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Wealth and labor supply heterogeneity

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ABSTRACT

This paper examines the importance of ex-ante heterogeneity for understanding the relationship between wealth and labor supply when markets are incomplete. An infinite horizon model is estimated where labor supply is indivisible and households are ex-ante heterogeneous in their labor disutility and market skills. The model replicates key features of the distribution of employment, wages, and wealth observed in the data. Importantly, it reverses the prediction that employment falls with wealth, a pervasive feature of models without ex-ante heterogeneity. A byproduct of the model's empirical performance is that it implies labor supply responses to unanticipated wage changes (e.g., Frisch elasticities) that are a half to two-thirds of those recovered from models with only ex-post heterogeneity.

1. Introduction

Heterogeneous agent models have become the workhorse of macroeconomics in answering quantitative questions where wealth helps shape individual decisions. Focusing on the labor supply decision, a large literature has burgeoned incorporating it to the standard Bewley–Huggett–Aiyagari model.[2] While successful in reproducing some features of wealth and labor supply, these models counterfactually predict that employment falls with wealth.[3] This prediction arises because infinitely lived agents accumulate enough precautionary savings to avoid working when their productivity is low. Equivalently, in these models wealthy individuals have reservation wages that are too high to reconcile the data. This paper examines modifications to these models that reverse this prediction and their implications for the inferred responsiveness of labor.

An incomplete markets model is presented with the following elements: (1) indivisible labor, (2) two-person households, (3) ex-ante heterogeneity in the labor disutility and market skills, (3) asset-based, means-tested social insurance, and (4) shocks to employment opportunities. Indivisible labor is assumed since worker movements in and out of employment

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[1] The views expressed in this paper are those of the author and do not necessarily represent the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

[2] See Krusell and Smith (1998), Chang and Kim (2006, 2007) for infinite horizon frameworks with competitive labor markets and Low (2005) and French (2005) for life cycle economies. Krusell et al. (2011), Bils et al. (2012), and Nakajima (2012) incorporate search frictions in the labor market to infinite horizon models.

[3] See Chang and Kim (2007). Relatedly, Castañeda et al. (1998) also show the difficulty in jointly accounting for salient features of the income, wealth, and unemployment distributions.

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account for a large fraction of fluctuations in aggregate hours.[4] Two-person households capture insurance within the household.[5] Heterogeneity in skills reflects educational or ability differences across individuals and allows the model to reproduce empirically reasonable wage dispersion. However, under balanced growth preferences, skill differences alone cannot generate empirically valid employment patterns because income and substitution effects cancel. Hence, heterogeneity in the disutility of work, which captures permanent differences in labor supply, is required. Correlation between skills and disutility allows the model to generate dispersion in reservation wages beyond what is suggested by wealth differences. Asset-based, means-tested transfers capture social insurance programs such as Supplemental Security Income (SSI) and help the model replicate the employment patterns of asset-poor households by distorting their incentives to work and save. Lastly, shocks to employment opportunities capture search frictions in the labor market and help the model match the frequency and duration of nonemployment observed in the data.

The model is estimated with data from individuals in the National Longitudinal Survey of the Youth (NLSY). The estimates imply a negative correlation between skills and the disutility of work. Importantly, the model replicates the observed labor supply patterns of asset-rich households by requiring them to be formed by individuals with high returns to employment because of their high market skills and low labor disutility. Meanwhile, asset-poor households choose to participate less in the market given the availability of social insurance and their comparatively lower returns to employment.

Aside from helping the model reconcile salient empirical features, ex-ante heterogeneity has implications for the responsiveness of labor to unanticipated wage changes. Simulations of the baseline model imply employment elasticities to wage changes of 0.18 and 1.46, respectively for men and women. Removing all ex-ante heterogeneity implies wage elasticities between 1.5 and 2 times larger. Removing skill heterogeneity implies wage elasticities very similar to the baseline model, suggesting labor disutility differences are key for these results.

The computed elasticities for men are within the range of estimates considered by Chetty et al. (2013). However, the current elasticities reflect preferences of a particular prime age cohort, rather than the entire U.S. economy. Additionally, the current model abstracts from other features that shape labor supply decisions. For example, the current model ignores the life cycle and human capital accumulation, which are the focus of Imai and Keane (2004). Rather than incorporating these elements, the current model instead focuses on permanent labor supply differences. This is a feature that life cycle models, like Erosa et al. (2011), abstract from in favor of matching other important empirical observations. Relative to those papers, the elasticities in this paper are smaller not only due to the consideration of ex-ante heterogeneity, but also because the current model misses the elastic labor supply decisions of the young and old. Alternatively, neither of the aforementioned studies considers social insurance or two-person households.

More closely related is the work of Chang and Kim (2006) (hereafter CK06) and Gourio and Noual (2009). Like CK06, this paper allows for incomplete markets, an explicit extensive margin, and two-person households. Calibrating to aggregate observations, they recover employment elasticities for men slightly below 1 and female elasticities above 1. Their model, however, implies a negative relationship between household wealth and individual employment. Gourio and Noual (2009) also focus on the extensive margin, however, their model precludes any discussion of the relationship between wealth and labor supply.

The estimated model also sheds light on an issue raised by Keane and Rogerson (2011), about whether models similar to CK06 and Chang and Kim (2007) (hereafter CK07) can produce empirically reasonable patterns for transitions between employment and nonemployment. The present analysis suggests shocks to employment opportunities are required as in Krusell et al. (2011). However, the results also suggest a role for ex-ante heterogeneity in simultaneously matching the frequency and duration of nonemployment for married men and women.

This paper also contributes to labor supply studies that structurally estimate heterogeneity in preferences. In a life cycle model, Heathcote et al. (2014) find that preference dispersion helps account for about one-third of cross-sectional dispersion in consumption and hours worked. Preference dispersion also explains the strongly positive empirical correlation between consumption and hours. Kaplan (2012) finds that heterogeneity in preferences for leisure helps account for the observed joint distribution of consumption, wages, and hours over the life cycle observed in U.S. data. In the current infinite horizon framework, preference dispersion helps explain the correlation between wealth and employment and generates dispersion in employment unrelated to wages. By abstracting from the life cycle, this paper may be overestimating the role of preference heterogeneity in labor supply. The work of Heathcote et al. (2014), Rupert and Zanella (2012), and Casanova (2013) suggests this is not the case. The former find that the bulk of cross-sectional preference dispersion is predetermined at age 27. Meanwhile, the latter two find increasing distaste for work later in the life cycle (ages 60+) helps generate retirement unrelated to changes in wages. Thus, preference heterogeneity may be even more relevant later in life.

This paper proceeds as follows. The next section describes the baseline model. Section 3 presents the NLSY sample used for the empirical analysis. Section 4 discusses the estimation procedure. Section 5 presents the estimation results and the model's fit to the data. Section 6 presents the simulated elasticities, while Section 7 concludes.

[4] See Heckman (1984) and Coleman (1984).

[5] See, for example, Attanasio et al. (2005). Guner et al. (2012) show the relevance of female labor supply for understanding taxes, while Guler et al. (2012) show the importance of female labor supply for search behavior of married couples.

2. Model

The economy is a heterogeneous agent model with incomplete markets and indivisible labor supply similar to the one considered in CK06. The current analysis is done in partial equilibrium with no aggregate uncertainty as the goal of this paper is to reconcile steady state differences in labor supply. Additionally, the economy differs from CK06 by allowing for ex-ante heterogeneity in skills and labor disutility across households, asset-based, means-tested transfers, and shocks to employment opportunities.

2.1. Households

Preferences. Households are formed by a male m and female f that live forever. Following Cho and Rogerson (1988), households have preferences over consumption c given by $2\ln(0.5c)$. Labor disutility d and market skills s are allowed to differ across households. Within households the following simplifying assumptions are imposed. First, it is assumed that skills within the household are identical, so $s = s_m = s_f$. This assumption is supported by evidence of positive assortative matching among married couples (e.g., Greenwood et al., 2012). Additionally, female labor disutility is a function of the male labor disutility within the household: $d_f = f(d_m) = \alpha_0 d_m^{\alpha_1}$. This assumption imbeds in a simple way heterogeneity in labor disutility across women in the economy. Additionally, it allows for correlation between female skills and labor disutility.[6]

Note that if high skilled individuals are the ones with the lowest disutility of work, then observed individual wages and employment will be positively correlated. Hence, the model requires a negative correlation between skills and disutility to reconcile this feature of the data. Additionally, to reverse the prediction that employment falls with wealth, sufficiently many low disutility individuals must be in wealthy households.

Shocks and savings. Households face two sources of uninsurable risk. First, the household is subject to uncorrelated productivity shocks to male and female labor, which evolve exogenously according to transition probability functions: $\pi_x^m(x'_m|x_m)$, $\pi_x^f(x'_f|x_f)$. Second, to capture involuntary unemployment or search frictions, households face uncorrelated *iid* shocks to individual employment opportunities denoted by λ_m and λ_f. With probability λ_m (λ_f) the male (female) in the household is unable to work in the current period. Meanwhile, with probability $\lambda_m\lambda_f$ neither member of the household is able to work in the current period.

Households can self-insure by trading one-period risk-free bonds a, which yield a rate of return r and are subject to a no borrowing constraint $a \geq 0$.[7] Labor supply is indivisible as in Hansen (1985) and Rogerson (1988), so hours take on the values $\{0, \bar{h}\}$. When employed, a worker $i = \{m, f\}$ with skills s must supply $h_i = \bar{h}$ units of labor and earns $wx_i s\bar{h}$, where w is the wage rate per unit of effective labor, which is normalized to one. With these assumptions, each household can supply at most $s\bar{h}(x_m + x_f)$ units of effective labor each period.[8]

Transfers. Asset-based, means-tested transfers are modeled following Hubbard et al. (1995). Transfers *TR* depend on household wealth a and labor earnings $ws(x_m h_m + x_f h_f)$. Like Hubbard et al. (1995), the following functional form is considered:

$$TR = \max\{0, \underline{c} - [a(1+r) + ws(x_m h_m + x_f h_f)]\}$$

where $\underline{c}$ is a minimum level of consumption guaranteed by the government. These transfers affect households' savings and labor supply decisions through two channels. First, since the transfer system raises income in low labor productivity states, the precautionary savings motive of the household is reduced. This leads households to save and work less since households can use labor supply as a margin of adjustment to smooth consumption (e.g., Pijoan-Mas, 2006). Additionally, there is a direct effect on savings and labor supply as the transfer system effectively places a 100 percent tax on assets and earnings above and beyond what is needed to meet the minimum consumption level $\underline{c}$. Note that the effect that transfers have on labor supply is absent in Hubbard et al. (1995) as they assume earnings evolve exogenously. More closely related is the work by Low et al. (2010), who consider income-based, means-tested transfers in a model of discrete labor supply.

Timing. The timing of shocks and decisions within a period evolves as follows. First, households receive new realizations of their idiosyncratic productivities x_m, x_f. Second, households receive realizations of their *iid* employment opportunity shocks λ_m, λ_f. Finally, labor supply and savings choices are made.

[6] If $\alpha_1 = 0$ then all women have the same labor disutility α_0, as in CK06. If $\alpha_1 = 1$ then there is perfect correlation between male and female labor disutility within the household. Yet, dispersion in female labor disutility still exists across households. In all scenarios there is still an insurance role of female labor supply.

[7] This follows Hubbard et al. (1995) to avoid borrowing against government transfers.

[8] For simplicity and following CK06, the model abstracts from a gender gap. This assumption will tend to bias upward the estimates of female disutility parameters as the returns to work in the model are higher than in actual data.

Recursive formulation. The value function of a household with both members currently employed is defined as:

$$\begin{aligned} V_{ee}(a,x_m,x_f,s,d_m) = \max_{a'}\bigl\{&2\ln(0.5c)-d_m-d_f+\beta\mathbf{E}\bigl[V\bigl(a',x_m',x_f',s,d_m\bigr)\bigm| x_m,x_f\bigr]\bigr\}\\ \text{s.t. } c &= ws(x_m h_m + x_f h_f)+(1+r)a-a'+TR\\ h_m &= \bar{h},\quad h_f=\bar{h}\\ d_f &= \alpha_0 d_m^{\alpha_1}\\ TR &= \max\bigl\{0,\underline{c}-\bigl[a(1+r)+ws(x_m h_m + x_f h_f)\bigr]\bigr\}\\ a' &\geq \underline{a}. \end{aligned} \tag{1}$$

The value functions for households with only one individual currently working (V_{en}, V_{ne}) or no individuals working (V_{nn}) are defined analogously.

The household labor supply decision depends on the valuation between these four alternatives and the realizations of the *iid* employment opportunity shocks:

$$\begin{aligned} V(a,x_m,x_f,s,d_m) = {} & (1-\lambda_m)(1-\lambda_f)\max\{V_{ee},V_{en},V_{ne},V_{nn}\}\\ & + (1-\lambda_m)\lambda_f\max\{V_{en},V_{nn}\}\\ & + \lambda_m(1-\lambda_f)\max\{V_{ne},V_{nn}\}+\lambda_m\lambda_f V_{nn} \end{aligned} \tag{2}$$

where the arguments of the value functions are omitted for expositional simplicity.

2.2. Discussion

There are three important elements missing from the current model. First, the model is a partial equilibrium model with fixed prices given the focus on steady states. Second, the model has no intensive margin of labor supply. Instead, it focuses on the extensive margin since worker movements in and out of employment account for a large fraction of fluctuations in aggregate hours.[9] Lastly, the model departs from the life cycle and uses an infinite horizon as in Hansen (1985), Rogerson (1988), CK06, and Gourio and Noual (2009). Thus, this model misses the elastic participation decisions of the young and old and instead focuses on the heterogeneity needed to explain the relationship between wealth and employment observed for prime-age individuals.

3. Data

This section describes the data used to estimate the model. Minimum data requirements are information on employment status, wages, and wealth given the interest in the relationship between wealth and labor supply. An additional data requirement is a long panel dimension, which is needed for the estimation of the stochastic process of individual productivity and identification of persistent employment differences. The data should be collected at a reasonably high frequency to circumvent the bias introduced by time aggregation.[10]

Given these requirements the NLSY79 is a sensible choice. The NLSY provides a long panel of individual histories for employment and wages. Additionally, observations can be constructed at a quarterly frequency as individuals are asked retrospective questions about employment history since the last interview.

A drawback of the NLSY is that the survey was not designed to be representative of the U.S. population, but rather a specific cohort. As such, the results of this paper, in particular those regarding the responsiveness of labor, cannot be easily applied to other cohorts. Instead, the exercise in this paper follows Keane and Rogerson (2011), who suggest identifying the underlying structural parameters of a well-specified choice problem and use that information to infer elasticities.

Additionally, because the NLSY is an individual level survey, information on the spouse's employment activities is scarce relative to the primary respondent's. In particular, only annual measures of spousal labor income and weeks worked are recorded. Using these reports would result in noisy estimates of spousal employment and wages.[11] These data limitations further support the simplifying assumptions made regarding ex-ante heterogeneity within the household because the NLSY precludes precise measurement of changes in labor supply within the household. Details of the sample selection appear in the Online Appendix.

[9] See for example, Coleman (1984) and Heckman (1984). Kimmel and Kniesner (1998) find that employment fluctuations account for three-fourths of wage-induced variation in labor hours.

[10] This point is emphasized by Erosa et al. (2011). They argue the wage rate obtained in the PSID as the ratio of annual earnings to annual hours is a noisy measure of the true returns to work faced by an individual during the year. This is because temporary low wage shocks will be unobserved in annual data if the individual chooses not to work during that portion of the year.

[11] For example, comparing wage rates of interviewed married women to those obtained by imputation, shows that husbands systematically report lower wages for their wives. This stems from the fact that they systematically report their wives working more weeks in the year compared to what interviewed married women report.

Table 1
Permanent employment and wages: NLSY married men and women.

	Men	Women
(1) Mean permanent employment rate (in %)	88.75	61.81
(2) Standard deviation of permanent employment rate	17.02	29.61
(3) Kurtosis of permanent employment rate	8.33	1.84
(4) Standard deviation of permanent wage rate	0.44	0.45
(5) Kurtosis of permanent wage rate	3.13	3.71
(6) Correlation between permanent employment and wage rate	0.29	0.33

Notes: Permanent employment rates are defined as the fraction of time an individual is employed throughout the entire sample. Permanent wages are the average hourly wage for an individual during all periods of employment. Wages are measured as residuals of log wages net of age, race, gender, marital status, and calendar effects.

3.1. Key empirical features

The main features of the data the model aims to reproduce are employment differences not solely explained by wage differences and the relationship between wealth, employment, and wages. These patterns are described below.

Permanent employment and wages. Given the interest in ex-ante heterogeneity, the following measures are defined. A permanent employment rate is the fraction of time an individual is employed throughout the entire sample. It captures an individual's labor supply unaffected by temporary factors and thus more likely to be related to preferences. Likewise, a permanent hourly wage rate is defined as the average log hourly wage rate observed for an individual during periods of employment. Since the model is stationary and abstracts from demographic differences (other than skills or education) residual log wages are used throughout the paper.[12] Therefore, permanent wages refer to the average over residual hourly wage rates when an individual is employed. This measure captures an individual's return to market work unaffected by temporary shocks, and hence, related to market skills. For most individuals in the sample, these measures are based on a span of over 20 years during their prime ages.

Values of these measures for each individual in the sample result in distributions of permanent employment rates and wages. Table 1 presents statistics on these distributions by gender. There are two important takeaways from this table. First, there is considerable dispersion in permanent employment rates. Second, wage differences only explain part of this dispersion as the correlation between wages and employment is roughly 30 percent for either gender.

Wealth, employment, and wages. The relationship between wealth and employment is the main feature of the data the model seeks to replicate. Table 2 displays the distribution of wealth and employment observed in the NLSY. The first row of the table shows that wealth is quite concentrated in the richest two quintiles. Moreover, the poorest quintile holds essentially no wealth. The second row shows that married male employment rates tend to rise with wealth.[13] This is in stark contrast to the predictions of indivisible labor supply models like CK07, which predict employment falling quickly with wealth.[14] Life cycle differences alone cannot explain this empirical regularity as the NLSY follows a single cohort with only small age differences within that cohort.[15] Even in samples more representative of the entire U.S. population, employment is nearly flat as wealth rises.[16] The third row shows that wealthier men tend to work more and earn higher wages based on average residual hourly wage rates computed in 2004. As education or skills are not controlled for when constructing residual wages, this suggests higher-skilled individuals tend to be wealthier. The last two rows of the table present equivalent statistics for married women. As seen in the fourth row, female labor supply displays a modest inverted-U shape with wealth, peaking at the third quintile. Lastly, the fifth row shows that women in wealthier households tend to earn more per hour worked.

4. Model parametrization and estimation

This section describes how the model is parametrized and the procedure used to estimate its key structural parameters. Computational details appear in the Online Appendix.

[12] More specifically, log hourly wage rates are regressed on a quadratic of age, year and quarter effects, and dummy variables for marital status, gender, and the eight cross-sectional samples in the NLSY.

[13] Measuring wealth and employment in other years results in very similar employment patterns.

[14] In a related exercise, Castañeda et al. (1998) find that an infinite-horizon heterogeneous agent model can replicate salient features of the income, unemployment, and wealth distributions only when the empirical wealth distribution is exogenously imposed.

[15] In fact, the average male age by wealth quintile in 2004 is essentially the same at 43 years.

[16] See Table 2 in CK07 for results using the PSID.

Table 2
Wealth, employment, and wages by wealth quintile: NLSY married men and women.

	Quintile of wealth in 2004				
	1	2	3	4	5
(1) Share of wealth (in %)	0.00	6.80	15.83	27.83	49.62
(2) Employment rate of married men in 2004 (in %)	68.80	88.76	89.91	91.76	93.45
(3) Wage rate of married men in 2004	−0.34	−0.17	0.04	0.08	0.32
(4) Employment rate of married women in 2004 (in %)	56.10	63.82	69.53	60.04	53.76
(5) Wage rate of married women in 2004	−0.27	−0.17	−0.02	0.14	0.27

Notes: Wealth is measured as family net wealth reported in the 2004 survey converted to 1983 dollars. The share of wealth by quintile is calculated as total wealth for the quintile divided by total wealth for the entire sample in 2004. Employment rates by quintile are calculated as the average fraction of quarters in 2004 each male (female) in the quintile is employed. Wage rates by quintile are calculated as the average residual wage rate earned by men (women) in the quintile when employed during 2004.

4.1. Parameters determined outside of the model

Time endowment and interest rate. For comparison purposes with the literature, the following choices are fixed. The unit of time is a quarter. An employed individual spends one-third of discretionary time working, so $\bar{h} = \frac{1}{3}$. The quarterly return on assets is set to 1 percent.

Idiosyncratic productivity. Idiosyncratic productivity is assumed to follow an $AR(1)$ process in logs: $\ln x' = \rho_x \ln x + \epsilon_x$, where $\epsilon_x \sim N(0, \sigma_x^2)$. According to the structure of the model, the current effective log wage rate earned by an individual (individual subscripts are subsumed for ease of notation) with skills s can be written as:

$$\ln w(s) = \ln w + \ln s + \ln x \tag{3}$$

where w represents the wage rate per unit of effective labor (normalized to 1 given the partial equilibrium assumption). Substituting in the process for $\ln x$ and rearranging terms yields:

$$\ln w(s) = (1 - \rho_x) \ln s + \rho_x \ln w_{-1}(s) + \epsilon_x \tag{4}$$

where $\ln w_{-1}(s)$ denotes an individual's wage rate in the previous period. Estimates of ρ_x and σ_x can be obtained by estimating (4) using panel data on individual wages and skills.

The NLSY is ideal in this regard as it provides information on an individual's education level and Armed Forces Qualifications Test (AFQT) scores. AFQT scores are based on respondents' performance on the Armed Services Vocational Aptitude Battery (ASVAB) tests. The ASVAB consists of a battery of 10 tests that measure knowledge and skill in areas such as general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, etc. Although ASVAB scores are imperfect measures of ability or skills, they are widely used in the literature as measures of cognitive achievement, aptitude, and intelligence.[17]

Eq. (4) is estimated separately for married men and women. The first term of the equation is proxied using AFQT scores, years of education (both in logs), and an interaction between the two. Residual log hourly wages (as previously defined) are used in place of $\ln w(s)$. Hence, age, race, gender, and calendar effects are excluded. Self-selection is taken into account using a Heckman (1979) correction. The selection equation is heavily influenced by the structural model and includes as controls the individual's AFQT score (in logs), a quadratic in age, an interaction between age and log years of education, a racial background indicator, net worth, and an individual's permanent employment and wage rates. Note that the probability of observing an individual employed in consecutive periods depends on their reservation productivity level. Based on the model, this value depends on assets, skills, and disutility of labor. These factors are captured empirically using net worth, education, AFQT scores, permanent wages, and permanent employment rates. The resulting estimates of ρ_x, σ_x by gender appear in Table 3.

The results from Table 3 suggest individual productivity shocks are more persistent for women than men, although the difference between estimates is not significant. Alternatively, productivity shocks are slightly more variable for men. Additionally, for both genders the null hypothesis of random selection is rejected with high statistical significance.

Compared to CK06, the current estimates imply nearly identical persistence of shocks for men. Meanwhile, productivity shocks for women in the NLSY appear statistically more persistent than their comparable estimates in the PSID. The biggest difference between the current estimates and CK06 lies in the variability of productivity shocks σ_x. Their estimates for σ_x range from (0.259–0.269) for males and (0.272–0.319) for females. The reason for this discrepancy is that they do not control permanent differences in market ability beyond what is predicted by years of schooling. The current estimate of σ_x for men is quite similar to the estimate found in Flodén and Lindé (2001) who estimate an $AR(1)$ process of wages with fixed-effects using PSID data.

[17] See Carneiro and Heckman (2002) and Belley and Lochner (2007).

Table 3
Estimates of quarterly individual productivity processes for married men and women in NLSY.

	Men	Women
(1) ρ_x	0.945	0.955
	(0.005)	(0.006)
(2) σ_x	0.147	0.129
	(0.006)	(0.005)
(3) Inverse Mill's ratio	−0.012	−0.013
	(0.002)	(0.003)
Number of observations	28,440	33,331

Notes: Estimates are based on quarterly hourly wage data on married men and women ages 25+ in the cross-sectional samples of the NLSY. AFQT scores, years of education (both in logs), and an interaction between the two are used to proxy for the first term in Eq. (4). Controls in the selection equation are: logged AFQT score, a quadratic in age, an interaction between age and log years of education, racial background indicator, net worth, and individual permanent employment and wage rates. Standard errors are clustered by individual and appear in parentheses.

It is worth emphasizing that by estimating the stochastic processes for individual productivity outside of the model, the spirit of the exercise in the paper is the following: how much ex-ante heterogeneity is needed to match salient features of the wealth, employment, and wage distributions *conditional* on empirically consistent processes for labor productivity?

4.2. Parameters determined inside the model

4.2.1. Calibrated parameters

The subjective discount factor β is pinned down by the average wealth to income ratio in 2004 of 2.06.[18]

4.2.2. Estimated parameters

The remaining parameters are estimated using simulated method of moments (SMM) as described below.

Skills and disutility of labor. As a balance between flexibility and computational efficiency, the distribution of male skills and disutility is discretized by assuming each attribute can take on two values, $(\{s_1, s_2\}, \{d_1, d_2\})$, yielding four distinct male types. Since skills within the household are identical and wife labor disutility is a function of the husband's, these assumptions also imply four distinct female types. To completely characterize the joint distribution of household skills and disutility three additional parameters must be determined:

- The fraction of males with type d_1 disutility: $p(d_1)$.
- The fraction of males of skill type s_1 conditional on having disutility d_1: $p(s_1|d = d_1)$.
- The fraction of males of skill type s_1 conditional on having disutility d_2: $p(s_1|d = d_2)$.

By normalization, the lowest skill level s_1 is set to one. All remaining proportions can be determined as complements of the above.

The choice of four distinct types is in part motivated by the literature. Castañeda et al. (1998) argue, based on PSID data, that partitioning the population into five types appears to be enough to account for most aspects of the income distribution. Given the NLSY sample used in the current paper is more homogeneous than a representative cross section in the PSID, four types is a reasonable choice. Additionally, this formulation is flexible enough to match distributions beyond the normal family. Moreover, the formulation keeps the estimation tractable even with two-earner households. As seen in the next section, these modeling choices seem to fit the data well.

Social insurance. The social insurance system is characterized by a minimum consumption level $\underline{c}$ and an asset limit above which households are ineligible to receive transfers. The value of $\underline{c}$ is estimated, while the asset limit is set to zero. This latter assumption follows Hubbard et al. (1995).[19]

Shocks to employment opportunities. These shocks are fully characterized by the *iid* arrival probabilities λ_m, λ_f.

[18] As argued by Kaplan and Violante (2013), there is a trade-off between matching the mean versus median of this ratio. While both statistics are quite similar in the current sample, the mean is chosen given the interest in matching the entire wealth distribution.

[19] Hurst and Ziliak (2004) find that asset restrictions have little effect on the saving decisions of the poor.

4.2.3. Estimation procedure

The aforementioned assumptions yield 11 structural parameters that must be estimated: $\Psi' = (s_2, d_1, d_2, p(d_1), \ldots, \alpha_0, \alpha_1, \underline{c}, \lambda_m, \lambda_f)$. The vector of structural parameters Ψ is estimated using a simulated method of moments (SMM) estimator with an identity weighting matrix.[20] The moments used to identify the structural parameters are described in detail below.

Permanent employment and wages. To estimate the six parameters characterizing male preferences and skills $(s_2, d_1, d_2, p(d_1), \ldots)$, the following moments are targeted: mean male permanent employment rate, standard deviations of male permanent employment and wages, kurtosis' of permanent employment and wages, and the correlation of these two distributions.[21]

These moments are sufficient to identify the six structural parameters governing male skills and disutility. The mean permanent employment rate helps determine the mean value of d. Dispersion in permanent employment rates helps determine the difference between d_1 and d_2. Next, if the mean permanent employment rate is high and the distribution displays high kurtosis then this implies a higher value for $p(d_1)$.[22] Likewise, greater dispersion in permanent wages implies greater skill dispersion. Finally, the kurtosis of wages and correlation between employment and wages determine the shares of high-skilled individuals for each disutility type: $p(s_2|d = d_1)$, $p(s_2|d = d_2)$.

To estimate the two parameters characterizing female preferences (α_0, α_1) the following moments are targeted: mean female permanent employment rate, standard deviation of female permanent employment rate, and the correlation between female permanent employment and wages.

The identification of female preferences readily follows from these moments. Varying α_0, while holding α_1 fixed, affects the average disutility of women and hence their mean permanent employment rate. α_1 governs dispersion in female labor disutility and the correlation between skills and disutility. Setting $\alpha_1 = 0$ results in no dispersion in labor disutility and no correlation between female skills and labor disutility. As α_1 increases from 0, dispersion in female disutility rises (conditional on dispersion of d_m) and the correlation between female skills and disutility changes from 0. Therefore, dispersion in predicted female permanent employment rates rises and the correlation between permanent employment and wages changes from zero.

Wealth, employment, and wages. As the primary goal is to account for the observed relationships between wealth, employment, and wages, an additional set of moments is used to further aid identification.

Based on the results from Table 2, the first three rows of the table are used as empirical targets. This yields 14 moments to be matched (four wealth shares, five male employment rates, and five male wage rates). The share of wealth of the poorest quintile is excluded as $\underline{a}$ is exogenously fixed at zero. The profiles of female employment and wages by wealth quintile are not targeted given the parsimonious description of female preferences.

Labor supply of the asset poor. The value of $\underline{c}$ is estimated to match the employment rate of men in the poorest quintile, as in Table 2.

Distributions of nonemployment. The average durations of nonemployment for men and women are used as empirical targets for λ_m and λ_f, respectively. All else equal, higher values for these parameters should result in longer duration and frequency of nonemployment per individual.

To summarize, there are 25 moments to help identify the 11 structural parameters of the model.

5. Estimation results

This section presents the estimation results. The estimated parameters of the model are presented first. The remaining subsections assess the goodness of fit of the model by showing how it performs in replicating the distributions of permanent employment rates and wages, the observed relationship between wealth, employment, and wages, and the frequency and duration of nonemployment.

5.1. Estimated model parameters

Table 4 presents the estimated values for Ψ, the vector of structural parameters of the model. Given that the lowest skill level is normalized to 1, the estimates imply that the highest skill type is over twice as productive as the lowest skill type. As anticipated, the estimates imply a negative correlation (-0.44) between skills and disutility.

[20] This choice follows Altonji and Segal (1996).

[21] The mean permanent wage rate is excluded as a moment for estimation as residual wages are used. In model simulated data observed wages are equivalently de-meaned.

[22] Here it is assumed without loss of generality that $d_1 \leq d_2$. Hence, d_1 types have higher permanent employment rates.

Table 4
Estimated parameter values two-earner model: NLSY married men and women.

Parameter	Value	95% confidence interval
d_1	0.22 (0.09)	[0.05, 0.39]
d_2	0.93 (0.03)	[0.87, 0.98]
s_2	2.15 (0.04)	[2.08, 2.22]
$p(d_1)$	0.59 (0.01)	[0.57, 0.61]
$p(s_1 \mid d = d_1)$	0.10 (0.01)	[0.07, 0.12]
$p(s_1 \mid d = d_2)$	0.49 (0.02)	[0.45, 0.53]
α_0	2.45 (0.03)	[2.38, 2.52]
α_1	0.88 (0.22)	[0.44, 1.31]
$\underline{c}$	0.50 (0.02)	[0.46, 0.54]
λ_m	0.01 (0.00)	[0.007, 0.02]
λ_f	0.00 (0.09)	[−0.16, 0.16]

Notes: Asymptotic standard errors appear in parentheses. Discount factor $\beta = 0.98808103$ is as in the text.

Focusing on the disutility parameters, the estimates suggest men on average a higher disutility of labor relative to women (0.51 versus 1.32). For comparison purposes, CK06 calibrate a male fixed cost of work of 0.57, which yields an average male employment rate of 77.3 percent.[23] The current estimation implies a lower fixed cost of work for males, but a significantly higher average employment rate. More strikingly, the median male in the current model has a fixed cost of work less than half of what CK06 calibrate and a participation rate above 98 percent. CK06 calibrate a female labor disutility cost of 0.92, but women in their model work only half of the time. By contrast, in the current model women face on average a higher labor disutility cost, yet have participation rates closer to 62 percent. Note that the median female in the current model has an employment cost of 0.65 and a participation rate of 86.4 percent.

These last comparisons point to the importance of preference dispersion. While there are no directly comparable measures of dispersion in labor disutility, a few studies provide guidance on the plausibility of these estimates. In a life cycle setting, Kaplan (2012) estimates coefficients of variation for the disutility of work ranging from 0.71 to 0.93, when using data on primary-earner males from the PSID. The implied coefficient of variation for men in this study is 0.69. Heathcote et al. (2014) estimate a variance in the disutility of work ranging from 0.048 to 0.063. The current estimated variance for men is higher at 0.12.

The estimated value of government transfers $\underline{c}$ matches favorably against actual social insurance programs. Converting model units to 1983 constant dollars implies that transfers are $1270 dollars.[24] By comparison, average monthly SSI benefits received by couples in 2012 were roughly $350 (in 1983 terms) with a maximum of $457.[25] Translating these values into quarterly benefits, implies an average payment of $1050 dollars and a maximum of $1371. Incorporating transfers such as food stamps into the calculation further aligns the model to the data. In 2012, average benefits per person participating in the Supplemental Nutritional Assistance Program (SNAP) were $60 (in 1983 terms).[26] Assuming one individual in the household qualifies for SNAP benefits increases average quarterly government transfers to $\$1230 = \$1050 + \$180$.

Lastly, the estimates of λ_m and λ_f imply small involuntary unemployment shocks for men and essentially no involuntary unemployment for women. Recall these parameters are used to target the average duration of nonemployment seen in the data. Absent of these shocks, the baseline model over predicts the duration of nonemployment for men. This occurs because high skill and low labor disutility men are rarely nonemployed. Adding these shocks forces these highly attached

23 The fixed cost is calculated as $B_m \frac{\bar{h}^{1+1/\gamma}}{1+1/\gamma}$ using their calibrated values for B_m, $\bar{h}$ and γ.

24 This conversion is done by having average assets in the model match average wealth observed in the NLSY.

25 See http://www.ssa.gov/policy/docs/statcomps/supplement/2013/7a.html and http://www.socialsecurity.gov/oact/COLA/SSIamts.html.

26 See http://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

Table 5
Permanent employment and wages: NLSY married men and women sample and baseline model.

	Men		Women	
	Data	Baseline	Data	Baseline
(1) Mean permanent employment rate (in %)	88.75	89.85	61.81	61.39
(2) Standard deviation of permanent employment rate	17.02	19.85	29.61	37.10
(3) Kurtosis of permanent employment rate	8.33	8.22	1.84	1.57
(4) Standard deviation of permanent wage rate	0.44	0.45	0.45	0.43
(5) Kurtosis of permanent wage rate	3.13	3.18	3.71	3.88
(6) Correlation between permanent employment and wage rate	0.29	0.52	0.33	−0.07

Notes: Data permanent employment and wage rates are defined in Table 1. Model statistics are based on averages of 100 simulations with 60,000 households followed for 100 model periods. Model permanent employment rates are calculated using all model periods within a given simulation. Model permanent wage rates are also calculated using all model periods for a given simulation.

individuals into involuntary unemployment. As they have below average duration of nonemployment the overall average falls. In contrast, even without these shocks the baseline model under predicts the duration of nonemployment for women. Adding these shocks exacerbates the prediction and hence the estimation implies these shocks must be essentially zero for women.

5.2. Empirical performance

5.2.1. Employment and wages

Table 5 presents the model's ability to match the first set of moments outlined in the previous section.

For men the model generates the high kurtosis and dispersion of the permanent employment distribution and the positive correlation between permanent wages and employment. In the model, the correlation between permanent wages and employment is higher relative to the data because of the presence of government transfers for asset-poor households. As these transfers provide insurance against bad productivity shocks, men in asset-poor households only work when their productivity is high, which causes their labor supply to track wages more than for the average male. Excluding these individuals lowers the overall correlation of male wages and employment from 0.52 to 0.32, which is essentially the same as the data.

Most of the model's predictions for women align with the data, though the model implies a correlation between wages and employment that is close to zero rather than positive. This is the result of two opposing forces. To prevent female employment from falling quickly with wealth the estimation requires wealthier women to work even when their productivity is low. This leads to a negative correlation between female wages and employment. Meanwhile, like men, women in poor households only work when their productivity is high because of the availability of social insurance. This leads to a positive correlation between female wages and employment. Overall, wages and employment are roughly uncorrelated.

5.2.2. Wealth distribution

Table 6 presents the main results of the paper. The first panel of the table duplicates the results from Table 2. The second panel presents equivalent statistics from the baseline model. For comparison purposes, the last panel of this table presents statistics from a model (Model V) that is equivalent to CK06, but calibrated using the current NLSY sample.[27]

The first rows of the top two panels show that the baseline model is broadly consistent with the distribution of wealth observed in the NLSY and replicates the high concentration of wealth in the top two quintiles. The model replicates the absence of wealth from the poorest quintile because no borrowing is allowed and asset-based transfers discourage saving.

The comparisons between the second rows of each panel highlight the current model's key success in replicating the high employment rates of wealthier men. Ignoring the first quintile, the baseline model implies a flat employment profile across wealth quintiles; in the data it is modestly increasing. For women, the baseline model also implies a relatively flat employment profile. In the data, by comparison, female employment rates display a modest inverted-U shape, peaking in the second quintile. Thus, at higher levels of wealth the model is overstating women's willingness to work.

In stark contrast, a model without ex-ante heterogeneity, transfers, or employment shocks (Model V) delivers employment profiles that are at odds with the data. Across quintiles, male employment monotonically declines with wealth. Notably, the employment rate of the wealthiest men is nearly 10 percentage points below its empirical target. Similarly, this model implies female labor supply declining with wealth and only matches the employment rate of women in the fourth quintile.

To understand what features are driving the differences between the baseline model and Model V, the middle panels of Table 6 present statistics for special cases of the baseline model. Relative to the baseline, Model II has no skill heterogeneity.

[27] This model is solved using the same stochastic processes as the baseline model. The disutility parameters for men and women are calibrated to match the mean permanent employment rates implied by the baseline model.

Table 6
Wealth, employment, and wages by wealth quintile: data and models.

	Quintile of wealth				
	1	2	3	4	5
NLSY					
(1) Share of wealth (in %)	0.00	6.80	15.83	27.83	49.62
(2) Employment rate of married men in 2004 (in %)	68.80	88.76	89.91	91.76	93.45
(3) Employment rate of married women in 2004 (in %)	56.10	63.82	69.53	60.04	53.76
Baseline					
(1) Share of wealth (in %)	0.00	2.30	9.19	22.69	65.67
(2) Employment rate of married men (in %)	67.51	95.96	95.52	96.07	95.10
(3) Employment rate of married women (in %)	39.29	61.13	68.20	69.76	68.98
Model II					
(1) Share of wealth (in %)	0.00	2.43	9.87	22.98	64.65
(2) Employment rate of married men (in %)	68.50	97.55	98.15	97.00	97.05
(3) Employment rate of married women (in %)	38.23	63.30	66.66	64.03	67.22
Model III					
(1) Share of wealth (in %)	0.00	2.51	10.91	23.51	62.96
(2) Employment rate of married men (in %)	67.78	98.24	97.30	96.77	94.14
(3) Employment rate of married women (in %)	43.68	71.07	66.11	66.64	60.03
Model IV					
(1) Share of wealth (in %)	0.00	2.57	10.83	23.79	62.69
(2) Employment rate of married men (in %)	67.93	98.10	97.05	96.39	92.65
(3) Employment rate of married women (in %)	45.61	71.46	65.59	65.27	59.23
Model V					
(1) Share of wealth (in %)	0.48	4.07	11.56	23.91	59.97
(2) Employment rate of married men (in %)	94.36	92.19	91.27	88.09	83.14
(3) Employment rate of married women (in %)	64.23	64.82	62.14	59.80	55.83

Notes: See Table 2 for definitions of data statistics. Model statistics are based on averages of 50 simulations with 60,000 individuals. Employment rates presented in (2) and (3) of the model panels are calculated using a single year's worth of data from each simulation. Relative to the baseline, Model II has no skill heterogeneity. Model III excludes any ex-ante heterogeneity, but allows for transfers and shocks to employment opportunities. Model IV excludes ex-ante heterogeneity and employment shocks, but still allows for government transfers. Model V has no ex-ante heterogeneity, transfers, or shocks.

Model III differs from Model II by excluding any ex-ante heterogeneity. Model IV excludes ex-ante heterogeneity and employment shocks, but still allows for government transfers.[28]

A comparison of these alternative models reveals that labor disutility differences are key to generate employment profiles similar to the ones observed in the data. Comparing the employment profiles of the baseline and Model II reveals that skill heterogeneity is not crucial for generating the relatively flat employment profiles of men and women. Excluding heterogeneity in the disutility of labor, as in Model III, does lead to declining employment across wealth quintiles for both men and women. Models III and IV suggest that shocks to employment opportunities do not have a material effect on the wealth and employment relationship. Lastly, a comparison between Models IV and V shows that asset-based, means-tested transfers are essential to generate the low labor supply patterns of asset-poor households.

5.2.3. *Frequency and duration of employment and nonemployment*

Table 7 presents summary statistics by gender on the frequency and duration of employment and nonemployment for the data and different models discussed in the previous section. Recall that in the baseline model the shocks to employment opportunities were targeted to match the average duration of nonemployment for each gender. As seen from the first rows of each panel, the baseline model matches these empirical targets well. Alternatively, models without ex-ante heterogeneity (Models III–V) overestimate (underestimate) the duration of nonemployment for men (women).

The remaining rows of Table 7 demonstrate the baseline model's ability to match empirical moments that were not targeted. For example, the baseline model predicts flow rates to and from employment that closely resemble the data (rows 3 and 6). Focusing on the predictions for women (bottom panel), the baseline and Model II suggest that ex-ante heterogeneity is very important for matching this aspect of the data. Alternatively, Models III–V, which exclude ex-ante heterogeneity, predict female flow rates into employment that are nearly twice as big as their data counterparts.

Figs. 1 and 2 display graphically how the baseline model matches the spell distributions for men and women, respectively. The top rows of each figure display the employment (left) and nonemployment (right) spell distributions for the baseline model. For comparison, the bottom rows display equivalent distributions derived from Model V, which excludes

[28] All models are solved using the same stochastic process for idiosyncratic productivity. Additional details appear in the Online Appendix.

Table 7
Duration and frequency of employment and nonemployment: NLSY married men, women and models.

	Data	Baseline	Model II	Model III	Model IV	Model V
Men						
(1) Mean duration of nonemployment (in q)	3.35	3.78	3.53	4.69	5.87	5.52
(2) Mean # of nonemployment spells	1.53	1.73	1.74	1.78	1.64	1.80
(3) Flow rate $N \rightarrow E$ (in %)	19.26	18.84	22.00	19.12	15.85	16.90
(4) Mean duration of employment (in q)	16.29	24.31	24.41	23.68	23.60	22.19
(5) Mean # of employment spells	2.59	2.79	2.78	2.68	2.44	2.60
(6) Flow rate $E \rightarrow N$ (in %)	2.09	2.12	2.06	1.98	1.72	1.91
Women						
(1) Mean duration of nonemployment (in q)	8.14	8.08	7.22	6.56	7.06	6.69
(2) Mean # of nonemployment spells	2.73	3.33	4.00	5.30	5.11	5.33
(3) Flow rate $N \rightarrow E$ (in %)	7.22	7.00	8.52	12.70	12.31	12.92
(4) Mean duration of employment (in q)	10.39	12.36	11.14	9.83	10.04	9.68
(5) Mean # of employment spells	2.92	3.29	3.98	5.48	5.34	5.56
(6) Flow rate $E \rightarrow N$ (in %)	4.77	4.40	5.71	8.02	7.79	8.13

Notes: Model statistics are based on averages of 50 simulations with 60,000 households followed for 100 model periods. Relative to the baseline, Model II has no skill heterogeneity. Model III excludes any ex-ante heterogeneity, but allows for transfers and shocks to employment opportunities. Model IV excludes ex-ante heterogeneity and employment shocks, but still allows for government transfers. Model V has no ex-ante heterogeneity, transfers, or shocks.

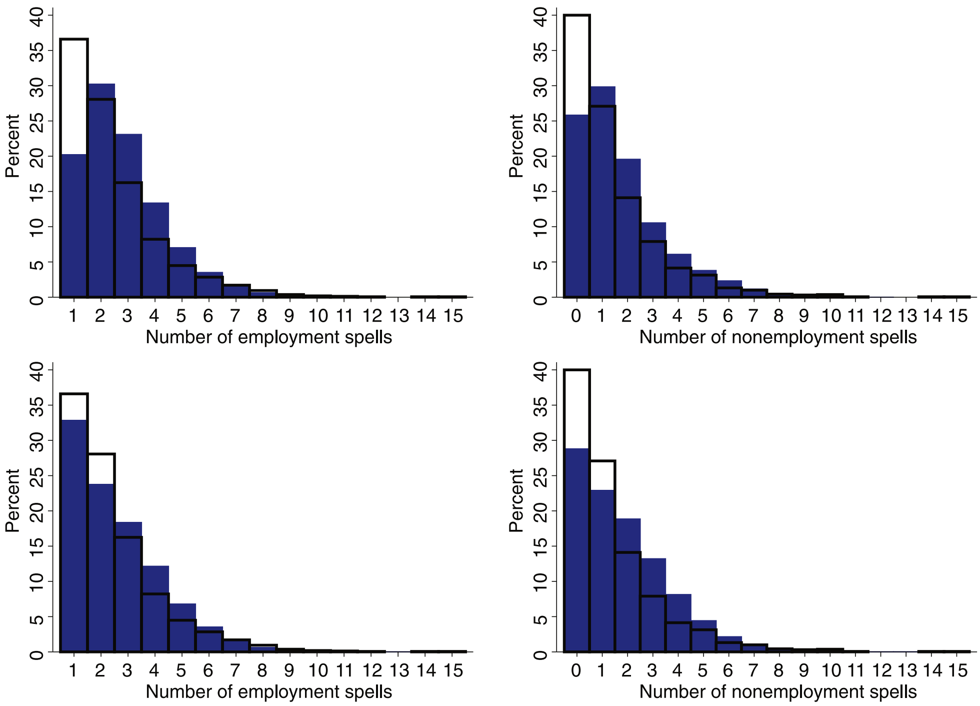

Fig. 1. Distributions of male employment (left) and nonemployment spells (right) for Baseline (top) and Model V (bottom). Notes: Transparent bars represent the corresponding data histogram. Solid bars represent the corresponding model histogram. Data histograms are calculated using the NLSY married men sample defined in the text. Model distributions are calculated by simulating 60,000 individuals for 100 model periods. Model V is a version of the baseline with no ex-ante heterogeneity, transfers, or shocks.

any ex-ante heterogeneity, transfers, or shocks.[29] In each graph, the transparent bars are the data generated histogram, while the solid bars are the corresponding model distribution.

Comparing the right-hand graphs of Fig. 1 suggests that the baseline model does modestly better than Model V in matching the overall shape of the nonemployment spell distribution for men. Notably, the baseline model predicts fewer individuals with three or more nonemployment spells.

Fig. 2 indicates that the baseline model performs noticeably better (relative to Model V) in matching both distributions of employment and nonemployment spells for women. In terms of employment, the baseline model predicts more women

29 The Online Appendix presents corresponding graphs for Models II–IV.

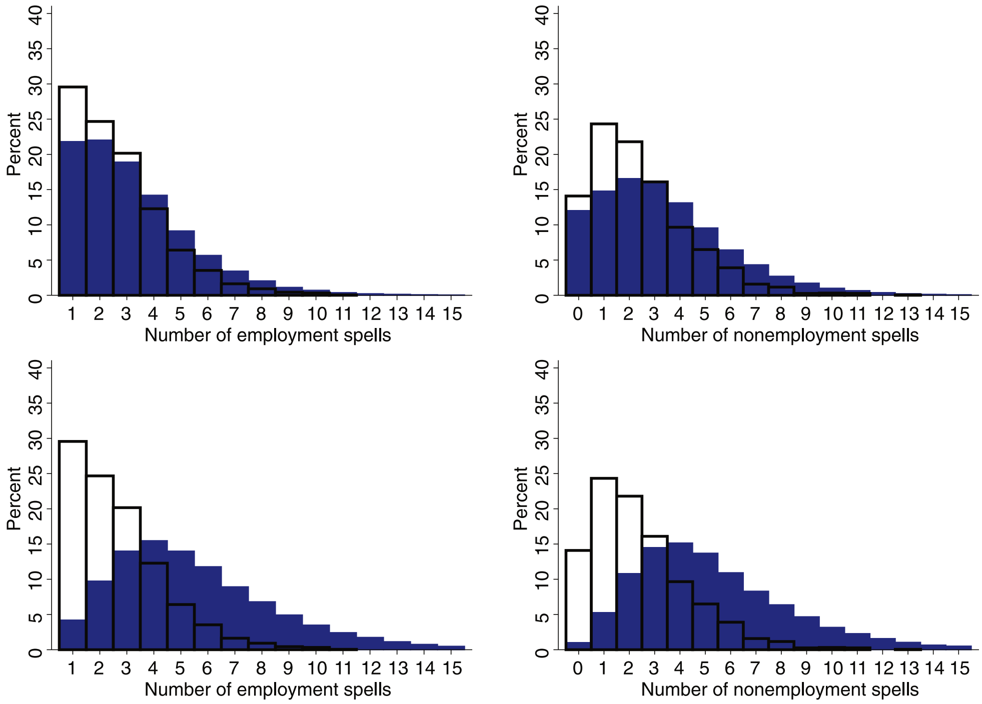

Fig. 2. Distributions of female employment (left) and nonemployment spells (right) for Baseline (top) and Model V (bottom). Notes: Transparent bars represent the corresponding data histogram. Solid bars represent the corresponding model histogram. Data histograms are calculated using the NLSY married women sample defined in the text. Model distributions are calculated by simulating 60,000 individuals for 100 model periods. Model V is a version of the baseline with no ex-ante heterogeneity, transfers, or shocks.

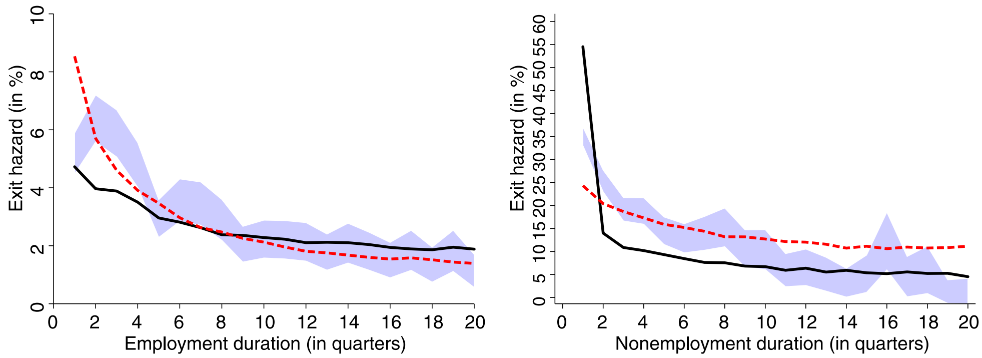

Fig. 3. Male hazard rates from employment to nonemployment (left) and nonemployment to employment (right) for Baseline (solid line) and Model V (dashed line). Notes: Hazard rates at duration t are calculated as the fraction of spells with duration greater or equal to t that end at duration t. Shaded area represents 95% confidence interval of the corresponding data hazard rate. Data hazard rates are calculated using the NLSY married men sample defined in the text. Model rates are calculated by simulating 60,000 individuals for 100 model periods. Model V is a version of the baseline with no ex-ante heterogeneity, transfers, or shocks.

with one to three spells of employment. In concert, the baseline also predicts more women with zero to two spells of nonemployment.

Lastly, Figs. 3 and 4 display the baseline model's ability to match the duration dependence of the flow rates into and out of nonemployment by gender. The left panel of each figure displays flow rates into nonemployment, while the right panel displays flow rates out of nonemployment. For each of these graphs, the shaded area corresponds to the 95% confidence interval of the data, the solid line represents the baseline model's prediction, and the dashed represents Model V's (i.e. no ex-ante heterogeneity, transfers, or employment shocks) prediction.

Focusing on men, the left panel of Fig. 3 shows that both the baseline model and Model V deliver flow rates into nonemployment that are statistically very similar to the data. The right panel of the figure shows that the baseline model predicts a flow rate out of nonemployment that matches the data at higher durations, but is too excessive at durations less than two quarters. The reason for this drastic difference is compositional. In the baseline model, transitions into employment

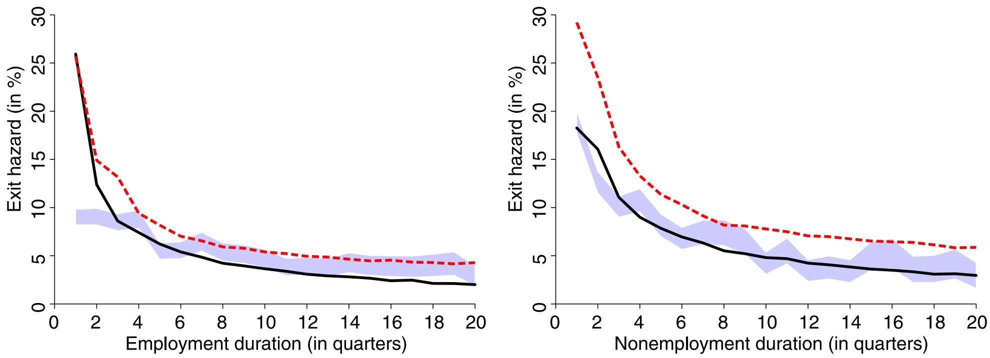

Fig. 4. Female hazard rates from employment to nonemployment (left) and nonemployment to employment (right) for Baseline (solid line) and Model V (dashed line). Notes: Hazard rates at duration t are calculated as the fraction of spells with duration greater or equal to t that end at duration t. Shaded area represents 95% confidence interval of the corresponding data hazard rate. Data hazard rates are calculated using the NLSY married women sample defined in the text. Model rates are calculated by simulating 60,000 individuals for 100 model periods. Model V is a version of the baseline with no ex-ante heterogeneity, transfers, or shocks.

Table 8
Simulated elasticities by model and gender.

	Men	Women
Baseline	0.18	1.46
Model II	0.13	1.82
Model III	0.27	2.15
Model IV	0.36	2.05
Model V	0.58	2.71

Notes: These elasticities reflect the simulated percentage change in employment (by gender) with respect to an unanticipated 10 percent change in wages. Elasticities are averages over 100 model periods with 60,000 households. Relative to the baseline, Model II has no skill heterogeneity. Model III excludes any ex-ante heterogeneity, but allows for transfers and shocks to employment opportunities. Model IV excludes ex-ante heterogeneity and employment shocks, but still allows for government transfers. Model V has no ex-ante heterogeneity, transfers, or shocks.

occurring within the first quarter of nonemployment are disproportionately executed by men with low disutility of labor and high skills. Because these workers have high returns to employment they engage in short-lived nonemployment spells.

Turning to Fig. 4, both panels show that the baseline model matches the data's flow rates for women. The baseline flow rate out of nonemployment (right) is within the 95% confidence interval of the data. The baseline flow rate into nonemployment (left) also matches the data, save for employment durations less than three quarters. This prediction, however, is common even to models without ex-ante heterogeneity.

These results shed light on an issue raised by Keane and Rogerson (2011) of whether models in the vein of Chang and Kim (2007) produce empirically reasonable patterns for transitions between employment and nonemployment. In general, these models require a source of involuntary unemployment, which is consistent with the findings of Krusell et al. (2011). However, the model comparisons this section reveal that ex-ante heterogeneity is also necessary to match other empirical features related to these transitions. Chiefly, ex-ante heterogeneity at the household level helps these models simultaneously match empirical patterns of married men and women.

6. Implications for the responsiveness of labor at the extensive margin

This section discusses the implications of ex-ante heterogeneity for the responsiveness of labor at the extensive margin (e.g., Frisch elasticity). To do so, a one period unanticipated wage change of 10 percent is simulated in the baseline model.[30] Table 8 presents the computed elasticities by gender. These elasticities represent changes in labor supply at the extensive margin holding wealth constant.

The top row of Table 8 shows the baseline model delivers elasticities of 0.18 and 1.46 for men and women, respectively. Thus, according to the estimated model, most married men are at a corner solution in their employment choice, and hence are not very responsive to wage changes. Alternatively, married women are more willing to change employment status given an unanticipated change in wages.

[30] Simulating the responses to changes in wages of 1 or 5 percent does not change the average elasticities computed, but does increase their variance.

To understand how each model component contributes to the computed baseline elasticity, the remaining rows of Table 8 display the elasticities for Models II–V. Abstracting from skill differences and only allowing for disutility differences across individuals (Model II) delivers elasticities that are very similar to the baseline model. Abstracting from any ex-ante heterogeneity (Model III) generates elasticities 1.5 times larger than the baseline model. Shocks to employment opportunities play an important quantitative role in the computed elasticities as their omission (Model IV) further increases the elasticity for married men. Lastly, a version of the model akin to CK06 (Model V) results in elasticities more than 3 times larger for men and more than 1.5 times larger for women, compared to the baseline model.

To place these values in context, CK06 obtain elasticities for married men ranging from 0.84 to 0.96, and for married women ranging from 1.36 to 1.71. Their model, like Model V, abstracts from any type of ex-ante heterogeneity and implies that labor supply monotonically decreases with wealth. Meanwhile, Chetty et al. (2013) synthesize six studies and obtain an (unweighted) average Frisch elasticity at the extensive margin of 0.32, with estimates ranging between 0.18 and 0.43.

7. Conclusion

This paper departs from the observation that standard infinite horizon heterogeneous agent models counterfactually predict that employment falls with wealth. Ex-ante heterogeneity across individuals is explored as a candidate solution. An incomplete markets model with indivisible labor supply is presented where households are ex-ante different in their disutility for labor and market skills. These differences are estimated using data on married men and women in the NLSY, which show large differences in employment rates that do not project on wages.

The estimated model implies skills and labor disutility are negatively correlated and successfully reverses the prediction that employment falls with wealth. In particular, it replicates the high employment rates of wealthy individuals by increasing their returns to work (through low labor disutility and high skills) relative to what a model without ex-ante heterogeneity predicts. The estimated model also suggests that asset-based, means-tested transfers are crucial for capturing the labor supply decisions of asset-poor households. Without these transfers, asset-poor households use labor supply as a mechanism to smooth consumption and are employed more frequently than what the data implies.

Additionally, ex-ante heterogeneity is found to have a quantitatively important effect on the measurement of labor supply elasticities. The labor supply elasticities for men and women in the baseline economy are 0.18 and 1.46, respectively. Removing ex-ante heterogeneity implies wage elasticities between 1.5 and 2 times larger. Labor disutility differences are key for these findings since a version of the baseline model where skill differences are null delivers elasticities very similar to the baseline economy.

Future research should consider allowing for some intensive margin adjustment as an extension of the present setting. Verifying that the choice of hours worked is consistent with what is observed in the data is another important check of the model's consistency. Additionally, extending the model to allow for business cycle shocks is also a promising direction of research. As highlighted by Chetty et al. (2013), formulating models that generate large fluctuations in employment over the cycle while matching small extensive margin elasticities remains a challenge.

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Appendix A. Supplementary material

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.red.2014.09.002.

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