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ABSTRACT

Household Search or Individual Search: Does It Matter? Evidence from Lifetime Inequality Estimates*

Search Models of the labor market are widespread and influential but they usually ignore that labor market decisions are frequently taken at the household level. We fill this gap by developing and estimating an household search model with on-the-job search and labor supply. We build on previous work (Dey and Flinn (2008) and Guler, Guvenen and Violante (2011)) to propose a novel identification strategy of the risk aversion parameters and a specification test. We find that ignoring the household as unit of decision-making has relevant empirical consequences. In estimation, the individual search specification implies gender wage offers differentials 200% larger than the household search specification. In the application, the individual search specification implies gender differentials in lifetime utility inequality 74% larger. The results of our policy experiments emphasize the importance of looking at lifetime utility inequality measures as opposed to simply cross-sectional wage inequality measures.

JEL Classification: J64, D63, C63

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1 Introduction

Search Models of the labor market are widespread and influential.[1] However, they usually ignore that labor market decisions are frequently taken at the household level and not at the individual level.[2]

Recent works have started to realize the importance of this omission. Dey and Flinn (2008) [DF] and Guler, Guvenen and Violante (2012) [GGV] develop a unitary model of the household where both spouses search for work. They show that the household search model generates different equilibrium decisions than the individual search model, unless agents are risk neutral. Albrecht, Anderson and Vroman (2010) and Compte and Jehiel (2010) provide theoretical results in a related and more general framework: search by committee. They also conclude that the unique symmetric equilibrium obtained under search by committee is different from the equilibrium obtained in the corresponding individual search problem.

As the theoretical importance of the household as unit of decision-making starts to be accepted and understood, the empirical relevance of this feature is much less studied and investigated. DF is the only published paper in the literature estimating an household search model to assess an empirical issue (the importance of employer-provided health insurance). Gemici (2011) is an interesting recent contribution developing and estimating a model of household migration with frictions. García Pérez and Rendon (2012) is a preliminary work looking at household search to evaluate the Unemployment Benefits system. Given the large body of empirical literature using estimations of search model to answer policy questions,[3] empirical relevance has become an important and pressing issue: Do the estimation and calibration of search models of the labor market that ignore the presence of the household imply a relevant and significant mispecification error? Would the estimates be very different and the policy implications be significantly affected if the mispecification error were to be removed?

This paper attempts to answer these questions by evaluating the empirical relevance of ignoring the household as unit of decision-making when estimating search models of the labor market. After developing an extended version of the model considered by DF and GGV, we estimate the model on the 2001-2003 panel of the *Survey of Income and Program Participation* (SIPP). The estimated model allows for on-the-job search and for labor supply decisions. The inclusion of the intensive margin of the labor supply in the model is rare in the search

[1] For a survey of the theoretical literature, see Rogerson, Shimer and Wright (2005). For a survey of the empirical literature, see Eckstein and van den Berg (2007). A very popular framework used as reference point for most of the macro literature is Pissarides (2000).

[2] For example, all the works mentioned in the exhaustive surveys cited in footnote 1 assume individual (single-agent) search.

[3] For example, Eckstein and Wolpin (1995) study returns to schooling; Ahn, Arcidiacono and Wessels (2011) and Flinn (2006) evaluate the employment and welfare impact of minimum wage legislation; Dey and Flinn (2005) the impact of employer-provided health insurance; Flabbi (2010) the effect of affirmative action legislation; and Cahuc, Postel-Vinay and Robin (2006) the impact of workers' bargaining power.

literature[4] but it is important to appropriately describe the behavior of spouses within the household, particularly women.

We evaluate the importance of considering that decisions are taken at the household level in three ways. First, we show if and how the estimated structural parameters are affected. Second, we perform a specification test of the individual search specification against the household search specification. Third, we choose a relevant empirical application to show how results are affected by assuming household search.

The empirical application focuses on the estimation and computation of lifetime inequality, i.e. a measure of inequality able to describe the entire labor market career of given agents. The contribution of this application is twofold. First, we provide measures of lifetime inequality and not simply of cross-sectional inequality. Second, and for the first time, we provide measures of lifetime inequality at the household level and not simply at the individual level.

There is a large empirical literature on income inequality focusing on dispersion in cross-sectional distributions of individual wages and earnings.[5] A typical analysis in this literature compares levels of inequality in a certain year or month conditional on a set of controls. This approach has two main shortcomings. First, measures of inequality based on cross-sectional distributions, while informative, can differ markedly from lifetime measures of inequality. Second, focusing on individual earnings and wages often ignores that most individuals live in households that pool resources and make labor market decisions together.

Empirical works that focus on mechanisms insuring individuals against risk have traditionally attempted to address both concerns. They focus on consumption and household-level variables and study how different types of shocks may impact the individual position in the inequality distribution.[6] However, they do not allow for wage and employment mobility as a result of optimal individual behavior.

Works estimating search models of the labor market to provide lifetime inequality measures[7] can solve this problem because they explicitly model employment decisions. However, they maintain the standard assumptions of search models of the labor market and therefore ignore that labor market decision may be taken at the household level.

For these reasons, we think developing and estimating an household search model able to take into account both optimal mobility and household level decisions will generate an interesting application. By estimating the model, we are able to compute lifetime inequality measures that we can compare with cross-

[4] Exceptions are Blau (1991); Bloemen (2008) and Flabbi and Moro (2010).

[5] For surveys see Levy and Murnane (1992) and Katz and Autor (1999).

[6] Early and influential contributions are: Shaw (1989) and Blundell and Preston (1998). Recently, the macro literature is also addressing similar concerns looking at the difference between income and consumption inequality, for example Krueger and Perri (2006) and Heathcote, Storesletten and Violante (2008).

[7] Flinn (2002) is the first contribution in this literature. Flabbi and Leonardi (2010) is the most recent. Bowlus and Robin (2004), while not estimating a search model, are similarly concern with optimal mobility and develop an innovative non-stationary model of job mobility which shares some important features with search models.

sectional measures. By looking at household search, we are able to compare individual-level inequality with household-level inequality. All these comparisons can be done in an equilibrium context since we are able to identify and estimate the structural parameters of the model. Our dual-search model also includes labor supply, a feature frequently ignored in the search literature that allows for a better fit of female labor market outcomes and a richer interaction within the household.[8]

We estimate the parameters of the model using the method of simulated moments in conjunction with data from the 2001-2003 panels of the Survey of Income and Program Participation (SIPP). The SIPP is the appropriate data set for this analysis since it collects monthly information on labor market activity and links detailed spousal labor market information across time.

We find that ignoring the household as unit of decision-making in standard search models of the labor market has relevant empirical consequences. In estimation, the individual search model specification implies gender wage offers differentials more than twice as large as the household search model specification. In the application, the individual search model specification implies gender differentials in lifetime utility inequality about 74% larger than the household search model specification. Our counterfactual experiments shows that most of this difference is due to biased parameters estimates.

A second result of our analysis is that lifetime measures of inequality based on utility values may generate very different policy implications than cross-sectional measures of inequality based on wages and earnings. For example, one of our policy experiments shows that a more efficient search and matching process does not necessarily increase utility inequality at the lifetime level but it does increase wage inequality at the cross-sectional level.

The plan of the paper is as follows. In Section 2, we develop the model of household search. In Section 3, we discuss the data source and present some descriptive statistics. In Section 4, we discuss identification and estimation of the model. In Section 5 we present and interpret the estimates of model parameters. In Section 6, we use our parameter estimates to simulate lifetime inequality measures and to perform counterfactual and policy experiments. A concluding discussion is provided in Section 7.

2 Model

We discuss two versions of the model: a simple version and an extended version. The simple version states the main equilibrium results and propositions and offers a better environment to understand the intuition behind them. The extended version is the version of the model that will be estimated. It adds

[8] Neither DF nor GVV allow for labor supply decision. Blau (1991) and Flabbi and Moro (2012) are two of the rare examples that estimate a search model of the labor market in the presence of a labor supply margin. Bowlus (1997) allows for a participation decision.

heterogeneity between the spouses and includes additional features relevant to fit the data and to provide richer counterfactual experiments.

2.1 Simple Version

2.1.1 Individual Search Model

Environment The simplest possible environment for a search model of the labor market in continuous time is characterized by four elements: a single-agent decision problem, a rate of arrival of job offers obeying a Poisson process (λ), an exogenous distribution of wage offers ($F(w)$), an instantaneous utility function $(u(c))$, and a discount rate (ρ). We additionally assume that consumption is the sum of non-labor and labor income ($c = Y + w$) and that there is no saving or borrowing.[9] We also assume no flow cost of search and no recall of past offer.

Value functions The stationary assumption allows to write the model recursively using value functions for each state in which the individual agent may be. If the agent is employed, the job lasts forever and therefore she will receive no shock. The value of being employed at a given wage will then simply be the corresponding discounted instantaneous utility:

$$\rho V(w) = u(Y + w) \tag{1}$$

When the agent is unemployed, she will receive shocks (the job offers). Therefore the value of unemployment will be the sum of the instantaneous utility while unemployed and the option value of changing labor market state:

$$(\rho + \lambda) U = u(Y) + \lambda \int \max\{U, V(w)\} dF(w) \tag{2}$$

The option value is the expected value of searching: an agent receiving a job offer decides if accepting the job offer or not by comparing the value of the current state with the value of being employed at the job (maximizes over $\{U, V(w)\}$).

Equilibrium Given this characterization, the optimal decision rule is straightforward to obtain: the value of employment is continuous monotone increasing in the wage while the value of unemployment does not depend on a specific

[9] This is a common assumption in the search literature that can be justified by risk neutrality or by market completeness. A handful of estimated search model allowing for savings decisions exist (Rendon (2006); Lentz (2009); and Lise (2011)) but they are faced with very difficult dynamic programming problems that force them to introduce restrictive assumptions. The complication derive from the difficulty of establishing global concavity of the value functions when savings are added to the job search model (Acemoglu and Shimer (1999); Lentz and Tranaes (2005)). Therefore, even if removing this assumption could be promising in our context because saving decisions can be potentially very different if they are taken at the individual or a the household level, we leave this extension to future research. García Pérez and Rendon (2012) are working in this area but the paper is still a working progress and no results are yet available for distribution.

wage. Therefore there exists a wage (the reservation wage) at which the agent is indifferent between the two states. We denote it by w^*:

$$w^* : V(w^*) = U \tag{3}$$

Her optimal decision rule will simply be to accept any job offer carrying a wage higher than the reservation wage and to reject otherwise. This optimal decision rule is incorporated in the value function as follows:

$$\rho U = u(Y) + \lambda \int_{w^*} [V(w) - U] \, dF(w) \tag{4}$$

We can now propose the following:

Definition 1 *Given*

$$\{\lambda, \rho, u(Y + w), F(w)\}, u \text{ continuous}$$

an ***individual search model equilibrium*** *is a set of values*

$$V(w), U$$

that solves equations (1) and (4).

2.1.2 Household Search Model

Environment The household search model maintains the same general structure of the individual search model but adds the household, extending the single-agent decision problem to a joint-search problem of two agents looking for jobs. Households are composed of two agents sharing and maximizing a common utility function and pooling income (that is, we assume a unitary model of the household). Each member of the household belongs to a different type and there are a total of two types in the economy. Conforming with the data we will use in estimation (married couples), we call individuals belonging to one type *wives* and to the other type *husbands*. The types are relevant because all the individuals belonging to the same type share the same structural parameters while this may not be true across types. In estimation, all the structural parameters with the exception of the discount rate are allowed to be type-specific but in discussing the theoretical model we impose that the two types share the same structural parameters.[10] Wives' parameters are denoted by the subscript $_W$ and individuals belonging to the set of wives are indexed by i. Husbands' parameters are denoted by the subscript $_M$ and individuals belonging to the set of husbands are indexed by j.

[10] This is the symmetric case extensively studied by GGV.

Value Functions The value functions are defined at the household level. When both household members are employed, the household receives value $V(w_i, w_j)$ defined by:

$$\rho V(w_i, w_j) = u(Y + w_i + w_j) \tag{5}$$

When one of the two member is unemployed (say, the wife), the household is subject to one job offers shock receiving value $T(w_i, 0)$ defined by:

$$(\rho + \lambda) T(w_i, 0) = u(Y + w_i) + \lambda \int \max\{T(w_i, 0), V(w_i, w), T(0, w)\} dF(w) \tag{6}$$

When both members are unemployed, the household is subject to two job offers shocks receiving value U defined by:

$$(\rho + 2\lambda) U = u(Y) + \lambda \left[\begin{array}{c} \int \max\{U, T(w, 0)\} dF(w) + \\ \int \max\{U, T(0, w)\} dF(w) \end{array} \right] \tag{7}$$

All the equations are straightforward generalizations of the corresponding equations in the individual search model with the exception of equation (6). Equation (6) shows the added margin implied by household search. Since the reservation wage of one spouse potentially depends on the reservation wage of the other spouse, it is possible that a wage that was acceptable to, say, the husband when the wife was unemployed becomes not acceptable when the wife is employed. As a result, equation (6) shows that the household is not maximizing simply over the current state (husband employed, wife unemployed,) and the usual alternative (wife employed, husband employed) but also over a state in which the wife accepts the job offer and the husband decides to quit his job.

Equilibrium The optimal decision rule are characterized by reservation wages but, by the argument just made, the reservation wage of one spouse may depend on the labor market status of the other spouse. We use the following notation to take into account this potential interdependence:

$$\begin{aligned} w_W^*(0) \quad &: \quad T(0, w_W^*(0)) = U & (8) \\ w_W^*(w_i) \quad &: \quad \max\{V(w_i, w_W^*(w_i)), T(0, w_W^*(w_i))\} = T(w_i, 0) & (9) \end{aligned}$$

Both reservation values exist and are unique because in both equations the LHS is monotone increasing in w_i while the RHS is constant with respect to w_i. The reservation wages of the husband $w_M^*(0)$ and $w_M^*(w_j)$ are analogously defined.

The implication of equation (8) is standard: an household where both spouses are unemployed accepts a job offer to one of the two partners if the wage is higher than the corresponding reservation wage ($w_M^*(0)$ for the husband and $w_W^*(0)$ for the wife). Incorporating the optimal decision rule in the value function (7) leads to:

$$\rho U = u(Y) + \lambda \left[\begin{array}{c} \int_{w_M^*(0)} [T(w, 0) - U] dF(w) + \\ \int_{w_W^*(0)} [T(0, w) - U] dF(w) \end{array} \right] \tag{10}$$

The implication of equation (9) is more subtle. In an household where one spouse is working and the other spouse is looking for a job, receiving a job offer may lead to three possible outcomes. Start with a couple where the wife is looking for job and the husband is working at a job paying a wage w_i. First, the household may decide to reject the offer and remain in the current state $(T(w_i, 0).)$ Second, the household may choose to accept the offer to the wife $(V(w_i, w_j).)$ Third, the household may choose to accept the offer to the wife and at the same time choose it is better off if the husband goes back to unemployment to search for a better job $(T(0, w_j).)$ This third option leads to the *endogenous* termination of the job relation and it is a relevant equilibrium channel which is not at work in the individual search framework. The intuition for this last possibility is straightforward. When the household had accepted the job offer to the husband, the wife was not working and therefore the outside option for the household was having both spouses in the unemployment state. When the wife receives an offer, the outside option is different and a decision that was optimal in the first case may not be optimal in the latter case. To deal with this possibility, we partition the set of wage offers to the wife conditioning on the husband being employed at a given wage w_i as:

$$\begin{aligned} \Gamma_E(w_i) &\equiv \{w_j : V(w_i, w_j) \geq T(w_i, 0), V(w_i, w_j) \geq T(0, w_j)\} \qquad (11) \\ \Gamma_U(w_i) &\equiv \{w_j : T(0, w_j) > T(w_i, 0), T(0, w_j) > V(w_i, w_j)\} \end{aligned}$$

The sets of wage offers to the husbands conditioning on the wife being employed ($\Gamma_E(w_j)$ and $\Gamma_U(w_j)$) are analogously defined. Incorporating this optimal decision rule in the value function (6) leads to:

$$\rho T(w_i, 0) = u(Y + w_i) + \lambda \left[\begin{array}{c} \int_{w \in \Gamma_E(w_i)} [V(w_i, w) - T(w_i, 0)] \, dF(w) + \\ \int_{w \in \Gamma_U(w_i)} [T(0, w) - T(w_i, 0)] \, dF(w) \end{array} \right] \qquad (12)$$

We can now propose the following:

Definition 2 *Given*

$$\{\lambda, \rho, u(Y + w_i + w_j), F(w_i), F(w_j)\}, u \text{ continuous}$$

a household ***search model equilibrium*** *is a set of values*

$$V(w, w), T(w, 0), T(0, w), U$$

that solves equations (5), (10) and (12).

2.1.3 Individual Search and Household Search Models Comparison

To make additional progress in characterizing the differences between the individual search equilibrium and the household search equilibrium we need to specify properties of the sets defined in (11). As shown in DF and GGV, the characterization crucially depends on the assumptions of the utility function.

Linear Utility Function Under linear utility:

$$u(c) = Y + w \tag{13}$$

agents are risk neutral and therefore the individual search model reverts to the standard partial equilibrium search model. Rewriting equation (4) we obtain the final equilibrium condition as:

$$w^* = \frac{\lambda}{\rho} \int_{w^*} [w - w^*] \, dF(w) \tag{14}$$

This condition characterizes the reservation wage as function of the primitive parameters. It is independent from nonlabor income because nonlabor income is received in any labor market state.

The linear utility function in the household search model is:

$$u(c_{ij}) = Y + w_i + w_j \tag{15}$$

We want to ask how the household search equilibrium compares to an environment with the same structural parameters but where each spouse is behaving as in an individual search model. The result is proved and discussed by DF and GGV and it can be summarized in our notation as follows:

Proposition 3 ***Equivalence of individual and household search under risk neutrality***

Given

$$u \text{ linear and } \{\lambda, \rho, u(Y + w_i + w_j), F(w_i), F(w_j)\}$$

a household search model equilibrium is equivalent to the equilibrium generated in an individual search model characterized by:

$$u \text{ linear and } \{\lambda, \rho, u(Y + w_a), F(w_a)\}, \quad a = i, j$$

As a result:

$$w_A^*(w_{-a}) = w_A^*(0) = w^*, \quad A = M, W; a = i, j$$

The result is equivalent to Proposition 1 in GGV and to Section 3.1 in DF. It is derived as follows. If the household utility is linear then the marginal utility of income is constant. If it is constant and individuals are maximizing income then it is irrelevant the flow value of income they are actually receiving when making decisions about future income streams. Therefore the decision of one spouse does not depend on the wage of the other spouse. If this the case then the set $\Gamma_U(w_i)$ is empty and the set $\Gamma_E(w_i)$ is the entire support of w_j which is equivalent to say that the household behaves as if the two spouses were optimally maximizing their individual income streams.

This result is quite powerful in terms of the objective of this paper. First, it states that there is the possibility of no mispecification error in assuming an individual search model when estimating search models of the labor market even if decisions are actually taken at the household level. Second, it allows us to develop a specification test for the individual search model. Third, it provides a strategy to identify risk aversion parameters. The last two implications arise from the comparison of the linear utility case with the concave utility case and they are discussed in the next section.

Concave Utility Function Assuming a concave utility function:

$$u(c) = u(Y + w), u''(c) < 0$$

introduces risk aversion. By rewriting equation (4) we obtain the following equilibrium condition for the individual search case:

$$u(Y + w^*) = u(Y) + \frac{\lambda}{\rho} \int_{w^*} [u(Y + w) - u(Y + w^*)] \, dF(w) \tag{16}$$

The reservation wage resulting from equation (16) is qualitatively different from the reservation wage from equation (14). The difference becomes clear when we perform a simple comparative static exercise: what is the impact of an increase of non-labor income Y on the reservation wage w^*? Studying this impact makes explicit the role of risk aversion in determining optimal equilibrium behavior. We know from equation (14) that the reservation wage is not affected by non-labor income in the linear case. In the concave case it must be, since the flow value of income has an impact on the marginal value of additional flows of income. First, an increase in nonlabor income increases the flow utility while searching therefore decreasing the marginal *cost* of search. Second, it decreases the option value of waiting for a better job therefore decreasing the marginal expected *gains* of search because the marginal benefit of a higher wage offer is now smaller.

In the household search model environment, the concave utility function is:

$$u(c_{ij}) = u(Y + w_i + w_j), u''(c) < 0 \tag{17}$$

The equilibrium follows the definition given in Definition 2 and it is now qualitatively different from the individual search case. The reason argument follows the discussion of the impact of nonlabor income on the reservation wage in the individual search case. Just as nonlabor income affects the marginal cost and the marginal expected benefit of search, the wage of one spouse affects the marginal cost and the marginal expected benefit of search of the other spouse, leading to a dependence between the reservation wages of the two partners. Nonlabor income and the spouse's wage are not equivalent, though, because nonlabor income is permanent and the spouse's wage is transitory since it depends on receiving a job offer shock. As a result, endogenous quits may occur unlike in the linear case. We state the result in the following proposition:

Proposition 4 ***Nonequivalence of individual and household search under risk aversion***

Given

$$u \text{ concave and } \{\lambda, \rho, u(Y + w_i + w_j), F(w_i), F(w_j)\}$$

a household search model equilibrium is different from the equilibrium generated in an individual search model characterized by:

$$u \text{ concave and } \{\lambda, \rho, u(Y + w_a), F(w_a)\}, \quad a = i, j$$

As a result:

1. *The reservation wages under individual and household search are different. For $A = M, W; a = i, j$ it holds:*

$$\begin{aligned} w_A^*(0) &\neq w^* \\ w_A^*(w_{-a}) &\neq w^* \text{ for at least some } w_{-a}, \end{aligned}$$

2. *In the household search equilibrium the reservation wage of one spouse depends on the wage and labor market status of the other spouse. For $A = M, W; a = i, j$ it holds:*

$$\begin{aligned} w_A^*(w_{-a}) &\neq w_A^*(0), \quad A = M, W; a = i, j \\ w_A^*(w_{-a}) &\neq w_A^*\left(w'_{-a}\right), w_{-a} \neq w'_{-a}, \quad A = M, W; a = i, j \end{aligned}$$

3. *Endogenous quits are possible. For $A = M, W; a = i, j$ it holds:*

$$\text{It exists a set of } w_a > w_A^*(0) \text{ such that } \Gamma_U(w_a) \text{ is nonempty}$$

The proposition is equivalent to Proposition 2 and 3 in GGV and to Section 3.3 in DF. The reason for the result is that the additional flow of income generated by the spouses' job has the same effect on household utility as the increase in nonlabor income had on individual utility in the individual search case: it decreases the marginal cost of search and it decreases the expected marginal benefit of search. As a result, it does matter if we are looking at a single-searcher problem or at a dual-searcher problem.

Given that the labor markets status of one spouse has an impact on the reservation wage of the other spouse then endogenous quit may occur. Start with a household where both spouses are unemployed and searching. Suppose the husband receives a wage offers $w_i > w_M^*(0)$ then the household will accept it, changing its state to a household composed by an husband working at a wage w_i and a wife searching for a job. If the wife receives an offer $w_j > w_W^*(w_i)$ and $T(0, w_j) > V(w_i, w_j)$ then the optimal behavior of the household mandates to the wife acceptance of the offer and to the husband quit of the current job. The symmetry in the environment faced by the two spouses - i.e. the fact the two spouses labor market are characterized by the same structural parameters - guarantees that for some values in the support of the wage offers this is always the case.[11] When symmetry is removed, as in the extended model we will estimate, endogenous quits may or may not occur depending on parameters.

We conclude this section by pointing out two empirical implications of Propositions 3 and 4. First, they clarify that in the linear case the labor market status of one spouse does not depend on the labor market status of the other spouse while in the concave case it does. If in the data we observe dependence between the labor market status of the two spouses then we can use that information to learn about the concavity of the utility function. Second, if we specialize the concave utility function to a parametric form that nests the linear case then we can test for linear utility. A test for linear utility is relevant because it is equivalent to a specification test for the individual search model.

2.2 Extended Version

2.2.1 Individual Search Model

Environment We add the following features to the environment discussed in the simplified version. First, we allow for exogenous termination of jobs. Exogenous terminations follow a Poisson process with parameter η. Second, we introduce on-the-job search. Job offers while employed follow a Poisson process with parameter γ. Both features are standard in the search literature and are necessary to fit job-to-job and job-to-unemployment transitions.

The third feature we add to the environment is less common in the literature[12] and it is motivated by our objective to fit household behavior. We will use a sample of households composed by husbands and wives, both participating in the labor market. As a result we have a relative large number of women in the sample and women tend to have a larger variance in labor supply than men, in particular at lower than full-time levels. We have therefore decided to introduce a labor supply decision in the model, albeit limited to the intensive margin. Adding an extensive margin is interesting and would fit more data features but it greatly complicates the computation problem during estimation. Moreover, we think that the comparison of individual search and household search is still very informative even if it is limited to labor market participants. We introduce the intensive margin of labor supply by assuming that job offers arrive as a pair of wage and hours requirement[13] (w, h). Their joint distribution is denoted by $F(w, h)$. Consumption is then defined as $c = Y + wh$, leisure as $l = 1 - h$ and the utility function as $u(c, l)$. To make the notation in the rest of the paper less cumbersome we define the function $v(w, h) \equiv u(Y + wh, 1 - h)$.

[11] See Proposition 2 in GVV. They label this situation the "breadwinner" cycle.

[12] Blau (1991) is the only example of an estimated search model including this feature, i.e. the joint offer of wage-hours pairs. Flabbi and Moro (2012) estimate a search model allowing for the choice between part-time and full-time work but the choice is contingent to a wage offer and it is bargained with the employer.

[13] This characterization is consistent with the usual assumption in implicit contract theory where firms post job package offers. See for example, Abowd and Card (1987); Hwang, Mortensen and Reed (1998).

Value Functions The value of being employed at given wage and hours requirement is equal to the sum of the flow utility of consumption and leisure allowed by the job, the option value of receiving a better wage offer, and the value of becoming unemployed if the job gets exogenously terminated:

$$\begin{aligned} V\left[v\left(w,h\right)\right] &= \left(\rho+\gamma+\eta\right)^{-1}\{v\left(w,h\right) \\ &+\gamma\iint \max\left\{V\left[v\left(w,h\right)\right], V\left[v\left(w',h'\right)\right]\right\}dF\left(w',h'\right) \\ &+\eta U\} \end{aligned} \tag{18}$$

The value of being unemployed is equal to the sum of the flow utility of consumption and leisure when unemployed, and the option value of receiving an acceptable job offer:

$$\begin{aligned} U &= \left(\rho+\lambda\right)^{-1}\{v\left(0,0\right) \\ &+\lambda\iint \max\left\{U, V\left[v\left(w,h\right)\right]\right\}dF\left(w,h\right)\} \end{aligned} \tag{19}$$

Equilibrium The optimal decision rule retains the reservation value property of the simplified version of the model but the critical value is now defined on the utility value. The reason, as discussed extensively in Blau (1991) and Hwang, Mortensen and Reed (1998), is that the mapping between the characteristics of a job offer and its utility value is not one-to-one: when both wage and hours enter the utility function, different combinations of job packages (w,h) generate the same level of utility.

Agents have two decisions to make: accept or reject a job offer while employed and accept or reject a job offer when unemployed. The reservation utility value while employed at a given job (w,h) is simply the instantaneous utility value of the current job. The reservation utility value while unemployed is defined in the same way as the reservation wage in the simplified model (equation (3)):

$$v^*: U = V\left[v^*\right] \tag{20}$$

Incorporating both decision rules in the value functions leads to the following value of employment at a job (w,h):

$$\begin{aligned} \rho V\left[v\left(w,h\right)\right] &= v\left(w,h\right) \\ &+\gamma \iint_{\{(w',h'):v(w',h')>v(w,h)\}} \left\{V\left[v\left(w',h'\right)\right]-V\left[v\left(w,h\right)\right]\right\}dF\left(w',h'\right) \\ &+\eta\left\{U-V\left[v\left(w,h\right)\right]\right\} \end{aligned} \tag{21}$$

and to the following value of unemployment:

$$\begin{aligned} \rho U &= \left(\rho+\lambda\right)^{-1}\{v\left(0,0\right) \\ &+\lambda \iint_{\{(w,h):v(w,h)>v^*\}} \left\{V\left[v\left(w,h\right)\right]-U\right\}dF\left(w,h\right)\} \end{aligned} \tag{22}$$

As a result, we obtain the following:

Definition 5 *Given*

$$\{\lambda, \gamma, \eta, \rho, u(c, l), F(w, h)\}, u \text{ continuous}$$

an ***individual search model equilibrium*** *is a set of values*

$$V[v(w, h)], U$$

that solves equations (21) and (22).

2.2.2 Household Search Model

Environment The extended household search model incorporates the features of the extended individual search model. It also removes the symmetry between the two spouses imposed in the simplified version. Agents belongs to two types - *husbands* and *wives* - and a household is composed by one member for each type. In estimation, all the structural parameters of the model will be allowed to be type-specific with the exception of the discount rate. We follow the notation of the simplified model by denoting with the subscripts $_W$ and $_M$ respectively the wives' parameters and the husbands' parameters and with the index j and i respectively individuals belonging to the set of wives and to the set of husbands.

Value Functions When both household members are employed, the household receives a value equal to the sum of the flow utility of consumption and leisure allowed by both jobs, the option value both spouses have of receiving a better wage offer, and the value of becoming unemployed if any of the two job relations gets exogenously terminated:

$$\begin{aligned} V[v(w_i, h_i, w_j, h_j)] &= (\rho + \gamma_M + \gamma_W + \eta_M + \eta_W)^{-1} \{v(w_i, h_i, w_j, h_j) \\ &+\gamma_M \iint \max\{V[v(w_i, h_i, w_j, h_j)], V[v(w_i', h_i', w_j, h_j)]\} dF_M(w_i', h_i') \\ &+\eta_M T[v(0, 0, w_j, h_j)] \\ &+\gamma_W \iint \max\left\{V[v(w_i, h_i, w_j, h_j)], V\left[v\left(w_i, h_i, w_j', h_j'\right)\right]\right\} dF_W\left(w_j', h_j'\right) \\ &+\eta_W T[v(w_i, h_i, 0, 0)]\} \end{aligned} \tag{23}$$

When only one of the two members is employed (for example, the husband), the household receives a value equal to:

$$\begin{aligned} T[v(w_i, h_i, 0, 0)] &= (\rho + \gamma_M + \lambda_W + \eta_M)^{-1} \{v(w_i, h_i, 0, 0) \\ &+\gamma_M \iint \max\{T[v(w_i, h_i, 0, 0)], T[v(w_i', h_i', 0, 0)]\} dF_M(w_i', h_i') \\ &+\eta_M U \\ &+\lambda_W \iint \max\left\{T[v(w_i, h_i, 0, 0)], V\left[v\left(w_i, h_i, w_j', h_j'\right)\right], T\left[v\left(0, 0, w_j', h_j'\right)\right]\right\} dF_W\left(w_j', h_j'\right)\} \end{aligned} \tag{24}$$

As in the simplified version of the model, an offer to the wife may generate the endogenous quit of the husband from his current job (last term of equation (24)).

When both spouses are unemployed, the household receives a value equal to:

$$\begin{aligned} U &= (\rho + \lambda_M + \lambda_W)^{-1} \{ v(0,0,0,0) \\ &+ \lambda_M \iint \max \{ U, T[v(w_i, h_i, 0, 0)] \} \, dF_M(w_i, h_i) \\ &+ \lambda_W \iint \max \{ U, T[v(0,0,w_j,h_j)] \} \, dF_W(w_j, h_j) \} \end{aligned} \tag{25}$$

Equilibrium The equilibrium is an extension of the equilibrium definitions previously discussed. The reservation values are defined over utility values, as in the individual search extended version of the model. The household, though, has more decisions to make because the optimal decision of one spouse depends upon the labor market status of the other spouse.

When both household members are employed, the household has to decide whether to accept or reject on-the-job job offers. The reservation value is the current utility value because the household is comparing in both cases the value of both spouses being employed.

When only one of the two members is employed (for example, the husband), the household has two qualitatively different decisions to make. First, it has to decide whether to accept or reject on-the-job job offers to the husband. The reservation value is the current utility value because the household is comparing in both cases the value of having the husband working and the wife searching. Second, it has to decide whether to accept or reject job offers to the wife. If the offer is accepted the optimal policy for the husband can be both staying on the job or quitting, just as in the simplified version of the model. The reservation utility value is therefore defined as:

$$v_W^*(w_i, h_i) : \max \{ V[v_W^*(w_i, h_i)], T[v_W^*(w_i, h_i)] \} = T[v(w_i, h_i, 0, 0)] \tag{26}$$

Notice that in $T[v_W^*(w_i, h_i)]$ it is the wife who is working while in $T[v(w_i, h_i, 0, 0)]$ it is the husband who is working. Since we remove the symmetry assumption imposed in the simplified version (and by GGV), the combinations of (w_j, h_j) and (w_i, h_i) that guarantee the same value of T are in general different. As in the simplified version, it is convenient to define the following sets:

$$\begin{aligned} \Gamma_E(w_i, h_i) &\equiv \left\{ \begin{array}{c} (w_j, h_j) : V[v(w_i, h_i, w_j, h_j)] \geq T[v(w_i, h_i, 0, 0)], \\ V[v(w_i, h_i, w_j, h_j)] \geq T[v(0, 0, w_j, h_j)] \end{array} \right\} \\ \Gamma_U(w_i, h_i) &\equiv \left\{ \begin{array}{c} (w_j, h_j) : T[v(0, 0, w_j, h_j)] > T[v(w_i, h_i, 0, 0)], \\ T[v(0, 0, w_j, h_j)] > V[v(w_i, h_i, w_j, h_j)] \end{array} \right\} \end{aligned} \tag{27}$$

The sets of wage offers to the husbands conditioning on the wife being employed ($\Gamma_E(w_j, h_j)$ and $\Gamma_U(w_j, h_j)$) are analogously defined.

When both spouses are unemployed, the household has to decide if accepting or rejecting job offers to the wife or to the husband. The reservation utility value is defined as:

$$v_W^*(0,0) : T\left[v_W^*(0,0)\right] = U$$

for the wife and analogously for the husband.

By incorporating the optimal decision rules in equations (23), (24), and (25), we obtain the equilibrium value for both spouses working:

$$\begin{aligned}
&\rho V\left[v\left(w_i,h_i,w_j,h_j\right)\right] = v\left(w_i,h_i,w_j,h_j\right) \qquad (28)\\
&+\gamma_M \iint_{\left\{\left(w_i',h_i'\right):v\left(w_i',h_i',w_j,h_j\right)>v\left(w_i,h_i,w_j,h_j\right)\right\}} \left\{\begin{array}{c} V\left[v\left(w_i',h_i',w_j,h_j\right)\right] \\ -V\left[v\left(w_i,h_i,w_j,h_j\right)\right]\end{array}\right\} dF_M\left(w_i',h_i'\right)\\
&+\eta_M\left\{T\left[v\left(0,0,w_j,h_j\right)\right] - V\left[v\left(w_i,h_i,w_j,h_j\right)\right]\right\}\\
&+\gamma_W \iint_{\left\{\left(w_j',h_j'\right):v\left(w_i,h_i,w_j',h_j'\right)>v\left(w_i,h_i,w_j,h_j\right)\right\}} \left\{\begin{array}{c} V\left[v\left(w_i,h_i,w_j',h_j'\right)\right] \\ -V\left[v\left(w_i,h_i,w_j,h_j\right)\right]\end{array}\right\} dF_W\left(w_j',h_j'\right)\\
&+\eta_W\left\{T\left[v\left(w_i,h_i,0,0\right)\right] - V\left[v\left(w_i,h_i,w_j,h_j\right)\right]\right\}
\end{aligned}$$

for one spouse working and the other searching:

$$\begin{aligned}
&\rho T\left[v\left(w_i,h_i,0,0\right)\right] = v\left(w_i,h_i,0,0\right) \qquad (29)\\
&+\gamma_M \iint_{\left\{\left(w_i',h_i'\right):v\left(w_i',h_i',0,0\right)>v\left(w_i,h_i,0,0\right)\right\}} \left\{T\left[v\left(w_i',h_i',0,0\right)\right] - T\left[v\left(w_i,h_i,0,0\right)\right]\right\} dF_M\left(w_i',h_i'\right)\\
&+\eta_M\left\{U - T\left[v\left(w_i,h_i,0,0\right)\right]\right\}\\
&+\lambda_W \left\{\begin{array}{l} \iint_{\left(w_j',h_j'\right)\in\Gamma_E\left(w_i,h_i\right)} \left\{V\left[v\left(w_i,h_i,w_j',h_j'\right)\right] - T\left[v\left(w_i,h_i,0,0\right)\right]\right\} dF_W\left(w_j',h_j'\right) \\ + \iint_{\left(w_j',h_j'\right)\in\Gamma_U\left(w_i,h_i\right)} \left\{T\left[v\left(0,0,w_j',h_j'\right)\right] - T\left[v\left(w_i,h_i,0,0\right)\right]\right\} dF_W\left(w_j',h_j'\right)\end{array}\right\}
\end{aligned}$$

and for both spouses searching:

$$\begin{aligned}
&\rho U = v\left(0,0,0,0\right) \qquad (30)\\
&+\lambda_M \iint_{\left\{\left(w_i,h_i\right):v\left(w_i,h_i,0,0\right)>v_M^*(0,0)\right\}} \left\{V\left[v\left(w_i,h_i,0,0\right) - U\right]\right\} dF_M\left(w_i,h_i\right)\\
&+\lambda_W \iint_{\left\{\left(w_j,h_j\right):v\left(0,0,w_j,h_j\right)>v_M^*(0,0)\right\}} \left\{V\left[v\left(0,0,w_j,h_j\right)\right] - U\right\} dF_W\left(w_j,h_j\right)
\end{aligned}$$

We can now propose the following definition.

Definition 6 *Given*

$$\left\{\lambda_{M,W}, \gamma_{M,W}, \eta_{M,W}, \rho, u\left(c,l_i,l_j\right), F_M\left(w_i,h_i\right), F_W\left(w_j,h_j\right)\right\}, u \text{ continuous}$$

a household ***search model equilibrium*** *is a set of values*

$$V\left[v\left(w_i,h_i,w_j,h_j\right)\right],T\left[v\left(w_i,h_i,0,0\right)\right],T\left[v\left(0,0,w_j,h_j\right)\right],U$$

that solves equations (28), (29) and (30).

2.2.3 Individual Search and Household Search Models Comparison

The extensions added to the model do not qualitatively change the main results with respect to the comparison between the individual and household search models: all the main arguments of the previous section carry through because we are only adding options without introducing major changes in behavior. However, in the extended version of the model the proofs of the previous propositions are more involved and less instructive than in the previous case due to the lack of symmetry between the two spouses, the possibility of on-the-job search and the presence of labor supply decisions. As a result, we propose here just a succinct discussion of the results and a selection of simulations tracing the optimal policy rules of the two spouses (Figures 1-4).

First, as stated in Proposition 3, if agents are risk neutral then the household search model equilibrium is equivalent to the individual search model equilibrium. The proof of the result in the simplified version of the model is based on the fact that the marginal utility of income is constant and therefore the actual flow value of income is irrelevant when maximizing future income streams. This basic fact does not change if we add exogenous job termination, on-the-job search and labor supply.

Second, as stated in Proposition 4, if agents are risk averse then the household search model equilibrium is different from the individual search model equilibrium because the optimal decision rule concerning the labor market status of one spouse is potentially affected by the labor market status of the other spouse. Since the result is implied by the concavity of the utility functions, it carries through when we add job termination, on-the-job search and labor supply. Adding these extensions simply add choices and options but it does not change the fact that concavity of the utility function makes the optimal decision rule of one spouse dependent on the labor market status of the other spouse.

We illustrate the features of the extended version of the model by drawing the reservation wages schedules in a series of Figures. We start with Figure 1 that we label the benchmark model because it is computed at the parameters estimates in our preferred specification (see Table 2, Columns 3 and 4). We report the reservation wage of a wife who is currently unemployed, receives a full-time job offer and is married to a husband working full-time. We compare this reservation wage schedule with the reservation wage the wife would be facing if she was a single-searcher in an individual search environment characterized by the same parameters of the household search environment.

The main results from Figure 1 are the following. First, we clearly see the strong dependence of the wife's reservation wage on the husband wage. At the minimum acceptable wage, the reservation wage for the wife is less than $2 per hour but, as the husband's wage increases, the wife's reservation value rapidly increases until about \$6 per hour. After that, it keeps increasing but at a lower rate. This pattern is in contrast with the reservation wage in the individual search case, which is constant at a value of little more than \$2 per hour. Second, the two reservation wage schedules cross. As a result, there is a range of husband wages such that the wife's reservation wage in the household search model is lower than the wife's reservation wage in the corresponding individual search model. We will show that this effect is important to explain some the gender wage gap in our sample. Third, the change in slope in the wife's reservation wage schedule shows the importance of allowing for endogenous quitting. When the husband is earning a relatively low wage (less than about \$6 per hour), he would prefer to quit his job when the wife accepts a full-time job offer. As a result, the wife's reservation wage is very sensitive to the husband wage. After the \$6 per hour threshold, the husband will remain employed even if the wife accepts a job offer: his wage is high enough that it is not optimal to go back to unemployment to receive job offers at an higher rate than in employment. As a result, the wife's reservation wage is less sensitive to the husband's wage.

Figure 2 reiterates the message of Propositions 3 and 4 about the impact of risk aversion. We show the wife's reservation wage schedule for different values of risk aversion, bounded between the two case most commonly used in the applied literature: the linear case (coefficient of relative risk aversion (rra) = 0) and the logarithmic case (coefficient of relative risk aversion (rra) = 1). We can clearly see that for rra values moving from 1 toward 0, the reservation wage schedule is changing from a positive sloped curve to a flat line and therefore the reservation wage of the wife is becoming less and less sensitive to the husband's wage. The husband's wage at which the wife's reservation wage schedule changes slope is decreasing as the risk aversion coefficient decreases: this is consistent with the amount of endogenous quitting decreasing as we get closer to risk neutrality.

Figure 3 shows the endogenous quitting behavior in more detail (notice the change of scale with respect to the previous Figure: now we focus on husband's wages between 0 and \$8 per hour). Figure 3 reports not only the wife's reservation wage schedule but also the husband's reservation wage schedule computed at the wife's reservation wage. The crossing of this curve with the 45 degree line partitions the husband wages support in two regions. The first region - up to the wage corresponding to the crossing - is the endogenous quitting region such (i.e. the $\Gamma_U(w_j, FT)$ set). The second region - above the crossing threshold - is the region where the husband remains employed at the current job no matter what the wife will do (i.e. the $\Gamma_E(w_j, FT)$ set). To see the result, first focus on the first region. Denote with w_i a husband's wage in this region and suppose the wife accepts a wage exactly at her corresponding reservation value, i.e. $w_W^*(w_i)$. The curve we denote as "Husband's w* at wife's w*" pins down the husband reservation wage when the wife is employed at $w_W^*(w_i)$, i.e. $w_M^*(w_W^*(w_i))$. By using the 45 degree line to project this reservation wage on the x-axis, we can see that $w_M^*(w_W^*(w_i)) > w_i$ and therefore the husband will quit his current job working full-time at w_i when the wife accepts a job offer paying at least the reservation wage. Now focus on the second region. Here, $w_M^*(w_W^*(w_i)) < w_i$ and therefore the husband will never quit his current job due to the wife accepting a job offer. Finally, we note that the wife's reservation wage schedule changes slope exactly where the husband reservation wage curve is crossing the 45 degree line, i.e. when the husband behavior changes from quitting the current job to keeping the current job as a result of the wife's accepting the job offer. This result confirms the discussion we provided commenting on Figure 1 where we claimed that the change in the slope of the wife's reservation wage schedule was due to the endogenous quitting behavior of the husband.

Figure 4 shows the impact of introducing labor supply and heterogenous nonlabor income in the household search model. We compare two levels of labor supply (part-time and full-time)[14] and two levels of nonlabor income ($Y = 0.44\$/h$ and $Y = 19.50\$/h$).[15] First, both factors have a significant impact on the reservation wages schedule. Consider a woman in a household with low nonlabor income and a husband's wage equal to \$10 per hour. Her reservation wage is a little more than \$6 per hour when offered a full-time job but it is more than \$8 per hour when offered a part-time job. Fixing labor supply at full-time, her reservation wage ranges from a little more than \$6 per hour if her household's nonlabor income is low to about twice as much if nonlabor income is high. Second, nonlabor income and labor supply have interesting interaction effects. At low values of nonlabor income, the part-time reservation wage is higher than the full-time reservation wage at any values of the husband's wage; the opposite is true at high values of nonlabor income. The reason is once again the curvature of the utility function. At low values of nonlabor income, individuals value consumption relatively more than leisure and therefore they will be more willing to accept a full-time job. At high level of nonlabor income, instead, the marginal benefits of additional consumption are lowered and leisure time becomes relatively more valuable making a part-time job more attractive. The rich impact of nonlabor income and labor supply points out that ignoring these sources of heterogeneity may lead to very different estimation results and may dramatically change the inference. Finally, another remark on endogenous quitting. Both nonlabor income and labor supply have an impact on the amount of endogenous quitting or, more formally, on the measure of the sets $\Gamma_U (w_j, h_j)$ and $\Gamma_E (w_j, h_j)$. Under our parametrizations, part-time and nonlabor income decrease the amount of endogenous quitting. Their combined effect leads to a case where there is no endogenous quitting, i.e. the reservation wage schedule is a straight line. This is the case for the second reservation wage schedule from the top where nonlabor income is high and the wife is offered a part time job.

2.2.4 Empirical Implications

The specification of the model, even in the extended version, is tractable enough to obtain identification and estimation of its structural parameters given the

[14] They correspond to the labor supply regimes we will use in estimation: part-time is defined as working less than 35 hours per week and full-time as working more than 35 hours per week.

[15] The first value corresponds to the average nonlabor income of households with nonlabor income higher than 0 but lower than the median. The second value corresponds to the average nonlabor income of households with nonlabor income higher than the median. They are two of the nonlabor income values at which we estimate the model.

appropriate dataset. We will discuss the issue in more detail in the identification section. In this section, we point out two relevant empirical implications of the model.

A first straightforward implication derives from Proposition 3: under linearity in preferences there is *no* mispecification error in assuming individual search behavior *even if decisions are actually taken at the household level.* In other words, the parameter estimates obtained from a given set of data using the individual search specification or the household search specification will be exactly the same if the utility function is linear. This is due to the equivalence of the two equilibria under the two specifications and it is the implication often used to justify the estimation of individual search models. In our context, we can use this implication to run a specification test. If we estimate the model under concave preferences that nest the linear case, then a test for the linear utility specification is equivalent to a test for the individual search specification.

A second more subtle empirical implication derives from Proposition 4. The identification of risk aversion parameters is notoriously non-trivial and is rarely attempted within the context of a search model.[16] Proposition 4, though, shows that the presence of risk aversion is exactly what makes the equilibrium of the household search model different from the equilibrium of the individual search model. Therefore, all the dependence of the labor market decisions of one spouse on the labor market status of the other spouse must come from the curvature of the utility function. As a result, we can use the correlation between the labor market decisions of the two spouses to identify the risk aversion parameters.

3 Data

We use data from the 2001-2003 panel of the *Survey of Income and Program Participation* (SIPP) to estimate the model. The main objective of the SIPP is to provide accurate and comprehensive information about the principal determinants of the income of individual households in the United States. The SIPP collects monthly information regarding individual's labor market activity including earnings, average hours worked, and whether the individual changed jobs within an employment spell. The main advantage of using the SIPP is the ease in creating labor market histories for all individuals in the sample and in linking detailed spousal labor market information across time. The second characteristic is clearly a fundamental requirement in our empirical application and it is not available at this level of precision in other commonly used panel data for the US. The main disadvantage is the relatively short time span over which the panel data are available. However, our model has enough structure to be able to identify and precisely estimate the main structural parameters even if

[16] As mentioned, the only previoulsy estimates household search model is DF. However, their identification of the risk aversion parameters is different because their data has an additional source of identification: the provision of employer-provided health insurance. GGV do not attempt to identify the risk aversion parameter and perform their calibrations fixing the relative risk aversion parameter at various values.

the time dimension of the panel is short.

3.1 Sample Restrictions

Although the target sample size for each SIPP panel is quite large, the size of our sample is reduced by several restrictions. As we describe in the econometrics section, we use point-in-time samples from the panel instead of the detailed individual-level event histories to estimate the model. Specifically, for each SIPP panel, we form point-in-time samples spaced three months apart for 24 months. We use wage and hours data from several of these eight point-in-time samples. For convenience we will refer to these times as times $t_1, t_2, .., t_8$.

In each of the selection criteria we describe, if at least one spouse fails to satisfy the criteria to remain in the sample, then both spouses are excluded from the sample. After imposing all selection criteria our sample consists of 3,984 individuals for a total of $1,992$ married couples.

We select married couples in which each spouse is aged between 25 and 50 (inclusive) at the beginning of the panel. Although this selection criteria excludes married couples in which the age of one spouse is outside this range and the age of the other spouse is within this range, we feel that it is better to be more restrictive due to differences in labor market outcomes for younger workers (aged 18 to 24 inclusive) and for older workers (aged 50 to 65 inclusive).[17] We only consider married couples in which each spouse is "present" in the household throughout the panel, meaning that we exclude any couples that are separated or not living together at any point in the panel. We do this because we do not model marriage formation and dissolution. Additionally, neither spouse must participate in the armed services throughout the sample period.

When using event history data, it is typical to observe a sequence of responses in which the individual is unemployed for several periods, then transitions to being out of the labor force (OLF), then re-enters the unemployed state, and finally obtains a job. We choose to include spouses in the sample who answer that they are OLF at some point in the panel, but have an employment spell or unemployment spell at other points in the sample. We exclude spouses if either spouse is OLF for the entire panel period or if either spouse transitions between OLF and unemployment, but does not work in the panel period. Finally, we exclude spouses if either spouse has a "broken" labor market history, such as being in the sample at the beginning and the end of the panel, but absent in between.

Hours and earnings information must also be observable at every point in the panel for any employed individual. Couples in which at least one individual supplies wage information, but does not supply how many hours per week he or she works are excluded from the sample. In most surveys that provide disaggregate labor market information, one usually observes a greater proportion

[17] The labor market outcomes of younger workers are typically characterized by high turnover rates between jobs and between employment and unemployment, and are affected by human capital investment decisions. The labor market outcomes of older workers are typically characterized by end-of-career decisions made well before individuals reach retirement age.

of employed individuals reporting hourly wages rather than weekly, monthly, or annual earnings when the average age of the respondents is younger. Because older workers are less likely to be paid at an hourly rate, we are forced to impute hourly wage rates for individuals who report weekly earnings and weekly hours worked. Thus, it is essential that we have hours of labor supplied for each employed individual.

We recode hours worked per week into part-time and full-time categories, that is our intensive margin of the labor supply is reduced to a distribution with two support points. We impose this assumption to simplify the computational problem implied by the solution and estimation of the model. We denote with p the probability of receiving a part-time offer. Individuals are coded as working part-time if they work less than 35 hours per week and full-time if they work at least 35 hours per week. We label the two resulting labor supply regimes with h_i^{pt} and h_i^{ft}. Their specific values in the simulation are calculated from the average hours worked in each hours category in the sample unconditional on gender. They are normalized for a time endowment available for work and leisure equal to 80 hours per week.

Empirical wage distributions are used extensively in the estimation procedure. The only adjustment we impose on the raw wage data is excluding couples in which there exist at least one spouse whose wage lies in the top 0.75 percent or the bottom 0.75 percent of the wage distribution conditional on gender. All wages are adjusted for inflation to the 2001 CPI.

3.2 Descriptive Statistics

Descriptive statistics of the estimation sample are reported in Tables 1 and 2. Since we separately estimate the model for couples with and without children younger than 18 years, we present the descriptive statistics conditioning on the presence of children. We add this control in estimation to partially take into account the systematic difference in labor market behavior induced by the presence of children. A better solution would have been to directly model fertility decisions but this is clearly a not trivial extension to the model.[18] Moreover, the short time dimension of the data does not provide a lot of information about this process in our sample. We use 18 years as cut-off point because it usually denotes the age at which children leave home therefore significantly changing the child-care requirements on the household.[19]

Table 1 contains descriptive statistics of the cross-sectional features of the data. We compute them at the beginning of the observation period (beginning of 2001) and then three months apart for the following 24 months. The values of the statistics are very stable across time and in Table 1 we just report values for the first point-in-time sample. The first and fifth columns report unconditional

[18] Erosa, Fuster and Restuccia (2002) and (2010) are among the few examples of models allowing for fertility decisions in a fully developed labor market search environment. However, their models do not allow for dual-search in the labor market.

[19] We have experimented with cut-off points at 16 and 14 years old without experiencing qualitative changes in the results.

moments while the other columns report moments conditional on the other spouse's labor market status.

Gender differentials are in line with the literature and the aggregate evidence: men are much more likely to work full-time (91.6% compared with 55.8% for women in household with children) and earn on average higher wages than women. The gender gap in full-time jobs is about 23%, almost equal to the gender wage gap at the median reported by the Bureau of Labor Statistics. The gender gaps are not significantly reduced on the sample without young children, pointing out the well known persistence of the phenomenon. There is indication of a full-time premium in accepted wages: average hourly wages are higher in full-time jobs than in part-time jobs on all the samples.[20] As a result, the gender gap in earnings is larger than the gender gap in wages, reaching 40% overall on the sample of couples with young children.

We describe cross-sectional inequality at the individual level by reporting coefficient of variations (CV) computed on hourly wages and weekly earnings. Inequality is higher for men than for women, a result commonly found in the literature.[21] Wages are more compressed among individuals working part-time and the higher incidence of part-time among women may explain why the gender gap in inequality is higher at the earnings level (weekly wages) than at the hourly wages level.

But the most relevant result emerging from the descriptive statistics is that the labor market status of one spouse varies with the labor market status of the other spouse. For example, in the sample with children, 26.5% of women are employed part-time overall but only 11.3% of the women married to an unemployed husband are employed part-time. Not only the labor market status but also the average wage varies with the labor market status of the husband. Average hourly wages for women working full-time decrease from 15.13 dollars an hour, to 14.94 dollars an hour, to 13.08 dollars an hour if, respectively, the husband works full-time, works part-time or is unemployed. Wage variation is also sensitive to the husband's labor market status: the coefficient of variation is different if the husband is working full-time, part-time, or he is unemployment. Husbands are less sensitive than wives to their spouse's labor market status but there are still non-negligible effects: the full-time employment rate decreases from 91.2% on the sample of men married to women working full-time to 87.8% on the sample married to unemployed women. The variation in average wages is more modest (average wages are 18.37 dollars an hour in the first sample and 18.74 dollars an hour in the second) but the variation in wage dispersion is very sensitive to the wife's labor market status (the coefficient of variation in hourly wages is much smaller if the wife is working than if the wife is unemployed).

[20] This is also a common results in the literature (Altonji and Paxson (1988)). Blank (1990) estimates large wage penalties for working part-time using Current Population Survey data but suggests that selection into part-time is significant and that the estimates are not very robust. Blau (1991) and Flabbi and Moro (2012) control for some of this selection adding a search model structure (as we do in this paper) and they also find a full-time premium.

[21] See for example Figure 4 in the survey by Katz and Autor (1999), Figure 3 in Autor, Katz, and Kearney (2008) or Table 1 in Dey and Flinn (2008).

The sample of couples without young children confirms the dependence of one's labor market status to the spouse's labor market status. In some cases the differences are larger than in the sample of couples with young children: for example, full-time employment range from 77.9% on women married to men employed full-time to 43.8% on women married to unemployed men. Even when the dependence is similar, however, the impact of the other spouse's labor market status may be different: on the sample of couples without young children we see women working more frequently full-time if the husband is employed while the opposite is true on the sample with young children.

Table 2 contains descriptive statistics of the labor market dynamics information contained in the data. We summarize the information reporting transition probabilities between the labor market state at the beginning of the period and the labor market state three months later. Again, we present the evidence conditioning and not conditioning on the other spouse's labor market status. There is persistence across labor market states, in particular on full-time employment. For example, 90% of women and 96% of men employed full-time are still employed full-time three months later. However, transitions across labor market states are not rare, in particular for men: 45% of men who are unemployed at the beginning of the period are employed three months later. This proportion is much lower on the female sample: only 15% of unemployed women are employed three months later.

The evidence conditioning on the spouse's labor market status confirms the dependence observed in Table 1. For example, in the sample with children an employed women married to an unemployed husband is much more likely to become unemployed (a frequency of 14.3% as opposed to about 4% if the husband is employed) and a woman working part-time is much more likely to do so three months later if also the husband is employed part-time. Males transitions are also sensitive to their wives labor market status: if they work part-time, they are 20 percentage points more likely to do so three months later if the wife works part-time than if the wife is unemployed. Qualitatively similar results are found in the sample without young children. However, a larger number of transitions are not observed due to the smaller sample size: for example, we observe zero transitions from part-time employment to unemployment on both the males and females samples.

In conclusion, both Table 1 and Table 2 show the dependence of one spouse's labor market status to the other spouse's labor market status. Explaining this dependence is one of the motivation of our paper since it constitutes evidence that cannot be generated by an individual search model. In fact, an individual search model with random matching should generate no correlation at all between the spouses' labor market states. It is also an empirical feature we will exploit in our identification strategy.

4 Estimation and Identification

4.1 Identification

We discuss the identification conditioning on the data set we just described and on the functional form assumptions we will use in estimation. The identification discussion can be more general but, given the contribution of the paper, we think it is better to discuss the identification within the framework actually used in the application.

We make three functional form assumptions. First, we need to assume a utility function that allows for risk aversion. We assume a Constant Relative Risk Aversion formulation (CRRA). The instantaneous utility for household i, j is:

$$u\left(c_{ij}, l_i, l_j; \delta, \boldsymbol{\beta}, \boldsymbol{\alpha}\right) = \tag{31}$$
$$(1 - \alpha_M - \alpha_W) \frac{c_{ij}^{\delta} - 1}{\delta} + \alpha_M \frac{l_i^{\beta_M} - 1}{\beta_M} + \alpha_W \frac{l_j^{\beta_W} - 1}{\beta_W}$$

We choose a CRRA specification because it nests the two main utility function specifications used in the applied micro literature: linear and log utility. It is also a utility function frequently used in the macro literature.[22]

Second, to simplify the computation problem we reduce the intensive margin labor supply decision to a choice between part-time work and full-time work. The probability of receiving a part-time job offer is denoted by p. The indexes $_{PT}$ and $_{FT}$ will be used to denote parameters referring to part-time and full-time jobs. Individuals are coded as working part-time if they work less than 35 hours per week and full-time if they work at least 35 hours per week. In the simulations, hours worked per week are normalized for a time endowment available for work and leisure equal to 80 hours per week.

Finally, due to the well-known non-identification result of Flinn and Heckman (1982), we need to assume a *recoverable* wage offers distribution[23] if we want to estimate the entire wage offer distribution and not simply fit the accepted wage distribution. Following the most common assumption in the recent literature, we will assume a lognormal distribution.[24] The wage offers distribution is allowed to be specific to the agent's types and to the hours requirement. The density for agents of type $I \in \{W, M\}$ and hours requirement $H \in \{PT, FT\}$ is:

$$f\left(w; \mu_I^H, \sigma_I^H\right) = \frac{1}{\sigma_I^H w} \phi[\frac{\ln(w) - \mu_I^H}{\sigma_I^H}],\ w > 0 \tag{32}$$

[22] GGV obtain their theoretical results for a larger class of utility functions but their calibration exercise is performed using a CRRA specification.

[23] A distribution is *recoverable* from it truncation if knowledge of the point of truncation and of the truncated distribution are enough to uniquely determine it.

[24] See Flabbi and Moro (2012), van der Klaauw and A. van Vuuren (2010), Yamaguchi (2010), Dey and Flinn (2008). The lognormal is frequently chosen because, on top of recoverability, it offers a very good fit of the accepted wage distribution.

where ϕ denotes the standard normal density.

Conditioning on these functional form assumptions, the set of parameters to be identified is denoted by the following set:

$$\theta = \left\{ \begin{array}{c} \lambda_{W,M}, \gamma_{W,M}, \eta^{PT}_{W,M}, \eta^{FT}_{W,M} \\ \\ \mu^{PT}_{W,M}, \sigma^{PT}_{W,M}, \mu^{FT}_{W,M}, \sigma^{FT}_{W,M}, p_{W,M} \\ \\ \alpha_{W,M}, \delta, \beta_{W,M} \end{array} \right\} \tag{33}$$

where the first row pertains to the mobility parameters, the second one to the wage offer distributions parameters and the third one to the utility parameters. The discount rate parameter ρ is not included in θ because it will not be estimated but fixed to 5% a year.

As quite clear from the discussion of the theoretical model, the mapping from the structural parameters to the data is too complicated to be solved analytically and therefore an analytical proof of identification cannot be provided. However, we can build on previous work on the identification of search model and point out where our model differs and what additional information we use to identify parameters specific to our model. It is useful to discuss the identification of the three groups of parameters (mobility parameters, wage offer distributions parameters and utility parameters) separately because they *mainly* use three different sources of information. Mainly does not mean exclusively since all the parameters have an impact on all the observed outcomes through the reservation wages and the optimal decision rules but the structure of the model is strong enough to make some parameters much more sensitive to some specific observed outcomes than others.

The mobility parameters are mainly identified by the steady state proportion of workers in each labor market states and by the transitions probabilities between labor market states.[25] To see this, recall that in our model the transition probability between two states (i.e. the hazard rate out of a given labor market states and into another) is equal to the (exogenous) shock probability times the (endogenous) probability that the transition is optimal for the agent. The are four exogenous shocks in our model corresponding to the four mobility parameters: arrival rate while employed or unemployed and termination rates while working full-time or part-time. The probability that the transition is optimal clearly depends on all the other parameters in the model but Flinn and Heckman (1982) shows that once the wage offers distribution is assumed to belong to a *recoverable* distribution, information on accepted wages and transitions probabilities (or, alternatively, durations) is enough to identify the mobility parameters. The intuition is that the endogenous acceptance probability is identified from accepted wage information leaving to the transitions

[25] Alternatively, and more conventionally, the duration information can be used in place of the transitions probabilities. Transition probabilities and durations contain the same information: we discuss transitions probabilities here because these are the moments we will use in estimation.

probability enough information to identify the mobility parameters. Transitions from unemployment to employment part-time or full-time identify the arrival rates $\lambda_{W,M}$. Job-to-job transitions identify the arrival rates while employed $\gamma_{W,M}$. Finally, transitions from employment part-time or employment full-time to unemployment identify the terminations rates, respectively, $\eta^{PT}_{W,M}$ and $\eta^{FT}_{W,M}$.

The wage offers distribution parameters are mainly identified from the accepted wages information. The model implies that the accepted wages are truncations of the wage offer distributions. If the wage offers distributions can be recovered from their truncation then accepted wage information is enough to identify the wage offers parameters. The recoverability condition we impose by assuming a lognormal distribution exactly defines this property and secures identification. Without imposing this assumption the probability mass below the reservation wage (i.e. the truncation point) cannot be recovered and therefore no counterfactual exercise or policy experiment can be run. What we add in our model is the labor supply margin. We discretize the decision by allowing individuals to choose between working part-time and full-time. Since we observe accepted wage distributions for individuals working part-time and full-time, we can replicate the same identification strategy separately on the two labor supply regimes and allow all the parameters to be part-time and full-time specific.

Finally, we have to identify the utility parameters. The weight on leisure ($\alpha_{W,M}$) represents the preference of consumption with respect to leisure and it is therefore identified by the labor supply decisions. More interestingly, the risk aversion parameters on consumption δ and the utility coefficient on leisure $\beta_{W,M}$ are identified by the dependence of one spouse's labor market status to the other spouse's labor market status. As stated in Proposition 4 the presence of risk aversion is what makes the equilibrium of the household search model different from the equilibrium of the individual search model, i.e. what creates the correlation between the two spouses labor market decisions. The fact that one spouse's reservation wage depends on the other spouse labor market status *only if* the utility function is nonlinear implies that if the transitions probabilities and the accepted wages we observe in the data are sensitive to the spouse's labor market states then we can secure identification of the δ and $\beta_{W,M}$ parameters. The descriptive statistics we have already presented amply support the presence of this dependence.

4.2 Estimation

We use the method of simulated moments to estimate the parameters of the model. We choose this estimation method as opposed to the more efficient simulated maximum likelihood estimator because our household search model in continuous time generates *simultaneous* changes in the labor market states of both spouses in a household (due to endogenous job terminations). While a pragmatic definition of simultaneity could be imposed on the data, it would necessarily be arbitrary and may potentially open the door to multiple equilibria issues.[26] We prefer the alternative proposed by DF: extracting moments from point-in-time samples that focus on steady states aggregated moments and transitions probabilities instead that on individual labor market histories. Of course, individual labor market histories are still at the center of the analysis because both the sample and simulated moments are computed based on individual-level data and the simulations themselves generate individual labor market histories.

Specifically, the estimation procedure works as follows. First, we select the T moments with which to estimate the K parameters of the model, where $T \geq K$. We calculate these moments in our original sample and reserve them for use in the criterion function to be defined below. Next we write a procedure that generates the simulated moments given a set of parameter estimates. Each time the simulation is run, the value functions are solved using fixed point methods. Next, we randomly assign each couple an initial labor supply configuration. We simulate a total of R labor market histories, where each labor market history denotes a sequence of transitions between labor market states for a pair of spouses.

To simulate one labor market history (call it the r^{th} history) for one pair of spouses, we draw a vector of pseudo-random draws denoted by ψ_r, where the dimension of ψ_r is $L \times 1$. Then the event history associated with the r^{th} replication when using parameter vector θ is

$$\Im_r(\theta) = J(\psi_r, \theta) \tag{34}$$

We choose a time $t_{ss} >> 0$ far enough into each household's history so that the household's initial state does not affect the likelihood of the household occupying any one state at time t_{ss}. We evaluate a household's labor market state and the wage of any employed spouse at time t_{ss}. From this simulated data, we can calculate a set of moments identical to the selected set of sample moments. In this fashion, the event history of all R households in the simulation, $\Im = (\Im_1(\theta), \Im_2(\theta), ...\Im_R(\theta))'$, is "mapped" into a simulated data set from which the simulated moments are then calculated.

We construct the column vector of T simulated moments $Q(\theta)$, where θ is the parameter vector, and choose a set of parameter values to minimize the simulated method of moments criterion function $(Q(\theta) - q_s)' W^{-1} (Q(\theta) - q_s)$, where q_s is a column vector of the T corresponding sample moments and W^{-1} is a symmetric, positive definite weighting matrix that is TxT. We define the simulated method of moments estimator as the parameter vector $\hat{\theta}_{SMM}$, where

$$\hat{\theta}_{SMM} = \arg\min_{\theta} (Q(\theta) - q_s)' W^{-1} (Q(\theta) - q_s) \tag{35}$$

The function is minimized using the Nelder-Mead Simplex Algorithm.

[26] Choosing when two events occour simultanously in the data would be similar to choose the length and boundaries of the time interval to apply on the data when specifying the model in discrete time. It is an arbitrary choice and, more importantly, may generate multiple changes of state in the same time interval and multiple equilibria.

We construct W so that the matrix W^{-1} weights the different moments in $Q(\theta)$ and q_s according to their sample variability. We calculate the matrix W by bootstrapping N_{boot} samples from the original sample of data and calculating the T sample moments for each bootstrapped sample, yielding an $N_{boot}xT$ matrix of sample moments. To form W, we replace the diagonal of an identity matrix with the sample variances of the sample moments among the bootstrapped samples. The inverse of W produces the desired weighting matrix. Thus, the estimation procedure places a greater importance on matching the sample moments with the lowest variance.[27]

We choose the moments to match in the estimation procedure by mirroring the identification strategy. The complete list of moments, including their predicted and sample values, are reported in the Appendix, Table A.1. We allow all the parameters to be gender-specific and therefore we compute the individual moments separately on husband and wives. The first group of moments pertains to the steady state transitions probabilities between labor market states and to the proportion of workers in each labor market states. This is the information that mainly identifies the mobility parameters. We have three possible labor market states and we compute transitions between labor market states one period and two periods apart. As a result, we obtain a total of 21 moments for each gender.

The second groups of moments pertains to the accepted wage distribution and mainly identifies the wage offers distributions parameters. We compute mean, standard deviation, skewness and wage growth on the accepted wage distribution for each gender and for each labor supply regime. We also introduce skewness to better capture that female wage distributions are frequently characterized by a high probability mass right above the reservation wage. From the accepted wage information, we obtain a total of 14 moments for each gender.

The third groups of moments are the cross-moments, i.e. the moments representing correlations in the labor market status of the two spouses. The presence and degree of this correlation are captured by the following moments. The contemporaneous and over-time correlations between the two spouses' accepted wages, conditioning on the labor supply regime. The mean and standard deviation of one spouse's wage given the other spouse's labor market status. And finally, the transition probabilities across labor market states conditional on the labor market status of the spouse. As a result, we obtain a total of 51 cross-moments.

To summarize, the estimation procedure is using 121 moments to estimate 23 parameters. We have chosen to fit a relatively large set of moments to avoid

[27] The weighting matrix also serves as a way to scale each of the moments so that they approximately possess the same magnitude. For example, since proportions are between 0 and 1 they will have very small variances that are close to 0. On the other hand, means of sample wages will have variances which which are generally more than three orders of magnitude larger than the sample variance of a proportion. Taking the inverse of these variances compensates for the differences in scale among the moments. There are also a few transitions we have chosen to match that occours very rarely leading to extremely small variances: we rescale the weight of these moments to be in the same scale of the (weighted) average wages.

making arbitrary decisions about which moments to fit and which moments to ignore. Once decided for identification purposes that some features of the data should be targeted, the number of moments in our household search moments becomes immediately quite large if we want to treat the two spouses symmetrically and we want to account for transitions over all the labor market states, including full-time and part-time. For example, if we want to fit transitions probabilities over 2 time periods given the spouse's labor market status, we have to generate at least 18 moments. Similarly, if we introduce a moment to fit the wives labor market behavior, we have to do the same for the husbands labor market behavior, doubling the number of moments to fit.

We build each moment by forming interaction variables between variables of interest (e.g. wages of female part-time workers) and dummy variables representing labor market status (e.g. a variable equal to 1 when the individual is a female part-time worker and equal to 0 otherwise). These procedure effectively creates unconditional moments. Using unconditional moments improves the stability of changes in the moments across iterations of the estimation algorithm since the moment is defined over the whole sample. They also enable the moment to be defined when the proportion of the sample in the simulation contributing information (e.g. male part-time workers) is equal to or close to zero.

5 Estimation results

5.1 Results

We report the estimation results in Tables 3 and 4. Table 3 reports the structural parameters estimates and Table 4 some relevant predicted values. The first four columns pertain to the sample of household with children younger than 18 years old and the last four columns to the sample without children younger than 18 years old.

The structural parameters estimates confirm the systematic differences by gender found in the literature. As the individual search model estimated by Flabbi (2010) on CPS data and by Bowlus (1997) on NLSY data, the individual search model we estimate on SIPP data show that there are differences by gender in all the structural parameters of the model, with the stronger differences concerning the wage offers distribution. As reported in Table 4, women are more likely to receive part-time job offers and when they receive full-time offers they are at lower wages on average. The wage offers differential we estimate in the individual search specification is about 19%, a value which is between the slightly lower value estimated by Bowlus (1997) (about 17% on the College Gradautes sample) and the higher value estimated by Flabbi (2010) (about 26% on the 2005 CPS).

More importantly, the structural parameters estimates confirm and reinforce the DF's result: parameters estimates obtained by estimating on the same sample an individual search model and a household search model are systematically different. This is a first indication that estimating under the assumption that decisions are taken at the individual level and not at the household level has important empirical consequences.

With respect to the mobility parameters, the main differences concern the female sample. The individual search model overestimates the two most important mobility parameters: the arrival rate of offers while unemployed (λ) and the termination rate when working full-time $\left(\eta^{ft}\right)$. The same result is obtained both on the sample with children and on the sample without children. The main impact of the presence of children is, as probably expected, on the rate of arrival of offers which is estimated to be higher for women without children younger than 18.

But the most relevant difference between the household search model and the individual search models is in the wage offers distributions estimates. The parameters imply that the average wage offers differentials between husbands and wives with children is two and a half times larger under the individual search specification than under the household search specification. Looking at the bottom panel of Table 4, the individual search model predict a 19.1% differential while the household search model a 7.3% differential. The result is robust to the presence of children: the drop on the sample without children is similar, moving from 15.5% to 5.1%. The reduction in the differential obtained under the household search specification is an extremely relevant result since it suggests that some of the gender wage differential in accepted wages we observe in the data (the "gender wage gap") may be due to the optimal behavior of women making decision at the household level. The mechanism works as follows. Assume for a moment that the mobility parameters are the same for men and women. Then the individual search model can fit lower accepted wages for women only with lower wage offers to women. The household search model, instead, may explain part of the gap through a decrease in the wives' reservation wages implied by the husbands' labor market status.

This is a different explanation than those usually proposed in the empirical labor search literature. These explanations accounts for the gender gap using differentials in productivity (Bowlus (1997)), the presence of discrimination (Flabbi (2010)), different preferences or different occupational choices (Flabbi and Moro (2012)).[28] Our results suggest that another factor should be added to the list, namely that the actual offers women are receiving may not be very different than the offers received by men but then women decide to accept lower wage offers as a result of their spouse's labor market state. Of course the other factors listed in the literature play a role and can be partially taken into account in our model: for example, we allow for gender-specific preferences and productivity. However, the comparison of the individual search model estimates with the household search model estimates indicates that these other factors are quantitatively less important than the mechanism we suggest. The mechanism we suggest is not new, it has been actually present in the theoretical literature

[28] In the main text, we are just referring to contributions within the empirical labor search but the empirical literaure in general is also using similar ingredients. For boader surveys and more complete references, see Fang and Moro (2011) and Altonji and Blank (1999).

since at least the influential *Treatise* by Becker (Becker (1981)). However, it has been notoriously difficult to quantify and it has never been before identified and estimated within a search model of the labor market.[29]

With respect to labor supply estimates, the individual search model estimates a similar rate of part-time offers for men and women (about 6%) while the household search specification estimates a rate three-times larger for women. This second finding seems more in line with the previous literature.[30]

The utility parameters are relatively stable across specifications but some important differences remain. The weight on leisure (α) is estimated to be similar across specifications on the sample without children but not on the sample with children. When children younger than 18 are present, it is estimated to be significantly higher for women under the household search specification. This is consistent with evidence indicating that the impact of the presence of children is asymmetric by gender and confirms the importance of estimating the model on households with and without children. It also indicates the limitations of our approach in this respect: leisure is essentially a different good if the sample includes households with or without children. In the sample without children what we call leisure is closer to actual leisure time while in the sample with children is likely to also include child-care work.

The coefficient of relative risk aversion, defined in our parametrization as $(1-\delta)$, is estimated to be close to 1 and it is not very sensitive to the sample and specification used. Our estimated value is higher than the one estimated by DF (about 0.5), lower than the preferred value in GGV (about 2)[31] and it is in general lower but comparable with values found in the micro literature (Chetty (2006)). Our parametrization nests the linear case since the utility function becomes linear in consumption when $\delta = 1$. A specification test for linearity is comfortably rejected on both sample.[32] By Propositions 3 and 4, this result also implies rejection of the individual search model specification with respect to the household search model specification.

5.2 Fit of the Model

We first judge the fit of the model by looking at the moments we explicitly target in the estimation procedure. The sample and estimated moments are re-

[29] At least since Becker's theory of the family (Becker (1981)), the importance of household-level decisions in affecting labor market outcomes has been clear. Many selection issues are taken into account in the empirical literature within this field but usually not in models able to generate equilibrium unemployment as in the search model we use. Thanks to this, our model can make a clear distinction between wage offers and accepted wages and provide an estimate of the gender gap in wage offers, arguably a better measure of the differential treatment received by men and women in the labor market.

[30] See for example Altonji and Paxson (1988) and Flabbi and Moro (2012).

[31] Recall, though, that GGV do not estimate the relative risk aversion coefficient. They simply say that, in their calibration exercise, when they fix the relative risk aversion coefficient at about 2 "the data are closest to the model" than when they fix it at values between 0 and 8.

[32] The null for the specification test is $\delta = 1$. The P-values on both the sample with children and the sample without children is smaller than 0.000.

ported in the Appendix, Table A.1. We have chosen to fit a relatively large set of moments with a relatively parsimonious specification so it should not be too surprising that we fit some data features better than others. The household search model does a very good job in fitting the husband's wage distributions, the equilibrium labor market state proportions, the transitions probabilities and most of the cross-moments. However, it generates a not too bad but clearly worse fit for the wives' wage distribution than for the husbands' wage distribution. This is a fairly common finding in the literature: DF have similar problems in fitting the cross-sectional moments of wives and both Flabbi (2010) and Bowlus (1997) obtain a better fit of the male wage distribution than the female wage distribution.[33]

To give a more concise idea of how the model match some relevant moments, we report in Table 5 some of the same descriptive statistics we reported in Table 1 and 2. Table 1 and 2 compute the descriptive statistics on the sample while Table 5 compute the statistics on the simulated sample where the simulations are run at the point estimates reported in Table 3. Notice that most of these moments are not explicitly target by the minimization procedure because they are conditional moments as opposed to the unconditional moments used in the procedure.

We first focus on the moments not conditioning on the spouse's labor market status. The labor market status proportions, the labor market status transitions and average earnings are predicted a little better by the household search model but overall both models generate a reasonable fit. The coefficient of variation on the male sample is also well predicted by both models while the individual search model over-estimate the coefficient of variation on the female sample and the household search model greatly under-estimate it.

When we condition on the spouse's labor market status, the individual search model obviously generates a poor fit because it cannot account for the variation in the descriptive statistics over the different spouse's labor market states. The household search model, instead, exhibits variation along this dimension that qualitatively match the data. However, the magnitude of the variation is almost always lower than the one observed in the data. For example, the data report an higher average weekly earnings for men when their spouses are unemployed than when their spouses are employed full-time; the opposite ranking holds on the sample of women. The household search model is able to fit both facts but the magnitude of the earnings differences is smaller in both cases. The most problematic moments to match are those conditioning on the other spouse been unemployed, probably because of sample size: the number of unemployed in the sample is relatively small, in particular on the sample without children and therefore the descriptive statistics could be quite noisy.

[33] Bowlus (1997) estimates the model separately for High School and College graduates: she obtains a worse fit for women than men on the High School sample and a better fit on the College sample but the High School sample has a larger sample size.

6 Inequality

Thanks to the estimation of the model structural parameters, we can simulate labor market careers for households and individuals. This labor market careers can then be used to compute inequality measures both cross-sectional and over-time. We call *lifetime inequality* the inequality that summarize the entire labor market careers of given agents. We give a formal definition below.

6.1 Simulations Procedure

The simulation procedure works as follows. We start by fixing the parameter vector: the parameter vector is set at the point estimates of the estimated model when computing the *benchmark* inequality measures and at a proper combination of the point estimates when computing the *counterfactual* inequality measures. Each household begins in the state in which both spouses are unemployed. Two random numbers are generated to determine the length of time until each spouse receives a job offer. Another random draw decides whether the job offer is a part-time or full-time job. The wage associated with each spouse's job offer is generated using another random number draw and the exogenous wage distribution, where the wage distribution is conditional on the part-time or full-time status of the job offer from the previous step. The length of time until a spouse first receives an acceptable offer is recorded as the duration spent in this first state. Other random numbers are used to determine (1) when job offers continue to arrive for the employed spouse and the unemployed spouse, (2) the wages associated with these job offers and the part-time or full-time status of the offer, and (3) the amount of time until each spouse is exogenously dismissed from his or her job (which depends on the part-time or full-time status of the job). The duration a household spends in each labor market state is recorded, along with the wages and hours associated with labor market states in which at least one spouse is employed. This process is repeated until the labor market history (the sum of the durations spent in all states) reaches 480 months (40 years).

Lifetime values are created for each household in the sample by integrating over discounted values of being in each labor market state over the full length of the labor market career. For example, the lifetime utility measure for the household i, j is defined as:

$$LU_{ij} = \sum_{s=1}^{S} \exp\left(-\rho t_s\right) \int_{t_{s-1}}^{t_s} u\left(c_{ij}, l_i, l_j; \delta, \boldsymbol{\beta}, \boldsymbol{\alpha}\right) \exp\left(-\rho v\right) dv \tag{36}$$

where s denotes a spell in which the labor market status of both partners is unchanged. When building this lifetime index for individuals or for wages and earnings we simply change appropriately the argument of the integral and the length of the spells. Our lifetime inequality comparisons will be based on computing inequality measures on indexes defined as LU_{ij}.

6.2 Simulations Results

Table 6 and 7 illustrate the results of the simulations by reporting the coefficient of variation for cross-sectional and lifetime inequality computed in utility, earnings, and wages. The top panel reports results on the benchmark models, i.e. the models generated by the point estimates in Table 3. The bottom panel reports results on two counterfactual experiments that have the objective of decomposing the sources of the differences in inequality between the individual search and the household search model. We discuss them in the next sub-section.

We first focus on the benchmark model under the household search model specification (Table 6, top panel, first three columns).[34] First, results show that cross-sectional measures can be substantially different from lifetime measures. This is particularly true for utility measures because cross-sectional utility inequality does not take into account durations in a given labor market state. Second, results show that lifetime utility inequality is higher for women than men. This is exactly the opposite of the result we obtain from looking only at cross-sectional wage or earnings inequality. Both results taken together confirm the point put forward by Flinn (2002) and also found by Bowlus and Robin (2004) and Flabbi and Leonardi (2010): cross-sectional measures of inequality based on wages or earnings are not enough to draw conclusive inference about lifetime welfare. Third, results show that lifetime utility inequality at the individual level is much larger than inequality at the household level, confirming the importance of looking at household level variable and behavior to have a better picture of inequality, as for example recently emphasized by Heathcote, Perri and Violante (2010).

We then focus on the comparison between the household search model and the individual search model under the benchmark parameters. The main result from the comparison mirrors what we have already found looking at predicted labor market outcomes: the gender differential is smaller under the household search model specification than under the individual search model specification. The differential on the most relevant variable - lifetime utility inequality - is about 54% in the individual search case and about 31% in the household search case. This significant decrease in the differential has a similar relative magnitude on the sample without young children (first row of Table 7).

6.3 Counterfactual Experiments

To interpret and investigate further this result, we perform two counterfactual experiments with the objective of decomposing the sources of the difference in inequality between the individual search and the household search model. There are two potential sources: differences in the *parameter estimates* obtained

[34]We obtain individual level wage and earnings inequality in the household search model environment by computing the inequality index on wages and earnings of each individual in the household. We assign individual level utility using the parameters estimated under the household search model specification, assigning to each individual his and her own wage and labor supply decision, and splitting non-labor income in two.

under the two specifications and differences in the *behavior* implied by the two modelling assumptions.

To disentangle the two, we use the following procedure.

1. *Impact of Behavior*: We fix the parameters at the estimated values from the benchmark model under household search (our favorite specification) but we run the simulations assuming individuals behave following the individual search model (which we consider the misspecified model). When running the simulations we take into account all the equilibrium effects involved. In other words, we will re-optimize to obtain optimal decision rules consistent with the household search estimated parameters but applied to an individual search environment. At the end of the simulations we compute exactly the same indexes we reported in the top panel of Table 6 and 7. If we obtain inequality indexes close to the inequality indexes obtained in the benchmark model under household search, then we claim the source of the difference to be misspecified behavior. We claim it is misspecified behavior because this is the only component we have changed with respect to the benchmark model.

2. *Impact of Parameters*: We fix the parameters at the estimates from the benchmark model under individual search but we run the simulations assuming individuals behave following the household search model. As before, we take into account all the equilibrium effects involved when running the simulations. If we obtain inequality indexes close to the inequality indexes obtained in the benchmark model under household search, then we claim the source of the difference to be biased parameters. The reason is the same as before: we have only changed the parameters with respect to the household search benchmark model and therefore we are able to isolate their impact.

Two important remarks. The first remark is about the interpretation of the results. Clearly, behavior plays an important role in both specifications because we could have not obtained the household search estimated parameters if we had not imposed the household behavior in the first place. However, one implication we want to gather from the exercise is the following. Since almost all search models have been estimated or calibrated using an individual search specification, it would be interesting to see if those parameters could be saved in evaluating policy interventions as long as the correct specification is used in the counterfactuals. The second remark is about the decomposition of the differential between the household search and the individual search inequality indexes. Since the indexes computed from the counterfactuals take into account equilibrium effects, the sum of the two effects (impact of parameters plus impact of behavior) will in general do not sum up to one.

Looking at the bottom panel of Table 6, we see that most of the difference in the two specifications is due to biased estimates. The lifetime inequality values generated by the household search model using individual search estimates (last two columns of the bottom panel) are very similar to those obtained using the same behavior but the correct household search parameters (first two columns 1 and 2, top panel). This means that differences in behavior are important because of the impact they have on the estimated parameters and not because of the different equilibrium they generate at same parameters. Results from the sample without children (Table 7, bottom panel) indicate, instead, that a combination of parameters and behavior is needed to explain the differential: neither the "impact of parameter" counterfactual nor the "impact of behavior" counterfactual comes close to replicating the lifetime inequality indexes of the target benchmark model.

Both results rule out for this particular application the validity of using parameters calibrated or estimated under an individual search specification to make inference about household search behavior. In general, the results point out that such procedure could be dangerous also in other contexts and support the estimation of the entire set of structural parameters before implementing counterfactual experiments.

6.4 Policy Experiments

We perform five policy experiments to estimate the impact of labor market changes and reforms on household inequality. We simulate the impact of changes in search frictions and job termination rates; the impact of an increase and a decrease in the proportion of part-time offers; and the impact of an increase in the dispersion of wages offers. Results are reported in Table 8: we report household inequality by computing the coefficient of variation of utility, earnings and wages both at the lifetime level and at the cross-sectional level. In each experiment, we change a specific set of parameters by 50% leaving the rest at the benchmark values. The benchmark is the household search estimated model. In the simulations at post-policy intervention values, we assume individuals behave following the household search model and we obtain the new equilibrium at post-policy values before proceeding to the simulations.

We first focus on the top panel, where we report results for the sample with children younger than 18 year old. The first column reports the benchmark values. Columns 2 evaluates the impact of a reduction in search frictions, i.e. we increase the arrival rates of wage offers $\left(\lambda_{W,M}, \gamma_{W,M}\right)$ by 50%. Reducing frictions reduces lifetime inequality by a large amount. The effect is mainly through shorter unemployment periods as shown by the relative more stable values in wages and earnings inequality. In column 3 we check if the positive impact of a reduction in frictions may be offset by an increase in exogenous job terminations, i.e. we increase both the dismissal rates $\left(\eta_{W,M}^{PT}, \eta_{W,M}^{FT}\right)$ and the arrival rates $\left(\lambda_{W,M}, \gamma_{W,M}\right)$. Results show that the decrease in inequality induced by lower search frictions is almost completely offset by an increase in terminations rates. The policy conclusion is that a more efficient search and matching process does not necessarily increase *utility* inequality at the *lifetime* level while, as expected, increases *wages* and *earnings* inequality at the *cross-sectional* level. As mentioned, this is due to shorter period of unemployment compensating for large inequality in accepted wages. It is a result that reiterates the importance of looking at lifetime inequality and not only at cross-sectional inequality and at utility indexes and not only at wages and earnings distributions. This is the main message of previous works based on individual search models (Flinn (2002) and Flabbi and Leonardi (2010) that we can confirm on a household search model. The main drawbacks of this approach is that the mobility parameters remain exogenous, i.e. we do not allow for endogenous job creation and job destruction. While this is an important omission relegating our policies to a partial equilibrium context, it is unlikely to reduce the importance of looking at lifetime utility inequality measures.

The second set of policies looks at the impact of part-time (columns 4 and 5). As we mentioned, the introduction of a labor supply margin in the model is unusual but we think it is justified to better match the labor market behavior of women. Women tends to work less hours than men and they highly value job flexibility.[35] The possibility of working part-time is still one of the most important institutional arrangement able to provide this flexibility. While previous works have tried to determine the presence of a "part-time penalties",[36] we can evaluate here the impact of the presence of part-time on overall inequality. Column 4 shows the impact of an increase in part-time offers as described by a 50% increase in the parameters $(p_{W,M})$. Results shows that household inequality experiences a small increase, which is all due to an higher number of husbands accepting part-time jobs. If we decrease part-time offers by 50%, the increase in inequality for women is almost exactly balanced by a decrease in inequality for men. Our conclusion is that lifetime inequality is not very sensitive to changes in the proportion of part-time offers.

The last policy we look at tries to mimic a demand-driven increase in the dispersion of wage offers distributions. Such a policy could be interpreted as a very stylized version of the "skill-biased technological change" viewed by many scholars as an important source of the significant increase in inequality in the US in this and, in particular, in the previous decade.[37] We implement the policy by changing the wage offers distribution parameters $\left(\mu_{W,M}^{PT}, \sigma_{W,M}^{PT}, \mu_{W,M}^{FT}, \sigma_{W,M}^{FT}\right)$ so that the Coefficient of Variation in full-time and part-time wage offers increases by 50% but the mean remains unchanged. The mean-preserving spread has a very large impact on cross-sectional inequality: cross-sectional indexes increase up to three times as much as in the benchmark model. However, optimal behavior is smoothing the impact in lifetime terms, leading to only a relatively modest increase in lifetime utility inequality. Once again, the lifetime perspective generates a different policy implication than the cross-sectional one.

The bottom panel of Table 8 reports results for the same policies but applied on the sample without children younger than 18. The main message remains but we observe a couple of differences. Inequality indexes are more sensitive to policies changing the mobility rates while both changes in part-time offers and the increase in mean-preserving spread generate a lower lifetime utility inequality. All these differences are essentially due to differences in the benchmark parameters, namely that we estimate higher mobility rates, lower part-time of-

[35] See for example, Altonji and Paxson (1988) and Flabbi and Moro (2012).

[36] For example, Blank (1990) estimates large wage penalties for working part-time using Current Population Survey data.

[37] Katz and Murphy (1992) is an influential earlier contribution; Acemoglou (2002) provides theoretical background; Eckstein and Nagypal (2004) documents skill-premia over a long time span.

fers and lower wage offers variance on the sample without children than on the sample with children.

7 Conclusions

Search Models of the labor market are widespread and influential but they usually ignore that labor market decisions are frequently taken at the household level. We fill this gap by developing and estimating a household search model of the labor market with on-the-job search and labor supply. Our objective is assessing the empirical relevance of ignoring the household as relevant unit of decision-making. We judge empirical relevance by comparing parameters estimates under different specifications, by running a specification test, and by studying a policy-relevant application using the estimated structural parameters. The application involves building lifetime inequality measures and studying their sensitivity with respect to counterfactual and policy experiments. We build on previous work (DF and GGV) to give our main theoretical results. We contribute a novel identification strategy of the risk aversion parameters. We also propose a straightforward but informative specification test.

We summarize our main results as follows.

First, we find that ignoring the household as crucial unit of decision-making has relevant empirical consequences, particularly on gender differentials. Ignoring the household leads to estimate gender differentials in average wage offers for full-time jobs two times larger. We find the same large impact on gender differentials when computing measure of lifetime inequality: gender differentials in lifetime utility inequality are more than 70% larger under the individual search specification than under the household search specification. Counterfactual experiments show that the main source of the differences in inequality measures between the two model specifications is the bias in the individual search model estimates.

Second, we confirm the previous literature[38] pointing out that cross-sectional measures of inequality based on wages or earnings are not enough to draw conclusive inference about lifetime welfare. In our application, we estimate that lifetime utility inequality is higher for women than men but that exactly the opposite is true for cross-sectional wage and earnings inequality. In our policy section, we find that a mean-preserving spread in wage offers has a very large impact on cross-sectional inequality but only a modest impact on lifetime utility inequality.

Finally, we perform three sets of policy experiments and we find that: (i) a more efficient search and matching process does not increase utility inequality at the lifetime level but increases wages and earnings inequality at the cross-sectional level; (ii) lifetime inequality is not very sensitive to changes in the proportion of part-time offers; and (iii) a mean-preserving spread in wage offers has a very large impact on cross-sectional inequality but only a modest increase in lifetime utility inequality.

[38] See for example, Flinn (2002), Bowlus and Robin (2004) and Flabbi and Leonardi (2010).

Our overall conclusion is that ignoring that labor market decisions are taken at the household level may be very costly. But we also find that the costs are application-specific since the mispecification errors may have a large impact on some margins (for example, gender differentials) but a negligible impact on others (for example, the exogenous labor market shocks).

We caution that these conclusions are obtained in a framework affected by three main limitations. We briefly list and propose them as promising venues for future work.

A first limitation is the unitary model assumption used to capture households' behavior. This assumption has been criticized for generating empirical implications inconsistent with consumption and time allocation decisions[39] but we have chosen to retain it for model tractability and because it generates a very useful comparison with previous literature (both DF and GGV assume a unitary model of the household). For our purposes, it would be interesting to argue that the assumption represents a possible bound of the difference between the individual search model and the household search model. There is certainly a sense in which this is the case since in the individual search model each individual retains control over all her own labor income while in the unitary model there is full income pooling. More complex household interactions models (such as cooperative behavior or non-cooperative but strategic behavior as in Nash Bargaining) generate different degrees of income sharing and may be considered intermediate cases between the individual search model and the household search model with a unitary household in this respect. However, it is not clear if the household search unitary model constitutes a bound with respect to the overall objective of this paper: the empirical relevance of considering that decisions are taken at the household level when studying equilibrium labor market outcomes in a search environment. Strategic household interaction may well generate an higher sensitivity of one's own labor market decisions with respect to the spouse's labor market status. However, since the theoretical implications are not clear and the empirical literature is very thin, this limitation should encourage additional empirical work in the area and our contribution should be interpreted as a first step in the right direction.

A second limitation is the lack of a joint location decision. This is certainly an empirically relevant feature that, for example, is the focus of GGV's calibration and of Gemici (2011)'s estimated model. Generating such an extension would not be theoretically challenging but the structure of the data we have is not appropriate to implement it.[40] For the purpose of this paper, however, adding this feature would only strengthen the main message, i.e. the presence of a spouse who is also a labor market searcher has important implications for the labor market decisions of the other spouse.

A third limitation is our assumptions of no saving or borrowing. This is a

[39] Albeit not in the context of a search model of the labor market.

[40] The appropriate data set is not easy to find. For example, PSID (used by Gemici (2011) and others in the internal migration literature) is a long panel that can track migration but it cannot measure monthly labor market transitions and therefore it cannot generate credible duration variables.

common assumption in the search literature that can be justified by risk neutrality or by market completeness. We actually test and reject risk neutrality in the paper and we provide identification and estimation of the relative risk aversion coefficients. As a result, an extension of our model allowing for saving decisions would be very interesting and it is likely to add a very active margin in the differentiation between the household search and individual search specification. However, such an extension would be challenging. The handful of estimated search models allowing for savings decisions (Rendon (2006); Lentz (2009); and Lise (2011)) are faced with very difficult dynamic programming problems that force them to introduce restrictive assumptions. The complication derive from the difficulty of establishing global concavity of the value functions when savings are added to the job search model (Acemoglu and Shimer (1999); Lentz and Tranaes (2005)). The model would become even less tractable in the presence of a dual-searchers specification. Therefore, even if removing this assumption could be very promising, we leave it for future research.

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Table 1: Descriptive Statistics:
Cross-Sectional Components

	Yes Children Younger than 18				No Children Younger than 18			
	$N = 3,340$				$N = 644$			
	Tot.	Spouse Lab Mkt Status			Tot.	Spouse Lab Mkt Status		
		Employed		Unemp.		Employed		Unemp.
		FT	PT			FT	PT	
Females								
Labor Mkt Status:								
Employed FT	0.558	0.556	0.550	0.613	0.755	0.779	0.625	0.438
Employed PT	0.265	0.275	0.217	0.113	0.168	0.159	0.313	0.188
Unemployed	0.177	0.170	0.233	0.275	0.078	0.062	0.063	0.375
Hourly Wages:								
Employed FT								
Mean	15.02	15.13	14.94	13.08	15.79	16.11	11.28	12.11
CV	0.517	0.516	0.537	0.504	0.510	0.506	0.479	0.371
Employed PT								
Mean	12.72	12.71	13.35	12.27	12.87	12.98	11.01	14.30
CV	0.605	0.608	0.605	0.501	0.555	0.578	0.432	0.385
Weekly Earnings:								
Mean	528.1	528.0	543.9	516.9	607.1	623.7	404.1	459.0
CV	0.640	0.644	0.632	0.553	0.584	0.578	0.563	0.425
Males								
Labor Mkt Status:								
Employed FT	0.916	0.912	0.950	0.878	0.901	0.930	0.852	0.720
Employed PT	0.036	0.035	0.029	0.047	0.050	0.041	0.093	0.040
Unemployed	0.048	0.053	0.020	0.074	0.050	0.029	0.056	0.240
Hourly Wages:								
Employed FT								
Mean	18.91	18.37	20.09	18.74	19.29	19.43	19.78	16.37
CV	0.509	0.490	0.471	0.616	0.490	0.507	0.384	0.513
Employed PT								
Mean	15.57	13.68	16.96	18.73	12.52	9.68	14.90	29.00
CV	0.681	0.491	0.556	0.916	0.601	0.374	0.629	0.000
Weekly Earnings:								
Mean	795.3	771.8	849.3	785.9	800.6	808.9	799.3	700.3
CV	0.526	0.508	0.484	0.634	0.520	0.536	0.441	0.502

Notes: Data are from the 2001-2003 panel of the Survey of Income and Program Participation (SIPP). The cross-sectional moments are computed from the first point-in-time sample extracted from the panel. CV stands for Coefficient of Variation.

Table 2: Descriptive Statistics:
Dynamic Components

	Yes Children Younger than 18 $N = 3,340$				No Children Younger than 18 $N = 644$			
	Tot.	Spouse Lab Mkt Status			Tot.	Spouse Lab Mkt Status		
		Employed		Unem.		Employed		Unem.
		FT	PT			FT	PT	
Females								
Labor Mkt Transitions:								
From Empl. FT to:								
Employed FT	0.902	0.909	0.879	0.796	0.926	0.934	0.800	0.857
Employed PT	0.050	0.048	0.091	0.061	0.037	0.031	0.200	0.000
Unemployed	0.047	0.042	0.030	0.143	0.037	0.035	0.000	0.143
From Empl. PT to:								
Employed FT	0.090	0.093	0.077	0.000	0.111	0.087	0.400	0.000
Employed PT	0.812	0.807	0.923	0.889	0.889	0.913	0.600	1.000
Unemployed	0.097	0.100	0.000	0.111	0.000	0.000	0.000	0.000
From Unemp. to:								
Employed FT	0.084	0.088	0.000	0.091	0.080	0.111	0.000	0.000
Employed PT	0.071	0.073	0.000	0.091	0.080	0.056	0.000	0.167
Unemployed	0.845	0.838	1.000	0.818	0.840	0.833	1.000	0.833
Males								
Labor Mkt Transitions:								
From Empl. FT to:								
Employed FT	0.960	0.954	0.974	0.958	0.948	0.947	0.978	0.889
Employed PT	0.016	0.019	0.012	0.012	0.017	0.018	0.022	0.000
Unemployed	0.024	0.027	0.014	0.031	0.034	0.035	0.000	0.111
From Empl. PT to:								
Employed FT	0.300	0.333	0.231	0.286	0.313	0.400	0.200	0.000
Employed PT	0.650	0.636	0.769	0.571	0.688	0.600	0.800	1.000
Unemployed	0.050	0.030	0.000	0.143	0.000	0.000	0.000	0.000
From Unemp. to:								
Employed FT	0.438	0.469	0.556	0.318	0.375	0.286	0.667	0.333
Employed PT	0.013	0.000	0.000	0.045	0.063	0.000	0.333	0.000
Unemployed	0.550	0.531	0.444	0.636	0.563	0.714	0.000	0.667

Notes: Data are from the 2001-2003 panel of the Survey of Income and Program Participation (SIPP). The transitions proportions are computed from the first point-in-time sample extracted from the panel to the point-in-time sample extracted three months later.

Table 3: Estimation Results:
Parameter Estimates

	Yes Children Younger than 18				No Children Younger than 18			
	Individual Search		Household Search		Individual Search		Household Search	
	Females	Males	Females	Males	Females	Males	Females	Males
λ	0.3069	0.3912	0.2356	0.2993	0.4079	0.3132	0.2568	0.3198
	(0.0167)	(0.0356)	(0.0168)	(0.0299)	(0.0302)	(0.0116)	(0.0156)	(0.0227)
γ	0.0790	0.0911	0.0857	0.1179	0.0737	0.1033	0.0932	0.1216
	(0.0013)	(0.0028)	(0.0041)	(0.0117)	(0.0019)	(0.0004)	(0.0057)	(0.0130)
η^{pt}	0.0083	0.0157	0.0127	0.0191	0.0097	0.0183	0.0171	0.0193
	(0.0003)	(0.0007)	(0.0020)	(0.0006)	(0.0003)	(0.0005)	(0.0008)	(0.0014)
η^{ft}	0.0314	0.0140	0.0153	0.0149	0.0189	0.0148	0.0186	0.0172
	(0.0007)	(0.0002)	(0.0034)	(0.0009)	(0.0008)	(0.0009)	(0.0016)	(0.0006)
μ^{pt}	2.1268	2.1295	2.1986	2.0361	2.2145	2.0905	2.2046	2.0225
	(0.0195)	(0.0153)	(0.0502)	(0.0881)	(0.0486)	(0.1246)	(0.0578)	(0.0886)
μ^{ft}	1.8029	2.0598	1.9497	1.9369	1.8406	2.1139	2.0265	1.9783
	(0.0133)	(0.0110)	(0.0259)	(0.0382)	(0.0213)	(0.0189)	(0.0366)	(0.0651)
σ^{pt}	0.5333	0.6655	0.4566	0.6871	0.5229	0.6039	0.4649	0.6518
	(0.0212)	(0.0242)	(0.0216)	(0.0399)	(0.0227)	(0.0590)	(0.0194)	(0.0425)
σ^{ft}	0.6885	0.6354	0.4103	0.6637	0.6767	0.5440	0.3794	0.6461
	(0.0068)	(0.0069)	(0.0267)	(0.0164)	(0.0224)	(0.0248)	(0.0105)	(0.0188)
p	0.0599	0.0600	0.1819	0.0588	0.0777	0.0563	0.1626	0.0511
	(0.0023)	(0.0033)	(0.0141)	(0.0045)	(0.0041)	(0.0038)	(0.0044)	(0.0056)
α	0.1561	0.1371	0.2082	0.1248	0.1485	0.1530	0.1564	0.1175
	(0.0174)	(0.0076)	(0.0075)	(0.0060)	(0.0223)	(0.0035)	(0.0081)	(0.0113)
δ	0.0487	0.0534	0.0439		0.0476	0.0527	0.0475	
	(0.0014)	(0.0031)	(0.0024)		(0.0011)	(0.0021)	(0.0017)	
β	0.0509	0.0335	0.0488	0.0547	0.0508	0.0368	0.0472	0.0470
	(0.0046)	(0.0038)	(0.0029)	(0.0035)	(0.0029)	(0.0007)	(0.0019)	(0.0020)
N	1,670	1,670	3,340		322	322	644	

Note: Data are from the 2001-2003 SIPP. Standard errors in parentheses are computed by boostrap with 30 replications.

Table 4: Estimation Results:
Predicted Values

	With Children Younger Than 18				Without Children Younger Than 18			
	Individual Search		Household Search		Individual Search		Household Search	
	Females	Males	Females	Males	Females	Males	Females	Males
Wage Offers:								
$E[w]$	7.809	9.652	8.073	8.709	8.121	9.607	8.471	8.931
	(0.079)	(0.061)	(0.284)	(0.325)	(0.202)	(0.198)	(0.276)	(0.487)
$V[w]$	35.563	46.762	12.985	42.285	36.299	32.292	12.624	41.373
	(0.877)	(1.105)	(1.769)	(4.156)	(3.778)	(4.912)	(1.146)	(4.721)
$E[w\|PT]$	9.670	10.496	10.003	9.701	10.498	9.707	10.102	9.346
	(0.223)	(0.298)	(0.429)	(0.891)	(0.626)	(1.456)	(0.597)	(0.905)
$V[w\|PT]$	30.759	61.380	23.193	56.789	34.652	41.478	24.621	46.229
	(3.978)	(7.718)	(2.386)	(13.540)	(7.953)	(23.823)	(4.126)	(12.241)
$E[w\|FT]$	7.690	9.599	7.644	8.647	7.921	9.601	8.154	8.908
	(0.085)	(0.076)	(0.248)	(0.336)	(0.246)	(0.189)	(0.318)	(0.523)
$V[w\|FT]$	35.869	45.830	10.715	41.378	36.438	31.743	10.295	41.111
	(0.954)	(0.966)	(1.835)	(4.604)	(4.398)	(4.468)	(1.237)	(5.159)
Durations:								
$E[t_o\|U]$	3.258	2.556	4.244	3.341	2.451	3.192	3.893	3.127
	(0.208)	(0.195)	(0.272)	(0.251)	(0.153)	(0.104)	(0.209)	(0.251)
$E[t_o\|E]$	12.653	10.982	11.674	8.479	13.560	9.678	10.734	8.222
	(0.206)	(0.372)	(0.470)	(1.262)	(0.348)	(0.034)	(0.571)	(1.038)
$E[t_e\|PT]$	120.445	63.563	78.634	52.331	103.261	54.578	58.343	51.817
	(4.079)	(2.499)	(9.511)	(1.966)	(3.477)	(1.806)	(2.680)	(4.605)
$E[t_e\|FT]$	31.850	71.259	65.498	67.295	52.993	67.492	53.620	58.301
	(0.699)	(1.010)	(10.357)	(4.115)	(2.433)	(5.986)	(5.457)	(2.098)
Gender Differentials:								
Wage Offers:								
$E[w]$	0.191		0.073		0.155		0.051	
$V[w]$	0.239		0.693		-0.124		0.695	
$E[w\|PT]$	0.079		-0.031		-0.081		-0.081	
$V[w\|PT]$	0.499		0.592		0.165		0.467	
$E[w\|FT]$	0.199		0.116		0.175		0.085	
$V[w\|FT]$	0.217		0.741		-0.148		0.750	
Durations:								
$E[t_o\|U]$	-0.275		-0.270		0.232		-0.245	
$E[t_o\|E]$	-0.152		-0.377		-0.401		-0.306	
$E[t_e\|PT]$	-0.895		-0.503		-0.892		-0.126	
$E[t_e\|FT]$	0.553		0.027		0.215		0.080	

Note: w are hourly wages; PT and FT part-time and full-time; t_o durations in months before job offer shock; t_e durations in months before job termination shock.

Table 5: Model Fit:
Descriptive Statistics on Simulated Data

	Yes Children Younger than 18					No Children Younger than 18				
	Ind. Search	Household Search				Ind. Search	Household Search			
		Tot	Spouse				Tot	Spouse		
			FT	PT	U			FT	PT	U
Females										
Labor Market Status:										
FT	0.655	0.574	0.575	0.519	0.592	0.818	0.771	0.770	0.765	0.789
PT	0.266	0.246	0.245	0.256	0.247	0.144	0.129	0.129	0.092	0.138
U	0.079	0.181	0.180	0.224	0.161	0.039	0.100	0.101	0.143	0.073
Labor Market Transition from FT to:										
FT	0.914	0.945	0.946	0.951	0.921	0.949	0.944	0.943	0.901	0.964
PT	0.016	0.012	0.012	0.012	0.000	0.010	0.015	0.014	0.044	0.014
U	0.070	0.044	0.042	0.037	0.079	0.041	0.041	0.043	0.055	0.021
Earnings:										
Mean	453.9	503.7	504.4	510.4	486.0	564.7	612.2	614.2	585.7	595.1
CV	0.713	0.368	0.370	0.358	0.334	0.641	0.354	0.356	0.317	0.345
Males										
Labor Market Status:										
FT	0.929	0.918	0.919	0.916	0.916	0.917	0.905	0.904	0.907	0.914
PT	0.024	0.031	0.028	0.033	0.039	0.016	0.024	0.024	0.017	0.034
U	0.048	0.051	0.053	0.051	0.045	0.067	0.071	0.073	0.076	0.052
Labor Market Transition from FT to:										
FT	0.965	0.960	0.962	0.960	0.956	0.960	0.952	0.953	0.945	0.961
PT	0.002	0.005	0.005	0.004	0.005	0.003	0.003	0.004	0.002	0.000
U	0.033	0.035	0.033	0.036	0.039	0.037	0.044	0.043	0.053	0.039
Earnings:										
Mean	807.79	772.9	754.4	793.9	802.9	763.2	658.9	651.8	682.4	682.6
CV	0.521	0.555	0.547	0.569	0.558	0.443	0.611	0.602	0.589	0.692

Notes: Simulations at the point estimates reported in Table 3. Statistics to be compared with the sample moments reported in Tables 1 and 2. Abbreviations: FT= employed full-time; PT= employed part-time; U= unemployed. CV= coefficient of variation.

Table 6: Inequality Measures and Counterfactual Experiments.
- With Children Younger Than 18 -

	BENCHMARKS:				
	Household Search			Individual Search	
	Females	Males	Household	Females	Males
Lifetime:					
Utility	0.767	0.526	0.219	0.785	0.361
Earnings	0.238	0.264	0.185	0.273	0.260
Wages	0.220	0.255	0.174	0.229	0.253
Cross-section:					
Utility	0.282	0.269	0.224	0.445	0.260
Earnings	0.362	0.554	0.438	0.703	0.523
Wages	0.350	0.552	0.431	0.617	0.518
	COUNTERFACTUALS:				
	Impact of Behavior			Impact of Parameters	
	Females	Males	Household	Females	Males
Lifetime:					
Utility	0.986	0.497	0.203	0.791	0.537
Earnings	0.269	0.256	0.186	0.172	0.268
Wages	0.238	0.247	0.173	0.182	0.261
Cross-section:					
Utility	0.325	0.235	0.223	0.379	0.278
Earnings	0.663	0.518	0.458	0.387	0.570
Wages	0.606	0.519	0.444	0.400	0.573

Notes: The Table reports coefficients of variation of the corresponding variable. Lifetime measure are computed as defined in equation (36). Cross-section measures are computed at 180 months. Counterfactual experiments are defined as follows: *Impact of Parameters* runs simulations of a model using the individual search model optimal behavior but the household search model paramters estimates; *Impact of Behavior* runs simulations of a model using the household search model optimal behavior but the individual search model parameters estimates.

Table 7: Inequality Measures and Counterfactual Experiments.
- Without Children Younger Than 18 -

	BENCHMARKS:				
	Household Search			Individual Search	
	Females	Males	Household	Females	Males
Lifetime:					
Utility	0.279	0.267	0.222	0.470	0.426
Earnings	0.294	0.558	0.411	0.277	0.218
Wages	0.334	0.546	0.403	0.251	0.212
Cross-section:					
Utility	0.577	0.491	0.209	0.394	0.242
Earnings	0.160	0.256	0.165	0.645	0.444
Wages	0.168	0.245	0.158	0.604	0.442
	COUNTERFACTUALS:				
	Impact of Parameters			Impact of Behavior	
	Females	Males	Household	Females	Males
Lifetime:					
Utility	0.582	0.530	0.198	0.528	0.451
Earnings	0.267	0.216	0.167	0.149	0.252
Wages	0.242	0.209	0.157	0.159	0.244
Cross-section:					
Utility	0.272	0.230	0.208	0.371	0.277
Earnings	0.594	0.396	0.408	0.331	0.575
Wages	0.556	0.390	0.396	0.367	0.568

Notes: The Table reports coefficients of variation of the corresponding variable. Lifetime measure are computed as defined in equation (36). Cross-section measures are computed at 180 months. Counterfactual experiments are defined as follows: *Impact of Parameters* runs simulations of a model using the individual search model optimal behavior but the household search model paramters estimates; *Impact of Behavior* runs simulations of a model using the household search model optimal behavior but the individual search model parameters estimates.

Table 8: Household Inequality Measures and Policy Experiments

	Benchmark	Policy Experiments				
		Reduce Frictions	Reduce Frictions and Increase Terminations	Increase Part-Time Offers	Reduce Part-Time Offers	Mean Preserving Spread in Wage Offers
With Children Younger Than 18:						
Lifetime:						
Utility	0.219	0.193	0.213	0.221	0.219	0.286
Earnings	0.185	0.172	0.161	0.181	0.187	0.302
Wages	0.174	0.163	0.152	0.170	0.179	0.201
Cross-section:						
Utility	0.224	0.206	0.229	0.229	0.228	0.644
Earnings	0.438	0.424	0.452	0.448	0.425	0.668
Wages	0.431	0.412	0.437	0.435	0.422	0.228
Without Children Younger Than 18:						
Lifetime:						
Utility	0.267	0.148	0.136	0.157	0.159	0.239
Earnings	0.558	0.152	0.141	0.165	0.165	0.249
Wages	0.546	0.184	0.206	0.214	0.210	0.205
Cross-section:						
Utility	0.491	0.391	0.412	0.413	0.405	0.527
Earnings	0.256	0.399	0.420	0.425	0.409	0.538
Wages	0.245	0.204	0.224	0.223	0.220	0.226

Note: The Table reports coefficients of variation of the corresponding variable. Lifetime measure are computed as defined in equation (36). Cross-section measures are computed at 180 months. Policy experiments are based on the household model estimation and assume household model behavior (the Benchmark). In each experiment we change a specific set of parameters by 50% leaving the rest at the benchmark values. In the policy experiments we change the following parameters: *Reduce Frictions*: increase $\left(\lambda_{W,M}, \gamma_{W,M}\right)$; *Reduce Frictions and Increase Termination*: increase $\left(\lambda_{W,M}, \gamma_{W,M}\right)$ and $\left(\eta^{PT}_{W,M}, \eta^{FT}_{W,M}\right)$; *Increase Part-Time Offers*: increase $\left(p_{W,M}\right)$; *Reduce Part-Time Offers*: decrease $\left(p_{W,M}\right)$; *Mean Preserving Spread in Wage Offers*: change $\left(\mu^{PT}_{W,M}, \sigma^{PT}_{W,M}, \mu^{FT}_{W,M}, \sigma^{FT}_{W,M}\right)$ so that the Coefficient of Variation in wage offers increases but the mean is unchanged.

Table A.1: Sample and Estimated Moments

Moments	Yes Children Younger than 18			No Children Younger than 18		
	Sample	Estimated		Sample	Estimated	
		Individ. Search	HH Search		Individ. Search	HH Search
			Males			
ave w1 pt t1	0.5594	0.5138	0.5937	0.6222	0.3368	0.4252
ave w1 ft t1	17.3235	17.6287	16.7546	17.3747	16.3802	15.7586
sd w1 pt t1	3.4738	3.6369	3.9992	3.1153	2.9333	2.7239
sd w1 ft t1	9.3406	9.5281	9.6465	9.1542	7.6499	9.1177
skewn w1 pt t1	9.4554	8.5813	9.7351	6.7316	10.4013	7.9098
skewn w1 ft t1	1.8436	2.0884	1.9253	2.0877	2.0518	2.0287
prop males u t1	0.0479	0.0476	0.0510	0.0497	0.0674	0.0544
prop males pt t1	0.0359	0.0236	0.0312	0.0497	0.0160	0.0288
prop males ft t1	0.9162	0.9288	0.9178	0.9006	0.9166	0.9168
diff ave w1 ptpt t12	0.0432	-0.0013	-0.0028	0.0016	0.0000	-0.0008
diff ave w1 ptft t12	-0.0147	-0.0085	0.0045	-0.0062	-0.0077	0.0208
diff ave w1 ftpt t12	0.0336	0.0249	0.0379	0.0055	0.0071	0.0140
diff ave w1 ftft t12	0.1867	0.1944	0.2114	-0.5345	0.1370	0.2634
diff ave w1 ptpt t14	-0.0053	-0.0005	-0.0013	0.0129	0.0000	-0.0008
diff ave w1 ptft t14	-0.0079	-0.0066	-0.0079	0.0761	-0.0185	0.0190
diff ave w1 ftpt t14	0.1412	0.0678	0.0716	0.0960	0.0265	0.0070
diff ave w1 ftft t14	0.3825	0.3452	0.2762	-0.4066	0.0791	0.4621
prop mftt2 mftt1	0.8796	0.8960	0.8814	0.8540	0.8798	0.8804
prop mptt2 mftt1	0.0144	0.0018	0.0046	0.0155	0.0026	0.0046
prop munt2 mftt1	0.0222	0.0310	0.0318	0.0311	0.0342	0.0318
prop mftt2 mptt1	0.0108	0.0034	0.0048	0.0155	0.0022	0.0028
prop mptt2 mptt1	0.0234	0.0190	0.0246	0.0342	0.0122	0.0244
prop munt2 mptt1	0.0018	0.0012	0.0018	0.0000	0.0016	0.0016
prop mftt2 munt1	0.0210	0.0266	0.0278	0.0186	0.0296	0.0318
prop mptt2 munt1	0.0006	0.0012	0.0014	0.0031	0.0010	0.0018
prop mptt2 munt1	0.0006	0.0198	0.0218	0.0280	0.0368	0.0208
prop mftt4 mftt1	0.8563	0.8798	0.8534	0.8416	0.8576	0.8580
prop mptt4 mftt1	0.0281	0.0072	0.0110	0.0217	0.0052	0.0078
prop munt4 mftt1	0.0317	0.0418	0.0534	0.0373	0.0538	0.0510
prop mftt4 mptt1	0.0162	0.0074	0.0116	0.0280	0.0064	0.0096
prop mptt4 mptt1	0.0144	0.0146	0.0180	0.0186	0.0078	0.0168
prop munt4 mptt1	0.0054	0.0016	0.0016	0.0031	0.0018	0.0024
prop mftt4 munt1	0.0246	0.0400	0.0426	0.0217	0.0538	0.0456
prop mptt4 munt1	0.0048	0.0026	0.0014	0.0031	0.0014	0.0032
prop munt4 munt1	0.0186	0.0050	0.0070	0.0248	0.0122	0.0056

Table A.1 (cont.): Sample and Estimated Moments

Moments	Yes Children Younger than 18			No Children Younger than 18		
	Sample	Estimated		Sample	Estimated	
		Individ. Search	HH Search		Individ. Search	HH Search
			Females			
ave w2 pt t1	3.3674	3.4490	4.1943	2.1588	2.3592	2.2121
ave w2 ft t1	8.3816	7.9591	7.4518	11.9177	11.4151	9.5959
sd w2 pt t1	6.2310	5.9640	6.9724	5.2671	6.0713	6.0030
sd w2 ft t1	7.6328	7.4114	5.2591	7.7581	8.2099	3.8027
skewn w2 pt t1	3.6498	3.2401	2.6195	4.0276	3.7085	3.6470
skewn w2 ft t1	2.7269	2.9288	2.0014	2.4359	2.5055	2.0179
prop females u t1	0.1772	0.0788	0.1806	0.0776	0.0388	0.1012
prop females pt t1	0.2647	0.2662	0.2456	0.1677	0.1436	0.1230
prop females ft t1	0.5581	0.6550	0.5738	0.7547	0.8176	0.7758
diff ave w2 ptpt t12	-0.0357	0.0080	0.0044	-0.0785	0.0000	0.0103
diff ave w2 ptft t12	0.0097	0.0183	0.0022	-0.0309	-0.0320	-0.0246
diff ave w2 ftpt t12	-0.0008	-0.0021	0.0250	0.0339	0.0336	0.0469
diff ave w2 ftft t12	0.0311	0.0596	0.0625	0.0669	0.1391	0.0483
diff ave w2 ptpt t14	0.0889	0.0239	0.0159	0.0326	0.0065	0.0062
diff ave w2 ptft t14	-0.0178	0.0001	-0.0341	-0.0554	-0.0445	-0.1067
diff ave w2 ftpt t14	0.0643	0.0405	0.1095	0.0510	0.0651	0.1223
diff ave w2 ftft t14	0.0553	0.0614	0.0702	0.0246	0.1236	0.0934
prop fftt2 fftt1	0.5036	0.5986	0.5422	0.6988	0.7762	0.7368
prop fptt2 fftt1	0.0281	0.0106	0.0066	0.0280	0.0078	0.0062
prop funt2 fftt1	0.0263	0.0458	0.0250	0.0280	0.0336	0.0328
prop fftt2 fptt1	0.0240	0.0060	0.0100	0.0186	0.0104	0.0064
prop fptt2 fptt1	0.2150	0.2564	0.2264	0.1491	0.1306	0.1104
prop funt2 fptt1	0.0257	0.0038	0.0092	0.0000	0.0026	0.0062
prop fftt2 funt1	0.0150	0.0486	0.0218	0.0062	0.0268	0.0280
prop fptt2 funt1	0.0126	0.0042	0.0106	0.0062	0.0028	0.0062
prop fptt2 funt1	0.0126	0.0260	0.1482	0.0062	0.0092	0.0670
prop fftt4 fftt1	0.4617	0.5682	0.4932	0.6739	0.7606	0.6984
prop fptt4 fftt1	0.0551	0.0280	0.0264	0.0435	0.0220	0.0214
prop funt4 fftt1	0.0413	0.0588	0.0542	0.0373	0.0350	0.0560
prop fftt4 fptt1	0.0419	0.0230	0.0236	0.0559	0.0268	0.0218
prop fptt4 fptt1	0.1880	0.2360	0.2038	0.1056	0.1130	0.0884
prop funt4 fptt1	0.0347	0.0072	0.0182	0.0062	0.0038	0.0128
prop fftt4 funt1	0.0216	0.0612	0.0504	0.0093	0.0334	0.0566
prop fptt4 funt1	0.0323	0.0076	0.0224	0.0093	0.0036	0.0096
prop funt4 funt1	0.1234	0.0100	0.1078	0.0590	0.0018	0.0350

Table A.1 (cont.): Sample and Estimated Moments

Moments	Yes Children Younger than 18			No Children Younger than 18		
	Sample	Estimated		Sample	Estimated	
		Individ. Search	HH Search		Individ. Search	HH Search
			Cross-moments			
corrwages ftft t1	0.0986		-0.0282	0.4078		-0.0022
corrwages ptpt t1	0.0012		0.0046	0.0947		-0.0088
corrwages ptft t1	-0.0173		-0.0129	-0.1246		0.0154
corrwages ftpt t1	0.1525		0.0250	0.0103		0.0022
corrwages ftft t1t4	0.0712		-0.0290	0.2637		0.0034
corrwages ptpt t1t4	0.0343		0.0053	-0.0108		-0.0011
corrwages ptft t1t4	-0.0295		-0.0016	-0.0432		0.0020
corrwages ftpt t1t4	0.1434		0.0217	0.0904		-0.0183
corrwages ftft t4t1	0.0987		-0.0087	0.2951		-0.0144
corrwages ptpt t4t1	-0.0069		0.0027	-0.0464		0.0175
corrwages ptft t4t1	-0.0067		-0.0142	-0.0062		-0.0011
corrwages ftpt t4t1	0.1450		0.0192	0.0202		0.0073
ave w1 given fun t1	3.0754		3.2873	1.0050		1.6635
ave w1 given fpt t1	5.1853		4.3746	3.0570		2.0136
ave w1 given fft t1	9.6221		9.6864	13.9349		12.5067
ave w2 given mun t1	0.4498		0.5829	0.3966		0.6388
ave w2 given mpt t1	0.3992		0.3554	0.5213		0.3403
ave w2 given mft t1	10.9001		10.7078	13.1586		10.8290
sd w1 given fun t1	8.4382		8.4562	4.5130		5.8550
sd w1 given fpt t1	10.0044		9.4291	7.7027		6.4839
sd w1 given fft t1	11.1842		11.3748	11.9292		10.9709
sd w2 given mun t1	2.6568		2.8807	2.3494		2.9619
sd w2 given mpt t1	2.7103		2.3964	2.5845		2.1597
sd w2 given mft t1	9.1915		7.5608	9.3599		6.4171
prop mftt1 fftt1	0.5090		0.5274	0.7019		0.7092
prop mptt1 fftt1	0.0198		0.0162	0.0311		0.0236
prop munt1 fftt1	0.0293		0.0302	0.0217		0.0430
prop mftt1 fptt1	0.2515		0.2250	0.1429		0.1136
prop mptt1 fptt1	0.0078		0.0080	0.0155		0.0028
prop munt1 fptt1	0.0054		0.0126	0.0093		0.0066
prop mftt1 funt1	0.1557		0.1654	0.0559		0.0940
prop mptt1 funt1	0.0084		0.0070	0.0031		0.0024
prop munt1 funt1	0.0132		0.0082	0.0186		0.0048
prop mftt4 fftt1	0.5024		0.5210	0.6677		0.7072
prop mptt4 fftt1	0.0269		0.0164	0.0404		0.0210
prop munt4 fftt1	0.0287		0.0364	0.0466		0.0476

Table A.1 (cont.): Sample and Estimated Moments

Moments	Yes Children Younger than 18			No Children Younger than 18		
	Sample	Estimated		Sample	Estimated	
		Individ. Search	HH Search		Individ. Search	HH Search
prop mftt4 fptt1	0.2443		0.2248	0.1553		0.1124
prop mptt4 fptt1	0.0126		0.0074	0.0031		0.0046
prop munt4 fptt1	0.0078		0.0134	0.0093		0.0060
prop mftt4 funt1	0.1503		0.1618	0.0683		0.0936
prop mptt4 funt1	0.0078		0.0066	0.0000		0.0022
prop munt4 funt1	0.0192		0.0122	0.0093		0.0054
prop mftt1 fftt4	0.4832		0.5206	0.6801		0.7124
prop mptt1 fftt4	0.0186		0.0168	0.0311		0.0222
prop munt1 fftt4	0.0234		0.0298	0.0280		0.0422
prop mftt1 fptt4	0.2581		0.2316	0.1398		0.1084
prop mptt1 fptt4	0.0090		0.0084	0.0155		0.0038
prop munt1 fptt4	0.0084		0.0126	0.0031		0.0072
prop mftt1 funt4	0.1749		0.1656	0.0807		0.0960
prop mptt1 funt4	0.0084		0.0060	0.0031		0.0028
prop munt1 funt4	0.0162		0.0086	0.0186		0.0050

Notes: The table reports the sample and simulated moments used in the quadratic form in equation (35). In describing the moments in the first column we use the following abbreviation: m and f stand for males and females; 1 and 2 stand for males and females; pt, ft and un for part-time, full-time and unemployment; t# stand for the time period (recall that each time period is three months apart).

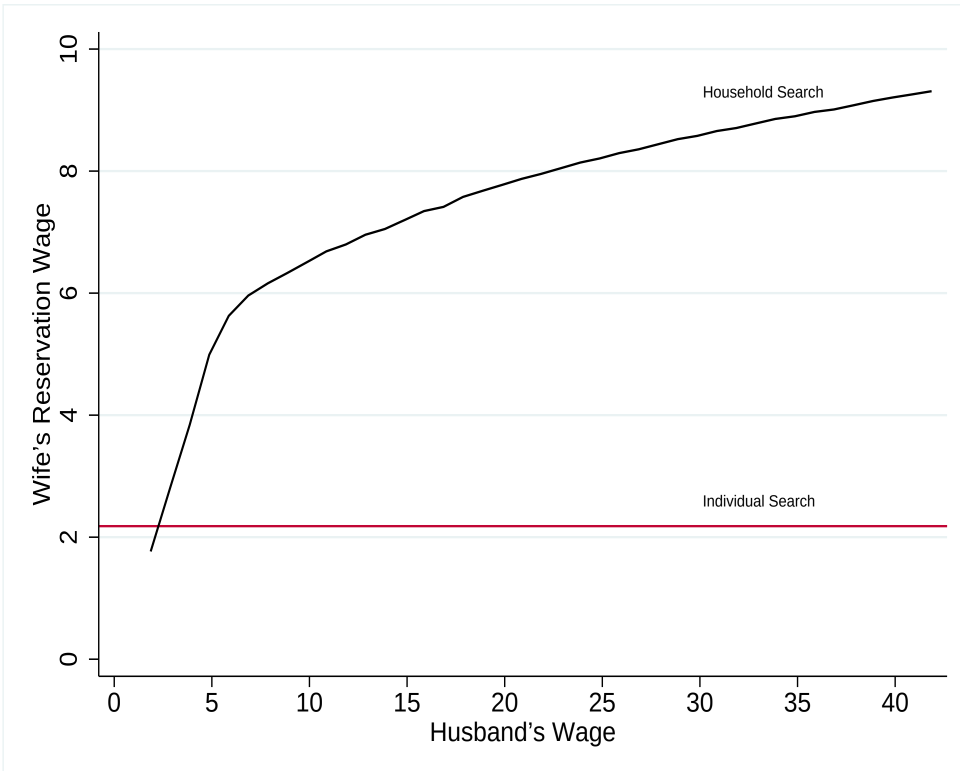

Figure 1: **Wife's Reservation Wage Out of Unemployement: Benchmark**

Note: Simulations based on parameter estimates from household search model with children (See Table 2, Columns 3 and 4). Labor supply regime: Full-time. Nonlabor Income = 0.44$/h.

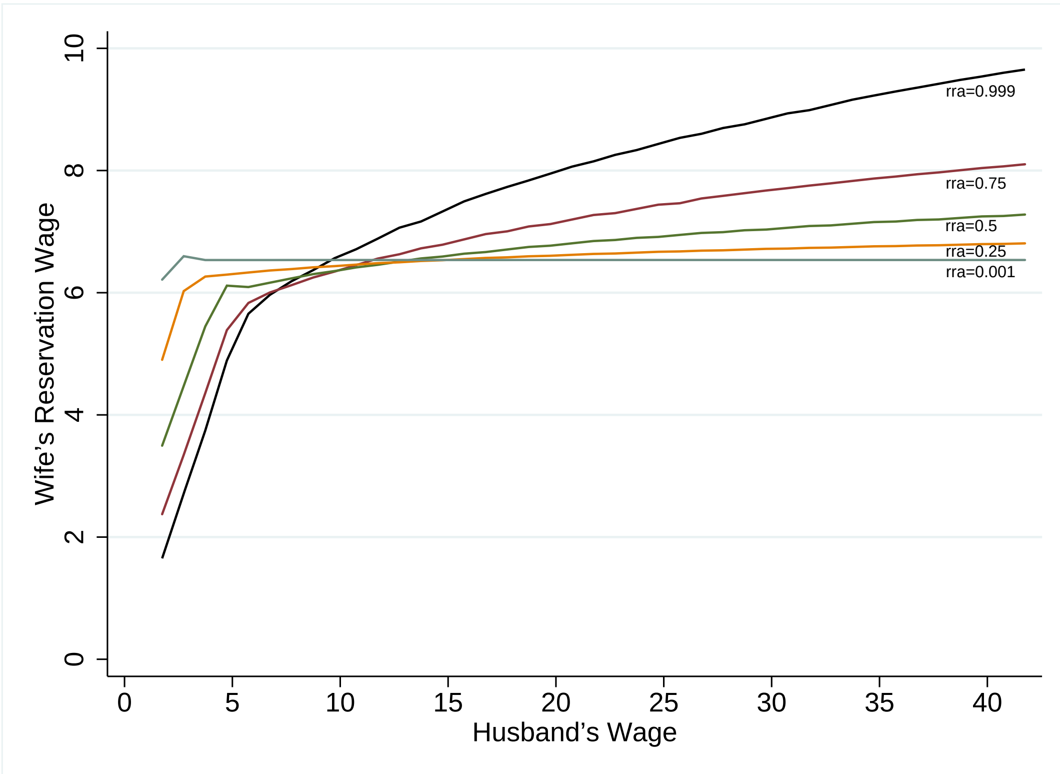

Figure 2: **Wife's Reservation Wage Out of Unemployement: Sensitivity to Risk Aversion**

Note: Simulations based on parameter estimates from household search model with children (See Table 2, Columns 3 and 4). Labor supply regime: Full-time. Nonlabor Income = 0.44$/h Relative Risk Aversion coefficient (rra=1-δ) ranges from 0.0001 to 0.999.

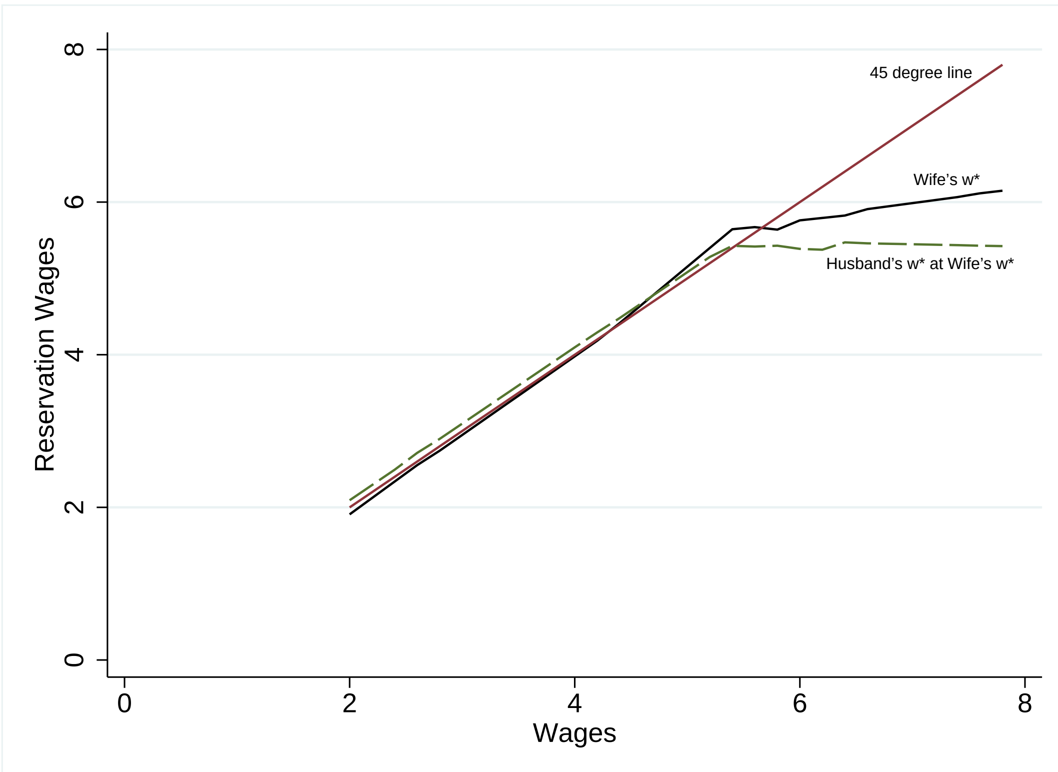

Figure 3: **Wife's Reservation Wage Out of Unemployement: Husband's Endogenous Quit**

Note: Simulations based on parameter estimates from household search model with children (See Table 2, Columns 3 and 4). Labor supply regime: Full-time. Nonlabor Income = 0.44$/h. Definitions: "Wife's w*" is the wife's reservation wage at given husband's wage on the x-axis; "Husband's w* at Wife's w*" is the husband's reservation wage corresponding to the the wife's reservation wage at given husband's wage on the x-axis.

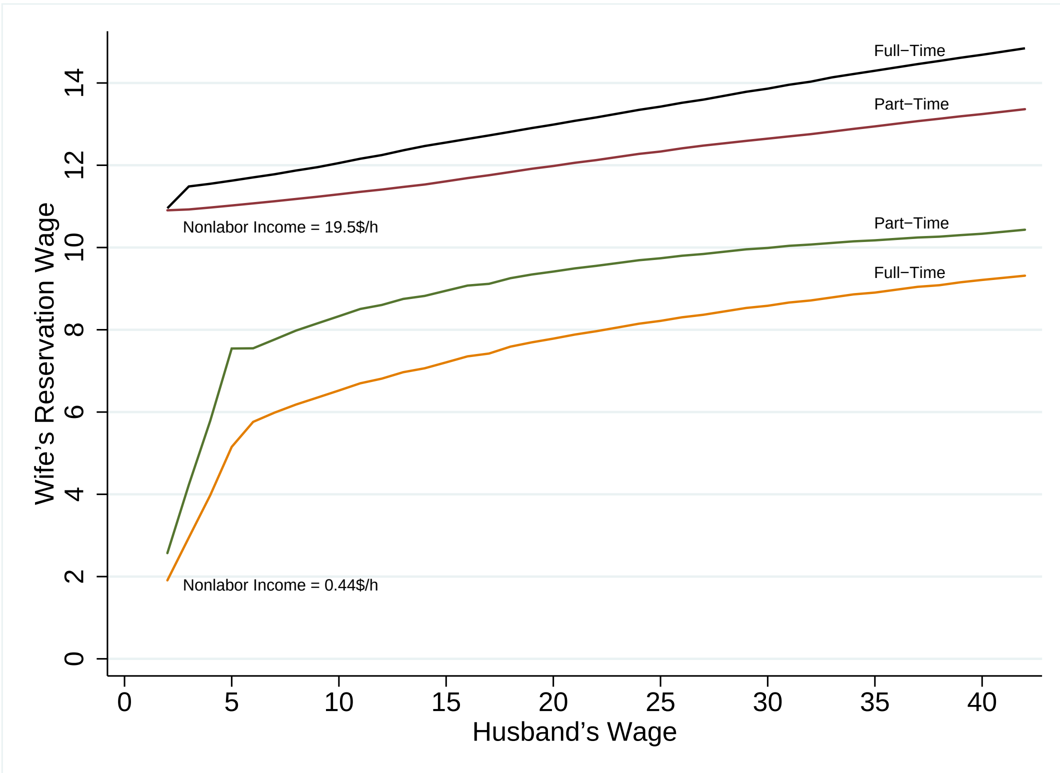

Figure 4: **Wife's Reservation Wage Out of Unemployement: Sensitivity to Labor Supply and Nonlaborincome**

Note: Simulations based on parameter estimates from household search model with children (See Table 2, Columns 3 and 4). Labor supply regime of the husband is always fixed at Full-time.