Household Lifetime Inequality Estimates in the U.S. Labor Market.[*]

Luca Flabbi[†]
IDB and *IZA*

James Mabli[‡]
Mathematica Policy Research

J. Mauricio Salazar[§]
IDB

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Abstract

This paper provides the first set of household lifetime inequality indexes derived from representative U.S. labor market data. We obtain this result by using estimates of the household search model proposed by Flabbi and Mabli (2012). Inequality indexes computed on the benchmark model shows that inequality in utility values is substantially different from inequality on earnings and wages and that inequality at the cross-sectional level is significantly different from inequality at the lifetime level. Both results deliver original policy implications that would have not been captured without using our approach. In particular, we find that a counterfactual policy experiment consisting in a mean preserving spread of the wage offers distributions increases lifetime inequality in wages and earnings but not in utility. When comparing inequality at the individual level between men and women, we find inequality in wages and earnings to be higher for husbands than wives but inequality in utility to be higher for wives. A counterfactual decomposition shows that the job offers parameters are the main source of the differential.

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[*]The views expressed in this paper are those of the authors and should not be attributed to the Inter-American Development Bank or Mathematica Policy Research.

[†]Research Department, Inter-American Development Bank, 1300 New York Avenue NW, Washington, DC 20005; lucaf@iadb.org; https://sites.google.com/site/lucaflabbi/

[‡]Mathematica Policy Research, 955 Massachusetts Avenue, Suite 801, Cambridge, MA 02139, JMabli@mathematica-mpr.com

[§]Research Department, Inter-American Development Bank, 1300 New York Avenue NW, Washington, DC 20005; jmsalazar@iadb.org

1 Introduction

Inequality is a crucial feature of a given labor market since most of the source of income for most individuals is labor income. It is also a fundamental indicator to judge an economy in its overall performance, efficiency and, of course, equity. Given its relevance, a lot of emphasis has been devoted to measurement issues both in terms of the theory behind appropriate indicators and in terms of data collection. We propose here a measure of inequality with two relevant yet relative understudy features: the first is the use of a lifetime perspective; the second is the focus on the household.

By lifetime inequality we mean a measure of inequality able to take into account labor market dynamic. Consider a standard measure of inequality based on cross-sectional wages. It is definitely informative but it cannot take into account that the position of a given individual over the wage distribution is temporary. Labor market dynamic implies that she may loose the job and become unemployed (employment risk) or that her wage may change (wage risk) or that she may simply decide to follow better opportunities (labor market mobility). A lifetime measure should provide a summary measure of inequality able to take into account all these events. Various empirical approaches have been used to tackle the issue. Starting from the seminal Gottschalk and Moffitt (1994), many contributions have focused on decomposing the overall wage variability in a transitory (over time) component and in a permanent component. In a similar vein, Buchinsky and Hunt (1999) and subsequent contributions focus on assessing the stability of an individual in the wage distribution by using transition probabilities. Yet another and larger group of contributions focuses on insurance against risk by working with consumption data and risk sharing mechanisms. Contributions in this line of research are popular and influential both in the micro literature[1] and in the macro literature.[2]

We follow a different strategy by defining *lifetime* as the dynamic implied by participating over time (but in steady state) in a given labor market characterized by frictions and wage and employment risk. All the main structural parameters of the labor market are estimated from the data. In this respect, we focus more attention on the modeling and estimating of the labor market than the contributions listed before. This emphasis explicitly allows for wage and employment mobility as a result of optimal individual behavior but it comes at the cost of loosing the life-cycle dynamic that some of the above contributions are able to consider. Our approach belongs to a still small but increasing literature which includes the seminal Flinn (2002) comparing inequality and mobility in the U.S. and Italian labor market; Bowlus and Robin (2004) developing an innovative non-stationary model of job mobility; and Flabbi and Leonardi (2010)

[1] Early seminal contributions are Attanasio and Davis (1996) and Blundell and Preston (1998). Low, Meghir and Pistaferri (2008) is one of the most complete models in this line of research.

[2] Kaplan (2012); Heathcote, Storesletten, Violante (2012); Heathcote, Perri, Violante (2010); Krueger and Perri (2006) are all contributions in the macro literature which model risk and are concerned with the difference between income and consumption inequality.

decomposing the increase in inequality in the U.S. in the 1990s.

What sets our contribution apart in this literature is our focus on the household: No previous contributions[3] provides estimates of lifetime household inequality. The importance of the focus on the household is straightforward: individuals engaged in stable relationships share resources and take important decisions together. As a result, evaluating inequality at the household level may be even more indicative of the state of an economy or a labor market than inequality at the individual level. The importance of the household has long been recognized by the literature. In particular, the third line of research listed above (see footnotes 1 and 2) has pointed out the importance of considering that decisions are taken at the household level and the relevance of sharing rules within the household. In our approach, we will be able to address only the first of the two issues since we will assume a unitary model of the household. However, in taking into account that decisions are taken at the household level we will need to develop a model of dual search in the labor market, a problem that provides a contribution in its own right and that has been tackled by the search literature only recently.[4]

We develop and estimate a standard but fairly complete search model of the labor market. We allow for search both on-the-job and during unemployment and we also allow for a very simple labor supply decision. The main feature of the model is showing allow for the interaction between labor market decisions of the two spouses. The two spouses search (and work) simultaneously in two labor market which are allowed to be gender-specific. We estimate the model by simulated methods of moments on the 2001-2003 panel of the *Survey of Income and Program Participation* (SIPP).

We compute three indicators of lifetime and Cross-sectional household inequality on the benchmark model. Each indicators compute inequality in wages, earnings and utility. Comparing lifetime and Cross-sectional inequality measures we find substantial differences in the magnitude of the inequality indexes and in their ranking between wages, earnings and utility.

We then proceed to perform a series of counterfactual and policy experiments. The first set of experiments shows the sensitivity of household inequality to the different labor market parameters. In particular we look at the impact of labor market frictions, dispersion of job offers and frequency of part-time offers. We find substantially different implications when judging the policies based on lifetime measures or on cross-sectional measures. The second set of experiments is motivated by a result found in the benchmark specification: women (wives) exhibit different levels of inequality than men (husbands). In particular, wives' wage and earnings inequality is lower but lifetime inequality is higher than those

[3]The only exception is our own Flabbi and Mabli (2012). This previous version of our work has now been updated and split in two contributions: the current paper focusing on inequality and Flabbi and Mabli (2015) focusing on the comparison between estimating a search model at the household level and at the individual level.

[4]Dey and Flinn (2008) is the first contribution estimating an household search model; Guler, Guvenen and Violante (2012) provides an exhaustive treatment of the impact of preferences in an household search model with a unitary household.

of their husbands. In the experiments we decompose the sources of these differentials in impact due to: labor market frictions, job offers and preferences. We find that the main source of the gender differential in inequality are the job offers distributions.

The paper is organized as follows. The next section briefly presents the model. Section 3 presents the Data. Section 4 briefly describes the identification strategy, specifies the estimator and presents the estimates. Section 5 contains the main contribution of the paper and it is devoted to the inequality exercise. We first precisely describe how we estimate lifetime values. We then define the inequality indexes we are going to use. We follow with a discussion of the benchmark case, before providing in separate subsections the counterfactual and policy experiments. Section 6 concludes.

2 Model

2.1 Environment

We develop a search model of the labor market where decisions are taken at the household level.[5] It is a natural extension of the usual single-agent decision problem to a joint-search problem of two agents looking for jobs simultaneously. The major simplification we introduce to keep the problem tractable is assuming a unitary model of the household: households consists of two agents sharing consumption, pooling income and maximizing a common utility function. Consistently with the data we will use in estimation (married couples), we call individuals belonging to one type *wives* and to the other type *husbands*. Wives' parameters are denoted by the subscript $_W$ and individuals belonging to the set of wives are indexed by j. Husbands' parameters are denoted by the subscript $_M$ and individuals belonging to the set of husbands are indexed by i.

The model is in continuous time in a stationary environment. Shocks follow Poisson processes with exogenous parameters. There are three types of shocks in the market. First, job offers while unemployed characterized by the arrival rate parameter λ_A. $A = M, W$ denotes parameters pertaining to husbands and wives. Second, there is also on-the-job search, leading to offers characterized by the rate γ_A. Once offers are accepted, can be terminated endogenously or exogenously. Endogenous termination may occur because one spouse may decide to quit the current job as a result of a change in the labor market status of the other spouse. Exogenous terminations are introduced in order to take into account other sources of job termination (firing, firm closing): they are modeled as an exogenous Poisson process with parameter η_A. Exogenous termination is the third and final shock characterizing the environment.

We also add labor supply, a nonstandard feature in the search literature[6]

[5]The environment is the same as the one labelled as *household search extended model* in Flabbi and Mabli (2012). We refer to the paper for a more detailed description of the model.

[6]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

that we introduce in order to match the relative large number of women present in the final estimation sample. Labor supply also generates a richer household interaction environment. To make the estimation tractable, we introduce the intensive margin of labor supply by assuming that job offers require either a full-time hours schedule or a part-time hours schedule.[7] The distribution of wage offers is conditional on the hours schedule requirement. We denote this by writing the wage offer distribution to gender $_A$ in part-time and full-time jobs as $F_A^{pt}(w)$ and $F_A^{pt}(w)$. Notice that the index pt, ft denote that all the parameters characterizing the wage offers distributions are conditional on the hours schedule requirement. The exogenous proportion of part-time offers is denoted by p.

The instantaneous utility functions of household i, j depends on the idiosyncratic components and on the time-invarying household-specific non-labor income y_{ij}. For identification purposes, we assume a Constant Relative Risk Aversion (CRRA) utility function. Household instantaneous utility is therefore defined as:

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

where:

$$\begin{aligned} c_{ij} &= w_i h_i + w_j h_j + y_{ij} \\ l_i &= 1 - h_i \\ l_j &= 1 - h_j \\ h_{i,j} &\in \{h^{pt}, h^{ft}\} \end{aligned}$$

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.

2.2 Value Functions

As a result of this environment, each spouse can be in three different states: unemployment, part-time employment and full-time employment. Since each spouse can be in three states, each household can be in nine different states, each subject to a different set of shocks. We report the list of each state together with the notation for the value function and the parameters characterizing the

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offer and it is bargained with the employer.

[7] 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). Wage-hours packages are embedded in a labor market search framework by Gorgens (2002). Other examples of empirical search model featuring job offers including not only a wage but an additional job characteristics are: Dey and Flinn (2008) and Aizawa and Fang (2013) adding health insurance; Flabbi and Moro (2012) adding job flexibility; and Meghir, Narita and Robin (2014) adding formality status.

shocks in Table 1. Notice that each household is also characterized by a time-invarying household-specific y_{ij}. For convenience, we drop the conditioning on y_{ij} in Table 1 and in the rest of this subsection. The value function V denotes the cases when both spouses are employed; T the cases when one spouse is employed and the other is unemployed; U the case where both spouses are unemployed.

The full expressions of the value functions in recursive form are available in a slightly more general form in Flabbi and Mabli (2012). Here we will just focus on one example to point out the richness of the interaction between spouses' labor market states allowed by the model. It is particularly instructive to look at the value of an household where one spouse is working full-time (say, the husband) and the other spouse is unemployed and searching. The value function for such household is denoted by $T\left[w_i, h^{ft}\right]$ and is characterized by the following equation:

$$
\begin{aligned}
(\rho+\gamma_M+\eta_M^{ft}+\lambda_W)T\left[w_i,h^{ft}\right] &= u\left(w_i h^{ft}+y_{ij},1-h^{ft},1\right) \qquad (2)\\
&+\gamma_M(1-p_M)\int \max\left\{T\left[w_i,h^{ft}\right],T\left[w',h^{ft}\right]\right\}dF_M^{ft}(w)\\
&+\gamma_M p_M\int \max\left\{T\left[w_i,h^{ft}\right],T\left[w',h^{pt}\right]\right\}dF_M^{pt}(w)\\
&+\eta_M^{ft}U\\
&+\lambda_W(1-p_W)\int \max\left\{\begin{array}{c} T\left[w_i,h^{ft}\right],V\left[w_i,h^{ft},w',h^{ft}\right], \\ T\left[w',h^{ft}\right]\end{array}\right\}dF_W^{ft}(w)\\
&+\lambda_W p_W\int \max\left\{\begin{array}{c} T\left[w_i,h^{ft}\right],V\left[w_i,h^{ft},w',h^{pt}\right], \\ T\left[w',h^{pt}\right]\end{array}\right\}dF_W^{pt}(w)
\end{aligned}
$$

An household where the husband works full-time and the wife searches enjoys flow utility $u\left(w_i h^{ft}+y_{ij},1-h^{ft},1\right)$ and it may receive three shocks: an on-the-job offer to the husband, a job offer to the wife, and a termination shock to the husband's job. Each job offers may be either part-time or full-time.

What is interesting in the dual search process detailed by our household search framework is that under our utility function assumption[8] a shock to one of the spouse may generate a change of the other spouse's labor market state. For example, consider the fifth row in equation (2) where the wife is receiving a full-time offer. If this full-time offer is accepted, the husband may react by staying in the current job but he may also react by quitting the current job (leading to household state $T\left[w',h^{ft}\right]$). This contemporaneous change of state result cannot be deal with without the joint modeling of both spouses' search processes as we do in the current formulation of the model.

[8]See Dey and Flinn (2008) and Guler, Guvenen and Violante (2012) for a formal proof. We provide a more detailed discussion of this result in section 2.3.

2.3 Equilibrium

The optimal decision rule of the dual-search problem in the household search context retains the reservation value property of the usual individual search model with linear utility with the only difference that the the critical value is now defined on the utility value.[9] Based on the choices and the value functions, utility reservation values can be derived in the same way as reservation wage values are derived in a standard linear-utility individual-search model: by finding the instantaneous utility values such that the household is indifferent between the relevant alternatives. The equations defining the reservation utility values and the formal definition of the equilibrium are notational heavy and are not reported. The extended version of the equations and the full equilibrium definition is available in Flabbi and Mabli (2012).

What is interesting to discuss for the objectives of this paper is the source of the dependence between spouses' labor market choices and states. If agents are risk neutral then the household search model equilibrium is equivalent to the individual search model equilibrium. The intuition for the result is very simple. With linear utility, the marginal utility of income is constant and therefore the decision of one spouse about job offers does not depend on the other spouse contributing income to the household by working or not.

Instead, if agents are endowed with our CRRA utility function, i.e. a utility function with curvature and risk aversion, then the income flow to the household is relevant in making decisions. For example, assume a household where the husband is looking for a job and the wife is working at a given wage. The wife's wage has now an impact on the husband decision rule: the higher the wife's wage, the higher the income flow to the household the lower the cost of search. This channel makes the husband pickier in accepting job offers. At the same time, the higher the wife's wage, the lower the expected gain from search. This second channel makes the husband less picky in accepting job offers. These simple channells generate two main results:

1. In the presence of CRRA utility, the labor market state of one spouse has an impact on the optimal labor market choices of the other spouse;

2. The direction of this impact with respect to a standard individual search model or an household search model with linear utility is ambiguous.

Both results are clearly pointed out in Dey and Flinn (2008). An extensive discussion, including conditions applied to more general formulations of the utility function and formal proofs, is in Guler, Guvenen and Violante (2012). Finally, an extensive and intuitive graphical discussion of the result is reported in Flabbi and Mabli (2012).

[9] This is due to the presence of a labor supply decision function of the hours worked regime. For extensive discussion and formal proofs see Blau (1991) and Hwang, Mortensen and Reed (1998). For a similar application see Flabbi and Moro (2012).

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 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. 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. 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.[10] Additionally, neither spouse must participate in the armed services throughout the sample period.

We exclude couples 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. We exclude spouses if either spouse is out of the labor force for the entire panel period or if either spouse transitions between out of the labor force and unemployment, but does not work in the panel period. Instead, we choose to include spouses in the sample who answer that they are out of the labor force at some point in the panel, but have an employment spell or unemployment spell at other points in the sample.

Hours and earnings information must be observable at every point in the panel for any employed individual. Couples in which at least one individual does not supply hours worked per week are excluded from the sample. We recode hours worked per week into part-time and full-time categories but we use the full hours worked variation to derive hourly wages when they are not directly reported in the hourly format. Individuals are coded as working part-

[10] Notice that the loss of information due to this restriction is limited since we require couples to be married only for our relative short period of observation (2 years).

time if they work less than 35 hours per week and full-time if they work at least 35 hours per week.

We only impose a small adjustment on the raw wage data: We exclude 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 2 and 3. 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. Moreover, the short time dimension of the data does not provide a lot of information about this process.[11]

Table 2 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 2 we just report values for the first point-in-time sample. The first and fifth columns report unconditional 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. 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. Hourly wages inequality is quite similar between men and women while overall inequality in weekly earnings is slightly higher for women. This is mainly due to the higher proportion of women working part-time and point out to the

[11] We use 18 years as cut-off point because it usually denotes the age when children leave home therefore significantly changing the child-care requirements on the household. We have experimented with different cut-off points without experiencing qualitative changes in the results.

importance of labor supply decisions in determining gender differentials in the labor market.

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. Women's average wages 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 decreasing as we move from the husband working full-time, to working part-time, to unemployment. Husbands are less sensitive than wives to the 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 of the wife is working than if the wife is unemployed). The sample of couples without young children confirms the sensitivity 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. Notice, however, that if the sensitivity is similar 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 does the same while the opposite is true on the sample with young children.

Table 3 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, transition 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 sensitivity observed in Table 2. 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 2 and Table 3 show the sensitivity of one spouse labor market status to the other's spouse labor market status. Accounting for this sensitivity is one of the motivation to use an household search model as we do in the current paper. It is also an empirical feature allowing for the identification of some important model's parameters.

4 Estimation and Identification

4.1 Identification

The identification discussion is based on a data set of linked information for husbands and wives, including accepted hourly wages, hours worked, labor market state dummies, transitions and wage growth over time and some individuals characteristics such as demographics and the presence of children. We present just the main intuition while we refer to Flabbi and Mabli (2012) for further details.

As a preliminary step, we have to add a few more functional form assumptions on top of those already presented in Section 2. First, due to the well-known non-identification result of Flinn and Heckman (1982), we need to assume a *recoverable* wage offers distribution 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 assume a lognormal distribution. The parameters of the distribution are conditional both on gender and hours requirement and they are denoted as $(\mu_A^{ft}, \sigma_A^{ft})$ and $(\mu_A^{pt}, \sigma_A^{pt})$.

Second, we consider how to integrate in the identification and estimation procedure two household heterogeneity characteristics: non labor income and the presence of children. Both imply a different optimal decision rules for each labor market state combination and therefore we introduce them in a very stylized way: they are both exogenous and they are time-invarying. Non-labor income assumes three values directly estimated from the data and the presence of children is used to split the sample in order to obtain a separate set of structural parameters for household with or without children. The age limit we impose on the children is 18 years old, that is we code as households with children all the households that have children 18 years old or younger.[12]

[12]Flabbi and Mabli (2012) use a different parameterization by introducing the excluding restriction that the presence of children has an impact only on the weight given to leisure in

As a result of these additional parametrization, the parameters to be estimated can be sorted in three groups:

1. mobility and cost of search parameters;
2. wage offer distributions parameters;
3. utility parameters.

Due to lack of identification, the discount rate parameter ρ is not estimated but fixed to 5% a year.

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. A detailed heuristic discussion of the identification of the model is provided in Flabbi and Mabli (2012). The intuition is as follows.

The mobility parameters and the wage offer distribution parameters are identified following the usual results from individual search models. As shown by Flinn and Heckman (1982), they are identified from information on, respectively, transitions between labor market states and accepted wages distributions.

The utility parameters identification is more interesting since search model usually assume linear utility. Labor supply information provides identification for the relative weight given to leisure in the utility function while the dependence between spouses' labor market decisions provide identification about the relative risk aversion coefficients. The second result is obtained from the theoretical implication discussed in Section 2.3: Labor market decisions of one spouse depend on labor market decisions of the other spouse only if the utility function is non-linear. As a result, the degree on non-linearity implied by risk aversion can be identified by the intensity of the dependence between spouses' labor market decisions.

4.2 Estimation Method

Due to the possibility of *simultaneous* changes in the labor market states of both spouses in a given household, we cannot estimate by maximum likelihood. We choose instead the method of simulated moments. Following Dey and Flinn (2008) and Flabbi and Mabli (2012), we extract moments from point-in-time samples that focus on steady states aggregated moments and transitions probabilities.

The estimation procedure works as follows. First, we select the moments with which to estimate the parameters of the model. We calculate these moments in our original sample and reserve them for use in the criterion function. Second, 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 and the optimal decision rules are obtained. Third, we randomly assign each couple an initial labor supply configuration and we simulate labor market histories, where each labor market history denotes a

the utility function α_A.

sequence of transitions between labor market states for a pair of spouses. Fourth, we compute in the simulated sample the same moments we want to target in the data. Fifth, we use a criterion function[13] to minimize the distance between sample and simulated moments. The minimizer of the criterion function is the estimator we propose.

The moments are chosen closely following the identification strategy outlined in Section 4.1. Transitions are important to identify mobility parameters therefore we include all the transitions between labor market states. Recall that there are 16 possible household states since each spouse can be in 4 different states. Transitions between all the 16 states are possible with only one exception: if both spouses are out of the labor force. Accepted wages are crucial to identify wage offers parameters. We include first, second and third moments of all the relevant wage offers distributions. Finally, interaction between spouses labor market states are important to identify the utility parameters: we include the above moments conditioning on the other spouse labor market states. For wages, we also add the correlation between spouses' wages.

Since we allow all the structural parameters (with the exception of the relative risk aversion parameter which is common to the household) to be different for husbands and wives, all the moments listed above are gender-specific. Finally, since we allow the presence of children to impact the structural parameters, all the moments listed above are computed for household with and without children. Overall, we have a total of 121 moments to estimate a total of 23 parameters for households with children and the same number of moments and parameters for households without children. The complete list of sample moments and of simulated moments at estimated parameters is reported in the Appendix of Flabbi and Mabli (2012).

4.3 Estimation Results

We report the estimation results in Tables 4 and 5. Table 4 reports the structural parameters estimates and Table 5 some relevant predicted values. The first two columns pertain to the sample of households with children younger than 18 years old; the last two columns to the sample of households 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 household 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 5, women are more likely to receive part-time job offers and when they receive full-time offers

[13]The criterion function is the usual quadratic form composed of the vector of the distance between sample and simulated moments weighted by a diagonal matrix. The weighting matrix we use is also standard in similar application and it is build by placing the inverse of the sample moment standard deviation on the main diagonal. See Flabbi and Mabli (2012) for additional details.

they are at lower wages, on average. With respect to labor supply estimates, the model estimates a rate of part-time offers three-times larger for women than men. This finding is in line with the previous literature.[14]

The point estimates of the utility parameters contain some interesting results. The weight on leisure (α) is estimated to be higher for women than men on both samples but more so on the sample of household with young children present. 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 on all the sample and specification. It is an estimated value higher than the one obtained by Dey and Flinn (2008) but lower than the preferred value used by Guler, Guvenen and Violante (2012). Overall, 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 strongly rejected for both samples.[15]

The fit of the model on the moments we explicitly target in the estimation procedure is overall quite good.[16] 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 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 an acceptable but worse fit on the wives' wage distributions. This is a fairly common finding in the literature: Dey and Flinn (2008) 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 of the female wage distribution.[17]

5 Inequality

The estimation of the model structural parameters allows us to simulate labor market careers for households and individuals. This labor market careers can then be used to compute inequality measures both cross-sectionally and over-time. We call *lifetime inequality* the inequality that summarize the entire labor

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

[15]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 0.0001.

[16]For a more detailed discussion of the model fit, see Section 5.2 in Flabbi and Mabli (2012).

[17]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.

market careers of given agents. We give a formal definition below. The final objective of this section is, on top of building a measure of lifetime inequality, to provide a decomposition of the sources of inequality and to assess the impact of policy variables on the level of inequality through counterfactual policy experiments.

5.1 Simulations and Lifetime Variables

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 moments and indexes in the *benchmark* model; it is set at a proper combination of the point estimates when computing moments and indexes in the *counterfactual* and *policy experiments* models. Each household begins in a given labor market state. Random numbers are generated to determine the length of time until each spouse receives a shock. When the shock is a job offer, the actual content of the job offer (wage level, part-time/full-time regime) is also drawn using a random number generator and it is drawn from the appropriate exogenous wage offers distribution. Recall that wage offers distribution are conditional on gender, part-time/full-time regime and presence of children in the household. 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).

One of the objective of the paper is to propose inequality measures that take into account not only the current position of an individual in the accepted wage distribution but also her transitions over labor market states and the evolution of her wage over the entire labor market career. We attempt to satisfy this objective by proposing a summary measure of the evolution over time that we label *lifetime* value. The concept is then applied to a variety of indicators describing inequality in wages, earnings and utility.

Lifetime values are created for each household and individual 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:

$$LU_{ij} = \sum_{s=1}^{S} \exp\left(-\rho t_s\right) \int_{t_{s-1}}^{t_s} u\left(c_{ij}, l_i, l_j; \delta, \beta, \alpha\right) \exp\left(-\rho v\right) dv \tag{3}$$

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} in equation (3).

5.2 Inequality Measures

We want to use inequality indicators that are flexible in terms of sensitivity to different part of the distribution. For this reason we use indicators belonging to the the Generalized Entropy class of inequality indexes which is defined in Shorrocks (1984) as:

$$GE(\nu) = \frac{1}{\nu(1-\nu)}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\overline{y}}\right)^{\nu} - 1\right] \tag{4}$$

where y_i is the variable of interest in a population of individuals $i = 1, 2, ...n$; $\overline{y}$ is the sample mean and ν is a parameter.

This class has two important properties useful for our objective: (i) the sensitivity to the top of the distribution is governed very parsimoniously by one parameter, the parameter ν: the more positive is ν the higher the sensitivity of the index to differences in the top of the distribution; (ii) all indexes are in the same scale making the comparisons among them very convenient. Among the indexes belonging to this class we will focus at most on the following three: $GE(2)$ which equals to half the square of the coefficient of variation, $GE(1)$ which is the Theil entropy index, and $GE(0)$ which is the mean log deviation. [18]

5.3 Benchmark Model Results

Table 6 reports the inequality indexes computed over variables extracted from simulations of the benchmark model. The benchmark model is the model run at the estimated parameters reported in Table 4. The top panel reports results on the sample of household with children younger than 18 and the bottom panel on household without children younger than 18. In each panel, the top rows report results on lifetime variables (see Equation (3) for the definition) and the bottom rows results on cross-sectional variables.

There are major differences in the patterns of the inequality measures obtained on lifetime variables and on cross-sectional variables. First, in the Cross-section, inequality at the utility level is lower than inequality at the wages and earnings level. This equalizing effect is not present when considering the lifetime horizon. It means that the durations in each state and the role played by shocks reverse this channel over time.

Second, when increasing the sensitivity to the top of the distribution - i.e. moving from $GE(0)$ to $GE(2)$ -, inequality increases in lifetime terms but decreases in the cross-section. However, the differences between indexes are not very large so we do not see this as a major result.

Third, inequality in wages and earnings between household and inequality in wages and earnings between individuals are ranked differently in the cross-

[18] This class of inequality measures is also used by two other papers looking at lifetime inequality measures in a search context: Flabbi and Leonardi (2010) and Flinn (2002).

section than over the lifetime.[19] Over the lifetime, the household has an equalizing effect both for husbands and wives: looking for example at $GE(2)$ on earnings, household inequality is 0.0171 compared with 0.0282 wives inequality and 0.0347 husband inequality. At the cross-sectional level, the household has an equalizing effect only for husbands: $GE(2)$ on earnings is 0.0953 for households, 0.0554 for wives and 0.1465 for husbands. This indicates that the assortative mating patterns can be very different in a static environment with respect to a dynamic environment.

Fourth, the results on the sample household without children younger than 18 repeats similar patterns but with different magnitudes. The most relevant difference in magnitudes refer to lifetime wages and earnings inequality for wives: it is much larger in the sample with children than in the sample without children. The use of part-time and difference preferences for leisure are among the important sources of this difference.

Overall, we think that these results deliver two main conclusions that support the motivation behind our approach: (i) inequality at the utility level is different than inequality on earnings and wages; (ii) inequality at the cross-sectional level is different than inequality at the lifetime level and may therefore deliver different policy implications. We explore this issue in the next two sections.

5.4 Counterfactual Experiments Results

5.4.1 Labor Market Structure and Household Inequality

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 at same mean. Results are reported in Table 7. Since the inequality indexes are not very sensitive to ν and to guarantee better readability, we report only the $GE(2)$ index. In each experiment, we change a specific set of parameters by 50% leaving the other parameters at the benchmark values. This new combination of parameters will generate different optimal decisions that we take into account when performing the simulations. The benchmark is the estimated model reported in Table 4.

We first focus on the top panel of Table 7, where we report results for the sample with children younger than 18 year old. The first row reports the benchmark values. The second row evaluates the impact of a reduction in search frictions, i.e. we increase the arrival rates of wage offers $(\lambda_{W,M}, \gamma_{W,M})$ by 50%. Reducing frictions reduces lifetime inequality. The effect is mainly through shorter unemployment periods as shown by the relative more stable values in

[19] It is straightforward to obtain measures of husbands and wives inequality by directly using their respective wages. It is more difficult to obtain measure of utility inequality for husbands and wives because utility is defined only at the household level. In Section 5.4.2 we will propose a summary measure of utility at the individual level to compare the gender gap on inequality but it requires very strong assumptions not fully consistent with usual models of household interaction.

wages and earnings inequality. In the third row we check if the positive impact of a reduction in frictions may be offset by an increase in turnover generated 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 $(\lambda_{W,M}, \gamma_{W,M})$. Results show that the decrease in inequality induced by lower search frictions is not offset by an increase in terminations rates. The policy conclusion is that a more efficient search and matching process decrease *utility* inequality both at the *lifetime* level and at the cross-sectional level. The process also increases average household utility, as shown by the values reported in the first column.

The second set of policies looks at the impact of part-time (rows 4 and 5 for lifetime variables and 10 and 12 for cross-section variables). 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 tend to work less hours than men and they highly value job flexibility.[20] 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",[21] we can evaluate here the impact of the presence of part-time on overall inequality. Row 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 in earnings experiences a small increase, which is mainly due to an higher number of husbands accepting part-time jobs. If we decrease part-time offers by 50%, the increase in inequality in earnings for women is almost exactly balanced by a decrease in inequality in earnings for men leading to a value very similar to the benchmark. Lifetime inequality in utility and wages increases slightly. 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 decade and, in particular, in the previous decade.[22] 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 wages and earnings inequality: cross-sectional indexes more than double with respect to the benchmark model and life time indexes are more than three times larger than in the benchmark. However, optimal behavior is smoothing the impact on utility, leading to only a relatively modest increase in cross-sectional utility inequality and to actually a *decrease* in lifetime utility inequality. The decrease in lifetime inequality

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

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

[22] 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.

is paired with the largest increase in average utility among the five experiments: mean lifetime utility increase from 379.5 in the benchmark model to 394.3 in the Mean-Preserving Spread Experiment. The experiment is therefore very instructive on a couple of dimensions: (i) it shows that even large increases in wage and earnings inequality may not lead to an increase in utility inequality; (ii) it shows once again the importance of a lifetime perspective since the previous result is missed in the cross-sectional measures.

The bottom panel of Table 7 reports results for the same policies but applied to the sample of households without children younger than 18. The main messages are confirmed, including the increase in lifetime utility and decrease in lifetime utility inequality of the mean-preserving spread experiment.

5.4.2 Decomposition of Gender Differentials in Inequality

We have seen that inequality in wages and earnings is quite different between husbands and wives and it may be instructive to use the model to find the sources of this differential. It would be also interesting to do the same on inequality based on utility measures. However, our household search model specification assumes household utility and not individual utility. Our proposed solution, at some cost in terms of theoretical coherence with the model, is to "re-assign" utility to the two spouses from the household model in the following way.[23] We impute individual utility - say, to the wife - from the household utility as:

$$u\left(c_j, l_j; \delta, \beta_W, \alpha_W\right) = \left(1-\alpha_W\right) \frac{c_j^{\delta}-1}{\delta} + \alpha_W \frac{l_j^{\beta_W}-1}{\beta_W} \tag{5}$$

where:

$$\begin{aligned} c_j &= w_j h_j + y_{ij}/2 \\ l_j &= 1 - h_j - s_j \\ h_j &\in \{h^{pt}, h^{ft}\} \end{aligned}$$

Equation (5) is a simple specialization of equation (1) where we focus on leisure and labor income of only one of the spouse and we split non-labor income in half.

There are two problematic issue in this formulation. First, in equation (5) we assign non-labor income to each individual spouse by splitting equally the household non-labor income between them. It is an arbitrary assumption but it is entirely driven by data limitation since we do not observe non-labor income

[23] This approach is used in Flabbi and Mabli (2012) to compare estimates derived from an household search model with those derived from an individual search model. This section borrow heavily from that paper.

individually assigned in the data. Second, the risk aversion coefficient δ is a coefficient estimated for the pooled household consumption and not for individual consumption. This assumption generate a contradiction with the theoretical model that we cannot solve. However, using the parameter in this way allows us to gain a reasonably meaningful formulation to compare utility inequality at the individual level. As a result, we have decided to report this expression when presenting our decomposition of the gender differential in inequality.

We propose the decomposition by performing the following experiments. Each experiment changes a specific set of parameters to be equal between husbands and wives. Parameters are always set at husbands' values. The first experiment, labelled Frictions, involves all the mobility parameters: λ, γ, η. The second experiment, labelled Job offers, involves all the job offers parameters: μ, σ, p. Finally, the third experiment, labelled Preferences, involves the gender-specific preference parameters: α, β.

Table 8 reports the results. For readability, we only report the $GE\,(2)$ index, i.e. half the square of the coefficient of variation. We first notice that in the benchmark model, inequality in wages and earnings is always higher for husbands than wives. This is a standard finding in the gender wag gap literature. In utility terms, instead, we find the opposite ranking with wives' inequality indexes always higher than husbands'. This differential is stronger at the lifetime level than at the cross-sectional level.

We the proceed with the decomposition of the differentials (rows 2-4 of each panel) in its three components. What we find is that the job offers are the main source of variation of gender differentials in inequality on earnings and wages: when wives values are set equal to husbands values (and individuals are allowed to reoptimize choices with the other parameters left at the benchmark gender-specific values), wives' inequality indexes become very similar to husbands' inequality indexes. This includes both the inequality indexes on wages and earnings (originally higher for men) and the inequality indexes on utility (originally higher for women). Interestingly, preferences will lead to a higher differential in cross-sectional inequality but not in lifetime inequality.

Finally, it is important to notice that in lifetime inequality terms, wives' indexes indicate more dispersion than husbands' indexes. In this case, the job offers parameters have an equalizing effect. However, in interpreting these results is important to keep in mind the caveat we have used in assigning individual utility from estimated obtained by a unitary model of the household.

6 Conclusions

This paper provides the first set of household lifetime inequality indexes derived from representative U.S. labor market data. We obtain this result by using estimates of the household search model proposed by Flabbi and Mabli (2012). Focusing on lifetime measures is important in order to take into account wage and employment risk, and mobility across labor market states. Focusing on household measures is essential to take into account that labor market decisions are taken at the household level and that couples share risk and resources.

Inequality indexes computed on the benchmark model shows that inequality at the utility level is substantially different from inequality on earnings and wages. They also point out that that inequality at the cross-sectional level is different than inequality at the lifetime level. Both results deliver original policy implications that would have not been captured without using our approach. In particular, we find that a counterfactual policy experiment consisting in a mean preserving spread of the wage offers distributions increases lifetime inequality in wages and earnings but not in utility.

When comparing inequality at the individual level between men and women, we find inequality in wages and earnings to be higher for husbands than wives but inequality in utility to be higher for wives. A counterfactual decomposition shows that the job offers parameters are the main source of the differential: when wives' job offers parameters are set equal to husbands' job offers parameters, the gender differential in inequality indexes strongly decreases.

References

[1] Acemoglu, Daron (2002), "Technical change, inequality and the labor market" *Journal of Economic Literature* 40 (1), 7–72.

[2] Ahn, T.; P. Arcidiacono and W. Wessels (2011), "The Distributional Impacts of Minimum Wage Increases When Both Labor Supply and Labor Demand Are Endogenous", *Journal of Business & Economic Statistics*, Vol. 29, Iss. 1.

[3] Acemoglu, D. and Shimer, R., (1999), "Efficient unemployment insurance", *Journal of Political Economy* 107 (5), 893–928

[4] Aizawa, N. and H. Fang (2013), "Equilibrium Labor Market Search and Health Insurance Reform", *NBER Working Paper* No. 18698.

[5] Albrecht, J. A. Anderson and S. Vroman (2010) "Search by Committe", *Journal of Economic Theory*, July 2010.

[6] Altonji J. and C. Paxson (1988) "Labor Supply Preferences, Hours Constraints, and Hours-Wage Trade-offs", *Journal of Labor Economics*, 6(2): 254-276.

[7] Autor, D.; L. Katz, and M. Kearney (2008), "Trends in U.S. Wage Inequality: Revising the Revisionist", *Review of Economics and Statistics*, 90(2): 300–323

[8] Becker, G. (1981), *A Treatise on the Family*, Cambridge: Harvard University Press.

[9] Blank, R. (1990) "Are Part-Time Jobs Bad Jobs?", in G. Burtless (ed.) *A Future of Lousy Jobs? The Changing Structure of U.S. Wages.* Washington, D.C.: Brooking Institution.

[10] Blau, D. (1991) "Search for Nonwage Job Characteristics: a Test for Reservation Wage Hypothesis", *Journal of Labor Economics*, 9(2): 186-205.

[11] Blau, F. and L. Kahn (2006) "The U.S. Gender Pay Gap in the 1990s: Slowing Convergence," *Industrial & Labor Relations Review*, Vol. 60, No. 1, article 3.

[12] Bloemen, H. (2008), "Job Search, Hours Restrictions, and Desired Hours of Work", *Journal of Labor Economics*, 26(1): 137-179.

[13] Blundell, R., and I. Preston (1998), "Consumption inequality and income uncertainty", *Quarterly Journal of Economics,* 113, 603-640.

[14] Bowlus, A., (1997) "A Search Interpretation of Male-Female Wage Differentials", *Journal of Labor Economics*, 15(4), 625-657.

[15] Bowlus, Audra J. and Jean-Marc Robin (2004), "Twenty Years of Rising Inequality in US Lifetime Labor Values", *Review of Economic Studies,* 71(3), 709-743.

[16] Bowlus, Audra J. and Jean-Marc Robin (2010), "An International Comparison of Lifetime Labor Income Values and Inequality: A Bounds Approach", *Journal of the European Economic Association.*

[17] Cahuc, P., F. Postel-Vinay and J-M. Robin (2006) "Wage Bargaining with On-the-Job Search: Theory and Evidence", *Econometrica* 74(2), 323-364.

[18] Chetty, R. (2006), "A New Method of Estimating Risk Aversion", *American Economic Review* 96: 1821–1834.

[19] Compte, O. and Jehiel (2010) "Bargaining and Majority Rules: A Collective Search Perspective", *Journal of Political Economy.*

[20] Dey, M. and C. Flinn (2008) "Household Search and Health Insurance Coverage", *Journal of Econometrics* 145: 43-63.

[21] Dey, M. and C. Flinn (2005) "An Equilibrium Model of Health Insurance Provision and Wage Determination", *Econometrica* 73, 571-627.

[22] Eckstein, Z. and E. Nagypal (2004), "The Evolution of U.S. Earnings Inequality: 1961-2002." *Federal Reserve Bank of Minneapolis Quarterly Review* 28 (December): 10-29.

[23] Eckstein, Z. and G. van den Berg (2007), "Empirical labor search: A survey", *Journal of Econometrics*, 136: 531-564.

[24] Eckstein, Z. and K. Wolpin (1995) "Duration to First Job and the Return to Schooling: Estimates from a Search-Matching Model", *The Review of Economic Studies*, 62(2), 263-286.

[25] Erosa, A, L. Fuster and D. Restuccia, (2010) "A General Equilibrium Analysis of Parental Leave Policies", *Review of Economic Dynamics*,13: 742–758.

[26] Erosa, A, L. Fuster and D. Restuccia, (2002) "Fertility Decisions and Gender Differences in Labor Turnover, Employment, and Wages", *Review of Economic Dynamics*, 5: 856-891.

[27] Fang, H. and A. Moro (2011), "Theories of Statistical Discrimination and Affirmative Action: A Survey", in: J. Benhabib, M. Jackson and A. Bisin (eds.) *Handbook of Social Economics*, Vol. 1A, The Netherlands: North-Holland.

[28] Flabbi, L. (2010), "Gender Discrimination Estimation in a Search Model with Matching and Bargaining", *International Economic Review*, 51(3): 745-783.

[29] Flabbi, L., and M. Leonardi (2010) ”Sources of Earnings Inequality: Estimates from an On-the-Job Search Model of the U.S. Labor Market”, *European Economic Review*, 54(6): 832-854, 2010.

[30] Flabbi, L., and J. Mabli (2012), “Household Search or Individual Search: Does it Matter? Evidence from Lifetime Inequality Estimates”, *IZA Discussion Paper No.*, 6908.

[31] Flabbi, L., and A. Moro (2012), “The Effect of Job Flexibility on Female Labor Market Outcomes: Estimates from a Search and Bargaining Model”, *Journal of Econometrics*, 168: 81–95.

[32] Flinn, C. (2006) “Minimum Wage Effects on Labor Market Outcomes under Search, Bargaining and Endogenous Contact Rates”, *Econometrica* 73, 1013-1062.

[33] Flinn, C. (2002), “Labour Market Structure and Inequality: A Comparison of Italy and the U.S.” *Review of Economic Studies,* 69, 611-645.

[34] Flinn, C. and J. Heckman (1982), “New Methods in Analyzing Structural Models of Labor Market Dynamics.” *Journal of Econometrics*, 18, 115-168.

[35] García Pérez, I. and S. Rendon (2012), ”Family Job Search and Consumption”, mimeo, SUNY-Stony Brook.

[36] Gemici, A. (2011), ”Family Migration and Labor Market Outcomes”, mimeo, NYU.

[37] Gørgens, T. (2002), ”Reservation wages and working hours for recently unemployed US women”, *Labour Economics* 9(1): 93-123.

[38] Guler, B; F. Guvenen and G. Violante (2012), ”Joint-Search Theory: New Opportunities and New Frictions”, *Journal of Monetary Economics*, Vol. 59(4): 352-369.

[39] Heathcote, J., F. Perri and G. Violante (2010), “Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States”, *Review of Economic Dynamics*, 13(1): 15–51.

[40] Heathcote, J., K. Storesletten and G. Violante (2008), “Insurance and opportunities: A welfare analysis of labor market risk”, *Journal of Monetary Economics*, 55: 501-525.

[41] Kaplan, G. (2012) “Inequality and the Lifecycle” *Quantitative Economics* 3, 471?525.

[42] Katz, L., and D. Autor (1999), “Changes in the Wage Structure and Earnings Inequality.” Chapter 26 *Handbook of Labor Economics* vol.3A. Amsterdam North Holland.

[43] Katz, Lawrence F., Murphy, Kevin M., (1992), "Changes in relative wages, 1963–1987: Supply and demand factors." *Quarterly Journal of Economics* 107 (1): 35–78.

[44] Krueger, D. and Fabrizio Perri (2006), "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *Review of Economic Studies* 73 (January): 163-93.

[45] Lentz, R. (2009), "Optimal unemployment insurance in an estimated job search model with savings", *Review of Economic Dynamics* 12: 37–57.

[46] Lentz, R. and Tranæs, T., (2005), "Job search and savings: Wealth effects and duration dependence", *Journal of Labor Economics* 23 (3), 467–490.

[47] Lise, J. (2011), "On-the-Job Search and Precautionary Savings: Theory and Empirics of Earnings and Wealth Inequality", mimeo, UCL.

[48] Meghir, C., R. Narita, and J-M Robin (2014), "Wages and Informality in Developing Countries", *American Economic Review* forthcoming.

[49] Pissarides (2000) *Equilibrium Unemployment Theory*, Cambridge, MA: MIT Press.

[50] Rendon, S. (2006) "Job Search and Asset Accumulation under Borrowing C onstraints", *International Economic Review*, Vol. 47, No. 1, pp. 233-263

[51] Richard Rogerson, Robert Shimer and Randall Wright, "Search-Theoretic Models of the Labor Market: A Survey." *Journal of Economic Literature*, 2005, 43(4), pp. 959-88.

[52] Yamaguchi, S. (2010) "Job Search, Bargaining, and Wage Dynamics", *Journal of Labor Economics*, Vol. 28, No. 3, pp. 595-631.

[53] van der Klaauw and A. van Vuuren (2010), "Job search and academic achievement", *European Economic Review*, Volume 54, Issue 2, 294–316.

Table 1: Household Labor Market States

State	Value Function	Shocks
FT, FT	$V\left[w_i, h^{ft}, w_j, h^{ft}\right]$	$\gamma_M, \eta_M^{ft}, \gamma_W, \eta_W^{ft}$
FT, PT	$V\left[w_i, h^{ft}, w_j, h^{pt}\right]$	$\gamma_M, \eta_M^{ft}, \gamma_W, \eta_W^{pt}$
FT, U	$T\left[w_i, h^{ft}\right]$	$\gamma_M, \eta_M^{ft}, \lambda_W$
PT, FT	$V\left[w_i, h^{pt}, w_j, h^{ft}\right]$	$\gamma_M, \eta_M^{pt}, \gamma_W, \eta_W^{ft}$
PT, PT	$V\left[w_i, h^{pt}, w_j, h^{pt}\right]$	$\gamma_M, \eta_M^{pt}, \gamma_W, \eta_W^{pt}$
PT, U	$T\left[w_i, h^{pt}\right]$	$\gamma_M, \eta_M^{pt}, \lambda_W$
U, FT	$T\left[w_j, h^{ft}\right]$	$\lambda_M, \gamma_W, \eta_W^{ft}$
U, PT	$T\left[w_j, h^{pt}\right]$	$\lambda_M, \gamma_W, \eta_W^{pt}$
U, U	U	λ_M, λ_W

Notes: The states acronym are defined as follows: FT= employed full-time; PT= employed part-time; U= unemployed. The first position and the indexes i and H refers to husbands. The second postions and the indexes j and W refers to wives

Table 2: 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 3: Descriptive Statistics: Longitudinal 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 4: MSM Estimation Results: Parameter Estimates.

	Yes Children Younger than 18		No Children Younger than 18	
	Wives	Husbands	Wives	Husbands
λ	0.2356	0.2993	0.2568	0.3198
	(0.0168)	(0.0299)	(0.0156)	(0.0227)
γ	0.0857	0.1179	0.0932	0.1216
	(0.0041)	(0.0117)	(0.0057)	(0.0130)
η^{pt}	0.0127	0.0191	0.0171	0.0193
	(0.0020)	(0.0006)	(0.0008)	(0.0014)
η^{ft}	0.0153	0.0149	0.0186	0.0172
	(0.0034)	(0.0009)	(0.0016)	(0.0006)
μ^{pt}	2.1986	2.0361	2.2046	2.0225
	(0.0502)	(0.0881)	(0.0578)	(0.0886)
μ^{ft}	1.9497	1.9369	2.0265	1.9783
	(0.0259)	(0.0382)	(0.0366)	(0.0651)
σ^{pt}	0.4566	0.6871	0.4649	0.6518
	(0.0216)	(0.0399)	(0.0194)	(0.0425)
σ^{ft}	0.4103	0.6637	0.3794	0.6461
	(0.0267)	(0.0164)	(0.0105)	(0.0188)
p	0.1819	0.0588	0.1626	0.0511
	(0.0141)	(0.0045)	(0.0044)	(0.0056)
α	0.2082	0.1248	0.1564	0.1175
	(0.0075)	(0.0060)	(0.0081)	(0.0113)
δ	0.0439		0.0475	
	(0.0024)		(0.0017)	
β	0.0488	0.0547	0.0472	0.0470
	(0.0029)	(0.0035)	(0.0019)	(0.0020)
N	3,340		644	

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

Table 5: MSM Estimation Results: Implied Values.

	Yes Children Younger than 18		No Children Younger than 18	
	Wives	Husbands	Wives	Husbands
Wage Offers:				
$E[w]$	8.073	8.709	8.471	8.931
	(0.284)	(0.325)	(0.276)	(0.487)
$V[w]$	12.985	42.285	12.624	41.373
	(1.769)	(4.156)	(1.146)	(4.721)
$E[w\|pt]$	10.003	9.701	10.102	9.346
	(0.429)	(0.891)	(0.597)	(0.905)
$V[w\|pt]$	23.193	56.789	24.621	46.229
	(2.386)	(13.540)	(4.126)	(12.241)
$E[w\|ft]$	7.644	8.647	8.154	8.908
	(0.248)	(0.336)	(0.318)	(0.523)
$V[w\|ft]$	10.715	41.378	10.295	41.111
	(1.835)	(4.604)	(1.237)	(5.159)
Durations:				
$E[t_o\|U]$	4.244	3.341	3.893	3.127
	(0.272)	(0.251)	(0.209)	(0.251)
$E[t_o\|E]$	11.674	8.479	10.734	8.222
	(0.470)	(1.262)	(0.571)	(1.038)
$E[t_e\|pt]$	78.634	52.331	58.343	51.817
	(9.511)	(1.966)	(2.680)	(4.605)
$E[t_e\|ft]$	65.498	67.295	53.620	58.301
	(10.357)	(4.115)	(5.457)	(2.098)

Notes: Data are from the 2001-2003 SIPP. Standard errors in parentheses are computed by boostrap with 30 replications. 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; E expected value; V variance.

Table 6: Household Inequality in the Benchmark Model.

	Household			Wives		Husbands	
	Utility	Wages	Earnings	Wages	Earnings	Wages	Earnings
			Yes Children Younger than 18				
Lifetime Variables:							
$GE\,(0)$	0.0235	0.0141	0.0159	0.0251	0.0309	0.0282	0.0302
$GE\,(1)$	0.0236	0.0145	0.0163	0.0241	0.0289	0.0297	0.0317
$GE\,(2)$	0.0240	0.0152	0.0171	0.0242	0.0282	0.0325	0.0347
Cross-section Variables:							
$GE\,(0)$	0.0286	0.1014	0.1056	0.0504	0.0563	0.1387	0.1436
$GE\,(1)$	0.0262	0.0907	0.0943	0.0491	0.0541	0.1313	0.1342
$GE\,(2)$	0.0250	0.0914	0.0953	0.0516	0.0554	0.1444	0.1465
			No Children Younger than 18				
Lifetime Variables:							
$GE\,(0)$	0.0225	0.0113	0.0124	0.0145	0.0142	0.0251	0.0269
$GE\,(1)$	0.0226	0.0117	0.0129	0.0150	0.0144	0.0266	0.0284
$GE\,(2)$	0.0230	0.0124	0.0137	0.0158	0.0148	0.0292	0.0312
Cross-section Variables:							
$GE\,(0)$	0.0302	0.0958	0.1009	0.0565	0.0593	0.1444	0.1510
$GE\,(1)$	0.0270	0.0859	0.0899	0.0564	0.0565	0.1361	0.1405
$GE\,(2)$	0.0253	0.0865	0.0905	0.0601	0.0573	0.1481	0.1520

Notes: Inequality Indexes are computed over variables obtained by simulating the model at the estimated benchmark values reported in Table 4. Lifetime variables are defined in Equation 3. $GE\,(\nu)$ are indicators belonging to the the Generalized Entropy class (see Equation 4). Specifically, $GE\,(2)$ is half the square of the coefficient of variation, $GE\,(1)$ is the Theil entropy index, and $GE\,(0)$ is the mean log deviation.

Table 7: Household Inequality: Impact of Labor Market Structure.

Experiments	$Mean$ Utility	Utility	$GE\,(2)$ Wages	Earnings
Yes Children Younger than 18				
Lifetime Variables:				
Benchmark	379.5	0.0240	0.0171	0.0152
Reduce Frictions (RF)	394.2	0.0186	0.0148	0.0132
RF and Increase Turnover	385.3	0.0208	0.0128	0.0117
Increase Part-Time Offers	379.0	0.0244	0.0164	0.0145
Decrease Part-Time Offers	379.5	0.0239	0.0174	0.0160
Mean-Preserving Spread Wage	394.3	0.0202	0.0456	0.0409
Cross-section Variables:				
Benchmark	1.889	0.0250	0.0953	0.0914
Reduce Frictions (RF)	1.951	0.0209	0.0868	0.0831
RF and Increase Turnover	1.905	0.0239	0.0923	0.0882
Increase Part-Time Offers	1.892	0.0260	0.0993	0.0945
Decrease Part-Time Offers	1.881	0.0259	0.0899	0.0881
Mean-Preserving Spread Wage	1.987	0.0262	0.2243	0.2082
No Children Younger than 18				
Lifetime Variables:				
Benchmark	422.2	0.0230	0.0137	0.0124
Reduce Frictions (RF)	439.8	0.0172	0.0114	0.0108
RF and Increase Turnover	429.9	0.0194	0.0098	0.0092
Increase Part-Time Offers	421.1	0.0233	0.0133	0.0123
Decrease Part-Time Offers	423.6	0.0222	0.0139	0.0128
Mean-Preserving Spread Wage	442.6	0.0206	0.0265	0.0243
Cross-section Variables:				
Benchmark	2.104	0.0253	0.0905	0.0865
Reduce Frictions (RF)	2.179	0.0203	0.0769	0.0732
RF and Increase Turnover	2.126	0.0231	0.0879	0.0833
Increase Part-Time Offers	2.111	0.0247	0.0885	0.0832
Decrease Part-Time Offers	2.102	0.0248	0.0850	0.0833
Mean-Preserving Spread Wage	2.215	0.0264	0.1540	0.1464

Notes: $GE\,(2)$ is half the square of the coefficient of variation. Each experiment changes a specific set of parameters by 50% leaving the rest at the benchmark values. Specifically, *Reduce Frictions*: increase $(\lambda_{W,M}, \gamma_{W,M})$; *Reduce Frictions and Increase Turnover*: increase $(\lambda_{W,M}, \gamma_{W,M})$ and $(\eta^{PT}_{W,M}, \eta^{FT}_{W,M})$; *Increase Part-Time Offers*: increase $(p_{W,M})$; *Reduce Part-Time Offers*: decrease $(p_{W,M})$; *Mean Preserving Spread Wage*: change $(\mu^{PT}_{W,M}, \sigma^{PT}_{W,M}, \mu^{FT}_{W,M}, \sigma^{FT}_{W,M})$ so that the Coefficient of Variation in wage offers increases but the mean is unchanged.

Table 8: Household Inequality: Gender Differentials Decomposition.

Set of	Wives $GE\,(2)$			Husbands $GE\,(2)$		
Parameters	Wages	Earnings	Utility	Wages	Earnings	Utility
			Yes Children Younger than 18			
Lifetime Variables:						
Benchmark	0.0242	0.0282	0.1071	0.0325	0.0347	0.0825
Frictions	0.0213	0.0266	0.1185	0.0324	0.0340	0.0861
Job offers	0.0355	0.0405	0.0973	0.0331	0.0350	0.0885
Preferences	0.0175	0.0164	0.1169	0.0333	0.0355	0.0859
Cross-section Variables:						
Benchmark	0.0516	0.0554	0.0384	0.1444	0.1465	0.0354
Frictions	0.0556	0.0617	0.0381	0.1524	0.1504	0.0359
Job offers	0.1630	0.1673	0.0400	0.1595	0.1602	0.0352
Preferences	0.0672	0.0602	0.0409	0.1638	0.1658	0.0368
			Yes Children Younger than 18			
Lifetime Variables:						
Benchmark	0.0158	0.0148	0.1213	0.0292	0.0312	0.0907
Frictions	0.0133	0.0125	0.1177	0.0289	0.0311	0.0889
Job offers	0.0300	0.0327	0.1031	0.0298	0.0318	0.0887
Preferences	0.0148	0.0125	0.1167	0.0280	0.0299	0.0888
Cross-section Variables:						
Benchmark	0.0601	0.0573	0.0394	0.1481	0.1520	0.0369
Frictions	0.0632	0.0563	0.0379	0.1460	0.1516	0.0350
Job offers	0.1521	0.1585	0.0409	0.1574	0.1615	0.0361
Preferences	0.0697	0.0543	0.0389	0.1570	0.1601	0.0366

Notes: $GE\,(2)$ is half the square of the coefficient of variation. Each experiment changes a specific set of parameters to be equal between husbands and wives. Parameters are always set at husbands' values. Frictions includes all the mobility paramters λ, γ, η; Job offers includes all the job offers parameters μ, σ, p; Preferences includes the preference parameters α, β