Personality Traits, Intra-household Allocation and the Gender Wage Gap*

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Abstract

A model of how personality traits affect household time and resource allocation decisions and wages is developed and estimated. In the model, households choose between two behavioral modes: cooperative or noncooperative. Spouses receive wage offers and allocate time to supplying labor market hours and to producing a public good. Personality traits, measured by the so-called Big Five traits, can affect household bargaining weights and wage offers. Model parameters are estimated by Simulated Method of Moments using the Household Income and Labor Dynamics in Australia (HILDA) data. Personality traits are found to be important determinants of household bargaining weights and of wage offers and to have substantial implications for understanding the sources of gender wage disparities.

JEL: D1, J12, J16, J22, J31, J71

Keywords: gender wage differentials, personality and economic outcomes, household bargaining, time allocations

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1 Introduction

Early models of household decision-making specified a unitary model that assumed that a household maximizes a single utility function. (e.g. Becker (1981)) In recent decades, however, researchers have made substantial progress towards modeling the household as a collection of individual agents with clearly delineated preferences, which permits consideration of questions related to the production and distribution of household resources. The agents are united through the sharing of public goods, through joint production technologies for producing public goods, through shared resource constraints, and through preferences. One approach is the cooperative approach that allows differences between spouses to affect household decision-making by specifying a sharing rule or the Pareto weights of what is essentially a household social welfare function. Cooperative models assume that the household reaches Pareto efficient outcomes. Variations in the class of cooperative models specify different ways in which households reach a particular point on the Pareto frontier (e.g. Manser and Brown (1980), McElroy and Horney (1981), and Chiappori (1988)). An alternative approach assumes that household members act noncooperatively. This approach is also based on a model with individual preferences, but assumes that realized outcomes are determined by finding a Nash equilibrium using the reaction functions of the household members. These equilibria are virtually never Pareto efficient (e.g. Lundberg and Pollak (1993), Bourguignon (1984), Del Boca and Flinn (1995)).

In reality, it is likely that different households behave in different ways and even that the same household might behave differently at different points in time. One of the few studies to combine these different modeling approaches into one paradigm is Del Boca and Flinn (2012). Their study estimates a model of household time allocation, allowing for both efficient and inefficient household modes of interaction. In their model, two spouses allocate time to market work and to producing a public good and their decisions are repeated over an indefinitely long time horizon. The model incorporates incentive compatibility constraints that require the utility of each household member to be no lower that it would be in the (non cooperative) Nash equilibrium. Del Boca and Flinn (2012) find that the constraints are binding for many households and that approximately one-fourth of households behave in an inefficient manner.

This paper adopts a cooperative/noncooperative modeling framework similar to that of Del Boca and Flinn (2012), but our focus is on understanding the role of personality traits in affecting household time allocation decisions and labor market outcomes. Personality trait measures aim to capture "patterns of thought, feelings and behavior" that correspond to "individual differences in how people actually think, feel and act" (Borghans et al. (2008)). The most commonly used measures, which are the ones used in this paper, are the so-called Big Five. They measure individual openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (the opposite of emotional stability).[1] The model we develop and estimate incorporates public and private goods consumption, labor supply at the extensive and intensive margins, and time allocated to home production. Personality traits operate as potential determinants of household bargaining weights and wage offers.

There is an increasing recognition that noncognitive traits play an important role in explaining a variety of outcomes related to education, earnings, and health. Heckman and Raut (2016) and Heckman et al. (2006) argue that personality traits may have both direct effects on an individual's productivity and indirect effects by

[1]The Big Five traits have the acronym OCEAN.

affecting preferences for schooling or occupation choices. A study by Fletcher (2013) finds a robust relationship between personality traits and wages using sibling samples to control for family-level unobservables. Specifically, conscientiousness, emotional stability, extraversion and openness to experience positively affect wages. Cubel et al. (2016) examine whether Big Five personality traits affect productivity using data gathered in a laboratory setting where effort on a task is measured. They find that individuals who exhibit high levels of conscientiousness and emotional stability perform better on the task.

Recent reviews of gender differences in preferences and in personality traits can be found in Croson and Gneezy (2009) and Bertrand (2011). Studies across many different countries find that women are on average more agreeable and more neurotic than men and that gender differences in personality are associated with differences in wages.[2] However, the most crucial traits in affecting wages differ by country. Using Dutch data, Nyhus and Pons (2005) find that emotional stability is positively associated with wages for both genders and agreeableness is associated with lower wages for women. Using data from the British Household Panel Study, Heineck (2011) analyzes correlations between Big Five personality traits and wages and finds a positive relationship between openness to experience and wages and a negative linear relationship between agreeableness and wages for men. He also finds a negative relationship between neuroticism and wages for women. Mueller and Plug (2006), using data from the Wisconsin Longitudinal Study, find that nonagreeableness, openness to experience and emotional stability are positively related to men's earnings, whereas conscientiousness and openness to experience are positively related to women's earnings. They find that the return that men receive for being nonagreeable is the most

[2] Women also exhibit differences in competitive attributes, risk aversion, preferences for altruism, and inequality aversion.

significant factor explaining the gender wage gap. Applying decomposition methods to data from the NLSY and using different measures of personality, Cattan (2013) finds that gender differences in self-confidence largely explain the gender wage gap, with the strongest effect being at the top of the wage distribution.[3] Braakmann (2009), using German Socioeconomic Panel (GSOEP) data, finds that higher levels of conscientiousness increase the probability of being full-time employed for both genders, while higher levels of neuroticism and agreeableness have the opposite effect.

It is only recently that survey data have been collected on the personality traits of multiple household members for large random samples, which permits analysis of how personality traits affect marriage and the division of labor/resources within the household.[4] Lundberg (2012) notes that personality traits can shape preferences and capabilities that affect the returns to marriage and that they may also influence the ability of partners to solve problems and to make long-term commitments. Using data from the German Socioeconomic Panel (GSOEP), she finds that Big Five traits significantly affect the probability of marriage, the probability of divorce, and the duration of marriage. Using data from the Netherlands, Dupuy and Galichon (2014) show that Big Five personality traits are significant determinants of marriage matches and that different traits matter for men and women.

In this paper, we use a structural behavioral model to explore the extent to which personality traits of husbands and wives affect household time and resource allocation decisions. In particular, we examine how personality traits affect the mode of interaction the household adopts (cooperative or noncooperative), the amount of labor each

[3] The National Longitudinal Survey of Youth Data do not contain the Big Five personality trait measurements. NLSY measurements include a ten-item scale of self-esteem ((Rosenberg, 1965)) and a four-item scale of locus of control (Rotter (1966)).

[4] Examples include the British Household Panel Study (BHPS), the German Socioeconomic Panel (GSOEP), and Household Income and Labor Dynamics in Australia (HILDA), from which the data used in this paper are drawn.

spouse supplies to home production and market work, the provision of public goods, wage offers and accepted wages. Our analysis focuses on couples where the head of the household is age 30-50, because education and personality traits have largely stabilized by age 30. The model is static and takes the observed marriage sorting patterns with regard to spouse characteristics as given. In the model, spouses have their own preferences over consumption of a private good and a public good. They choose the amount of time to allocate to market work and to the production of a public good. There is a production technology that specifies how household members' time translates into public good production. The model incorporates household bargaining weights that may depend on the personality characteristics of both spouses, their education levels, ages,and cognitive abilities.[5]

We use data from the Household Income and Labor Dynamics survey in Australia (HILDA). An unusual feature of these data is that they contain the Big Five personality measures at three points in time (over a span of eight years) for multiple household members. In addition to the personality trait measures, we also use information on age, gender, educational attainment, cognitive ability, wages, hours worked, and time spent engaging in home production.

Model parameters are estimated using the Method of Simulated Moments. The moments used in estimation pertain to wages, labor market hours, housework hours and labor force participation of different types of households. Model parameters are chosen to minimize the weighted distance between moments simulated using the model data generating process and moments based on the data.

We use the estimated model to analyze the determinants of male-female earnings differentials. The vast majority of papers in the gender earnings gap literature

[5] This formulation differs from Del Boca and Flinn (2012).

(e.g. Altonji and Blank (1999), Blau and Kahn (1997, 2006); Autor et al. (2008)) consider male and female earnings without taking into account that most adults are tied to individuals of the opposite sex through marriage or cohabitation and that these ties likely affect their decision-making. There are a few papers, however, that analyze male and female labor supply decisions and wage outcomes within a household framework. For example, Gemici (2011) analyzes household migration decisions in response to wage offers that males and females receive from different locations. Gemici and Laufer (2011) studies household formation, dissolution, labor supply, and fertility decisions. Tartari (2015) studies the relationship between children's achievement and the marital status of their parents within a dynamic framework in which partners decide whether to stay married, how to interact (with or without conflict), on labor supply and on child investments. Joubert and Todd (2016) analyze household labor supply and savings decisions within a collective household model, with a focus on the gender gap in pension receipt.

Within a household modeling framework, we analyze the manner in which households make decisions regarding whether a man or woman works in the labor market, how many hours they work, how many hours they devote to housework and the implications for earnings. Given the model's assumptions concerning male and female preferences, wage offer distributions, and the method of determining household allocations, we are able to assess the impact of individual and household characteristics not only on observed differences in wages but also the utility realizations of household members. Below, we will show that differences in utility levels of males and females inhabiting households together are more important indicators of systematic gender differences than are differences in observed wage rates.

Our analysis yields a number of potentially important findings. First, personality traits are significant determinants of household bargaining weights and of offered wages. Second, men and women have different traits on average and their traits are valued differently in the labor market as reflected in estimated wage offer equations. The combined effect of personality traits on offered wages is comparable in magnitude to the effect of education. Third, decomposition results show that gender differences in market valuations of personality traits explain a significant fraction of observed wage gaps. We find that if women were paid according to the male wage offer equation, the observed wage gap would be eliminated. Fourth, we find that the gender gap in accepted wages is smaller than the gap in offered wages. This difference arises because of the labor market participation decisions of husbands and wives, notably, because women are more selective than men in accepting employment. Fifth, we find that 38.7 percent of households choose to behave cooperatively, which also affects working decisions. Cooperation tends to increase the desired level of household public goods, which require both time and monetary investment, and therefore tends to increase labor supply for both men and women. Sixth, the marriage market exhibits positive assortative matching on personality traits, which tends to increase gender gaps in accepted wages relative to what it would be if spouses were randomly matched.

The paper proceeds as follows. The next section presents our baseline model. Section 3 describes the data. Section 4 discusses the econometric specification and estimation implementation. Section 5 and 6 present the estimation results and counterfactual experiments. Section 7 concludes.

2 Model

We begin by describing the preferences of the household members and the household production technology. Next, we describe the cooperative and noncooperative solutions to the model. The section concludes with an examination of the choice of the household members to behave cooperatively or not, and the potential role that personality traits play in this decision.

2.1 Preferences and Household Production Technology

A household is formed with a husband and a wife, distinguished by subscripts m and f, respectively. Each individual has a utility function given by

$$\begin{aligned} U_m &= \lambda_m \ln l_m + (1-\lambda_m) \ln K \\ U_f &= \lambda_f \ln l_f + (1-\lambda_f) \ln K, \end{aligned}$$

where λ_m and λ_f are both elements within $(0, 1)$, l_j denotes the leisure of spouse j $(j = m, f)$, and K is the quantity of produced public good. The household production technology is given by

$$K = \tau_m^{\delta_m} \tau_f^{\delta_f} M^{1-\delta_m-\delta_f},$$

where τ_j is the housework time of spouse j, δ_j is a Cobb-Douglas productivity parameter specific to spouse j, and M is the total income of the household. Income M depends on the labor income of both spouses as well as nonlabor income:

$$M = w_m h_m + w_f h_f + y_m + y_f,$$

Here, w_j is the wage rate of spouse j, h_j is the amount of time that the supply to the labor market, and y_j is their amount of nonlabor income. The time constraint of each spouse is given by

$$T = \tau_j + h_j + l_j, \ j = m, f.$$

A few comments are in order concerning this model specification. We have assumed that all of the choice variables relate to time allocation decisions, with no explicit consumption choice. This is standard since most data sets used by microeconomists contain fairly detailed information on labor market behavior and some information on housework, with little in the way of consumption data. We have made Cobb-Douglas assumptions regarding individual preferences and the household production technology. Because we assume that there exists heterogeneity in the preference parameters, λ_m and λ_f, and the production function parameters, δ_m and δ_f, we are able to fit patterns of household behavior very well, even under these restrictive functional forms.[6]

To this point, we have largely followed Del Boca and Flinn (2012); Del Boca et al. (2014). Our points of departure are the addition of personality traits to their formulation, the addition of working decisions, and the addition of wage offer equations to the model. Del Boca and Flinn (2012) restricted their sample to include only households in which both spouses work and they simply conditioned on husbands' and wives' observed wages. Because one of the main focuses of our analysis is to examine the impact of personality traits on household behavior and on a woman's labor market participation decision, it is necessary for us to estimate wage equations for both husbands and wives. Let x_j denote observable characteristics of spouse j and θ_j the personality characteristics of spouse j. Then a household is characterized

[6]Del Boca and Flinn (2012) actually estimate the distribution of the individual characteristics nonparametrically, and show that by doing so the model is "saturated." That is, there are the same number of free parameters as there are data points. Model fit is perfect in such a case. For the purposes of this exercise, we assume that these characteristics follow a parametric distribution, but we utilize one that is flexible and capable of fitting patterns in the data quite accurately.

by the state vector

$$S_{m,f} = (\lambda_m, \delta_m, w_m, y_m, \theta_m, x_m) \bigcup (\lambda_f, \delta_f, w_f, y_f, \theta_f, x_f).$$

Given $S_{m,f}$, either mode of behavior is simply a mapping

$$(\tau_m, h_m, l_m, \tau_f, h_f, l_f) = \Psi_E(S_{m,f}),\ E = NE, PW$$

where $E = NE$ is the (noncooperative) Nash equilibrium case and $E = PW$ is the (cooperative) Pareto weight case. We note that each spouses' wage offer w_j is observed by the household, but the analyst will not observe w_j if $h_j = 0$. Certain elements of $S_{m,f}$ may not play roles in the determination of equilibrium outcomes in certain behavioral regimes.

In our static model, couples do not have an option to get divorced. With an additional divorce option, couples might choose to cooperate when their utility from cooperation exceeds the utility from the inefficient Nash equilibrium and the utility from divorce. Of course there are many additional considerations other than current period utility in modeling divorce decisions, such as the division of assets upon divorce, the presence of children, child support, alimony and the state of the marriage market. For the sake of simplicity, our model focuses on married couples without considering divorce, which may to some extent limit external validity.

We now turn to a detailed description of the non-cooperative and cooperative solutions.

2.2 Non-Cooperative Behavior

In the noncooperative regime, the nature of interaction between the spouses is limited and personality characteristics only play a role through their effects on wage offers. Under modeling assumptions that are the same as ours, Del Boca and Flinn (2012) show that there exists a unique equilibrium solution in reaction functions, at least in the cases in which spouses are both in or both out of the labor market.[7] Because ours is a model of complete information, each spouse is fully aware of the other's preferences, productivity characteristics, wage offer, and non-labor income. The decisions made by each spouse are best responses to the other spouse's choices, and are (most often) unique and stable. In this environment, little interaction between the spouses is required.

Each spouse makes three time allocation choices. Because they must sum to T, it is enough to describe the equilibrium in terms of each spouse's choices of labor supply and housework time. The reaction functions given the state vector $S_{m,f}$ are

$$\begin{aligned}\{h_m(NE), \tau_m(NE)\}(h_f, \tau_f; S_{m,f}) &= \arg\max_{h_m,\tau_m} \lambda_m \ln l_m + (1-\lambda_m)\ln K \\ \{h_f(NE), \tau_f(NE)\}(h_m, \tau_m; S_{m,f}) &= \arg\max_{h_f,\tau_f} \lambda_f \ln l_f + (1-\lambda_f)\ln K,\end{aligned}$$

where

$$K = \tau_m^{\delta_m}\tau_f^{\delta_f}(w_m h_m + w_f h_f + y_m + y_f)^{1-\delta_m-\delta_f}$$

For $\lambda_j \in (0,1)$, $j = m, f$, and $0 < \delta_m$, $0 < \delta_f$, and $\delta_m + \delta_f < 1$, Del Boca and Flinn (2012) show that there is a unique equilibrium for their case in which both spouses in the households supply labor to the market. However, if we remove the constraint that the Nash equilibrium always results in both spouses choosing to supply a positive amount of time to the labor market, the possibility of multiple equilibria arises. The multiple equilibria occur due to the constraint that working hours are nonnegative for both spouses. There can be at most two Nash equilibria, with each having only one of the spouses supplying a positive amount of time to the market, and the other in which the spouses switch roles in terms of who is supplying time to the

[7]BecauseDel Boca and Flinn (2012); Del Boca et al. (2014) conditioned their analysis on the fact that both spouses were in the labor market, the noncooperative solution was unique.

market and who is not. When both supply time to the market, the equilibrium is unique, as it is when neither supplies time to the market. Furthermore, it is the case that when one supplies time to the market and the other does not, the equilibrium may either be unique or not. Given the structure of the model and the estimated parameters, the frequency of multiple equilibria is small. However, when they do occur, a position must be taken as to which of the two equilibria are selected. We will follow convention and assume that the equilibrium in which the male participates and the female does not is the one selected.[8] A detailed description of how the non-cooperative equilibrium is computed and selected is provided in Appendix A.2.

The utility value of this equilibrium to spouse j is given by

$$V_j(NE) = \lambda_j \ln(T - h_j(NE) - \tau_j(NE)) + (1-\lambda_j)\ln K(NE), \ j = m, f,$$

with

$$K(NE) = \tau_m(NE)^{\delta_m}\tau_f(NE)^{\delta_f}(w_m h_m(NE) + w_f h_f(NE) + Y_m + Y_f)^{1-\delta_m-\delta_f},$$

where we have suppressed the dependence of the equilibrium outcomes on the state vector $S_{m,f}$ to avoid notational clutter.

2.3 Cooperative Behavior

The Benthamite social welfare function for the household with the Pareto weight α is given by

$$W(h_m, h_f, \tau_m, \tau_f; S_{m,f}) = \alpha(S_{m,f})U_m(h_m, h_f, \tau_m, \tau_f; S_{m,f})$$
$$+(1-\alpha(S_{m,f}))U_f(h_m, h_f, \tau_m, \tau_f; S_{m,f}),$$

[8] Alternatively, one could allow the selection mechanism to depend on personality characteristics. However, our estimation results indicate multiple equilibria rarely occur (9 out of 1443 households). Thus, the selection mechanism is unlikely to play a major role in the estimation.

where we have eliminated the leisure choice variable $l_j, j = f, m$ by imposing the time constraint. The Pareto weight $\alpha(S_{m,f}) \in (0, 1)$, and, as the notation suggests, will be allowed to be a function of a subset of elements of $S_{m,f}$. In the cooperative (efficient) regime, the household selects the time allocations that maximize W, or

$$(h_m, h_f, \tau_m, \tau_f)(S_{m,f}) = \arg \max_{h_j, \tau_j, j=m,f} W(h_m, h_f, \tau_m, \tau_f; S_{m,f}).$$

Because this is simply an optimization problem involving a weighted average of two concave utility functions, the solution to the problem is unique. Then the utility levels of the spouses under cooperative behavior is

$$V_j(PW) = \lambda_j \log(T - h_j(PW) - \tau_j(PW)) + (1 - \lambda_j) \log K(PW),\ j = m, f,$$

with

$$K(PW) = \tau_m(PW)^{\delta_m} \tau_f(PW)^{\delta_f} (w_m h_m(PW) + w_f h_f(PW) + y_m + y_f)^{1-\delta_m-\delta_f}.$$

Once again, we have suppressed the dependence of solutions on the state variable vector $S_{m,f}$. In the cooperative model, there is no danger of multiple equilibria, since it is not really an equilibrium specification at all, but simply a household utility-maximization problem.

2.4 Selection Between the Two Allocations

Del Boca and Flinn (2012) constructed a model in which the Pareto weight, α, was "adjustable" so as to satisfy a participation constraint for each spouse that enforced

$$V_j(PW) \geq V_j(NE),\ j = m, f.$$

With no restriction on the Pareto weight parameter α, the $V_j(PW)$ could be less than $V_j(NE)$ for one of the spouses (it always must exceed the noncooperative value for at least one of the spouses). For example, if $V_m(PW) < V_m(NE)$, the husband has no incentive to participate in the "efficient" outcome, because he is worse off under it. To give him enough incentive to participate, the value of α, which is his weight in the social welfare function, is increased to the level at which he is indifferent between the two regimes. Meanwhile, his spouse with the "excess" portion of the household surplus from cooperation has to cede some of her surplus by reducing her share parameter, $(1-\alpha)$, in this case, to the point at which the husband is indifferent between the two regimes.

In such a world, and in a static context, an efficient outcome could always be achieved through adjustment of the Pareto weight, α. As a result, all households would behave cooperatively. To generate the possibility that some households would behave noncooperatively, even when able to adjust α, Del Boca and Flinn assumed a pseudo-dynamic environment, in which the spouses played the same (static) stage game an infinite number of times. They assumed a grim-trigger punishment strategy, so that any deviation from the agreed upon cooperative outcome by either spouse in any period results in a punishment state in which the Nash equilibrium is played in perpetuity. In such a case, the value of the discount factor, $\beta \in [0, 1)$, used to weight future rewards, is critical in determining whether a cooperative arrangement is implementable. The value to individual j of playing the cooperative outcome forever is simply $V_j(PW)(1 + \beta + \beta^2 + ...) = V_j(PW)/(1 - \beta)$. The present value of the noncooperative outcome is $V_j(NE)/(1 - \beta)$. If individual j cheats on the agreement in any period and the spouse does not, the value of cheating in the period is denoted by $V_j(C)$, and it is straightforward to show that $V_j(C) > V_j(PW)$. By cheating in any period, the individual knows that the spouse will not cooperate in all future periods, so that the gain to cheating (assuming the spouse does not) is

$$V_j(C) + \beta \frac{V_j(NE)}{1-\beta},$$

whereas the gain from playing cooperatively throughout (assuming that the spouse does as well) is

$$\frac{V_j(PW)}{1-\beta}$$

Any implementable agreement will have $V_j(PW) > V_j(NE)$ for each j. We can define a critical discount factor β_j^* as one that equates the value of cheating with not cheating in any period for individual j, and this critical value is given by

$$\beta_j^* = \frac{V_j(C) - V_j(PW)}{V_j(C) - V_j(NE)},$$

where it follows that $\beta_j^* \in [0, 1)$. There will be a reallocation (characterized by a value of α) of the cooperative surplus for which the two critical discount factors are equal, and we define this common value as $\tilde{\beta}$, where $\tilde{\beta} = \beta_1^* = \beta_2^*$. Del Boca and Flinn show that if all individuals in the population share the same discount factor, β, then a given household will be able to implement the cooperative outcome if and only if $\beta \geq \tilde{\beta}$. The intuition is fairly straightforward. If individuals are myopic, they give excessive weight to the potential gains from cheating now and far less weight to the costs they will incur in the future by being in the noncooperative regime forever. Both spouses have to be sufficiently forward-looking to be able to implement the cooperative agreement in this simple dynamic setting. Del Boca and Flinn (2012) estimate a common discount factor β, and find that approximately 25 percent of households in their sample behaved in a noncooperative manner given their parameter estimates.

In our model, which focuses on the role of personality traits in explaining wage and welfare differences between husbands and wives, we think of the Pareto weight α as being determined, in part, by the personality characteristics of the husband and wife. For example, someone who is very agreeable and who is married to a nonagreeable person might receive a lower Pareto weight. In this case, it is somewhat problematic to assume that the α can be freely adjusted to satisfy the participation constraint of one of the spouses and more reasonable to assume that α is fixed for each household. Fixed pareto weights simplifies the cooperative versus noncooperative decision of the household, as well as the computation of the model. In this set-up, personality characteristics of both spouses are potentially key factors in how they settle on a particular mode of behavior.[9]

A household will behave cooperatively if and only if both of the following weak inequalities hold:

$$\begin{aligned} V_m(PW) &\geq V_m(NE) \\ V_f(PW) &\geq V_f(NE). \end{aligned}$$

Thus, there is no scope for "renegotiation" in this model. There is a positive probability that any household behaves cooperatively that is strictly less than one given our preference heterogeneity specification. The simplest way to characterize the cooperation decision in our framework is as follows. We begin by explicitly including the value of α in the cooperative payoff function for household j, so that

$$V_j(PW|S_{m,f},\alpha),\ j = m, f.$$

[9]In a more elaborate model, we could imagine a situation in which the Pareto weight could be adjusted, but with a cost depending on the personality characteristics of the spouses. From this perspective, we are assuming that the costs of adjusting the Pareto weight are indefinitely large for one or both of the spouses.

Given that the function $V_m(PW|S_{m.f}, \alpha)$ is monotonically increasing in α and given that $V_f(PW|S_{m,f}, \alpha)$ is monotonically decreasing in α, we can define two critical values, $\underline{\alpha}^*(S_{m,f})$ and $\overline{\alpha}^*(S_{m,f})$ such that

$$\begin{aligned} V_m(PW|S_{m,f}, \underline{\alpha}^*(S_{m,f})) &= V_m(NE|S_{m,f}) \\ V_f(PW|S_{m,f}, \overline{\alpha}^*(S_{m,f})) &= V_f(NE|S_{m,f}). \end{aligned}$$

The set of α values that produce cooperative behavior in the household is connected, so that the household will behave cooperatively if and only if

$$\alpha(S_{m,f}) \in [\underline{\alpha}^*(S_{m,f}), \overline{\alpha}^*(S_{m,f})].$$

For a given value of the state variables, $S_{m,f}$, the household will either behave cooperatively or not; there is no further stochastic element in this choice after we have conditioned on $S_{m,f}$. The probabilistic nature of the choice is due to the randomness of $S_{m,f}$. Although some elements of $S_{m,f}$ are observable (and do not include measurement error under our assumptions), others are not. There are a subset of elements that are not observed for any household, which include the preference and household production parameters. We denote the set of unobserved household characteristics by $S^u_{m,f} = \{\lambda_m, \delta_m, \lambda_f, \delta_f\}$, with the set of (potentially) observed characteristics given by $S^o_{m,f} = \{w_m, y_m, \theta_m, x_m, w_f, y_f, \theta_f, x_f\}$. We say that these elements are all potentially observable because the wage offers, $w_j,\ j = m, f$, are only observed if spouse j supplies a positive amount of time to the labor market. The state variable vector $S^o_{m,f}(i)$ that is observed for household i will have a degenerate marginal distribution. The unobserved vector $S^u_{m,f}(i)$ will always have nondegenerate marginal distributions. Let the distribution of $S^u_{m,f}(i)$ be given by G_i, and assume that $G_i = G$ for all i. Then the probability that household i is cooperative is simply the measure of the set of $S^u_{m,f}(i)$ such that the cooperation condition is satisfied, or

$$P(PW|S^o_{m,f}(i)) = \int \chi[\underline{\alpha}^*(S_{m,f}(i)) \leq \alpha(S_{m,f}(i)) \leq \overline{\alpha}^*(S_{m,f}(i))]dG(S^u_{m,f}).$$

For any household i, $0 < P(PW|S^u_{m,f}(i)) < 1$, due to what is essentially a full support condition. The preference weight on leisure for spouse j lies in the interval $(0,1)$. As $\lambda_j \to 1$, spouse j only cares about leisure and gives no weight to the public good. In the Nash equilibrium, their contribution to household production through time and money will converge to 0, and the cooperative solution, which results in greater production of the public good, will be of no value to them. As $\lambda_j \to 0$, the individual will demand little leisure and will spend all of their time in the labor market and household production. For cases in which λ_m and λ_f are both arbitrarily close to 1, the household will be noncooperative. For cases, in which λ_m and λ_f are close to 0, the household will be cooperative. Thus, independently of the other values in the state vector, variability in the preference parameters on the full support of their (potential) distribution is enough to guarantee that no household can be deterministically classified as cooperative *a priori*.

3 Data Description

3.1 Selection of the Estimation Sample

We use sample information from the Household Income and Labour Dynamics in Australia (HILDA) longitudinal data set. HILDA is a representative one in one thousand sample of the Australian population. It is an ongoing longitudinal annual panel starting in the year 2001 with 19,914 initial individuals from 7,682 households. (Summerfield et al. (2015)) Our paper makes use of the following variables: (1) labor market outcomes including annual labor earnings and working hours; (2) housework split information; (3) self-completion life style questions including a question about perceived fairness of the housework arrangement; (4) education levels; (5) cognitive test scores on three tests and (6) the "Big Five" personality traits assessment (collected three times, in waves 5, 9, and 13).

To the best of our knowledge, HILDA has the highest quality information on personality traits among all nationwide data sets.[10] For the majority of respondents, we observe three repeated measurements of personality traits over an eight-year time window. As described in Section 1, the personality trait measurements are based on the Five Factor ("Big Five") Personality Inventory, which classifies personality traits along five dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability (John and Srivastava (1999)). "Big Five" information in HILDA is constructed by using responses to 36 personality questions, which are shown in table 1.[11] Respondents were asked to pick a number from 1 to 7 to assess how well each personality adjective describes them. The lowest number, 1, denotes a totally opposite description and the highest number, 7, denotes a perfect description. According to Losoncz (2009), only 28 of 36 items load well into their corresponding components when performing factor analysis. The other 8 items are discarded due to either their low loading values or their ambiguity in defining several traits.[12] Our construction of the "Big Five" follows the procedure provided by

[10] The only other two nation-wide data sets providing personality traits inventory assessments are the German Socio-Economic Panel (GSOEP) study and the British Household Panel (BHPS) study. Both of them also collected "Big Five" measures.

[11] The source of these 36 adjectives come from two parts. Thirty of them are extracted from Trait Descriptive Adjectives - 40 proposed by Saucier (1994), which is a selected version of Traits Descriptive Adjective - 100 (Goldberg (1992)) to balance the time use and accuracy. And the other additional six items come from various sources.

[12] The way to check each item's loading performance is to calculate the loading value after doing oblimin rotation. The loading values of 8 abandoned items were either lower than 0.45, or did not load more than 1.25 times higher on the expected factor than any other factor.

Losoncz (2009). We include all individuals who have at least one personality trait measurement. For the individuals whose personality traits are surveyed in multiple waves, we use the average value.

In addition to the information on personality traits, HILDA also collected information on cognitive ability once in wave 12.[13] We construct a one-dimensional measure from three different measures: (i) Backward Digits Span, (ii) Symbol Digits Modalities and (iii) a 25-item version of the National Adult Reading Test. We construct a single measure by first standardizing each of the three measures and then taking the mean.

The repeated measures of personality traits for the same person during eight-year window allow us to explore how the personality traits evolve over the life-cycle. Following Cobb-Clark and Schurer (2012), we define the mid-term change as the change in reported traits between 2005 and 2009 and the long-term change as the change between 2005 and 2013. The changes range from -6 to 6. Table 2 reports summary statistics for mid-term and long-term changes. Personality trait changes are approximately normally distributed with a mean of 0 and a standard deviation of around 0.80. The majority of individuals (more than 70%) experience changes in their personality traits within one standard deviation. Figure 1 shows the mean midterm changes in personality traits by age. The figures show that traits are more malleable at younger ages. For example, the average change in conscientiousness is above 0 before age 30 and close to 0 after that. We perform an F-test of whether changes in personality traits are independent of age for individuals age 30-50 and do not reject the null. However, the null is rejected with p-value less than 0.001 when the age group is expanded to ages 15-50. The observed pattern is consistent with

[13] According to the report of Wooden (2013), the response rate is high, approximately 93%.

other evidence from the psychology literature that personality traits stabilize with age. For example, Terracciano et al. (2006) and Terracciano et al. (2010) report that intra-individual consistency increases up to age 30 and thereafter stabilizes.

We focus our attention on households whose heads are between the ages 30 and 50 for two reasons. First, household structure may change during earlier ages due to marriage and fertility. Second, as noted, personality traits stabilize after age 30. Thus we can reasonably treat a spouse's personality traits as being fixed after age 30. We drop households for which housework information, labor market information or personality traits are missing. Among 3151 intact households with complete information and with the husband and wife present, 1881 of them have at least one period in which the household head is age 30-50 when surveyed. When a household has multiple qualifying periods, we randomly select one observation period. The hourly wage is calculated by dividing annual earnings by annual working hours. We truncated the top five percent of hourly wage rates to eliminate unrealistically high values. We set the total time available for leisure, housework, and labor supply in a week, T, to 116. Working time has an upper bound of 60 hours while housework has an upper bound of 56 hours.

In general, housework time can be divided into two components: time spent with children and other activities, such as cleaning house, cooking or running errands. Women with younger children are most likely to have their labor supply choices influenced by children. Because our model does not explicitly account for time spent child-rearing, we restrict our estimation sample to only include families that do not have very young children. In table 3, we examine the effects of this restriction by comparing three alternative samples with different age selection criteria. The first sample does not impose any age restriction, the second sample excludes households with any child below age 8 and the third sample excludes families with a child below age 14. The sample size shrinks from 1,881 to 1,443 and 973 with the more stringent age restrictions. However, the average age of husbands is around 40 and the age of wives around 38 in all three samples. The labor market participation of husbands is also similar across the three samples. As is typically found, husbands spend more time in the labor market than do their wives. The employment rate for males is 94% and the average number of working hours (conditional on working) is around 44 hours per week.

The key differences across the three samples are observed in female labor market participation and reported housework time. The average housework hours of husbands decreases from 23.11 hours in sample 1 to 18.19 hours in sample 2 and 14.92 hours in sample 3. The average housework hours of wives decreases from 43.27 hours in sample 1 to 27.87 hours in sample 2 and 20.27 hours in sample 3. These decreases are mainly caused by the reduction of the time spent with children. As shown in table 3, the average time spent with children is 9.12 hours for husbands and 20.89 hours for wives. The time spent with children shrinks to 4.10 and 7.15 hours in sample 1 to 1.47 and 1.89 hours in sample 2. Wives with older children spend fewer hours caring for children and have a higher labor force participation rate, both at the intensive and extensive margins. The employment rate increases from 72% in sample 1 to 85% in sample 1 and 88% in sample 3. The average working hours increases from 30.16 hours in sample 1 to 33.48 hours in sample 2 and 36.29 in sample 3.

In all three samples, the distributions of wives' working hours and housework hours are more dispersed than that of husbands'. Their accepted wages are also lower. In general, the time allocations described in our paper using the HILDA dataset are consistent with patterns described in Del Boca and Flinn (2012); Del Boca et al.

(2014) for US Panel Study of Income Dynamics (PSID) data (the 2005 wave).

We use the sample of households without children below age 8 (sample 2) as the primary estimation sample. However, for comparison purposes, we also provide in the appendix estimation results based on the more restricted sample (sample 3).

With regard to personality traits and cognitive ability, Table 3 shows significant gender differences but similar patterns across the three samples. On average, men have lower scores on agreeableness, extraversion and conscientiousness compared with women. Gender differences in openness to experience and emotional stability are less significant. In our sample, wives have higher cognitive scores than husbands.

We estimate a preliminary OLS regression to examine the relationship between measured personality traits and log wages (for those who were working) and their relationship with labor participation decisions. The regression results with log wage as the dependent variable are shown in the first two columns in Table 4. We find for both that men and women that education and cognitive ability increase earnings. In addition, conscientiousness increases wages for men. In the last two columns in Table 4, the dependent variable is labor force participation. Higher education and cognitive scores are associated with higher rates of labor force participation for both men and women. Openness to experience tends to decrease labor force participation for both men and women. Conscientiousness is associated with higher rates of participation but only for women.

3.2 Assortative Matching of Personality Traits

Although our paper does not explicitly model the marriage market, we are able to examine marital sorting on personality traits and cognitive scores in our sample. Figure 2 displays the scatter plots of spousal personality traits as well as cognitive abilities. We observe a strong positive assortative matching in the cognitive ability dimension with a correlation equal to 0.34. Among the "Big Five" personality traits, emotional stability and openness to experience are the traits that exhibit the most significant pattern of positive sorting (correlation larger than 0.1), whereas agreeableness has a less strong positive sorting pattern. There is no significant correlation in the extraversion and conscientiousness traits of husbands and wives. There is also strong positive marital sorting on cognitive ability.

3.3 Other Variables: Fair Share

Despite the important role played by the by the Pareto weight in cooperative models of the household, there is no direct measurement proposed in the literature. The HILDA data provide a fairly high quality record of household activities. We consider the following question, completed by the respondent in the self-completion portion of the questionnaire, to be potentially related to the household allocation rule: "Do you think you do your fair share around the house?" The respondent has the option of choosing: (1) I do *much more* than my fair share. (2) I do *a bit more* than my fair share. (3) I do my fair share. (4) I do *a bit less* than my fair share. (5) I do *much less* than my fair share.

The distribution of fair share choices for both men and women is shown in table 5. The majority of husbands report that they do a fair share of housework, while the majority of wives report doing more than their fair share. The significantly negative correlation between men and women's report indicates that a better condition for the husband implies a worse condition for the wife, consistent with a Pareto weight interpretation.

We do not make direct use of the fair share variable in estimation. Rather, as described below, we will examine how simulations based on the estimated model relate to the fair share variable as a way of examining support for the model.

4 Econometric Implementation

As previously noted, a household i is uniquely characterized by the vector $S_{m,f}(i) = (\lambda_{im}, \delta_{im}, w_{im}, y_{im}, \theta_{im}, exp_{im}, edu_{im}, c_{im}, a_{im}) \bigcup (\lambda_{if}, \delta_{if}, w_{if}, y_{if}, \theta_{if}, exp_{if}, edu_{if}, c_{if}, a_{if})$.[14] Given the vector $S_{m,f}(i)$, the equilibrium of the game that characterizes the time allocations of the household is uniquely determined.[15] The log-wage equation for males and females comprising household i is specified:

$$\begin{aligned} \ln w_{im} &= \gamma_{0m} + \gamma_{1m}\theta_{im} + \gamma_{2m}edu_{im} + \gamma_{3m}c_{im} + \gamma_{4m}exp_{im} + \gamma_{5m}exp_{im}^2 + \epsilon_{im} \\ \ln w_{if} &= \gamma_{0f} + \gamma_{1f}\theta_{if} + \gamma_{2f}edu_{if} + \gamma_{3f}c_{if} + \gamma_{4f}exp_{if} + \gamma_{5f}exp_{if}^2 + \epsilon_{if} \end{aligned}$$

This specification is treated as a standard Mincer equation with additional personality trait θ_{if} and cognitive ability c_{if} components. The potential working experience term $\exp_{ij}$ is defined as $age - 6 - edu$. The disturbances $(\epsilon_{im}, \epsilon_{if})$ are assumed to follow a joint normal distribution:

$$\begin{bmatrix} \epsilon_{im} \\ \epsilon_{if} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{\epsilon m}^2 & \rho\sigma_{\epsilon m}\sigma_{\epsilon f} \\ \rho\sigma_{\epsilon m}\sigma_{\epsilon f} & \sigma_{\epsilon f}^2 \end{bmatrix} \right)$$

where $\sigma_{\epsilon m}$ denotes the standard deviation of the male's wage, $\sigma_{\epsilon f}$ denotes the standard deviation of the wife's wage, and ρ denotes the correlation of the wage disturbances.

[14] $\{\lambda_{im,}\delta_{im}, \lambda_{if}, \delta_{if}\}$ are the unobserved preferences and production technology of household i drawn from distribution $G_u(S_{m,f}^u)$. $\{w_{im,}y_{im}, w_{if,}y_{if}\}$ are wages and other incomes in the household. Finally, $\{\theta_{im}, exp_{im}, edu_{im}, c_{im}, a_{im}, \theta_{if}, exp_{if}, edu_{if}, c_{if}, a_{if}\}$ are personality traits θ, potential working experience exp, education attainment edu, cognitive ability c and age a for both spouses m and f in household i.

[15] As noted above, in the noncooperative case, there is the possibility of two equilibria existing, one with the husband supplying time to the market and the wife not, and the other in which the wife works in the market and the husband does not. We use the convention that the one in which the male supplies time to the market is the one that is implemented.

The model incorporates household heterogeneity in preferences and in the production technology by assuming the parameters, $(\lambda_m, \lambda_f, \delta_m, \delta_f)$ are drawn from a joint distribution $G_u(S^u_{m,f})$, where the u subscript denotes the fact that these parameters are unobserved to the analyst, although they are assumed known by both spouses. The distribution G_u is parametric, although it is "flexible" in the sense that it is characterized by a high-dimensional parameter vector. The distribution is created by mapping a four-dimensional normal distribution into the appropriate parameter space using known functions. Define the random vector $x_{4\times1} \sim N(\mu_1, \Sigma_1)$, where μ_1 is 4×1 vector of means and $\sum_1$ is a 4×4 symmetric, positive-definite covariance matrix. The random variables $(\lambda_m, \lambda_f, \delta_m, \delta_f)$ are then defined using the link functions

$$\begin{aligned} \lambda_m &= \tfrac{\exp(x_1)}{1+\exp(x_1)} \\ \lambda_f &= \tfrac{\exp(x_2)}{1+\exp(x_2)} \\ \delta_m &= \tfrac{\exp(x_3)}{1+\exp(x_3)+\exp(x_4)} \\ \delta_f &= \tfrac{\exp(x_4)}{1+\exp(x_3)+\exp(x_4)} \end{aligned} \tag{1}$$

The joint distribution of preference and production technology parameters, $(\lambda_m, \lambda_f, \delta_m, \delta_f)$, is fully characterized by 14 parameters.

We assume that the household Pareto weights may depend on education, cognitive scores and personality traits as well as the ages of both spouses through the following parametric specification:

$$\alpha(i) = \frac{Q_m(i)}{Q_m(i) + Q_f(i)}, \tag{2}$$

where

$$Q_j(i) = \exp(\gamma_{6j} + \gamma_{7j}\theta_j(i) + \gamma_{8j}edu_j(i) + \gamma_{9j}c_j(i) + \gamma_{10j}a_j(i)),\ j = m, f.$$

The coefficients of γ_{7j},γ_{8j},γ_{9j},γ_{10j} capture the effects of personality traits, education, cognitive ability and age on the Pareto weight of the husband in household i. The

Pareto weight of the wife is simply $1 - \alpha(i)$, the weights are both positive and normalized so as to sum to 1.

Dividing both the numerator and denominator of (2) by $Q_f(i)$, we have

$$\alpha(i) = \frac{\tilde{Q}(i)}{1 + \tilde{Q}(i)},$$

where

$$\begin{aligned} \tilde{Q}(i) &= Q_m(i)/Q_f(i) \\ &= \exp\left(\sum_{k=6}^{10}[\gamma_{km} z_{km}(i) - \gamma_{kf} z_{kf}(i)]\right), \end{aligned}$$

where the index k runs over all of the characteristics included in the $\alpha(i)$ function, and where $z_{6j}(i) = 1$, $z_{7j}(i) = \theta_j(i)$, $z_{8j}(i) = e_j(i)$, $z_{9j}(i) = c_j(i)$, and $z_{10j}(i) = a_j(i)$. We note that as long as the values of $z_{kj}(i)$ differ for husbands and wives in a sufficiently large number of households, the parameters γ_{km} and γ_{kf} are separately identified. With regard to the constant terms, only the difference $\gamma_{6m} - \gamma_{6f}$ is identified.

We compute the elasticity of husband's Pareto weight $\alpha(i)$ with respect to his personality traits $\theta_m(i)$ as

$$\eta_m(i) = \frac{\partial \alpha(i)}{\partial \theta_m(i)} \frac{\theta_m(i)}{\alpha(i)}, \tag{3}$$

and the elasticity of wife's Pareto weight $1 - \alpha(i)$ with respect to her personality traits $\theta_f(i)$ as

$$\eta_f(i) = \frac{\partial(1 - \alpha(i))}{\partial \theta_f(i)} \frac{\theta_f(i)}{(1 - \alpha(i))}, \tag{4}$$

for each household. In section 5 below, we will present the distribution of these elasticities for the five-dimensional personality traits included in the Pareto weight function.

4.1 Identification

The model described in section 2 is not nonparametrically identified, for reasons related to those given in Del Boca and Flinn (2012). It is useful to discuss identification in that model to see what the complicating factors are here. Del Boca and Flinn (2012) condition their analysis on both spouses being employed, which means that wages are observable. Del Boca and Flinn (2012) show that it is possible to nonparametrically identify the joint distribution of $(\lambda_m, \lambda_f, \delta_m, \delta_f, w_m, w_f, y_m + y_f)$ given $(h_m, \tau_m, h_f, \tau_f, w_m, w_f, y_m, y_f)$ under the assumption that all households behave noncooperatively (Nash equilibrium). They show that such a model is saturated, i.e., there are the same number of parameters to estimate as there are data points. A cooperative version of this model adds an additional parameter, either a scalar or a function, to select a point on the Pareto frontier that corresponds to the household's allocation. With this addition, the model is under-identified; to remedy this, the authors impose the assumption that $\alpha = 0.5$. If one is willing to assume either that all households use the value $\alpha = 0.5$ or that spouses reach a cooperative outcome where each obtains no less utility than they would in the Nash equilibrium, then cooperative models are also nonparametrically identified.[16]

The most important difference between the problem in Del Boca and Flinn (2012) and ours is the introduction of wage equations that are both independent objects of interest and that are required to correctly account for nonrandom selection into the

[16] In the latter case, individual utility is first computed assuming the weight $\alpha = 0.5$. At this outcome, if one spouse has a lower utility than in the Nash equilibrium, their weight is increased until that spouse is made indifferent between the cooperative and Nash equilibrium outcome. This means that in the population, a mass of households will have a weight of $\alpha = 0.5$, namely those households for which the participation constraint does not bind, with a distribution of ex post values of α not equal to 0.5 for households in which the participation constraint is binding.

labor force for husbands and wives.[17] These wage equations take the generic form

$$\begin{aligned}\ln w_{im} &= \gamma_{0m} + \gamma_{1m}\theta_{im} + \gamma_{2m}edu_{im} + \gamma_{3m}c_{im} + \gamma_{4m}exp_{im} + \gamma_{5m}exp_{im}^2 + \epsilon_{im} \\ \ln w_{if} &= \gamma_{0f} + \gamma_{1f}\theta_{if} + \gamma_{2f}edu_{if} + \gamma_{3f}c_{if} + \gamma_{4f}exp_{if} + \gamma_{5f}exp_{if}^2 + \epsilon_{if}\end{aligned}$$

We know that the sample selection problem leads to inconsistent OLS estimates of $\gamma_{kj}, k = 0,1,2,3,4,5, j = f, m$ if only using observations with observed wages, because in general $E(\epsilon_{ij}|\theta_{ij}, edu_{ij}, c_{ij}, exp_{ij}) \neq 0$ for $j = m, f$. The selection mechanism that operates jointly on $(\epsilon_{im}, \epsilon_{if})$ is a rather complex one in our decision-making framework. Moreover, the parameters of the wage function that we attempt to estimate are just a subset of the parameters characterizing the household's decision problem and choices.

Under our model specification, the data generating process (DGP) depends on the observed characteristics of the husband and wife, and G_u, the distribution of preference and production technology parameters, and F_ϵ, the bivariate normal distribution of (ϵ_m,ϵ_f). Draws from G_u and F_ϵ along with the observed values of state variables $\{\theta_m, \theta_f, a_m, a_f, edu_m, edu_f, c_m, c_f, exp_m, exp_f\}$, determine the household's preference and production technology $\{\lambda_m, \lambda_f, \delta_m, \delta_f\}$, the wage offers $\{w_m, w_f\}$, and the household's value of α. Based on these state variable realizations, each of the household's four choices are determined (which are the labor market $\{h_m, h_f\}$ and housework time allocations $\{\tau_m, \tau_f\}$ of each spouse given the endogenous equilibrium choice). We denote all of the unknown parameters to be estimated by Ω. The model generates a joint conditional distribution over the endogenous variables $A_E \equiv (w_m, w_f, h_m, h_f, \tau_m, \tau_f)'$ given the vector of observed exogenous covariates A_C and the parameter vector Ω,

$$Q(A_E|A_C, \Omega).$$

[17] Allowing for spouses being out of the labor market in the Del Boca and Flinn (2012) model would have required the introduction of wage equations and would have also resulted in the model being no longer nonparametrically identified (even given an assumed value of the Pareto weight α).

This distribution cannot be expressed in a closed-form, but it is straightforward to simulate it by taking a large number of draws from G_u and F_ϵ. The conditional distribution $Q(A_E|A_C,\Omega)$ is the basis of the estimator described in more detail in the following subsection.

If the selection criteria sorting households into cooperation and spouses into labor market participation were less complex, it would be possible to employ a maximum likelihood estimator directly constructed from the conditional distribution $Q(A_E|A_C,\Omega)$ for each household. Parameter identification is relatively straightforward to analyze in such a case simply by determining whether the first order conditions are linearly independent. When using moment-based estimators, as we do, typically it is not possible to explicitly demonstrate the identification of all of the model parameters. The hope is that by including enough sample statistics, all of the model parameters will be identified and precisely estimated. Moments of the data are chosen, $m_h(A_E,A_C)$, $h = 1,...,H$ where H is at least as large as the dimensionality of the parameter space, given by $\#\Omega$.[18] For example, one of the moments used in forming the estimator is the proportion of wives in the sample with characteristics $a_C \in A_C$ who are in the labor market, in which case $m(A_E,A_C) = N^{-1}\sum_{i=1}^{N}\chi[h_f(i) > 0; a_C \in A_C, \Omega]$, where χ is the indicator function and N is the number of households in the sample. In general, there does not exist a unique deterministic solution $\bar{\Omega}$ such that $M = \tilde{M}(\bar{\Omega})$. Instead, we define a distance function, $D(\tilde{M}(\Omega),M)$, and the minimum distance estimator of Ω is given by

$$\hat{\Omega} = \arg\min_{\Omega} D(\tilde{M}(\Omega),M).$$

Whether or not the model is "well-identified" using a particular vector of sample

[18]In our case, we use 85 moments to identify 54 parameters $\#\Omega = 54$. Appendix A.3 provides a list of moments used in estimation.

moments is often determined after estimation has been attempted. Different sets of moments can yield different point estimates and associated standard errors in small samples, but it is seldom possible to determine an "optimal" vector of moments to use in a reasonably complex estimation problem. A specific parameter is said to be precisely estimated if the ratio of its point estimate to its estimated standard error is large in absolute value. In our case, it is almost never the case that this ratio of the parameter to its standard error is close to zero.

4.2 Model Estimation

We estimate the model using a relatively standard Method of Simulated Moments approach. Given a set of parameters, we repeatedly draw from the distributions of household preference parameters, production function parameters, and potential wage offers, $(\delta_m^r, \lambda_m^r, w_m^r, \delta_f^r, \lambda_f^r, w_f^r)$, R times for each household. Combined with other observed variables
$(y_m, \theta_m, c_m, a_m, edu_m, exp_m, y_f, \theta_f, c_f, a_f, edu_f, exp_f)$, we solve for the time allocation of the household $(h_f^r, \tau_f^r, h_f^r, \tau_f^r)$ within the selected equilibrium. Model parameters are estimated by choosing the parameters that minimize the quadratic distance function,

$$\hat{\Omega} = \arg\min_{\Omega}(\tilde{M}_{NR}(\Omega) - M_N)' W_N (\tilde{M}_{NR}(\Omega) - M_N),$$

where W_N is a positive definite weighting matrix. The NR subscript on $\tilde{M}$ signifies that these population analogs are computed from R simulations for each of the N households in the sample. Under standard conditions used to obtain consistency of GMM estimators, $plim_{N,R\to\infty}\hat{\Omega} = \Omega$ for any positive definite W. We compute the weighting matrix W_N following Del Boca et al. (2014) using a resampling method.[19]

[19]We resample the original N observations a total of P times (where $P = 100$), and compute the vector of sample characteristics at each simulation s, which is given by M_N^p.

The weight matrix is the inverse of the diagonal of the bootstrapped covariance matrix of M_N:

$$W = P^{-1} \left(\sum_{p=1}^{P} (M_N^p - M_N)(M_N^p - M_N) \right)^{-1}.$$

Standard errors associated with the parameters $\hat{\Omega}$ are obtained using the standard asymptotic formula for generalized method of moments estimators.

4.3 Principal Component Analysis

Because many of the model parameters are associated with personality traits, the moments used in estimation need to capture the relationship between choices, outcomes and personality traits. There are five traits, each of which can take on values ranging from 1 to 7. To specify the moments in a parsimonious way, we first apply principal-components analysis (PCA) to the five personality trait variables to obtain linear combinations of traits that are used in estimation.[20]

We do the PCA separately for husbands and wives and, for each, retain the first two principal components, which have eigenvalues greater than 1. They are shown in Table 6. For the first component, the most crucial loadings are conscientiousness, agreeableness and emotional stability (.517, .543 and .493) in the male case. For women, all traits except openness to experience contribute almost equally to the first component. For the second component, loadings are concentrated on openness to experience for both males and females (.788 and .789). We then discretize the first two principal components into three levels (low, middle and high) and construct

[20]Principal components is a statistical procedure that converts a set of possibly correlated variables into a set of linearly uncorrelated variables called principal components. The transformation is defined so that the first principal component has the largest possible variance (accounts for as much of the variability in the data as possible), and each succeeding component has the highest variance possible under the constraint that it is orthogonal to the preceding components.

moments conditioning on these components and categories.[21]

4.4 Selection of Sample Characteristics

We estimated the above parameters by matching the following six groups of moments: (1) proportion employed; (2) average working hours ; (3) average housework hours; (4) average wage for the employed workers; (5) standard error of male's log wage and female's log wage; (6) fraction of working hours in certain intervals; (7) fraction of housework hours in certain intervals; (8) Covariance between men and women's time allocations; (9) Correlation between men and women's accepted wages. We calculated moments 1-7 for husbands and wives separately. For moments 1-4 we use marginal moments conditional on education level (college, no college), principal component 1 range (low, middle and high) and principal component 2 range (low, middle and high). The remaining moments are unconditional. In total, there are 85 moments. A detailed description can be found in Appendix A.3.

5 Estimation Results

5.1 Model Estimates

Table 7 reports the estimated model parameters. Part 1 (the upper panel) displays the coefficient estimates associated with personality traits in the wage offer function and their impact on the Pareto weight for husbands and wives. Given our specification, we obtain a *certeris paribus* effect of personality traits on log wages, conditional on education and cognitive ability. Personality traits are also likely to be important at younger ages in shaping education choices and cognitive skills. There

[21]The cut-offs to assign observations to the low, middle and high categories correspond to the 33rd and 66th percentiles.

is evidence that attending college also influences the evolution of personality traits. (e.g.Todd and Zhang (2017)) We cannot use our static model to fully examine the influence of personality traits over an individual's lifetime as they operate through various channels at different ages. Rather, we use the model to examine the role played by personality traits in determining household interaction, wages and labor supply, above and beyond that of other characteristics, such as education and cognitive ability.

The parameter estimates show that the education coefficient (conditional on the other included variables) is somewhat larger for women (0.0673) than for men (0.0538). Personality traits are important determinants of wage offers for men but individually are not statistically significant determinants for women. Of the personality traits, conscientiousness significantly increases male wage offers and agreeableness significantly lowers wage offers. Cognitive ability increases wage offers for both men and women. The wage return for cognitive ability is twice as high for men (0.12) as for women (0.06).

Table 8 reports F-statistics and associated p-values from Wald tests for the joint statistical significance of the five personality traits in the wage equations and in the pareto weights for both men and women. We reject the null that personality traits are not significant in all cases.

The estimated parameters that determine the Pareto weights are shown in Table 7. The Pareto weights for both men and women are significantly influenced by personality traits, education and cognitive ability. Extraversion and emotional stability have a ceteris paribus positive effect on the Pareto weight, whereas openness to experience and agreeableness have a negative effect. Conscientiousness increases the Pareto weight for women but decreases it for men. Age increases the Pareto weight for both men and women and cognitive ability decreases it.

When particular personality traits have negative ceteris paribus effects on the Pareto weight, it does not mean that individuals with higher values of these traits necessarily have a lower household Pareto weight. This is because it is the the relative difference between spouses rather than the absolute value that determines the overall Pareto weight. With assortative matching on traits, individuals with high scores on certain traits are likely to have spouses with high scores on the same traits. We will further explore the importance of this assortative matching in affecting the degree of household cooperation below.

To better understand how personality traits of both spouses affect the Pareto weight, we calculate $\{\eta_m(i), \eta_f(i)\}$, the elasticity of Pareto weights with respect to their personality traits separately, following equation 3 and 4 described in the last section. Figure 3 displays the distribution of $\eta_m(i)$ and $\eta_f(i)$. In general, personality traits demonstrate significant asymmetric effects on Pareto weights. Among all personality traits, agreeableness is the most important trait in determining the Pareto weights. The average elasticities of agreeableness are -0.861 for men and -0.880 for women. That is, a percent increase of the husband's agreeableness decreases his Pareto weight (α) by 0.861%. A percent increase in wives' agreeableness decreases her Pareto weight ($1-\alpha$) by 0.880%.

Next, we explore how the Pareto weight affects the possibility of a household adopting a cooperative allocation. Table 9 displays the fraction of cooperative households for different values of α. Although α assumes values from 0 to 1, the Pareto weights of most households lie in the range [0.20,0.80], indicating that spouses in most households share fairly equal weights. Also, we observe that households are more likely to adopt a cooperative interaction mode when the Pareto weight is close to 0.5. Around 61.8% and 69.4% of households choose to play cooperatively when $\alpha \in [0.40, 0.50)$ and $\alpha \in [0.50, 0.60)$, whereas none of households play cooperatively when the value of α is extreme ($\alpha > 0.80$ or $\alpha < 0.20$).

We next describe the estimated distribution of the spousal preference and production parameters $\{\delta_m, \delta_f, \lambda_m, \lambda_f\}$. Figure 5 (a) shows the marginal distributions of the preference and production parameters. The distribution of husbands' leisure preferences and the distribution of wives' leisure preference are similar. The husbands' production parameter distribution is more left-skewed than wives'; males are estimated to be less efficient in producing public goods than females.

Figure 5 (b) plots the bivariate distribution of spousal preference and production parameters. There is a strong relationship between both the preference (λ_1 and λ_2) and the production parameters (δ_1 and δ_2) over most of the support of the distribution. That is, husbands and wives exhibit a substantial degree of positive assortative matching with respect to both preference and production characteristics, although the sorting on the production parameter is less pronounced. For husbands, there is a weak positive correlation between the preference and production parameters as seen in figure 5(b) - subfigure (c). For wives (figure 5(b) - subfigure (d)), there is little evidence of a systematic relationship between productivity and preference parameters. Although the sample used for our estimation differs from that used in Del Boca and Flinn (2012), the estimated unobserved preference and production distributions are similar.

5.2 Goodness of Model Fit

The goodness of model fit is shown in tables 10, 11 and 12. Table 10 shows the mean labor participation rate, accepted wage, working hours and housework hours. All moments are conditional on education levels and on ranges of values of the first and second principal components. The model captures well the proportion working, the average wages for workers, the average hours for workers and the hours of housework by education level (low or high) for the different categories.

Table 11 shows the fit of the time allocation distribution, where time is divided into three intervals, chosen so that the number of observations in each interval is roughly equal. Although the model reproduces the distribution of household hours fairly well (both for men and women), it under-predicts the number of individuals with working hours in the middle interval. This underestimation is caused by non-smoothness of working hour distribution, as many people report working hours equal to 40. The fraction of men's working hour in (40,46) is only 0.157, which is much close to our simulation.

5.3 External Validation

As previously noted, we use the "fair share" question as a way of examining the validity of the model's implications. To determine a fair share reference point, we use the estimated model to simulate housework time allocations under the case where husbands and wives have equal pareto weights. We compare the housework hours implied by the model with $\alpha = 0.5$ to that reported by the household. If the "fair share" question is informative, then individuals who report "I do *much more* than my fair share" should be observed to do more housework than their "fair share " and vice versa.[22]

Table 13 reports the housework hours and Pareto weight for both spouses cat-

[22]A household's optimal time allocation may change over time with changes in job opportunities as well as the number of children, and respondents' interpretation of fair share might be one that views allocation over a span of time. Given that our model is static, though, we interpreted the response to the "fair share" as relating to the present time.

egorized by "fair share" question. The column "Relative Difference" displays the difference between the actual housework hours and the simulated housework hours under the Pareto weight set equal to 0.5. When individuals report doing more than their "fair share", the actual housework hours are larger than the simulated hours, and when the opposite is true the individual tends to work less time in the household than the simulated hours.

5.4 Wage Decomposition

We next do a series of wage decompositions to understand the importance of education and personality traits in explaining gender gaps in accepted and offered wages. In our first decomposition, we decompose the mean log wage gap into five sources:

$$\begin{aligned}
\underbrace{log\bar{w}_m - log\bar{w}_f}_{\text{mean wage gap}} &= \underbrace{\gamma_{0m} - \gamma_{0f}}_{\text{unexplained part}} + \underbrace{(\gamma_{1m}\bar{\theta}_m - \gamma_{1f}\bar{\theta}_f)}_{\text{explained by traits}} + \underbrace{(\gamma_{2m}\bar{e}_m - \gamma_{2f}\bar{e}_f)}_{\text{explained by education}} + \underbrace{(\gamma_{3m}\bar{c}_m - \gamma_{3f}\bar{c}_f)}_{\text{explained by cognition}} \\
&+ \underbrace{(\gamma_{4m}e\bar{x}p_m - \gamma_{4f}e\bar{x}p_f)}_{\text{explained by experience}} + \underbrace{(\gamma_{5m}e\bar{x}p_m^2 - \gamma_{5f}e\bar{x}p_f^2)}_{\text{explained by experience}^2} + \underbrace{(\bar{\epsilon}_m - \bar{\epsilon}_f)}_{\text{selection bias}}
\end{aligned}$$

Table 14 shows the gender wage gap attributable to these different sources. The gap in accepted wages is 16.10%, while the gap in offered wages is 19.31%. As was seen in Table 7, females receive a slightly higher return for their educational attainment than males. Education narrows the offered-wage gap by 18.19 percentage points and the accepted-wage gap by 18.69 percentage points. However, the female advantage in the return to education is largely offset by a relative disadvantage in the return to potential work experience. Work experience increases the offered-wage gap by 11.11 percentage points and the accepted-wage gap by 11.06 percentage points. Among the "Big Five" personality traits, conscientiousness and emotional stability are the most important two traits contributing to a widening of the wage gap (11.95

percentage points and 25.02 percentage points for the offered-wage gap). Agreeableness, on the other hand, narrows the gender offered wage gap by 13.37 percentage points. The impact of openness to experience and extraversion in explaining the log wage gap is not significant. In total, personality traits explain 15.25 percentage points of the offered log wage gap. Their combined contribution to explaining the gender gap is the same magnitude as the contribution of education and working experience. Cognitive ability explains only a small fraction of the wage gap.

Figure 6 plots the distributions of both offered wages and accepted wages. Female workers are on average more selective than male workers; that is, a lower fraction of females (85.2 percent) accepts the offered wage and works in the labor market. Male workers' accepted wages are on average 1.63 percent higher than offered wages, whereas female workers accepted wages are on average 4.45 percent higher than offered wages. For this reason, the gender gap in accepted wages is smaller than the gap in offered wages.

Table 14 shows that personality traits and education levels are both important to explaining gender wage gaps. Wage gaps can arise either because women have on average different traits and/or because women receive different payoffs in the labor market for their traits (as was evident in Table 7). We next explore whether and to what extent the gender gap is explained by differences in observed traits or differences in the market valuation of those traits. Following Oaxaca (1973) and Blinder (1973), we perform the following decomposition:

$$\gamma_{1m}\bar{\theta}_m - \gamma_{1f}\bar{\theta}_f = \underbrace{\gamma_{1m}(\bar{\theta}_m - \bar{\theta}_f)}_{\text{personality difference}} + \underbrace{(\gamma_{1m} - \gamma_{1f})\bar{\theta}_f}_{\text{coefficient difference}}$$

The first term is interpreted as the part of the log wage differential due to differences in traits, and the second term is the difference arising from gender differences in the estimated coefficients associated with those traits. The decomposition results are reported in table 15.

In general, gender wage gaps are largely explained by gender differences in labor market evaluations of characteristics (education, personality traits and potential working experience). For example, the differences in personality traits mean values explain 0.44 percentage points of the offered wage gap, but the differences in trait premia/penalties explain 8.67 percentage points. The gender difference in the valuation of emotional stability widens the offered wage difference by 25.06 percentage points and is the most important single factor to explain the gender wage gap. Another important factor is the male-female difference in the premium for conscientiousness, which widens the offered wage gap by 13.13 percentage points. In contrast, the gender difference in the valuation of agreeableness shrinks the gender wage gap by 15.73 percentage points. The contributions of other two traits - openness to experience and extraversion - in explaining gender differences in wage offers are minor.

6 Counterfactual Experiments

6.1 Comparing Different Modes of Interaction between Spouses

We next examine how household behaviors differ in the cooperative and noncooperative regimes by using the estimated model to simulate behaviors that would result if all households interacted in a cooperative or noncooperative manner. We compare the time allocations and outcomes to our baseline model, where we found that 38.4 percent of sample households choose to cooperate. As seen in Table 16, under the cooperative regime, both men and women supply more hours to market work and to household work than in the baseline case. The working hours for men and women increase on average by 5.0 and 8.5 hours, respectively, while housework hours increase by 3.8 hours and 5.0 hours. The gap in accepted wages increases from 15.2 percent in the baseline model to 21.5 percent in the cooperative regime. In the noncooperative regime, both men and women supply fewer hours to the labor market and to household work and devote more hours to leisure. The accepted wage gap is largest under the cooperative regimes, and the average utility levels for men under this regime is also the highest. The accepted wage gap is lowest under the noncooperative regime and the average utility values are also lowest. This indicates that reducing the observed gender wage gap is not necessarily welfare improving.

The explanation for the different time allocations under cooperative and noncooperative regimes is intuitive. For any set of state variables characterizing the household, when both the public good K and the private good l are valued by husbands and wives, the household will produce more of the public good in the cooperative equilibrium. The Nash equilibrium is inefficient in that neither spouse takes account of the fact that by spending more time in the market and housework they will increase the welfare of their spouse, and so leisure is over-consumed relative to its efficient level. In any efficient equilibrium (i.e., whatever the value of α), more K will be produced than in the Nash equilibrium. Because both labor supply, that generates income, and housework time are inputs in the production of K, both will generally increase. The reservation wage of either spouse will be lower for each spouse in the cooperative equilibrium. There is an increase gender wage gap in part because women are now willing to work at lower wages. Although the cooperative allocation is always an efficient equilibrium, it does not guarantee that both husbands and wives are able to attain a higher welfare level simultaneously compared with their baseline levels. In our case, the cooperative allocation improves men's utility but hurts women's utility on average. This also explains why the cooperative equilibrium is not chosen by all households.

6.2 The Effect of Positive Assortative Matching

According to Figure 2 and Figure 5(b), married couples display positive assortative matching on both unobserved preference and production parameters as well as on observed personality traits and cognitive abilities. We perform two counterfactual experiments to measure the effect of positive assortative matching on the gender wage gap. In the first, we randomly assign males and females from the original sample to form new households, and we refer to this environment as one of "pure random matching." In the second experiment, we preserve the education and the age of the matched spouses but reshuffle the personality traits of households. The comparison of these two experiments to the baseline scenario allows examination of the effects of positive sorting on cooperation and on household time allocation.

Table 17 suggests that eliminating positive assortative matching between spouses generates significant effects on labor force participation rates and wage gaps. In the pure random matching experiment, the labor participation rate of males and females decreases by 10.5 and 10.1 percentage points, and the accepted wage increases by \$1.0 for men and by \$1.3 for women. As a result, the gender gap in accepted wages shrinks from 15.2 percent in the baseline case to 13.4 percent in the pure random matching case. Meanwhile, the "limited" random matching experiment displays a very similar effect. The labor participation rate of males and females decreases by 10.0 and 9.8 percentage points, and the gender wage gap decreases to 13.1%. The driving force behind these results in both experiments is the decrease numbers of cooperative households. The reason is that extreme Pareto weights are easier to generate when matching is random, resulting in a lower fraction of cooperative households. When households adopt noncooperative behaviors, they obtain less utility from the public good. Consequently, they choose to work fewer hours and gender a lower level of public goods. Thus, labor force participation rates also fall (especially for females). By comparing the two counterfactual experiments (random match and limited random match), we can ascertain that the effect of age and education sorting on cooperation is relatively small.

6.3 Equalizing pay opportunities

Lastly, we use our model to simulate household time allocations and wage outcomes that would result if women were paid according to the male wage offer equation. That is, women may still receive different wage offers from men because their personal attributes differ, but their education, personality traits, and cognitive skill are valued in the same way in the labor market as they are for men.

As seen in Table 18, when men and women have the same wage offer equation, then women have better opportunities in the labor market on average. Women choose to spend more hours and men fewer hours doing market work. In terms of housework, women decrease their housework hours relative to the baseline and men increase their housework hours. Interestingly, when women and men have the same wage offer functions, the accepted wages for women are on average similar to the accepted wages for men. The gender wage gap in accepted wages changes from 15.2 percentage points in the baseline model to -2.45 percentage points in this "equal pay opportunities" simulation.

Figure 7 displays the distributions of offered wages and accepted wages in both the baseline and the counterfactual models. In the baseline model, the female's wage distribution is more left-skewed than male's wage distribution, indicating that the offered wages and accepted wages are lower for women than for men. However, this gap is totally eliminated and under the equal pay opportunities simulation.

7 Conclusions

In this paper, we study the role of personality traits in household decision-making, specifically with regard to decisions about time allocation to housework and market work and the implications for gender wage disparities. First, we find that personality traits are significant determinants of household Pareto weights for both men and women. Second, we find that personality traits are also statistically significant determinants of offered wages for both men and women. Males receive a positive return for being conscientious and a negative return for being agreeable. For women, the individual personality traits are not statistically significant but they are jointly significant. Overall, the effect of personality traits on the wage equation is comparable to the effect of education and potential work experience. Third, an Oaxaca-Blinder type decomposition analysis shows that the gender wage gap largely is attributable to gender differences in market valuations of traits rather than to differences in the levels of those traits. Male-female differences in the return to conscientiousness and emotional stability emerge as the most important factors contributing to a widening of the wage gap. Differences in the return to agreeableness and to education contribute to a narrowing of the wage gap.

The model we estimated allows households to choose to behave cooperatively or noncooperatively, with personality attributes potentially affecting household Pareto weights. We find that 38.7 percent of households behave cooperatively. Cooperation leads a household to assign a higher value to public goods that require both monetary and time investments to produce. This leads both men and women to supply a greater number of hours to the labor market and to housework than they would under a noncooperative regime. Observed wage gaps are higher under a cooperative regime but utility is also higher.

We also document positive assortative matching of men and women with regard to education and personality traits. The assortative matching tends to lead to higher levels of cooperation than would be observed under random matching of personality types. Simulation results show that eliminating the positive sorting decreases the gender gap of accepted wage from 15.2 percent to 13.5 percent, largely because of the reduction in the proportion of households behaving cooperatively.

We use the model to simulate time allocations that would result if women would receive the same wage offer equation as men. Simulation results show that women would work about 4.2 hours more per week and the accepted wage gap would be eliminated, with women having 2.45 percent higher wages than men.

There are several ways that our analysis could be extended in future work. First, we focused on individuals age 30-50 who do not have children under the age of 8 living in their home. Children and their effects on housework and labor supply decisions could be explicitly incorporated into the model. Second, our model viewed the household decision as a static decision at each age, but it could be extended to an explicit dynamic life-cycle framework.

A Appendix

A.1 Comparison of estimated parameters based on restricted sample 1 and restricted sample 2

In this appendix, we compare the estimation results obtained using the sample that excludes the households with any child age less than 8 (sample 1, the one that was used in the estimation for the paper) and the results obtained using a more restrictive sample that excludes households with any child age less than 14 (sample 2). The left panel in table 19 displays the key differences between the two samples. When restricting the sample to households without dependents below age 14, the housework time of both spouses is reduced. The average housework hours of husbands decreases from 18.19 to 14.29, and the average hours of wives decreases from 27.87 to 20.27. For females, the reduction in housework time is associated with an increase in hours supplied to the labor market. The working hours in sample 2 are 3 hours more than that in sample 1.

The differences in the parameter estimates reasonably reflect different features of these two samples. Sample 1 also has different home production technology (δ_1,δ_2) that generates a greater male-female division of labor. Woman appear to be relatively more efficient in the home sector when children are young compared to when children are older. Therefore, we observe more hours of home production but fewer hours for market labor supply for females in sample 1. The greater division of labor also is associated with a higher degree of household cooperation. Our estimation shows that 38.7% households choose to cooperate in sample 1, whereas only 19.3% households cooperate in sample 2.

A.2 Algorithm used to solve and select equilibrium under non-cooperative regime

1. We solve the optimal allocation $(h_m^*, h_f^*, \tau_m^*, \tau_f^*)$ without constraint using the best reaction arrays (R_m, R_f):

$$\begin{aligned} R_m(h_m^*, \tau_m^*)(h_f, \tau_f) &= \arg\max_{h_m, \tau_m} \lambda_m \ln l_m + (1-\lambda_m)\ln K \\ R_f(h_f^*, \tau_f^*)(h_m, \tau_m) &= \arg\max_{h_f, \tau_f} \lambda_f \ln l_f + (1-\lambda_f)\ln K \end{aligned}$$

2. If h_m^* and h_f^* are both non-negative, this is the equilibrium with inner allocation.

3. If either $h_m^* < 0$ or $h_f^* < 0$, then the equilibrium is a boundary case.

   (a) Guess and verify the case when female is out if labor force $h_f = 0$

      i. Guess: the allocation $(\hat{h}_m, \hat{\tau}_m, 0, \hat{\tau}_f)$ with the constraint female is out of labor force

      ii. Verify: whether this allocation $(\hat{h}_m, \hat{\tau}_m, 0, \hat{\tau}_f)$ is an equilibrium by inserting $\left(\hat{h}_m, \hat{\tau}_m\right)$ into $R_f(\widetilde{h}_f, \widetilde{\tau}_f)(\hat{h}_m, \hat{\tau}_m)$. It is truly an equilibrium if and only if $\widetilde{h}_f \leq 0$

   (b) Guess and verify the case when male is out if labor force $h_m = 0$

      i. Guess: the allocation $(0, \hat{\tau}_m, \hat{h}_f, \hat{\tau}_f)$ with the constraint female is out of labor force

      ii. Verify: whether this allocation $(0, \hat{\tau}_m, \hat{h}_f, \hat{\tau}_f)$ is an equilibrium by inserting $\left(\hat{h}_f, \hat{\tau}_f\right)$ into $R_m(\widetilde{h}_m, \widetilde{\tau}_m)(\hat{h}_f, \hat{\tau}_f)$. It is truly an equilibrium if and only if $\widetilde{h}_m \leq 0$

   (c) If only one in (a) and (b) is an equilibrium, choose this one.

   (d) if both (a) and (b) are equilibria, we choose the one female is out of labor force. $(\hat{h}_m, \hat{\tau}_m, 0, \hat{\tau}_f)$

A.3 List of Moments used in Estimation

This appendix provides a list of the moments used in estimation. Each moment is based on all the households in the estimation sample, so that the N is the same value for each of the moments (N is same for males and females as they are husbands and wives). In each case, we use indicator functions to select particular subsets of the sample. For example, the average wage for the males in the sample is the fraction of individuals who are male and who are working times the average wage for those individuals plus the fraction of individuals who are not male or not working times zero.

Husband's employment rate for sub-groups

1.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}(Education = High)$

2.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}(Education = Low)$

3.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$(First principal component $\leq rank(33\%)$)

4.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank(33\%) <$First principal component$\leq rank(66\%)$)

5.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank(66\%) <$First principal component)

6.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$(Second principal component $\leq rank(33\%)$)

7.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank(33\%) <$Second principal component $\leq rank(66\%)$)

8.$\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank(66\%) <$Second principal component)

Wife's employment rate for sub-groups 9.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}(Education = High)$

10.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}(Education = Low)$

11.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$(First principal component$\leq rank(33\%)$)

12.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(33\%) <$First principal component$\leq rank(66\%)$)

13.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(66\%) <$First principal component)

14.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$(Second principal component$\leq rank(33\%)$)

15.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank$(33%) <Second principal component$\leq$ $rank$(66%))

16.$\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank$(66%) <Second principal component)

Husband's average wage for sub-groups

17. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($Education = High$)

18. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($Education = Low$)

19. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$(First principal component$\leq$ $rank$(33%))

20. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank$(33%) <First principal component$\leq$ $rank$(66%))

21. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank$(66%) <First principal component)

22. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$(Second principal component$\leq$ $rank$(33%))

23. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank$(33%) <Second principal component$\leq$ $rank$(66%))

24. Husband's average wage $\mathbf{I}$(Husband's Work Hours > 0)$\mathbf{I}$($rank$(66%) <Second principal component)

Wife's average wage for sub-groups

25. Wife's average wage $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($Education = High$)

26. Wife's average wage $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($Education = Low$)

27. Wife's average wage $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$(First principal component$\leq$ $rank$(33%))

28. Wife's average wage $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank$(33%) <First principal component$\leq$ $rank$(66%))

29. Wife's average wage $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank$(66%) <First principal com-

ponent)

30. Wife's average wage $\mathbf{I}$(Wife's Work Hours $>$ 0)$\mathbf{I}$(Second principal component$\leq$ $rank$(33%))

31. Wife's average wage $\mathbf{I}$(Wife's Work Hours $>$ 0)$\mathbf{I}$($rank$(33%) $<$Second principal component$\leq$ $rank$(66%))

32. Wife's average wage $\mathbf{I}$(Wife's Work Hours $>$ 0)$\mathbf{I}$($rank$(66%) $<$Second principal component)

Husband's average working hours for sub-groups

33. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($Education = High$)

34. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($Education = Low$)

35. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$(First principal component$\leq$ $rank$(33%))

36. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($rank$(33%) $<$First principal component$\leq$ $rank$(66%))

37. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($rank$(66%) $<$First principal component)

38. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$(Second principal component$\leq$ $rank$(33%))

39. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($rank$(33%) $<$Second principal component$\leq$ $rank$(66%))

40. Husband's average working hours$\mathbf{I}$(Husband's Work Hours $>$ 0)$\mathbf{I}$($rank$(66%) $<$Second principal component)

Wife's average working hours for sub-groups

41. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}(Education = High)$

42. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}(Education = Low)$

43. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$(First principal component $\leq rank(33\%)$)

44. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(33\%) <$First principal component $\leq rank(66\%)$)

45. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(66\%) <$First principal component)

46. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$(Second principal component $\leq rank(33)$

47. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(33\%) <$Second principal component $\leq rank(66\%)$)

48. Wife's average working hours $\mathbf{I}$(Wife's Work Hours > 0)$\mathbf{I}$($rank(66\%) <$Second principal component)

Husband's average housework hours for sub-groups

49. Husband's average housework hours $\mathbf{I}(Education = High)$

50. Husband's average housework hours $\mathbf{I}(Education = Low)$

51. Husband's average housework hours $\mathbf{I}$(First principal component$\leq rank(33\%)$)

52. Husband's average housework hours $\mathbf{I}$($rank(33\%) <$First principal component$\leq rank(66\%)$)

53. Husband's average housework hours $\mathbf{I}$($rank(66\%) <$First principal component)

54. Husband's average housework hours $\mathbf{I}$(Second principal component$\leq rank(33\%)$)

55. Husband's average housework hours $\mathbf{I}$($rank(33\%) <$Second principal component$\leq rank(66\%)$)

56. Husband's average housework hours $\mathbf{I}$($rank(66\%) <$Second principal component)

Wife's average housework hours for sub-groups

57. Wife's average housework hours $\mathbf{I}(Education = High)$

58. Wife's average housework hours $\mathbf{I}(Education = Low)$

59. Wife's average housework hours $\mathbf{I}$(First principal component $\leq rank(33\%)$)

60. Wife's average housework hours $\mathbf{I}(rank(33\%) <$First principal component $\leq rank(66\%))$

61. Wife's average housework hours $\mathbf{I}(rank(66\%) <$First principal component)

62. Wife's average housework hours $\mathbf{I}$(Second principal component $\leq rank(33\%)$)

63. Wife's average housework hours $\mathbf{I}(rank(33\%) <$Second principal component $\leq rank(66\%))$

64. Wife's average housework hours $\mathbf{I}(rank(66\%) <$Second principal component)

Moments for the distribution of time allocation

65. Prob. of husband's working hours in [0,40]

66. Prob. of husband's working hours in (40,46]

67. Prob. of husband's working hours in (46,60]

68. Prob. of husband's housework hours in [0,11]

69. Prob. of husband's housework hours in (11,20]

70. Prob. of husband's housework hours in (20,56]

71. Prob. of wife's working hours in [0,24]

72. Prob. of wife's working hours in (24,38]

73. Prob. of wife's working hours in (38,60]

74. Prob. of wife's housework hours in [0,16]

75. Prob. of wife's housework hours in (16,34]

76. Prob. of wife's housework hours in (34,56]

77. Corr. between husband's working hours and wife's working hours

78. Corr. between husband's working hours and wife's housework hours

79. Corr. between husband's working hours and husband's housework hours
80. Corr. between husband's housework hours and wife's working hours
81. Corr. between husband's housework hours and wife's housework hours
82. Corr. between wife's working hours and wife's housework hours
83. S.D. of husband's log wage$\mathbf{I}$(Husband's working hours > 0)
84. S.D. of wife's log wage$\mathbf{I}$(Wife's working hours > 0)
85. Corr. between wife's wage and husband's wage

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Tables

Table 1: Personality traits questionnaire

B19 How well do the following words describe you? For each word, cross <u>one</u> box to indicate how well that word describes you. There are no right or wrong answers.

*(Cross ☒ <u>**one**</u> box for <u>**each**</u> word.)*

	Does not describe me at all					Describes me very well
	1	2	3	4	5	6	7
talkative	1	2	3	4	5	6	7
sympathetic	1	2	3	4	5	6	7
orderly	1	2	3	4	5	6	7
envious	1	2	3	4	5	6	7
deep	1	2	3	4	5	6	7
withdrawn	1	2	3	4	5	6	7
harsh	1	2	3	4	5	6	7
systematic	1	2	3	4	5	6	7
moody	1	2	3	4	5	6	7
philosophical	1	2	3	4	5	6	7
bashful	1	2	3	4	5	6	7
kind	1	2	3	4	5	6	7
inefficient	1	2	3	4	5	6	7
touchy	1	2	3	4	5	6	7
creative	1	2	3	4	5	6	7
quiet	1	2	3	4	5	6	7
cooperative	1	2	3	4	5	6	7
sloppy	1	2	3	4	5	6	7

	Does not describe me at all						Describes me very well
	1	2	3	4	5	6	7
jealous	1	2	3	4	5	6	7
intellectual	1	2	3	4	5	6	7
extroverted	1	2	3	4	5	6	7
cold	1	2	3	4	5	6	7
disorganised	1	2	3	4	5	6	7
temperamental	1	2	3	4	5	6	7
complex	1	2	3	4	5	6	7
shy	1	2	3	4	5	6	7
warm	1	2	3	4	5	6	7
efficient	1	2	3	4	5	6	7
fretful	1	2	3	4	5	6	7
imaginative	1	2	3	4	5	6	7
enthusiastic	1	2	3	4	5	6	7
selfish	1	2	3	4	5	6	7
careless	1	2	3	4	5	6	7
calm	1	2	3	4	5	6	7
traditional	1	2	3	4	5	6	7
lively	1	2	3	4	5	6	7

Table 2: Summary statistics of personality traits and their changes over time

	Level		Mid-term change between 05-09					Long-term change between 05-13				
	Mean	S.D.	Mean	S.D.	10th	50th	90th	Mean	S.D.	10th	50th	90th
Openness	4.27	1.03	-0.074	0.776	-1.000	0	0.833	-0.004	0.817	-1.000	0	1.000
Conscientiousness	5.15	1.02	0.028	0.772	-0.833	0	1.000	0.106	0.824	-0.833	0	1.167
Extraversion	4.42	1.08	-0.036	0.744	-1.000	0	0.833	-0.049	0.786	-1.000	0	0.833
Agreeableness	5.40	0.88	-0.010	0.761	-1.000	0	1.000	0.087	0.794	-1.000	0	1.000
Emotional Stability	5.19	1.07	0.092	0.870	-1.000	0	1.167	0.100	0.919	-1.000	0	1.167

Data come from wave 2005, 2009 and 2013. The sample consists of 6,330 individual observations (2,913 males and 3,417 females) with three completed repeated measures. S.D.= standard deviation.

Table 3: Key variables in HILDA, means and (standard errors)

	Sample 1		Sample 2		Sample 3	
	Full sample		Excluded households with dependents < 8		Excluded households with dependents < 14	
Variable	Male	Female	Male	Female	Male	Female
Age	40.00	37.86	41.17	39.20	40.04	38.12
	(6.41)	(7.21)	(6.56)	(7.65)	(7.30)	(8.72)
Employment	0.94	0.72	0.94	0.85	0.94	0.88
	(0.24)	(0.45)	(0.24)	(0.35)	(0.24)	(0.32)
Hourly Wage	30.10	25.49	29.52	24.85	29.06	25.33
	(15.02)	(13.91)	(14.60)	(12.46)	(15.99)	(14.63)
Working hours	44.08	30.16	44.10	33.48	44.03	36.29
	(9.84)	(13.25)	(9.54)	(12.31)	(9.70)	(13.14)
Housework	23.11	43.27	18.19	27.87	14.92	20.27
	(15.83)	(25.54)	(12.86)	(17.59)	(10.62)	(13.48)
Time with Children	9.12	20.89	4.10	7.15	1.47	1.89
	(9.89)	(23.64)	(6.49)	(11.16)	(3.64)	(5.83)
Education	13.22	13.31	13.16	13.22	13.17	13.37
	(2.38)	(2.38)	(2.38)	(2.40)	(2.37)	(2.44)
Other Income	335.0	-	333.7	-	311.9	-
	(251.4)	-	(256.9)	-	(251.0)	-
Obs.	1,881	1,881	1,443	1,443	973	973
Average values of personality traits and cognitive ability						
Cognition	0.13	0.23	0.12	0.23	0.13	0.22
	(0.70)	(0.66)	(0.70)	(0.65)	(0.70)	(0.66)
Openness	4.37	4.24	4.39	4.23	4.41	4.27
	(0.96)	(0.98)	(0.96)	(0.99)	(0.95)	(1.00)
Conscientiousness	5.09	5.29	5.11	5.34	5.12	5.38
	(0.94)	(1.00)	(0.93)	(0.98)	(0.94)	(0.98)
Extraversion	4.32	4.65	4.29	4.63	4.31	4.61
	(0.99)	(1.13)	(1.00)	(1.15)	(0.99)	(1.14)
Agreeableness	5.22	5.74	5.20	5.73	5.20	5.70
	(0.85)	(0.76)	(0.85)	(0.76)	(0.85)	(0.77)
Emotional Stability	5.14	5.18	5.15	5.19	5.14	5.15
	(1.00)	(0.99)	(0.97)	(0.98)	(0.96)	(0.99)

(1) Both employment and hourly wage are conditional on being employed. (2) The other income is the pooled household income other than labor earnings.

Table 4: The Effects of Personality on Earnings and Labor Market Participation

	Log Hourly Earning		Labor Market Participation	
	Males	Females	Males	Females
Openness	-0.027	-0.013	-0.023***	-0.040***
	(0.015)	(0.015)	(0.008)	(0.010)
Conscientiousness	0.050***	0.027	0.013	0.034***
	(0.015)	(0.015)	(0.007)	(0.010)
Extraversion	0.009	0.023	0.005	0.019
	(0.013)	(0.012)	(0.006)	(0.008)
Agreeableness	-0.040*	-0.041*	0.006	0.001
	(0.017)	(0.020)	(0.008)	(0.013)
Stability	0.011	-0.006	-0.002	-0.014
	(0.015)	(0.016)	(0.007)	(0.010)
Education	0.053***	0.065***	0.007*	0.023***
	(0.006)	(0.006)	(0.003)	(0.004)
Cognition	0.124***	0.064**	0.057***	0.067***
	(0.020)	(0.022)	(0.010)	(0.015)
Exp	0.031**	0.016*	0.004	0.007
	(0.010)	(0.006)	(0.006)	(0.004)
$Exp^2/100$	-0.080***	-0.045**	-0.010	-0.020
	(0.024)	(0.023)	(0.016)	(0.012)

*Notes:*Robust standard errors are reported in parentheses. The potential experience is calculated by "Age - 6 - education years" as a standard approach in the literature.

* Statistically significant at the .05 level; ** at the .01 level; *** at the .001 level.

Table 5: Responses to the "fair share" question

Percentage(%)	Male	Female
Much More(1)	1.80	19.89
A bit More(2)	12.54	37.98
Fair Share(3)	58.21	36.87
A bit Less(4)	25.09	4.78
Much Less(5)	2.36	0.49
Correlation	-0.379	

Table 6: Principal-components analysis for five dimensional personality traits

	Male		Female	
	1	2	1	2
Eigenvalues	1.47	1.22	1.59	1.18
Variance	29.4%	24.5%	31.8%	23.5%
Openness to experience	0.144	0.771	0.087	0.820
Conscientiousness	0.556	-0.086	0.511	-0.066
Extraversion	0.363	-0.168	0.466	-0.009
Agreeableness	0.543	0.407	0.456	0.408
Emotional stability	0.493	-0.452	0.553	-0.397

Table 7: Parameter estimates

Part 1	Male			Female	
	Estimates	S.E.		Estimates	S.E.
		Log wage equation			
γ_{0m}	2.2467	(0.1448)	γ_{0f}	2.1326	(0.2008)
$\gamma_{1m}(Opn)$	-0.0256	(0.0217)	$\gamma_{1f}(Opn)$	-0.0141	(0.0152)
$\gamma_{1m}(Cos)$	0.0504	(0.0132)	$\gamma_{1f}(Cos)$	0.0259	(0.0336)
$\gamma_{1m}(Ext)$	0.0087	(0.0089)	$\gamma_{1f}(Ext)$	0.0146	(0.0199)
$\gamma_{1m}(Agr)$	-0.0446	(0.0215)	$\gamma_{1f}(Agr)$	-0.0171	(0.0212)
$\gamma_{1m}(Stb)$	0.0091	(0.0133)	$\gamma_{1f}(Stb)$	-0.0392	(0.0243)
$\gamma_{2m}(Edu)$	0.0538	(0.0108)	$\gamma_{2f}(Edu)$	0.0673	(0.0143)
$\gamma_{3m}(Cog)$	0.1230	(0.1073)	$\gamma_{3f}(Cog)$	0.0610	(0.0620)
$\gamma_{4m}(Exp)$	0.0294	(0.0085)	$\gamma_{4f}(Exp)$	0.0163	(0.0066)
$\gamma_{5m}(\frac{Exp^2}{100})$	-0.0786	(0.0450)	$\gamma_{5f}(\frac{Exp^2}{100})$	-0.0447	(0.0290)
$\sigma(\epsilon_m)$	0.6366	(0.0713)	$\sigma(\epsilon_f)$	0.8571	(0.1000)
ρ	0.7548	(0.1542)			
		Pareto Weight			
$\gamma_{6m}-\gamma_{6f}$	-0.2616	(0.0685)			
$\gamma_{7m}(Opn)$	-0.1406	(0.0396)	$\gamma_{7f}(Opn)$	-0.2390	(0.0429)
$\gamma_{7m}(Cos)$	-0.0776	(0.0205)	$\gamma_{7f}(Cos)$	0.1393	(0.0275)
$\gamma_{7m}(Ext)$	0.0651	(0.0407)	$\gamma_{7f}(Ext)$	0.0412	(0.0394)
$\gamma_{7m}(Agr)$	-0.3630	(0.1099)	$\gamma_{7f}(Agr)$	-0.2739	(0.0755)
$\gamma_{7m}(Stb)$	0.1322	(0.0480)	$\gamma_{7f}(Stb)$	0.0052	(0.0060)
$\gamma_{8m}(Edu)$	0.1391	(0.0288)	$\gamma_{8f}(Edu)$	0.0631	(0.0215)
$\gamma_{9m}(Cog)$	-0.6623	(0.1064)	$\gamma_{9f}(Cog)$	-0.2805	(0.2935)
$\gamma_{10m}(Age)$	0.0401	(0.0187)	$\gamma_{10f}(Age)$	0.0945	(0.0317)

Part 2	*Preference and Production Parameters*				
	Mean (μ)	Co-variance (σ^2)			
λ_m	0.3621	0.0123	0.0092	-0.0008	0.0016
S.E.	(0.0145)	(0.0024)	(0.0028)	(0.0007)	(0.0006)
λ_f	0.3372	0.0092	0.0099	0.0019	-0.0009
S.E.	(0.0132)	(0.0038)	(0.0051)	(0.0012)	(0.0006)
δ_m	0.1395	-0.0008	0.0019	0.0072	-0.0002
S.E.	(0.0221)	(0.0007)	(0.0012)	(0.0058)	(0.0016)
δ_f	0.1953	0.0016	-0.0009	-0.0002	0.0170
S.E.	(0.0190)	(0.0006)	(0.0006)	(0.0016)	(0.0100)

Table 8: Joint Wald test for the explanatory power of "Big-five" personality traits in the wage equation and in the bargaining equation

	Null Hypothesis	$F-value$	$p-value$
Wage (Male)	$\gamma_{1m}=0$	137.8	0.000
Wage (Female)	$\gamma_{1f}=0$	35.3	0.000
Bargaining (Male)	$\gamma_{5m}=0$	169.6	0.000
Bargaining (Female)	$\gamma_{5f}=0$	872.1	0.000

Table 9: The fraction of households playing cooperatively along with Pareto weight α

α	Fraction	Obs.
[0.10,0.20)	0	11
[0.20,0.30)	0	59
[0.30,0.40)	0.243	169
[0.40,0.50)	0.618	280
[0.50,0.60)	0.694	359
[0.60,0.70)	0.266	293
[0.70,0.80)	0.068	205
[0.80,0.90)	0	65
[0.90,1.00]	0	2
Total	0.387	1,443

Note: all Pareto wights α are within range [0.1,1]. The mean and S.D. of α are 0.555 and 0.151.

Table 10: Sample fit of husbands' and wives' wages and time allocations (mean level)

	Probability work > 0 hours				*Wages if work (avg.)*			
	Male		Female		Male		Female	
	Simulated	Data	Simulated	Data	Simulated	Data	Simulated	Data
Education								
Low	0.937	0.917	0.821	0.790	24.003	21.688	15.505	14.709
High	0.969	0.966	0.887	0.909	30.869	31.058	27.414	27.912
First Principal Component								
Low	0.927	0.925	0.859	0.790	26.473	26.304	20.667	19.587
Middle	0.961	0.943	0.859	0.882	26.174	25.064	20.638	21.634
High	0.966	0.949	0.844	0.878	28.832	26.56	21.524	20.936
Second Principal Component								
Low	0.950	0.950	0.828	0.858	27.321	25.675	19.615	20.817
Middle	0.950	0.933	0.857	0.868	27.617	26.331	20.945	20.645
High	0.951	0.934	0.877	0.825	26.516	25.887	22.306	20.752
	Hours worked if work (avg.)				*Hours of housework (avg.)*			
	Male		Female		Male		Female	
	Simulated	Data	Simulated	Data	Simulated	Data	Simulated	Data
Education								
Low	40.511	42.765	25.416	23.379	18.545	18.651	25.479	26.747
High	43.197	44.58	38.610	37.847	17.713	17.637	30.096	29.266
First Principal Component								
Low	40.163	43.82	31.322	27.811	18.151	18.052	28.207	27.785
Middle	40.814	43.829	31.959	30.389	18.639	18.180	26.792	27.342
High	44.207	43.135	31.028	31.675	17.713	18.358	27.662	28.518
Second Principal Component								
Low	42.464	44.421	29.291	29.243	17.511	17.526	28.544	27.650
Middle	42.289	43.2	32.337	30.867	18.654	19.102	26.184	27.871
High	40.415	43.148	32.714	29.831	18.349	17.940	27.950	28.115

Table 11: Sample fit of husbands' and wives' wages and time allocations (distribution)

	Male			Female	
	Simulated	Data		Simulated	Data
Working Hours					
[0,40]	0.420	0.501	[0,24]	0.400	0.356
()40,46)	0.161	0.157	(24,38)	0.219	0.238
[46,60]	0.420	0.342	[38,60]	0.381	0.406
Housework Hours					
[0,11)	0.301	0.322	[0,16)	0.295	0.311
[11,20)	0.337	0.321	[16,34)	0.382	0.349
[20,56]	0.360	0.357	[34,56]	0.322	0.340
S.D. of log wages					
S.D.	0.334	0.364	S.D.	0.360	0.351
Corr	0.686	0.410		0.686	0.410

Table 12: Sample fit of covariance matrix of time allocation

Correlation	Working (M)		Housework (M)		Working (F)		Housework (F)	
of Hours	Sim	Data	Sim	Data	Sim	Data	Sim	Data
Working (M)	1.000	1.000	-0.092	-0.123	-0.092	-0.123	0.077	-0.029
Housework (M)	-0.092	-0.123	1.000	1.000	0.093	0.105	0.127	0.106
Working (F)	0.204	0.243	0.093	0.105	1.000	1.000	-0.421	-0.374
Housework (F)	0.077	-0.029	0.127	0.106	-0.421	-0.374	1.000	1.000

Table 13: The average housework hours categorized by "fair share" question

	Male			Female		
Fair share	Housework hours	Relative difference	Number of obs.	Housework hours	Relative difference	Number of obs.
Much More(1)	31.38	10.86	26	35.00	3.72	287
A bit More(2)	21.34	0.97	181	28.30	-1.15	548
Fair Share(3)	18.64	-2.21	840	25.15	-4.75	532
A bit Less(4)	15.55	-5.55	362	17.78	-14.01	69
Much Less(5)	8.68	-13.80	34	9.29	-15.36	7

Note: "Relative difference" column displays the relative difference between the actual household hours and the simulated housework hours when setting Pareto weight $\alpha = 0.500$.

Table 14: The decomposition of gender wage gap

	Offered Wage	Accepted Wage
$\Delta\gamma_0$	0.1142	0.1142
Education	-0.1819	-0.1869
Conscientiousness	0.1195	0.1200
Openness	-0.0529	-0.0528
Stability	0.2502	0.2495
Agreeableness	-0.1337	-0.1338
Extraversion	-0.0306	-0.0308
Cognitive	0.0006	0.0012
Experience	0.3220	0.3271
Experience^2	-0.2109	-0.2165
$\Delta\epsilon$	0	-0.0303
Total	0.1931	0.1610

Table 15: The Oaxaca-Blinder decomposition for personality traits, education and working experience

	Total difference	Due to characteristic	Due to coefficients
Constant	0.1142	0.1142	0.0000
Education	-0.1819	-0.0032	-0.1787
Conscientiousness	0.1195	-0.0117	0.1313
Openness	-0.0529	-0.0040	-0.0489
Stability	0.2502	-0.0003	0.2506
Agreeableness	-0.1337	0.0236	-0.1573
Extraversion	-0.0306	-0.0029	-0.0277
Cognitive	0.0006	-0.0138	0.0144
Experience	0.3220	0.0596	0.2624
Experience^2	-0.2109	-0.0516	-0.1593
Total	0.1965	0.1098	0.0867

Table 16: The new allocations under different forms of interactions

	Gender	Participation rate	Housework hours	Working hours	Accepted wages	Wage Gap	Utility
Baseline	Males	95.2%	18.2	41.7	27.2	15.2%	5.45
	Females	85.0%	27.5	35.0	23.3		5.50
Cooperative	Males	95.9%	22.0	46.7	27.1	21.5%	5.48
	Females	92.7%	32.5	43.5	22.8		5.49
Non-cooperative	Males	93.6%	16.0	37.5	27.2	13.6%	5.42
	Females	80.2%	24.6	31.9	23.7		5.47

Note: The average working hours To be consistent with the previous wage decomposition, the wage gap here is defined as $\log W_m - \log W_f$

Table 17: The counterfactual experiment of random match

	Gender	Participation rate	Housework hours	Working hours	Accepted wages	Wage Gap	Cooperative Fraction
Baseline	Males	95.2%	18.2	41.7	27.2	15.2%	38.7%
	Females	85.0%	27.5	35.0	23.3		
Pure random matching	Males	84.7%	18.5	42.5	28.2	13.4%	32.6%
	Females	74.9%	26.9	38.7	24.6		
Limited random matching	Males	85.2%	18.6	42.3	28.2	13.1%	33.1%
	Females	75.2%	26.9	38.7	24.7		

Table 18: The new allocations under equal pay experiment

	Gender	Participation rate	Housework hours	Working hours	Accepted wages	Wage Gap	Cooperative Fraction
Baseline	Males	95.2%	18.2	41.7	27.2	15.2%	38.7%
	Females	85.0%	27.5	35.0	23.3		
Equal pay	Males	90.9%	19.3	38.3	27.4	-2.45%	38.8%
	Females	92.0%	25.9	39.2	28.1		

Table 19: Estimated parameters under two alternative estimation samples

	Data	Sample 1	Sample 2	Parameters	Sample 1	Sample 2
Male	Working Hours	44.10	44.03	λ_m	0.3625	0.3584
	S.D.	(9.54)	(9.70)		(0.1109)	(0.1220)
	Housework	18.19	14.29	δ_m	0.1367	0.1201
	S.D.	(12.86)	(10.62)		(0.0755)	(0.0744)
Female	Working Hours	33.48	36.29	λ_f	0.3365	0.3289
	S.D.	(12.31)	(13.14)		(0.0960)	(0.1123)
	Housework	27.87	20.27	δ_f	0.1936	0.1416
	S.D.	(17.59)	(13.48)		(0.1237)	(0.1103)

Note: while we only show selected estimates for sample 2 in this table, the full list of parameters is available upon request.

Figure Captions

Figure 1. Changes in Big-Five personality over the life-cycle (age 15-60)

Figure 2. Assortative matching of personality traits and cognitive ability

Figure 3. The distributions of both $\eta_m(i)$ and $\eta_f(i)$

Figure 4. Histograms of spousal production and preference parameters

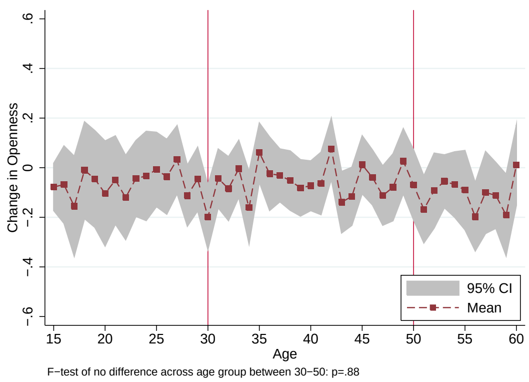
Figure 5. Bivariate relationships between production and preference parameters

Figure 6. Distributions of accepted wages and offered wages

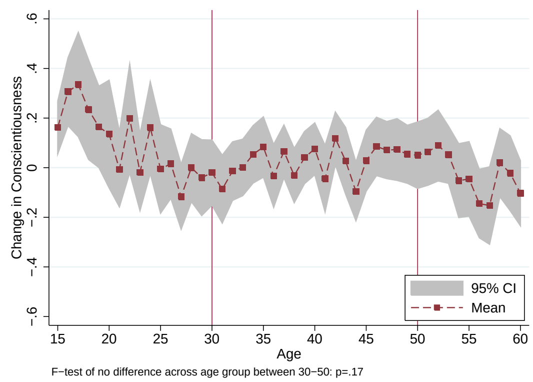
Figure 7. Distributions of accepted wages and offered wages

Figures

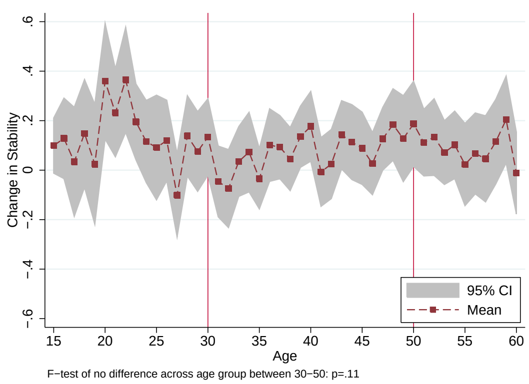
Figure 1: Changes in Big-Five personality over the life-cycle (age 15-60)



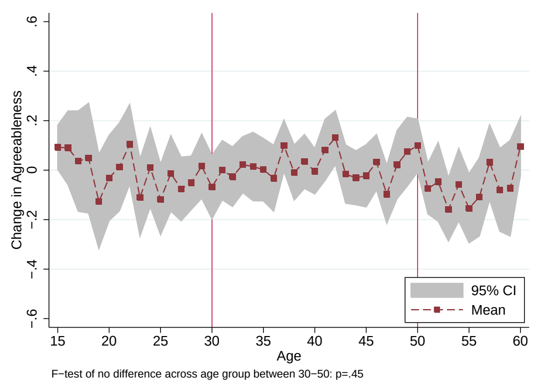
(a) Openness to experience



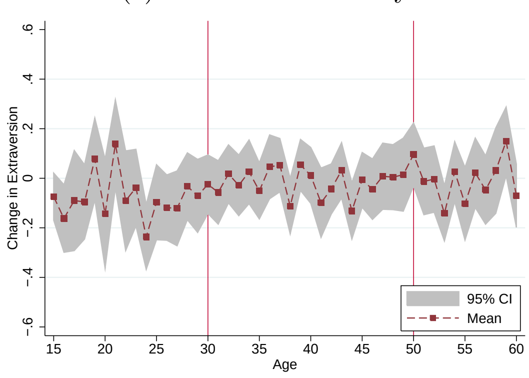
(b) Conscientiousness



(c) Emotional stability

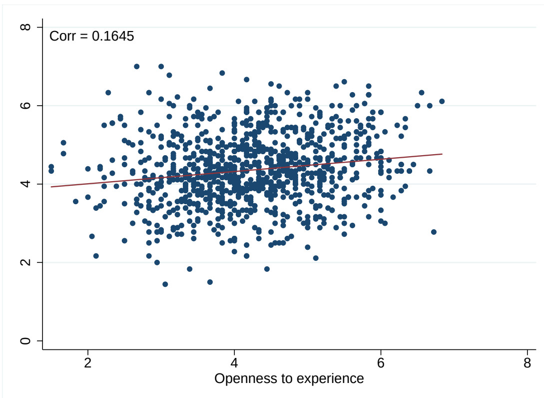


(d) Agreeableness

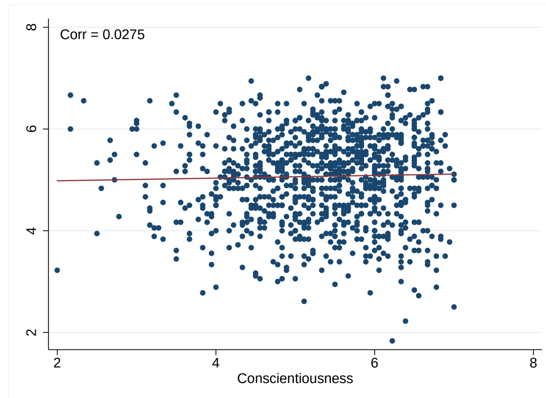


(e) Extraversion

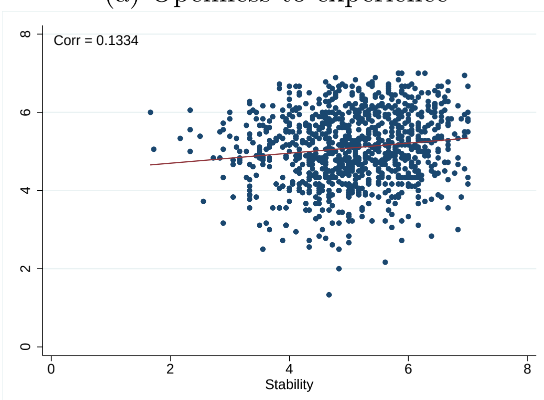
Figure 2: Assortative matching of personality traits and cognitive ability



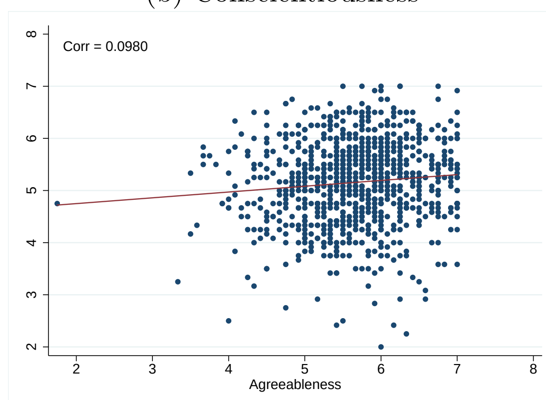
(a) Openness to experience



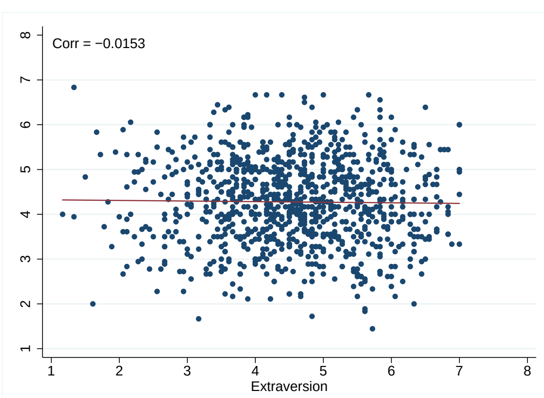
(b) Conscientiousness



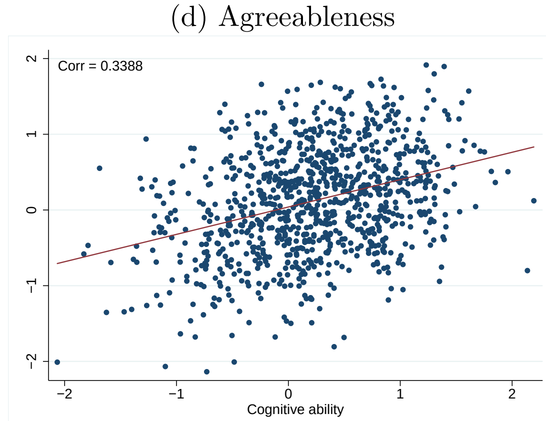
(c) Emotional stability



(d) Agreeableness



(e) Extraversion



(f) Cognitive ability

Figure 3: The distributions of both $\eta_m(i)$ and $\eta_f(i)$

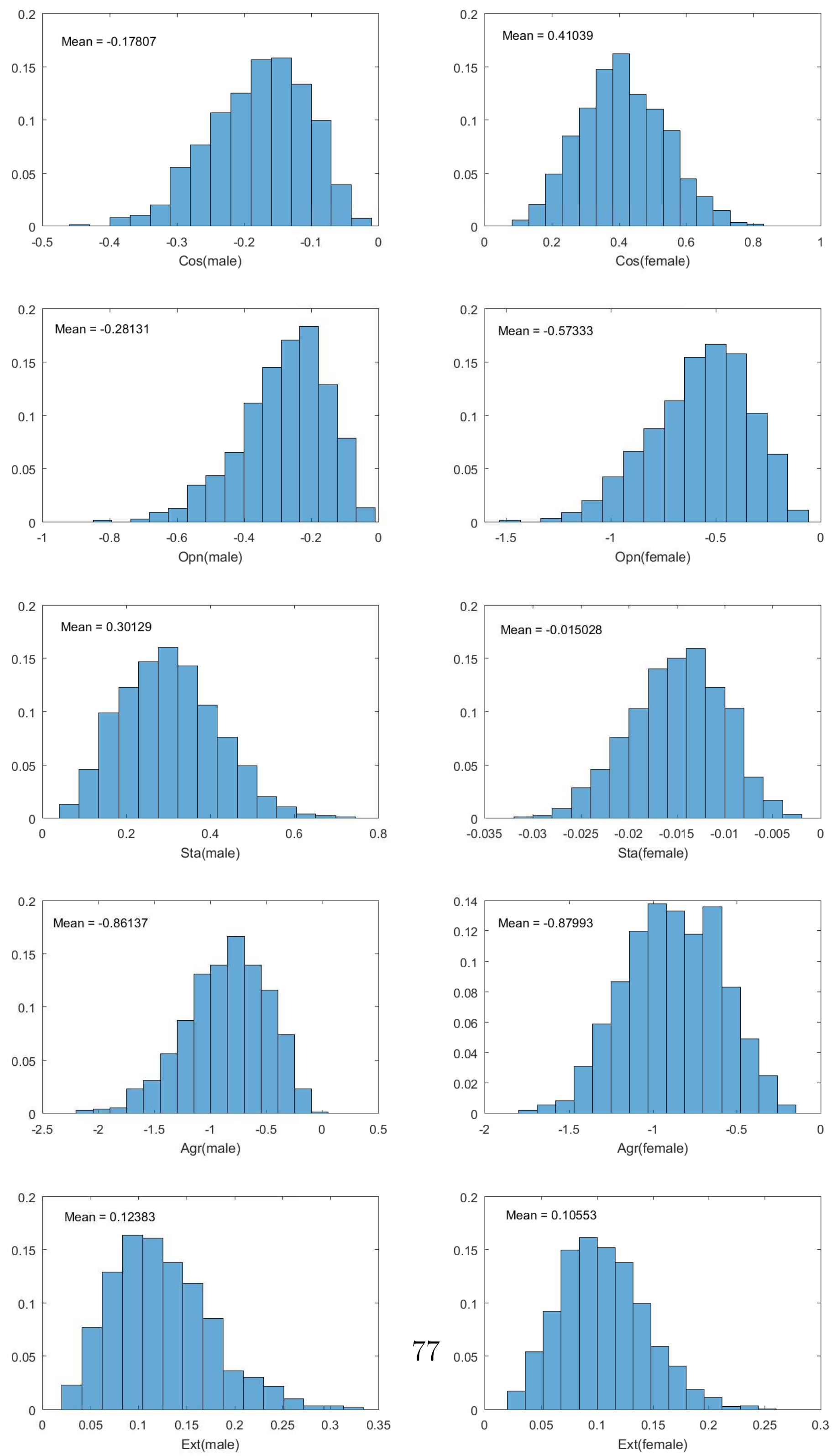
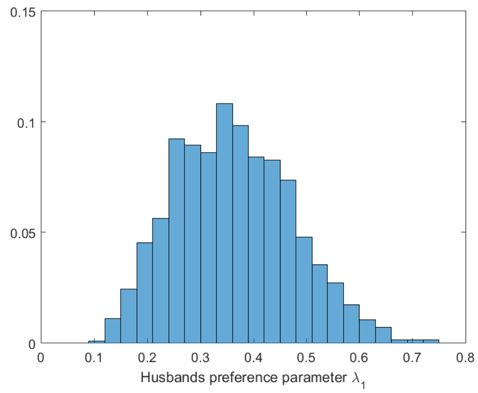
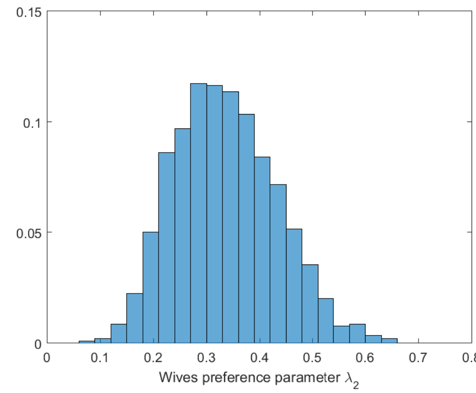


Figure 4: Histograms of spousal production and preference parameters

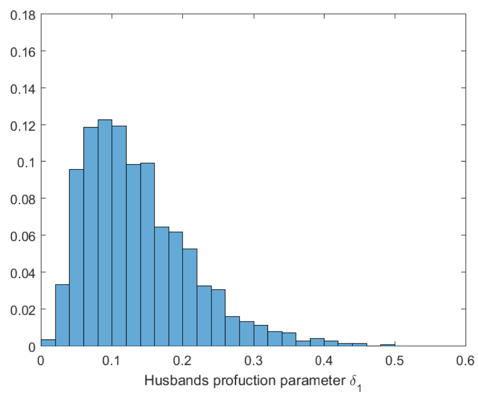
(a) Husbands' preference parameters λ_m



(b) Wives' preference parameters λ_f



(c) Husbands' production parameters δ_m



(d) Wives' production parameters δ_f

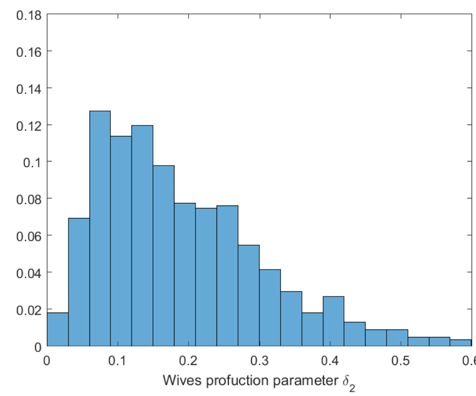
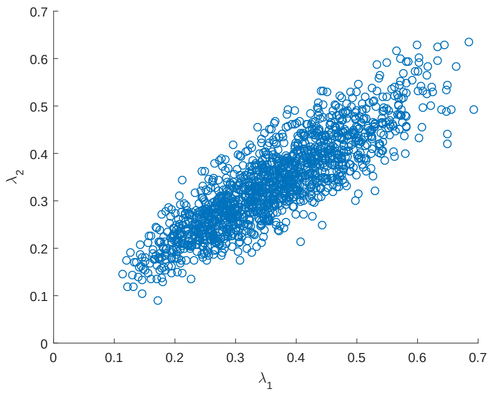
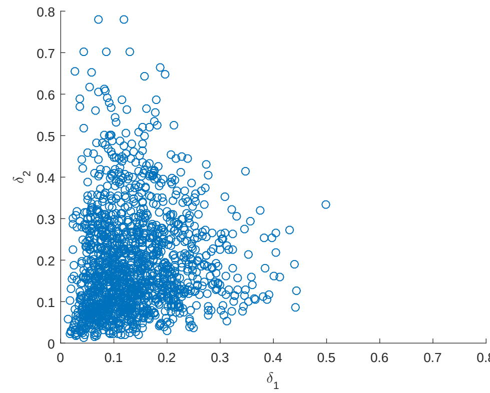


Figure 5: Bivariate relationships between production and preference parameters

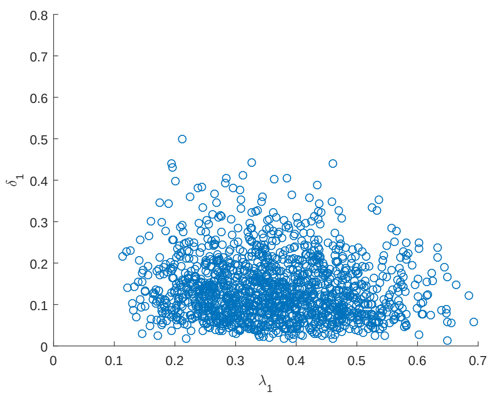
(a) Spousal preference parameters



(b) Spousal productivity parameters



(c) Husbands' primitive parameters



(d) Wives' primitive parameters

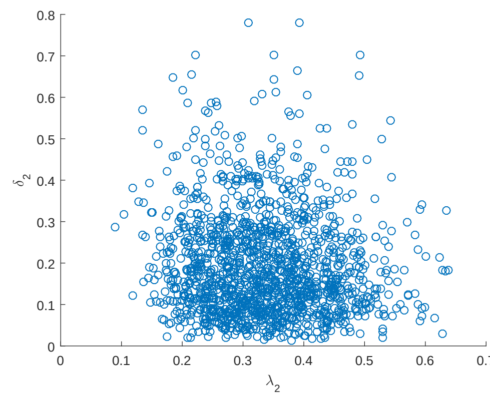
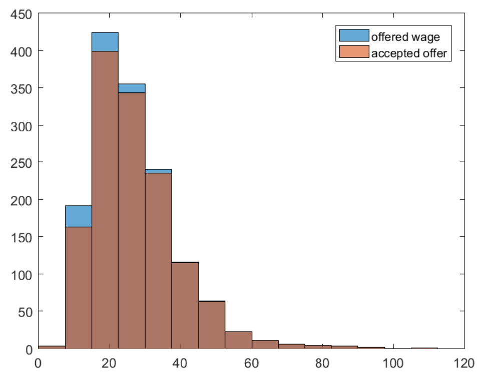


Figure 6: Distributions of accepted wages and offered wages

(a) Male's offered wage and accepted wage



(b) Female's offered wage and accepted wage

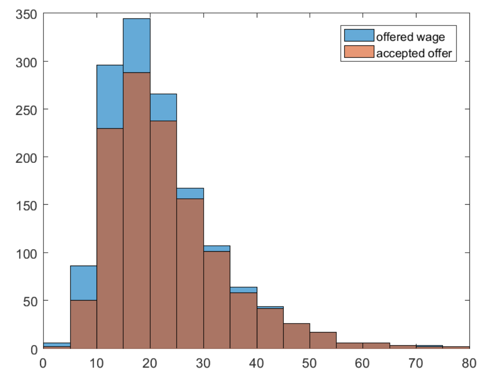
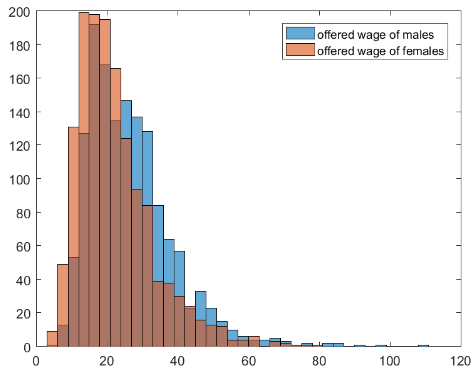
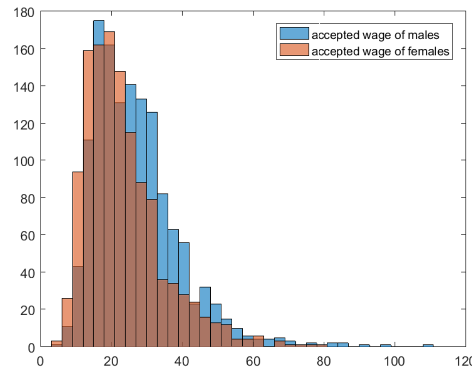


Figure 7: Distributions of accepted wages and offered wages

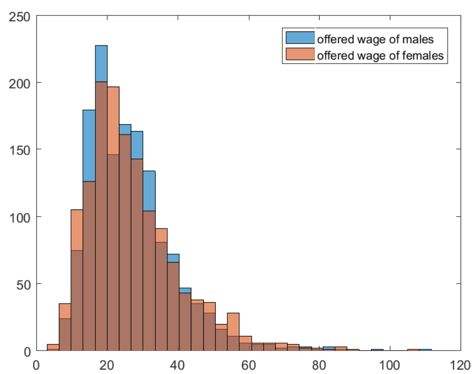
(a) Offered wages in baseline model



(b) Accepted wages in baseline model



(c) Offered wages in equal pay experiment



(d) Accepted wages in equal pay experiment