and match quality as discussed below. These earnings are used to consume market goods. We assume, however, that there are some expenditures required by being employed, e.g. for transportation or clothing, that are not valued in c_{mt}. We set these expenditures to ω per period employed. Because they constitute a smaller share of earnings for high-wage, high-hours workers, this is an added source of market comparative advantage for these workers. If unemployed, a worker receives an unemployment income benefit of ϕ. In calibrating we assume ϕ to be proportional to worker's long-term earnings as captured by a and b.

There are two technologies in this economy—one that describes the production of output by a matched worker-entrepreneur pair and another that describes the process by which workers and entrepreneurs become matched. A matched pair produces output

$$y_t = a x_t z_t h_t,$$

where a is the worker's ability, x_t is idiosyncratic match-specific productivity (i.e., match quality), z_t is aggregate productivity, and h_t are market hours worked. Idiosyncratic match productivity and aggregate productivity evolve over time according to Markov processes, respectively

[3] We label c_n as home production, but one could alternatively view it as the value of leisure. The interpretation as home production strikes us as slightly more natural, given that we allow heterogeneity across workers in the efficacy of their non-market time. But one can certainly contemplate workers differing in how they view the payoffs to leisure activities. Burda and Hammermesh (2009) examine how the unemployed spend their time based on time-use surveys. They find that the unemployed spend most of their extra non-market time in added leisure and personal maintenance. But, by contrast, when the unemployment rate increases disproportionately in an area cyclically the reduced time in market work is offset almost entirely by added time allocated to household production.

$Pr[x_{t+1} < x'|x_t = x] = F(x'|x)$ and $Pr[z_{t+1} < z'|z_t = z] = D(z'|z)$.

We assume that the matching markets are segmented by worker type (a, b). These separate markets can be interpreted as search and matching that is directed by skill and by desired hours, as workers with a high value of home time will be interested in shorter hours (e.g., part-time jobs).[4] The number of new meetings between the unemployed and vacancies in each market is determined by a matching function

$$m_{it} = \eta u_{it}^{1-\alpha} v_{it}^{\alpha}.$$

v is the number of vacancies, while u is the number of unemployed workers. Each market is indexed by i where i reflects $a \otimes b$. The matching rate for an unemployed worker is $p(\theta_t) = m_t/u_t = \eta\theta_t^{\alpha}$, where $\theta_t = v_t/u_t$ is the vacancy-unemployment ratio, i.e. labor market "tightness" The probability that a vacant job matches with a worker is $q(\theta_t) = m_t/v_t = \eta\theta_t^{\alpha-1}$.

A matched worker-firm constitutes a bilateral monopoly. We assume the wage is set by bargaining between the worker and firm over the match surplus, as discussed just below, where match surplus reflects the value of the match relative to the summed worker's value of being unemployed and the entrepreneur's value of an unmatched vacancy (which is zero in equilibrium). There are no wage or other bargaining rigidities. Therefore, separations are efficient for the worker-firm pair, occurring if and only if match surplus falls below zero. Furthermore the choice of hours worked within the match is efficient, maximizing match value.

The timing of events is as follows. (1) At the beginning of each period matches from the previous period's search and matching are realized. Also aggregate productivity z and each match's idiosyncratic productivity x are realized. (2) Upon observing x and z, matched workers and entrepreneurs decide whether to continue as an employed match. Workers breaking up with an entrepreneur become unemployed, with the match permanently ended. (3) For matched workers, hours and wages are chosen and production takes place. Hours are chosen to maximize match surplus with the wage reflecting worker-firm bargaining. Concurrent with production, unemployed workers and vacancies engage in the search/matching process.

[4] Guerrieri, Shimer, and Wright (2009) characterize separating contracts in a search environment, such as here, with distinct types. Signalling high labor supply, by searching in a market that specifies employment with longer hours, will be more costly for low-labor-supply workers. We have verified that for our calibrated model high-b (low-labor-supply) workers have higher expected utility in their prescribed market than they would expect in the low-b market, working low-b hours.

2.2. Value functions and choices for hours, separations, and wages

We turn next to describing the value functions for employed and unemployed workers, as well as the determination of hours and wages within matches. The assumptions above of linear utility in consumption, linear production in labor, and a constant returns to scale matching function imply that choices for vacancies, separations, hours, and wages in the market for one labor group are independent of choices and outcomes in the other labor markets. For simplicity we dispense with a market index i in this section. We also dispense with time subscripts: variables are understood to refer to time period t, unless marked with a prime ($'$) denoting period $t+1$.

First, consider the choice of hours. We assume that firms and workers bargain efficiently, maximizing the value of match surplus. This requires choosing hours to equate the marginal product of an hour in the market to its marginal benefit at home: $axz = ab(1-h)^{-1/\gamma}$. So optimal hours at the intensive margin for a worker are

$$h^* = 1 - (\frac{b}{xz})^{\gamma} .$$

Turning to the value functions, a worker's valuation of being employed is

$$W(x,z) = (w(x,z) - \omega) + \frac{ab}{1-\frac{1}{\gamma}}((\frac{b}{xz})^{\gamma-1} - 1) + \beta E\left[\max\{W(x',z'),U(z')\}|\, x,z\right] .$$

Note that the expenditures necessitated by employment, ω, are netted from the wage payment. The value of home production reflects the optimal choice of market hours h^*. The maximization problem implicit in $W(x,z)$ is to choose a cut-off value, x^*, such that the match persists only if match quality x exceeds that value.

The value of being unemployed is

$$U(z) = \phi(a,b) + \beta(1-p(\theta))E\left[U(z')|\, z\right] + \beta p(\theta)E\left[W(\bar{x},z')|\, z\right] ,$$

Home production for the unemployed is normalized to zero. Recall that $p(\theta)$ is the probability that an unemployed worker matches with a vacancy. We assume that new matches begin with a match quality equal to the mean, $\bar{x}$, for the distribution of x. For the parameter values we consider, this ensures that workers will in fact accept new matches.[5]

[5] Alternatively, we could allow that new matches draw from a distribution of match qualities. The creation of new employment matches would then mimic our endogenous model of the separation decision–new employment matches would occur conditional on both matching and drawing a match quality x above a critical value x^*. Our

For an entrepreneur the value of a matched job is:

$$J(x,z) = axz(1 - (\frac{b}{xz})^{\gamma}) - w(x,z) + \beta E\left[\max\{J(x',z'),V(z')\}\middle|\, x,z\right] .$$

The value for current production reflects the optimal choice for hours. For a Frisch elasticity γ strictly greater than zero, hours are procyclical. In turn, this adds to the procyclicality of J. The value of a matched job J reflects the option value of being able to end the match for $t+1$ if match quality falls below x^*.

The value of a vacancy is:

$$V(z) = -\kappa(a,b) + \beta q(\theta)E\left[J(\bar{x},z')\middle|\, z\right] + \beta(1-q(\theta))E\left[V(z')\middle|\, z\right] ,$$

where recall that κ is the vacancy posting cost and $q(\theta)$ is the probability that a vacancy is filled. With free-entry in creating vacancies, in equilibrium $V(z)$ will equal zero.

We assume the wage payment is set by Nash bargaining between the worker and firm over the match surplus according to:

$$\underset{w}{\operatorname{argmax}} \; \Big(W(x,z) - U(z)\Big)^{\chi}\Big(J(x,z) - V(z)\Big)^{1-\chi},$$

where $0 \leq \chi \leq 1$ reflects worker share of match surplus. This wage payment is predictably increasing in ability a, especially since a increases the value of non-market as well as market time. For $\chi < 1$, the wage will also be increasing in relative home productivity b. For $\chi > 0$, the wage payment is increasing in match productivity x and aggregate productivity z. The impacts of x and z on the wage payment reflect not only their direct roles in productivity, but also their positive impacts on hours worked.

3. Cross-sectional Patterns from SIPP Data

We first describe the SIPP data, then use it to construct statistics on employment and turnover for four distinct groups based on workers' long-run hourly wages and hours worked when employed. In Section 4 we calibrate the model to feature four groups that align with the wage and

model predicts less creation of vacancies for workers with low comparative advantage in the market, resulting in these workers having a lower finding rate. Our model also predicts that these workers will exhibit a higher value for critical match quality x^*. Therefore, extending the model to allow for endogenous take up of new matches would reduce the finding rate further for workers with low comparative advantage. We do not pursue this, largely because the model already predicts a lower finding rate for workers with low hours than we observe in the SIPP data.

hours dispersion we see in the SIPP, then describe the model's steady-state features.

3.1. Our SIPP sample

The SIPP is a longitudinal survey of households designed to be representative of the U.S. population.[6] It consists of a series of overlapping longitudinal panels. Each panel is about three years in duration. Each panel is large, containing samples of about 20,000 households. Households are interviewed every four months. At each interview, information on work experience (employers, hours, earnings) are collected for the three preceding as well as most recent month. The first survey panel, the 1984 panel, was initiated in October 1983. Each year through 1993 a new panel was begun. New, slightly longer, panels were initiated in 1996 and again in 2001. In our analysis we pool the 12 panels, with the exception of the panel for 1989, which is very short in duration. Given the timing of panels, the number of households in our pooled sample will vary over time, with a gap between surveys at the beginning of 1996 and during 2000.

For our purposes the SIPP has some distinct advantages. Compared to the CPS, its panel structure allows us to compare workers by long-term wages or hours. It also provides information on employer turnover. Unlike the CPS, respondents who change household addresses are followed.[7] The SIPP has both a larger and more representative sample than the PSID or NLS panels. Individuals are interviewed every four months, rather than annually, so respondents' recall of hours, earnings, and employment turnover since the prior interview should be considerably better.

We restrict our sample to men between the ages of 20 and 60. Individuals must not be in the armed forces, not disabled, not be attending school full-time, and must have remained in the survey for at least a year. We further restrict the analysis to those who averaged at least one month of employment per year (so at least three separate months for someone with a typical three years of interviews) and who have data on both hours worked and earnings for at least one month.[8] The pooled sample that results consists of 73,416 separate individuals, representing data on employment status for 1,925,354 monthly observations.[9]

[6] We do employ SIPP sampling weights, however, in constructing all reported statistics. These weights are designed to maintain a representative sample despite sample attrition.

[7] Fujita, Nekarda, and Ramey (2007) present detailed results on the cyclicality of separation and finding rates for all workers in the SIPP, comparing these to patterns in the CPS.

[8] We treat self-employed workers as employed, rather than unemployed. We base a worker's market wage rates and hour worked only on months working for an employer (not self-employed) and only on months with usual weekly hours of at least 10.

[9] The SIPP interviews provide distinct answers on employment status and weeks worked for each of the prior four months. But for wage rates and weekly hours the data attribute the same values for each of the four months covered in an interview. Therefore, we restrict attention to the survey month observations in examining the

We focus on a respondent's monthly rates for being employed in a match, separating from employment, finding employment, hours worked, and hourly wages. We define a worker as employed in a match if he reports being with a job the entire month (with no more than two weeks without pay) and reports no weeks primarily involved in search. We also classify a worker who is temporarily away from work as employed in a match provided he returns to the same employer within three months and reports no weeks of searching. In this case, weeks not actively working are reflected in the worker's measured hour worked conditional on being matched–the intensive margin.[10] We will typically refer to men not employed in a match as unemployed. We believe this best conforms to the model's definition of unemployment. But note that, unlike official unemployment statistics, this classification does not require that the unemployed worker report actively searching for employment. Our sample of men averages an employment (matched) rate of 92.9%, with 7.1% for unemployed (unmatched). Our measures for monthly job separation and finding rates follow immediately given the definition for being matched with an employer: A separation corresponds to transiting from being matched to unmatched; a job finding is a transition from unmatched to matched. These rates average, respectively, 1.5% and 18.5% monthly for our sample.

Our measure of hours worked in a month (the intensive margin) reflects variations in hours worked per week, weeks worked per month, and occurrences of temporary layoffs.[11] We first multiply hours worked per week times weeks worked per month, then take the natural log. To reflect temporary layoffs, we then add to this a term $(\Gamma/\bar{\Gamma} - 1)$, where Γ is a zero/one variable equal to one if not on temporary layoffs, and $\bar{\Gamma}$ is the mean value of Γ (0.995 for our sample). But variability in this component, temporary layoffs, contributes relatively little to the variability of our measured intensive margin either cyclically or in judging workers' relative long-term hours. We measure the wage rate by the hourly rate of pay on the main job. More than sixty percent of workers report a wage in this form. For the others we construct an hourly rate from their reported hours and earnings, based on how the hourly wage projects on these variables for those who do report an hourly wage. We deflate the wage rate by the Consumer Price Index.

cyclicality of hours and wage rates in Section 4.

[10] Just under one-half of one percent of our sample fall under this "temporary layoff" category. So it does not have much impact on rates of employment and unemployment.

[11] Our measured weeks worked adjusts for the number of weeks in a month. Measured hours worked per week can reflect hours worked at up to two jobs.

3.2. Employment and turnover by long-term wages and hours in the SIPP

For each worker we first calculate their average (long-run) wage rate and average (long-run) hours worked. We then put the workers into one of four bins based on whether their long-run wage is above or below the median value and whether their long-run hours are above or below the median. To construct these we average a worker's (ln) hourly wage rates and (ln) hours worked over all months employed.[12] The median long-term wage is \$16.63 per hour in January 2009 dollars. The median long-term hours worked is 180 per month. The standard deviations equal 42% for the hourly wage and 19% for hours worked. The correlation between long-term wage and long-term hours is positive, but fairly small, at 0.15. Figure 1 presents the joint distribution of long-term wages and hours in the SIPP data.

Statistics for the four groups, low-wage/low-hours, low-wage/high-hours, and so forth, broken at the medians of wages and hours are contained in Table 1 through 3. Table 1 reports each group's share in the sample. Reflecting the modest positive correlation between long-term wage and hours, the diagonal groups, low-wage/low-hours and high-wage/high-hours are modestly larger, each at 26.7% of the sample, than the off-diagonal groups, low-wage/high-hours and high-wage/low-hours, each at 23.3% of the sample. But it is worth noting that the off-diagonal groups still combine for nearly half (46.6%) of the sample. For this reason, it would greatly misrepresent the data to model heterogeneity in labor supply as captured only by heterogeneity in market skills. We will often refer to groups by their location in the tables, e.g., northwest group for the low-wage and low-hours workers, southeast for high-wage, high-hours.

Table 2 reports each group's mean long-term (ln) wage and mean long-term (ln) hours, both expressed as its deviation from the mean for the entire sample. Overall, the high-wage workers exhibit 68% higher wages than the low-wage workers, with this differential 71% among workers with low hours and 64% among workers with high hours. High-hours workers, overall, work 25% more market hours than low-hours workers, with this differential a little larger among workers with low wages, 28%, than among low-wage workers, 22%.[13]

[12] We first project the natural log of a worker's hourly wage for each month, the natural log of his hours per month conditional being actively employed, and his value for the temporary layoff variable ($\Gamma/\bar{\Gamma} - 1$) on a full set of monthly dummies to obtain the worker's residual wage, hours, and layoff variable relative to other person's for that month. (This regression also includes a dummy variable for whether data is drawn from the earlier or later SIPP panels, as some hours and earnings variables change slightly beginning with the 1996 panel.) The residuals for these variables are then averaged across months for an individual to obtain his long-term wage and hours worked. Long-term hours worked reflects the sum of the variables for the worker's long-term hours worked conditional on being actively employed and his long-term mean for the variable capturing not on temporary layoff ($\Gamma/\bar{\Gamma} - 1$).

[13] Appendix tables A1 and A2 report on the distributions of schooling attainment and age for each of the four

Table 3 reports employment and turnover rates across the four groups. We focus first on the two extreme groups along the diagonal. The northwest group (low-wage/low-hours), those with weak comparative advantage in the market, exhibit an employment rate of only 87.6% compared to 96.8% for the southeast group (high-wage/high-hours), those with strong comparative advantage. This differential appears more extreme if viewed in terms of the unemployment rates, representing a rate nearly four times as large (12.4%) for the northwest group compared to that (3.2%) for the southeast group. Given this extreme differential, it is not surprising that the low-wage/low-hours workers display both higher separation rates and lower finding rates. But this difference is much more striking for separation rates. Workers in this northwest(low wages and low hours) show three times the separation rate as the opposite extreme group in the southeast (2.4% versus 0.8%), whereas their finding rate is only lower by a factor of about 20 to 25%. Thus, most of the difference in employment rates between the two extreme groups can be mapped back to the difference in separation rates.

Employment rates for the off-diagonal groups are intermediate to these two extremes. The employment rate for the southwest group (low-wage/high-hours) is 92.1%; for the northeast (high-wage/low-hours) it is 95.0%. Rates of separation project much more on workers' long-term wage rates, whereas finding rates are better explained by differences in hours worked. Workers with low-wages and high-hours actually show a slightly higher finding rate (22.1%) than high-wage/high-hours workers (21.3%). But the separation rate for these workers (1.9%) is much closer to that of the low-wage/low-hours workers. Similarly, the finding rate for high-wage/low-hours workers is even lower than that for the extreme group with both low wages and hours. But their separation rate (1.0%) is much closer to the southeast group with high wages and hours.

groups. The high-wage groups average about 1.5 more years of schooling than the low-wage groups, while the high-hours groups are, on average, about 2.1 years younger than those working less than the median number of hours. (Workers ages 51 to 60 are less common among low-wage workers who work high hours.) But it is clear that schooling and age differences capture only a modest part of the dispersion in wages and hours across groups. Appendix table A3 reports the fraction of workers in each group employed in cyclical industries–manufacturing, construction, and transportation. The fraction in cyclical industries is fairly similar across the four groups. So differences in employment cyclicality by group, reported below, should not heavily reflect differences in industry composition. The fraction in cyclical industries is modestly higher for the high-wage workers, averaging 43%, than for the low-wage, 34%. It is essentially the same for high-hours workers, 39%, and low-hours workers, 38%.

4. Calibration and Steady State

4.1. Calibrating to SIPP data

There are four types of workers in our model economy, with these types distinguished by two distinct values for market ability, a, and two distinct values for home productivity relative to market, b. We proceed by first calibrating the preference and matching parameters, which we assume to be common across the groups. We then present values for a and b to map out dispersion in wage rates and hours comparable to those in Table 2 from the SIPP data. Finally, we turn to choices for the remaining parameters that matches the average rates of employment, separations, and job finding across groups in Table 3.

The two preference parameters to calibrate are the discount factor and the Frisch elasticity for the intensive labor margin. We use a monthly discount factor β of 0.9966, implying an annualized real interest rate of 4%. The Frisch elasticity, equal to $\gamma(\frac{1-h}{h})$, reflects both the parameter γ and the level of hours worked. Recall that hours worked equal $1-(\frac{b}{xz})^{\gamma}$. We normalize, for all groups, the mean for the distribution of match quality, x, and steady-state aggregate productivity, z, both to one. This implies market hours, evaluated at mean match quality, of $1-b^{\gamma}$. We then set b and γ so that these market hours equal 0.5, with a Frisch labor supply elasticity of one third, for our high hours workers. This requires $\gamma = 1/3$ and $b = 1/8$. Kimball and Shapiro (2003) and Hall (2009) each survey estimates for the Frisch elasticity. Much of the evidence suggests a value of 0.5 or below. Hall, largely based on Pistaferri (2003), chooses a value of 0.7. We impose the same parameter value of 1/3 for γ across our four groups. This implies a larger Frisch elasticity for workers who work shorter hours, with the average Frisch elasticity across our groups equal to about 0.44.

We set both the bargaining share for workers χ equal to 0.5, corresponding to symmetric Nash bargaining. We also set the matching power α to 0.5 so that the Hosios (1999) condition holds. We believe these values achieve comparability with the widest range of the literature.

We now turn to the parameters that differ across groups. We choose the size of the four groups to match those in the SIPP data: 27% for the two extreme groups along the diagonal and 23% for the off-diagonal groups. We normalize market ability a for the higher productivity groups to one. We choose the earnings ability for low-wage groups ($a = 0.5$) to make the cross-sectional dispersion of log wages across our four groups in the model roughly comparable to that of long-term wages in the SIPP data. For the low-hours groups, we set relative home productivity (relative to market) equal to 0.25 in order to generate a cross-sectional dispersion in log hours that mimics the data. Table 4 presents the ability parameters (a, b) respectively each of the four groups.

The key outcomes we target across groups are the average rates of separations and job finding in the SIPP data. In turn, these rates depend primarily on the replacement rate while unemployed, the size of idiosyncratic shocks to matches, and the vacancy posting cost. The size of the replacement rate reflects the unemployment benefit, ϕ, the expenditure saved by not working, ω, and the extra home production when unemployed.

We assume the unemployment benefit (ϕ) is proportional to each group's earnings evaluated in steady state at match quality equal to one (the unconditional mean of its distribution).[14] We set the unemployment benefit to correspond to 20% of long-term earnings.[15] Shimer (2005) assumes a replacement rate of 40%; but for his calibration this rate should reflect any gains with unemployment from increased leisure or home production, whereas we have this as an explicit, separate component. We set the expenditure necessitated by work, ω, at 0.05. This represents 10% of long-run earnings for workers with high wages and hours and, at the other extreme, nearly 27% of earnings for workers with both low wages and low hours.[16] The gain in home production while unemployed for the two high-hours groups (given the values for h, b, and γ) equals 37.5% of market productivity; whereas for the two groups with low hours it is 51.3%. Combined with the unemployment benefits and expenditures required for working, this yields a steady-state replacement ratio equivalent to 67.5% of market output for the southeast group. This value is considerably higher than the 40% employed by Shimer's calibration, but close to the replacement rates assumed by Costain and Reiter (2003) and by Hall (2005a). Those authors, however, employ that ratio for all workers, whereas we employ it only for high-wage/high-hours workers. The replacement rates for each of the four groups is presented in Table 4. We view

[14] Anderson and Meyer report the level of unemployment benefits by wage decile based on the 1993 panel of the SIPP data. Benefits, as a share of earnings, are much lower at higher wages. But unemployment is also greatly skewed toward lower wage workers. If the breakdowns in benefits by wage from Anderson and Meyer are viewed together with a breakdown in unemployment by wage, this suggests an elasticity of unemployment benefits with respect to wage that is close to one.

[15] Hall (2005b) shows that the replacement rate has been about 15 percent in recent years. We prefer to err on the high side in calibrating the replacement rate, as a lower rate would serve to reinforce our negative conclusions for the model discussed in Section 5.

[16] Aguiar and Hurst (2009) argue, based on life-cycle spending patterns, that an important component of spending on food away from home, clothing, and transportation reflect employment variation over the lifecycle. They regress spending shares by category on separate dummy variables for employment of the husband and wife. The estimated impact of employment, given total consumption, just on these three categories support assuming that 5% or more of consumer spending is driven by employment expenses. In addition, any costs that fall on the employer that have a fixed, per worker, nature should also be folded into ω, as these costs would act in the model precisely like the expenditures in ω. One example of such costs are payroll taxes (e.g., FICA or for UI) that have a per worker component or are capped above some earnings level.

this as a generous calibration for these replacements rates–the average rate across the groups is 82%, with low-wage, low-hours workers (which make up 27% of the labor force) assumed to have very low rents from employment.[17]

We assume shocks to match-specific productivity that are highly persistent, setting their autocorrelation equal to 0.98. We then set the volatility of these shocks, σ_x, together with the vacancy posting cost, κ, in order to mimic the monthly separation and finding rates that we reported for each group in the SIPP data in Table 3. For instance, for the high-wage, high-hours group this is achieved by $\sigma_x = 0.027$ and $\kappa = 0.31$.

For $\sigma_x = 0.027$, the model generates wage dispersion for employed workers in the southeast group of 5% from differences in match quality. It generates cross-sectional dispersion in monthly wage growth of about 3%. We view these values as conservative relative to the empirical literature.[18] Table 5 reports the calibrated values of σ_x for each of the four groups. For the two groups with low hours σ_x is close to 3%, and close to that for the southeast group. But for the southwest group (those with low wages, but high hours) σ_x is considerably higher at 7.6%. The higher value for these workers is required to capture their high separation rates in conjunction with working high hours when employed.

For each group we compute the expected vacancy posting cost per hire, $\kappa/q(\theta)$, the cost of recruiting a worker, and then scaling this expected cost by months of worker output, $\frac{\kappa/q(\theta)}{ah}$. According to Table 5, for high-hours workers (the southeast and southwest groups) this expected cost is about 1.5 months of output. For the northwest group (low-hours and low wage group) the expected cost is only about a half month's earnings. This lower cost is required for the model to explain why these workers, while having far below average earnings, exhibit a finding rate that is nearly ninety percent that of the overall average. These facts push the model in the direction of a spot market for this group, that is, relatively low vacancy costs with relatively high rates of turnover.

[17] This is evaluated for match quality, x, equal to its unconditional expected value of 1. Workers select into values of match quality that average higher, as bad matches lead to separations. For our calibration, this selection raises wages by 3% for high-wage workers and by 10% for low-wage. So, for instance, for the southeast group the replacement rate relative to mean actual earnings is about 65 percent.

[18] For instance Topel and Ward (1992), based on administrative data, report a standard deviation in annual rates of growth in earnings of 19%. This dispersion is considerably greater than generated by our model with $\sigma_x = 0.027$. Increasing σ_x would reinforce our conclusion that the DMP model fails to generate cyclicality in the extensive margin. A higher σ_x causes match rents to become more disperse, making separations and employment less responsive to aggregate shocks.

4.2. Steady State

Table 6 presents the model's steady-state wages and hours worked for each of the four labor groups. Across low-hours workers, the high-wage group displays a wage that is 68% greater than the low-wage group. Across high-hours workers the wage differential between wage groups is lower at 58%. This reflects both that high-hours workers exhibit a lower reservation match quality for staying employed and bargain for a slightly lower wage given productivity. The difference in wages across groups in Table 4 matches pretty closely the average differential by group observed in the SIPP data (Table 2). But wage dispersion in the SIPP, with standard deviation of 42%, is greater than the 32% for our model economy as it reflects dispersion within as well as between the four groups. Turning to hours, each high-hours group for the model displays hours worked of about 30% higher than that for the low-hours group with comparable wage rates. This is close to what we see in the SIPP data, where those differentials are about 25%. The model generates an overall standard deviation in hours worked of 15%, lower than that of 19% for the SIPP data. The cross-sectional correlation of log hours and log wages in our model is 0.09, somewhat lower than that in the SIPP (0.15). The higher standard deviations of wages and hours, and their slightly higher correlation, in the SIPP data reflects its heterogeneity of wages and hours within each of the four groups. This is missing for the model simulated data, except for the effects of small differences in match quality. For this reason, in examining the cyclical behavior of hours for each group in Section 4, we correct for any cyclical compositional effects within each group.

The model has been calibrated to capture the separation and finding rates by group; so the model's steady state produces these rates that match quite closely those reported from the SIPP data in Table 3, as well as each groups employment rate. Most of the differences in employment rates across the four groups is captured just by the differences in the values of market and non-market productivity by group, parameters a and b.[19]

The differences in separation and finding rates across the four groups are directly related to the rents to employment. These rents are represented by the difference between the match quality, x, that a worker has in employment versus the critical match quality, x^*, at which the

[19] We considered a more parsimonious calibration where these are the only parameters that differ by group, with both the standard deviation of match shocks and the vacancy posting cost, relative to worker product, constrained to be equal across groups. That more restrictive version generates comparable dispersion in employment rates across the four groups, but under-predicts the separation rates for the low-wage groups and under-predicts the finding rate for the northwest group. The cyclical predictions for that more parsimonious calibration are similar to those reported below, with the primary difference that it predicted greater cyclicality of separations for the low-wage, high-hours workers. These results are presented in our NBER working paper by this title.

match would be dissolved—a match with $x = x^*$ would have zero rents. In Figure 2 we present the distributions of match rents (measured by $x - x^*$) separately for each of the groups. The low hours groups (northwest and northeast) show distinctly less surplus than the high-hours groups. In particular, the fraction of matches with $x - x^*$ less than 0.02 is nearly twice as large for the low-hours workers than those with higher hours. These distributions of match rents, especially at low values of $x - x^*$, are telling for the cyclical behavior of separations and employment across the four groups, which we examine next. For the northwest group about 5% of matches exhibit $x - x^*$ smaller than 0.02, whereas for the southwest group about only about 2% of matches exhibit $x - x^*$ smaller than 0.02. This implies that a 2% decrease in aggregate productivity would make more than 5% of current matches dissolve for northwest group whereas for southwest group only about 2% of matches would dissolve in that event. In sum, the larger number of workers with low values for match rent for the low-hours groups predicts a sharper increase in separations during a downturn for these workers–a prediction dramatically supported by the data.[20]

5. Business Cycles

We are now in position to compare the labor market business cycles produced by our calibrated model to what we observe from the SIPP data. We create business cycles for the model by hitting each group with persistent shocks to aggregate productivity z. (These shocks display an autocorrelation of 0.97, with innovation standard deviation of 0.77%, chosen to match the cyclical property of labor productivity.) We first compare the model and data in terms of their predictions for the relative size of cyclical fluctuations in employment across the four groups. Secondly, we examine whether the model and data conform in their predictions for the relative importance of the intensive, hours margin and the extensive, employment margin for each of the groups. Thirdly, we look in more detail at the employment response by examining the cyclicality of separation and finding rates across the four groups. Lastly, we examine the cyclical implications of aggregating our four labor groups.

5.1. Cyclicality in Hours and Employment

In Table 7 we compare the response of employment for each of the four groups to aggregated employment (the estimated coefficient from the regression on aggregate employment), comparing

[20] The lower average value of $x - x^*$ for these workers means that a decline in aggregate productivity, which increases x^*, will create a greater percentage drop in $x - x^*$, in turn causing a larger reduction in vacancy creation rates and finding rates for workers with low hours. This prediction is not supported by the data.

the model predictions to the evidence from the SIPP. For both the SIPP and model series we HP filter with monthly smoothing parameter 900,000. We also remove monthly seasonals for the SIPP-based series.[21] We instrument for aggregated employment reported in the SIPP based on the U.S. unemployment rate for men and average weekly hours for workers, both reported by the BLS. (The unemployment rate is based on the Current Population Surveys, weekly hours on Current Employment Statistics.) We instrument so that measurement error in the SIPP does not influence the estimated relative importance of employment responses across groups or the relative importance of employment and hours responses.

Focusing on the extreme groups in Table 7, both the model and the data display much larger cyclical employment responses for low-wage, low-hours workers than for those workers with higher wages and hours, but for the model this contrast is more extreme. For the data, the employment response for the northwest group (low-wage/low-hours), those with weak comparative advantage, is 1.71 times the aggregate response, whereas for the model that ratio is 2.59. For the data, the employment response for the southeast group (high-wage/high-hours) is only 0.42 times the aggregate response; but for the model is only 0.24. In the SIPP data the intermediate groups each display cyclical employment responses that are 0.7 times the aggregate response. For the model these responses are 0.76 for those with high wages, but low hours, and 0.41 for those with low wages, but high hours. In sum, for the model employment cyclicality is confined to a greater degree to the low-wage workers compared to what we see in the data.

In Table 8 we compare the response of hours worked and employment to cyclical movements in aggregate total labor hours—the regression coefficient of the variable on aggregate labor hours.[22] We instrument for aggregated total hours reported in the SIPP, again based on the national unemployment rate for men and national weekly hours. The model and the data match best for the low-wage, low-hours workers (the northwest group)–both predict a greater cyclical response for the extensive margin. But for the model the employment response is 1.5 that in hours, whereas in the data employment responds by 2.5 times as much. For each of the other

[21] The SIPP surveys have breaks in coverage during 1996 and 2000. These breaks are exaccerbated because we restrict our employment series to months that reflect at least half of a full SIPP panel, and a panel rotates in (and out) over a four month period. This results in a time series for employment from August 1983 to September 2003, with 226 monthly observations plus 16 missing months. (We base the HP filter for a SIPP-based series on that series with interpolated values for the missing gaps.)

[22] Aggregated total labor hours equals the average across all workers of the sum of ln(hours) and the percentage deviation of the zero/one employment rate from its mean value. For the data, the hours statistics correct for cyclical compositional changes by long-term hours *within* each group. For each group we calculate a time-series for the mean fixed effect of employed workers for hours. The series for the fixed effect in hours is then netted from the time series for hours.

three groups the model substantially under predicts the relative cyclicality of the employment margin. For both intermediate groups (the northeast and southwest) the model predicts cyclical responses in the hours margin that are more than double that for employment; but in the data this ratio is nearly reversed. For the high-wage, high-hours group both the data and the model show a greater response in hours, rather than employment. But the model predicts an hours response that is four to five times the magnitude of that for employment, whereas in the data these responses are comparable in size.

5.2. Cyclicality in Separation and Finding Rates

The responses, by group, of separation and finding rates to the aggregate total labor hours are given in Table 9. We know from Table 8 that the response in employment in the data exceeds that predicted by the model for each of the groups except those with low wages and low hours. The results in Table 9 suggest whether this reflects an inability to predict the cyclicality of separations or that of findings.

The results differ notably by group. The model predicts greater cyclicality in separations for low-hours workers. For the northwest group, those with weakest comparative advantage, the job separation rate decrease by 2.8% in response to a 1% increase in aggregate labor hours, while for the northeast group the predicted decrease is similarly 2.5%. In the data, the separation rate decreases dramatically for both low-hours groups. So qualitatively this is a success for the model—separations are much more cyclical for these workers. But in the data separation rates for low-hours worker, both low and high-wage, are much more cyclical than even captured by the model. Pooling the two groups, a 1% increase in aggregate labor hours is associated with a response in separation rate of -5.5% (with standard error of 1.5%). By contrast, pooling the two high-hours groups in the SIPP data producing an insignificant response in separations (coefficient of -0.2%, with standard error of 1.5%). Turning to finding rates, we see that both the data and model display procyclical finding rates for all four groups. But for the most cyclical workers, those with low wages and low hours, the model predicts the finding rate increases by 7.08% in response to a 1% increase in aggregate total labor hours whereas this rate increases by 2.41%. For this group most of the cyclical action in the SIPP data occurs through counter-cyclical separations. By contrast, the model under predicts a strong cyclicality in finding rate for high-hours workers. Pooling the two high-hours groups in the data, a 1% increase in aggregate labor hours is associated with an increase in finding rate of 5.0% (with standard error of 0.9%). This is actually much more cyclical than the coefficient of 2.3% (standard error 1.1%) obtained by pooling the low-hours groups.[23]

To summarize, the model does not generate enough counter-cyclicality in separations of low-hours workers (those with weak comparative advantage), or enough procyclicality in job-finding rates of high-hours workers (those with strong comparative advantage).

5.3. Aggregate patterns

Aggregation puts more weight on the low-wage, low-hours workers over the business cycle due to their much greater cyclicality. Table 10 presents statistics on cyclicality of hours versus employment, for the SIPP data and for our model economy, aggregating the workers into a single workforce. In the data cyclical fluctuations in employment are more important, contributing about 70% of fluctuations in total hours. The model's aggregated simulated data predicts that cyclical fluctuations are actually reflected more in hours (58%) than in employment (42%). So the model substantially understates the importance of the extensive margin. Aggregating does increase the importance of the employment margin for the model, compared to the simple average of its importance across each of the four groups reported in Table 8. This reflects the disproportionate weight of the low-wage, low-hours workers in aggregate fluctuations. For this group the model does generate that the majority of fluctuations occur through the extensive margin.

Table 11 presents the responses of aggregate turnover rates to total labor hours for both the data and model. For our model a 1% increase in aggregate total hours is associated with a decrease in the separation rate of 1.73%. The data show a larger decrease of 3.0%. The cyclicality of the finding rate, again conditioning on the same 1% increase in total labor, is modestly larger for the model than data (4.6% for model compared to 3.9% for the data). This discrepancy can largely be traced to the low-wage, low-hours workers. From Table 9, the model predicts that much of cyclicality for this group occurs through the finding rate, whereas in the data cyclicality of employment is much more driven by the separation rate. This group receives disproportionate weight in determining the aggregate cyclicality of the finding rate as they make up nearly half of the unemployed. For this reason, the aggregated statistics show a coefficient

[23] Shimer (2005) and Hall (2005a) each point to wage rigidities as a possible explanation for very procyclical finding rates. But wages are actually more procyclical for this group, those with low-wages and high hours, than for the other three. More generally, we do not draw comparisons of wage cyclicality for the model and data because it is difficult to ascertain the allocative wage if there is wage smoothing as anticipated by the implicit contracting literature. For example, we find an aggregate response of wages to total hours of 0.34 (standard error of 0.12) compared to a model prediction of 1.02. But if we restrict the sample to new hires, those hired within the past 12 months, the wage response in the SIPP data increases from 0.34 to 0.90 (with standard error of 0.32).

of cyclicality for the finding rate, conditional on a change in total labor, that is well above the model's average across the four groups and well above that displayed by the data.[24]

For both the model and data, we see that separations are skewed during recessions toward workers who work fewer hours, independently of the cycle. In turn, this creates a compositional shift during recessions toward a pool of unemployed who typically work fewer hours. For the model a percentage point drop in employment reduces the average long-term hours worked of the unemployed by almost 1% purely from this compositional impact on the shares of the four groups in the unemployed pool. For the data we find that this same compositional effect reduces the average long-term hours of the unemployed by 0.3%.

5.4. Alternative Specifications

We find that the model best explains cyclicality for the group of low-wage, low-hours workers, though even for this group it considerably understates employment fluctuations. This raises the question whether model could do better if we partitioned the data so as to allocate more workers to the low-wage, low-hours group. We do not find this to be the case. If we raise the maximal wage and maximal hours that define the low-wage, low-hours workers this produces higher average wages and hours in each of the four groups. In turn, calibrating to these new groupings will yield greater employment rents within each group—predicting less cyclical employment by group result in higher thresholds, raise earnings in each group, so while putting more workers in the relatively cyclical, the calibrated model would imply more rents, less cyclicality of employment

[24] Shimer (2005) stresses that his calibrated DMP model generates a standard deviation for (ln)unemployment relative to that for labor productivity that is about one half, whereas in the data this ratio is about 10. We have not emphasized this statistic. Because we cannot say that the only disturbance to employment is productivity shocks, we do not want to judge the model by unemployment's volatility relative to volatility only in measured productivity. But it is useful to report these relative volatilities for our model's simulated business cycles to facilitate comparing our model to others in the literature. Appendix Table A7 reports this statistic for the model for each group. It also reports the correlation between unemployment and vacancies, the Beveridge Curve, by group. When aggregated, the model economy generates a standard deviation for unemployment, relative to that of labor productivity, of 3.7. This is much larger than for Shimer's calibration, though only a third that for the data. There are three reasons for this. Most importantly, Shimer assumes a 40% replacement whereas the average of this rate across our four groups is much higher at 82%. Second, Shimer assumes a constant separation rate, whereas our model's separation rate is countercyclical and with a standard deviation nearly that for the unemployment rate. Third, because volatility increases non-linearly with the replacement rate, the very high volatility for our low-wage, low-hours group is not offset by the low volatility of the high-wage, high-hours group. If we simulated our model economy with the same average replacement rate, average σ_x, and average hiring cost per unit of output, but with no heterogeneity, it would produce a standard deviation for (ln)unemployment that is lower by nearly a third. The model economy generates a Beveridge curve for low-earnings workers, but little for others. The correlation between unemployment and vacancies equals -0.57 for low-wage, low-hours workers, but only -0.05 for the group with high wages and hours. When aggregated, the model economy generates as strong of a Beveridge Curve, correlation -0.57, as that just for those with low wages and hours. This reflects the disproportionate importance of the low-wage, low-hours workers in the unemployment pool. It also reflects the cyclical shift of the unemployed pool during recessions toward this group, which generates a lower vacancy rate.

for each group. For instance in appendix tables A4 through A6 we report statistics for four groups partitioned based on whether long-term wages and hours are above the 75th percentile of each distribution. The newly defined northwest group (low-wage, low-hours) is of course now much larger, at 57% of the sample. But this group now displays a 19% higher average wage and 7% higher average hours. As result, when we calibrate parameters a and b to hit these higher earnings, we find that our northwest group, while twice as large, exhibits less than half as much cyclicality in its separation, finding, and unemployment rates. Furthermore, looking at the Table A4, we see that earnings go up considerably for each of the other three groups; so the model will predict less cyclicality for each of these groups as well. We also explored breaking the population more finely into 9 groups (3 wage by 3 hours groups). But this did not qualitatively alter our conclusions.

Models with higher replacement rates would generate a larger employment responses in general. However, the model does not capture the cyclicality of employment for workers with comparative advantage even though the replacement rates we allow for these workers–67% for high-wage/high-hours workers and an average of 80% for the two groups off the diagonal–is fairly high. More importantly, increasing replacement rates, for example by raising the fraction of earnings replaced by unemployment insurance, is not a reasonable solution. To generate a cyclical response in employment (relative to hours) for high-wage/high-hours workers like what we see in the data requires doubling unemployment insurance, from 20 to 40% of earnings. But calibrating unemployment insurance at this level, while respecting the wage and hours differences across workers, drives the total replacement rate on average above 100% for the other three groups. In particular, the replacement rate for workers with low wages and hours goes well above 100%. As a result, the model predicts zero employment for these workers, whereas in the data their employment rate is over 80%.

We assume that Frisch elasticities for hours is one third for high-hours workers and a little over one half for workers with lower hours. One might conjecture that the model's failure to capture the relative importance of the extensive versus intensive margins could be fixed by assuming smaller Frisch elasticities. But this is problematic. Reducing the Frisch elasticity makes market and non-market work poorer substitutes, which acts to increase the gains from employment. For instance, cutting the Frisch elasticities in half reduces the effective replacement value from leisure by 18% of earnings for high-hours workers and by 23% of earnings for low-hours workers. As a result, the model will generate much smaller employment fluctuations for all groups. This is exacerbated by the fact that, to generate realistic separations with the higher employment rents, the calibrated model requires larger match-specific shocks (larger σ_x), further insulating employment from cyclical shocks. Thus, reducing the Frisch elasticity to low values does not correct the failure of the model to predict the cyclicality of employment compared to hours.

6. Conclusions

We have examined the ability of a DMP model of unemployment to explain cyclical fluctuations in both the employment and hours margins. Key to generating large fluctuations in the DMP model is the presence of sufficiently many workers who have little comparative advantage in the market (low rents to employment). Using the model, we map high market comparative advantage to working high hours conditional on being employed. This allows us to calibrate our model to the distribution of long-term wages and hours in panel data (the SIPP data).

The model predicts, qualitatively correctly, more cyclical separations and employment for low-hours workers. But the model under predicts cyclicality in separations for low-hours workers (those with weak comparative advantage) and especially under predicts cyclicality in finding rates for high-hours workers (those with strong comparative advantage). As a result, it under-predicts the cyclicality of employment, especially for workers with higher comparative advantage in the market, that is, those with higher hours and earnings.

TABLE 1
Shares by group from SIPP data

	Wage Group	
Hours Group	Low wage	High wage
Low hours	26.7%	23.3%
High hours	23.3%	26.7%

TABLE 2
Deviation from Sample Means in Long-term Wages and Hours by Group
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	high wage
Low hours	Wage: −37% Hours: −15%	+34% −10%
High hours	−30% +13%	+34% +12%

Based on sample of 73,416 men. Overall means are 2.70 for ln(wage) and 5.23 for ln(hours). Overall standard deviations are 0.42 for ln(wage) and 0.19 for ln(hours). Correlation between long-term wage and hours equals 0.15.

TABLE 3
Employment, separation, and finding rates by group
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Employment: 87.6% Separations: 2.36% Findings: 16.8%	95.0% 0.97% 15.5%
High hours	92.1% 1.89% 22.1%	96.8% 0.77% 21.3%

Overall means are 92.9% for employment (7.1% for non-employment rate), 1.45% for separation rate, and 18.5% for finding rate.

TABLE 4
Calibrated productivities and replacement rates by group

	Wage Group	
Hours Group	Low wage	High wage
Low hours	a = 0.5 b = 0.25 replace rate = 98.4%	a = 1.0 b = 0.25 replace rate = 84.8%
High hours	a = 0.5 b = 0.125 replace rate = 77.5%	a = 1.0 b = 0.125 replace rate = 67.5%

TABLE 5
Match-specific productivity shocks and vacancy posting cost across group

	Wage Group	
Hours Group	Low wage	High wage
Low hours	$\sigma_x = 3.5\%$ $\kappa / q(\theta) = 0.09$ $\frac{\kappa / q(\theta)}{ah} = 0.46$	$\sigma_x = 2.45\%$ $\kappa / q(\theta) = 0.40$ $\frac{\kappa / q(\theta)}{ah} = 1.07$
High hours	$\sigma_x = 7.6\%$ $\kappa / q(\theta) = 0.36$ $\frac{\kappa / q(\theta)}{ah} = 1.43$	$\sigma_x = 2.7\%$ $\kappa / q(\theta) = 0.76$ $\frac{\kappa / q(\theta)}{ah} = 1.51$

TABLE 6

Deviation from Overall Means in Long-term Wages and Hours by Group

(***Model simulations***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Wage: −34% Hours: −14%	+34% −16%
High hours	−29% +16%	+29% +13%

Overall standard deviations are 0.32 for ln(wage) and 0.15 for ln(hours). Correlation between long-term wage and hours equals 0.09.

TABLE 7
Relative business cycles in Employment by Group, Data compared to Model

	Wage Group			
Hours group	Low wage		High wage	
	SIPP data	Model	SIPP data	Model
Low hours	1.71 (0.09)	2.59 (0.11)	0.71 (0.12)	0.76 (0.23)
High hours	0.73 (0.07)	0.41 (0.03)	0.42 (0.06)	0.24 (0.04)

Coefficients are responses of (ln) employment rate to aggregated (ln) employment rate. For the SIPP data, the employment rate is instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for the model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 8
Business cycles in Hours and Employment by Group, Data compared to Model

		Wage Group			
Hours group		Low wage		High wage	
		SIPP data	Model	SIPP data	Model
Low hours	Hours:	0.46 (0.06)	0.73 (0.05)	0.26 (0.03)	0.80 (0.04)
	Employ-ment:	1.19 (0.09)	1.11 (0.14)	0.50 (0.07)	0.33 (0.03)
High hours		0.31 (0.08)	0.46 (0.02)	0.33 (0.05)	0.49 (0.03)
		0.48 (0.07)	0.17 (0.02)	0.28 (0.04)	0.11 (0.01)

Coefficients are responses of (ln) hours and (ln) employment rate to aggregated (ln) total hours (employment times hours). For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for the model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 9
Business cycles in Separation and Finding Rates, Data compared to Model

		Wage Group			
Hours group		Low wage		High wage	
		SIPP data	Model	SIPP data	Model
Low hours	Sep's:	−5.62 (1.69)	−2.82 (0.31)	−5.08 (1.85)	−2.48 (0.20)
	Find's:	2.41 (1.08)	7.08 (0.33)	2.55 (1.75)	3.45 (0.09)
High hours		0.28 (1.58)	−0.51 (0.14)	−2.22 (2.00)	−1.29 (0.28)
		5.35 (0.99)	1.97 (0.08)	3.43 (1.71)	1.89 (0.08)

Coefficients are responses of of (ln) separation rate and (ln) finding rate to aggregate (ln) total hours (employment times hours). For the SIPP data, aggregate total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; standard deviations for the simulations are in parentheses.

TABLE 10
Aggregate Business cycles in Hours, and Employment, Data compared to Model

	SIPP data	Model
Hours	0.31 (0.03)	0.58 (0.04)
Employment	0.69 (0.03)	0.42 (0.04)

Coefficients are responses of aggregated (ln) hours and (ln) employment rate to aggregated (ln) total hours (employment times hours). For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; the standard deviations for the simulations are in parentheses.

TABLE 11
Aggregate Business cycles in Turnover, Data compared to Model

	SIPP data	Model
Separation rate	−3.02 (1.38)	−1.73 (0.20)
Finding rate	3.90 (0.80)	4.59 (0.20)

Coefficients are responses of (ln) separation rate and (ln) finding rate to the aggregated (ln) total hours. For the SIPP data, total hours are instrumented based on U.S. average weekly hours and the unemployment rate for men. All monthly series are HP-filtered, with parameter of 900,000. SIPP data are seasonally adjusted. The SIPP data reflect 223 monthly observations per group. Standard errors (Newey-West corrected) are in parentheses. Statistics for model are means across 100 simulations; the standard deviations for the simulations are in parentheses.

TABLE A1
Schooling by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	mean: 12.5 years 21.4% < 12 yrs 40.2% = 12 yrs 38.4% > 12 yrs	13.7 years 8.6% 35.1% 56.4%
High hours	12.7 years 17.4% 41.6% 41.0%	14.5 years 4.6% 25.6% 69.8%

Overall statistics: Mean 13.3 years, 13.9% <12 years, 35.9% =12 years, and 50.2% >12 years.

TABLE A2
Ages by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	mean: 37.2 years 31.4% are 20-29 51.3% are 30-50 17.3% are 51-60	41.2 years 13.3% 65.8% 21.0%
High hours	34.2 years 40.4 50.8 8.9	39.9 years 14.0 70.7 15.3

Overall statistics: Mean 38.1 years, 25.2% are 20-29, 58.9% are 30-50, 15.9% are 51-60.

TABLE A3

Fraction in Cyclical Industries by Wage and Hours Group (SIPP data)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	34.6%	43.5%
High hours	32.8%	42.2%

Industries classified as cyclical are construction, manufacturing and transportation. The overall fraction of workers in these industries is 38.3%.

TABLE A4

Shares by Group from SIPP data with Breaks at 75th percentiles

	Wage Group	
Hours Group	Low wage	High wage
Low hours	57.0%	18.0%
High hours	18.0%	7.0%

TABLE A5
Deviations in Long-term Wages and Hours with Breaks at 75th percentiles
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	high wage
Low hours	Wage: −18% Hours: −8%	+51% −5%
High hours	−14% +23%	+53% +22%

Based on sample of 73,416 men. Overall means are 2.70 for ln(wage) and 5.23 for ln(hours). Overall standard deviations are 0.42 for ln(wage) and 0.19 for ln(hours). Correlation between long-term wage and hours equals 0.15.

TABLE A6
Employment, separation, and finding rates by group with breaks at 75th percentiles
(***SIPP data***)

	Wage Group	
Hours Group	Low wage	High wage
Low hours	Employment: 91.0% Separations: 1.80% Findings: 18.1%	95.5% 0.92% 16.3%
High hours	94.3% 1.40% 21.8%	97.4% 0.61% 20.0%

Overall means are 92.9% for employment (7.1% for non-employment rate), 1.45% for separation rate, and 18.5% for finding rate.

TABLE A7

Cyclical Statistics for Model: Standard Deviation for Ln(unemployment) verus Ln(productivity), and correlation of Ln(unemployment) and Ln(vacancy rate)

	Wage Group		
Hours Group		Low wage	High wage
Low hours	σ_u/σ_z	5.29	3.83
	ρ_{uv}	−0.57	−0.24
High hours		1.49	2.17
		−0.38	−0.05

For the model economy aggregated σ_u/σ_z equals 3.67 and ρ_{uv} equals −0.57.

Figure 1: Kernel Density of Wages and Hours

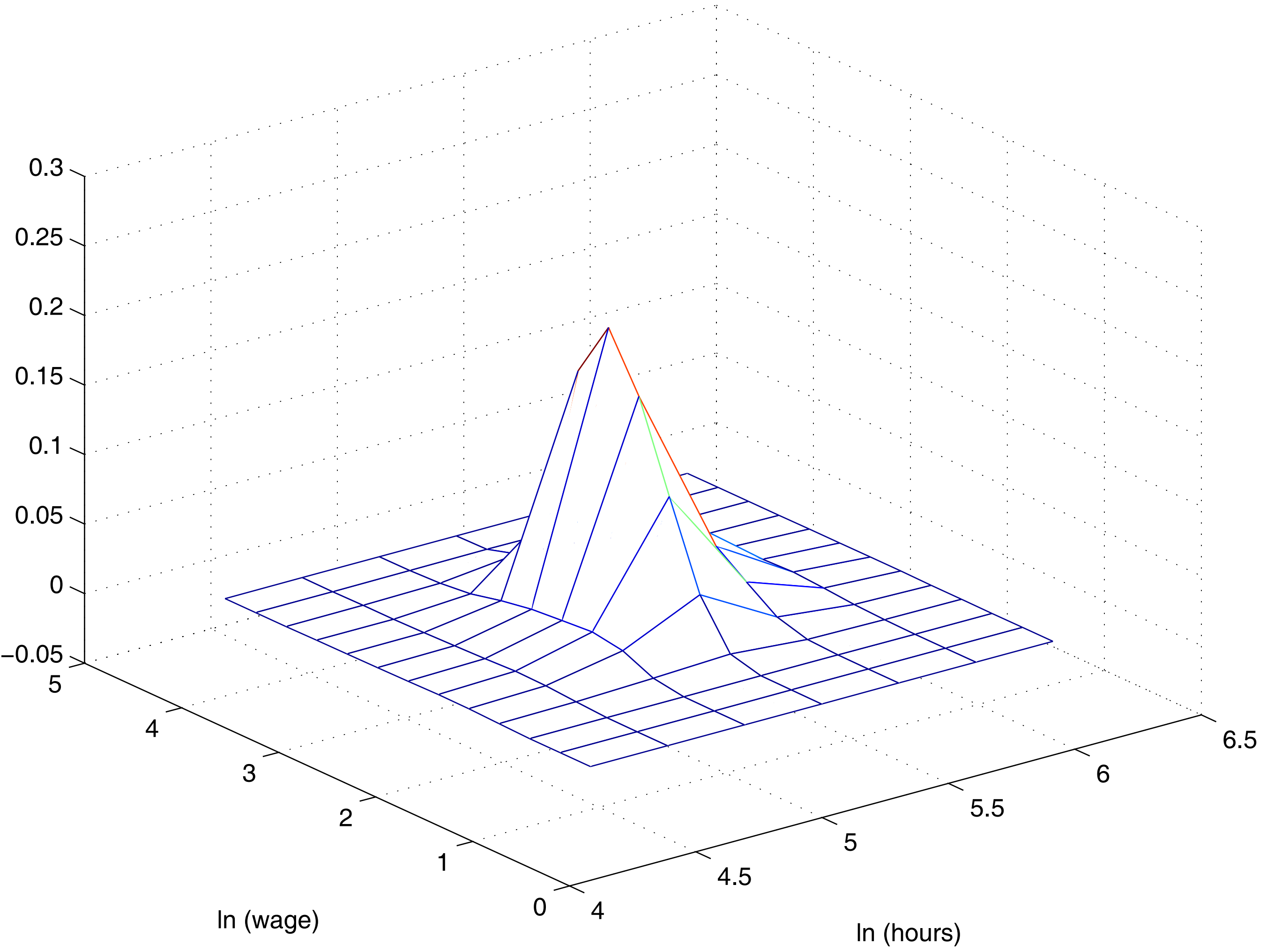
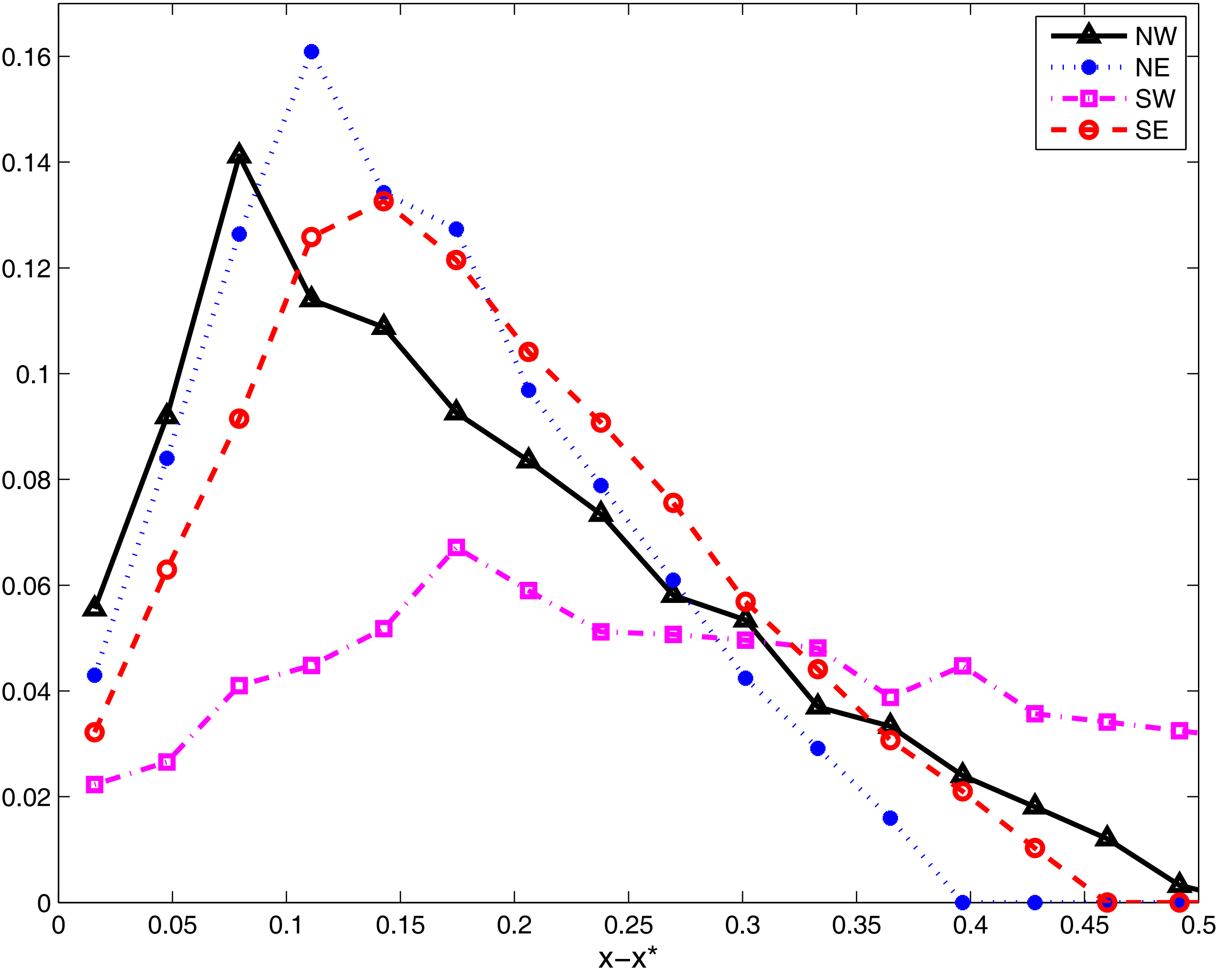


Figure 2: Distribution of Match Rents



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