Heterogeneous Couples, Household Interactions and Labor Supply Elasticities of Married Women*

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September, 2014

Abstract

This paper estimates labor supply elasticities of married men and women allowing for heterogeneity among couples (by educational attainments of husbands and wives) and modeling explicitly how household members interact and make their labor supply decisions. We find that the labor supply decisions of husbands and wives depend on each other, unless both spouses are highly educated (college or above). For high–educated couples, the labor supply decisions of husband and wife are jointly determined only if they have pre–school children. We also find that labor supply elasticities differ greatly among households. The participation own wage elasticity is largest (0.77) for low–educated women married to low educated men, and smallest (0.03) for high–educated women married to low educated men. The own wage elasticities for low educated women married to high–educated men and for high–educated women married to high–educated men are similar and fall between these two extremes (about 0.30). For all types of couples, participation elasticity of non–labor family income is small. We also find that cross wage elasticities for married women are relatively small (less than -0.05) if they are married to low educated men and larger (-0.37) if they are married to high–educated men. Allowing for heterogeneity across couples yields an overall participation wage elasticity of 0.56, a cross wage elasticity of -0.13 and an income elasticity of -0.006 for married women. The analysis in this paper provides a natural framework to study how changes in educational attainments and household structure affect aggregate labor supply elasticities.

Keywords: Labor supply elasticity, household labor supply, household interactions, educational homogamy.

JEL Classification: J22, D10, C30.

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*I am grateful to Nezih Guner and Joseph Hotz for detailed comments and help. I thank Arnaud Maurel, Gabrielle Fack, Joan Llull, Manuel Arellano, Richard Blundell, Thomas Lemieux and Virginia Sánchez Marcos for valuable suggestions. I also benefited from discussions with seminar participants at the Labor Lunch Seminar at Duke University. The usual disclaimers apply.

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1 Introduction

Estimates of labor supply elasticities have a central place in empirical research in labor economics (Blundell and MaCurdy (1999) and Keane (2011) provide extensive surveys of this literature). This is not surprising given the key role labor supply elasticities play in policy analysis, e.g. taxation, and in models of macroeconomic fluctuations.[1] With few notable exceptions, e.g. Lundberg (1988), however, the empirical literature studies labor supply elasticities of males or females without allowing the possibility that husbands' and wives' labor supply decisions affect each other. Furthermore, labor supply elasticities are usually estimated for males or females as a group, and as a result labor supply decisions, and hence, labor supply elasticities, do not depend on educational attainment of females, or relative education levels of husbands and wives (i.e. who is married with whom).

While the empirical studies on labor supply elasticities do not usually contemplate interactions between household members, a growing, theoretical and empirical literature on household decision making emphasizes the importance of modeling households as a collection of individuals, each with his/her own utility function.[2] The conventional unitary model, which considers the family as a single decision unit has received little empirical support and it's theoretical foundations have been questioned. Several papers have proposed alternative models of family labor supply decision to incorporate preferences of different individuals living in the same household and to explain the interaction between family members. The alternative models include the cooperative bargaining models suggested by Manser and Brown (1980) and McElroy and Horney (1981), collective approach proposed by Chiappori (1988, 1992) and non-cooperative models developed by Konrad and Lommerud (1995).

This paper estimates labor supply elasticities of married men and women allowing for heterogeneity among couples (by educational attainment of husbands and wives) and modeling explicitly how household members interact and make their labor supply decisions. Our questions are: How do husbands and wives interact when they decide their labor supply? Do families differ in the way they make their labor supply decisions? How do these differences affect labor supply elasticities of different households?

[1] See, Chetty, Guren, Manoli and Weber (2011), Keane (2011) and Keane and Rogerson (2012).

[2] There a few studies in the empirical literature, e.g. Hausman and Ruud (1984), Kooreman and Kapteyn (1990), and Ransom (1987), that estimate the joint family labor supply. However, in all these studies, the household is considered as a single decision-maker and preferences of household members are represented by a joint household utility function.

We focus on the static labor supply decision of couples along the extensive margin. Couples differ in the education levels of husbands and wives, as well as the way they take their labor supply decisions. In particular, we consider two educational categories, below and above college degree (low and high). Since there are two education groups, we distinguish four types of couples: (i) low–educated husband and wife (homogamy–low) (ii) high–educated husband and low–educated wife (heterogamy–husband high) (iii) low–educated husband and high–educated wife (heterogamy–wife high), and (iv) high–educated husband and wife (homogamy-high). Once we move away from the standard unitary model and also allow for interactions between husbands and wives, we need to specify the way husbands and wives make their employment decisions. We consider five models of household decision making behavior: (i) a model without interactions between spouses' decisions, (ii) a non–cooperative Nash model, (iii) a Stackelberg model with the husband as the leader, (iv) a Stackelberg model with the wife as the leader, and (v) a mixed model of Pareto-optimality and Nash equilibrium. Using data from the 2000 U.S. Census, we estimate the parameters of each of these models for each type of households using a maximum likelihood estimation strategy. Then, given the parameter estimates, we select the model that predicts best the observed labor supply behavior of a particular couple in the sample. As a result, for each type of household, we know the fraction of couples that follows of a particular decision making process. Once we assign a particular decision making process for each household, we calculate labor supply elasticities of household members.

Our results show that couples differ in the way they make their labor supply decisions. The labor supply decisions of husbands and wives exhibit strong interactions unless both of the spouses are high–educated. In particular, for more than 48% of homogamy-low and heterogamy couples, the joint labor supply decisions of husbands and wives are determined by Stackelberg–wife leader game, whereas for 20% of the household decisions are predicted best by Nash/Pareto optimality model. The remaining homogamy-low and heterogamy type couples make their joint labor supply decision either independently, or following a non–cooperative Nash game or a Stackelberg–husband leader game. For homogamous–high couples, on the other hand, more than 45% of household decisions can be justified as coming from a model without interactions between spouses and more than 26% of household decisions as coming from a Nash game. The joint labor supply decision of remaining homogamy-high type couples are determined either by a Stackelberg leader game or Nash/Pareto optimality model. When we also consider the presence of children, we find that labor supply decisions of spouses are more likely to be independent of each other if there are no children of pre–

school age in the household. The presence of children matter most for homogamy–high couples. While without children, we do not observe any interactions for majority of households, with children their employment decisions follow a non–cooperative Nash game.

Moreover, the labor supply elasticities of married women of different types vary to a great extent when the heterogeneity is taken into account. The participation own wage elasticity is largest (0.77) for low–educated women married to low educated men, and smallest (0.03) for high–educated women married to low educated men. The own wage elasticities for low educated women married to high–educated men and for high–educated women married to high–educated men are similar and fall between these two extremes (about 0.30). We find that for all types of couples, participation elasticity of non–labor family income is rather small. We also find that cross wage elasticities for married women are relatively small (less than -0.05) if they are married to low educated men and larger (-0.37) if they are married to high–educated men.

Allowing for heterogeneity across couples yields an overall participation wage elasticity of 0.56, a cross wage elasticity of -0.13 and an income elasticity of -0.006 for married women. These elasticities are larger than the recent estimates of labor supply elasticities of married women (e.g. Blau and Kahn, 2007; Heim, 2007).[3] The current analysis differ from these studies as we allow for household interactions and we let these interactions differ across different types of households. Our analysis show that just allowing for household interactions –allowing for differences among couples in the way they make their labor supply decisions– while ignoring heterogeneity among households generates a lower labor supply wage elasticity (about 0.25) and higher labor supply cross wage (-0.24) and non–labor income (-0.006) elasticities for married women.

The results of this study has important implications for policy analysis. Since, many policies are designed to target specific groups, it is essential to understand the potential impacts on labor supply of different individuals. For instance, U.S. income transfer and tax policies –such as earned income tax credit (EITC) or Temporary Assistance for Family Needs (TAFN) programs– target to encourage work among low–income families or families with children.[4] The differences in labor supply elasticities of married women

[3] Heim (2007) shows that married women's participation wage elasticity declined from 0.66 to 0.03 and the participation income elasticity declined from -0.13 to -0.05 between 1979 and 2003 in the U.S. Blau and Kahn (2007) find that participation own wage elasticity of married women fell from 0.53–0.61 in 1980, to 0.41–0.44 in 1990, and to only 0.27–0.30 by 2000. The effect of spouse wages on participation also fell from -0.20 to -0.24 in 1980 to -0.11 to -0.13 in 2000, with most of the decline occurring over the 1980s.

[4] Since, estimates of labor supply elasticities are of key interest to policymakers, a substantial

based on the spouses' education levels is a dimension that has been overlooked by the literature. Earlier studies mostly focus on the heterogeneity associated to the presence of pre–school children (see Blundell and MaCurdy (1999) for a survey). We further show that differential responses of married women based on the spouses' education levels are present among married women, independent of whether children are present in the household or not.

Over the last decades, there has been dramatic changes in the educational composition of population in the U.S. Not only the educational attainment levels of men and women increased, but also the resemblance of husbands and wives on educational attainment increased substantially (Mare 1991; Pencavel 1998; Schwartz and Mare 2005).[5] The variation in labor supply elasticities of married women raises a natural question: What is the impact of compositional changes in population on women's overall labor supply elasticities? In order to get an idea of the effect of compositional changes on the married women's labor supply responsiveness we carry out a counterfactual exercise. We calculate what the overall labor supply elasticities would be, if the married women had the responsiveness of 2000 but the distribution of couples would have been as of 1980s. We find a participation own wage elasticity of 0.63, a participation cross wage elasticity of -0.11 and a participation non–labor income of -0.004. This implies that, although, compositional changes do not have a considerable effect on the participation cross wage and participation non–labor income elasticities of married women, changing composition of couples accounts for a decline in participation own wage elasticity of married women –from 0.63 to 0.56– between 1980 and 2000.

This paper is related to three strands of literature. First, it is naturally related to the large empirical literature that provides empirical estimates of labor supply elasticities of married women. Heim (2007) and Blau and Kahn (2007) are recent examples of papers in this group. Both studies find a decline in women's labor supply elasticities over the last decades. The decline in the labor supply elasticities of married women have been attributed to the increasing marriage instability and increasing work opportunities for women (Goldin, 1990; Blau and Kahn, 2007). However, marriage instability and work opportunities of women depend on educational attainment of women and also

macroeconomic literature concerned about modeling labor supply decision of married men and women to study optimal taxation policies. Recent examples of this literature includes Alesina, Ichino, and Karabarbounis (2011) and Guner, Kaygusuz and Ventura (2012a and 2012b).

[5] Greenwood, Guner, Kocharkov, and Santos (2012) develop a model of marriage, divorce, educational attainment and married female labor-force participation to understand the increase in assortative mating, and the differences in the fall in marriage and the rise in divorce in the U.S. They show that technological progress in the household sector and changes in the wage structure are important for explaining these facts.

educational similarity of spouses.[6] Since factors that might affect the labor supply responsiveness of married women differ by educational attainment and educational similarity of spouses, it is natural to think so does the labor supply responsiveness. In addition, Heim (2007) and Blau and Kahn (2007) abstract from the interactions between household members. There are few empirical studies estimated joint labor supply of husbands and wives as opposed to individual labor supply, examples are by Hausman and Ruud (1984), Kooreman and Kapteyn (1990), Lundberg (1988) and Ransom (1987). However, except Lundberg (1988), the estimates of these studies are based on a unitary model without considering the nature of households interactions. Lundberg (1988) tests alternative theories of family labor supply behavior and considers the role of presence of young children on household interactions. However, she abstracts from the labor supply decisions along the extensive margin.

Second, this paper is related to the literature that study household interactions. The models that we employ to estimate labor supply elasticity for women come from non-cooperative and cooperative models.[7] In non-cooperative models, developed by Ulph (1988) and Konrad and Lommerud (1995), each individual within a household maximize their own utility, relative to their own budget constraints, taking the actions of other household members as given and hence equilibrium is self-enforcing (Chen and Woolley, 2001). Cooperative approach includes cooperative bargaining models suggested by Manser and Brown (1980) and McElroy and Horney (1981) and collective models developed by Chiappori (1988, 1992). The collective approach suppose that household decisions are Pareto-efficient. Cooperative bargaining models, which is a particular case of collective models, represent household allocations as the outcome of some specific bargaining process and cooperative allocation reached depends crucially on the threat point, i.e. what happens in case of disagreement among couples.[8] Based on this literature, we consider two equilibrium concepts, non–cooperative Nash and Stackelberg leader game, and the approach which imposes Pareto optimality of

[6]Earlier studies show that high–educated women have lower marital dissolution rates than other women (Bumpass, Martin and Sweet, 1991; Martin, 2006). Moreover, the marriage instability is higher for couples with dissimilar education levels than couples with similar education levels (Martin, 2006; Tzeng, 1992). The direction and the magnitude of the effect depend on which spouse is more educated (Bitter, 1986; Bumpass, Martin and Sweet, 1991). On the other hand, highly educated women have gained the most, in terms of labor market opportunities, and labor force gains have been largest for wives married to highly educated and high earning husbands (Cohen and Bianchi, 1998; Juhn and Murphy, 1997).

[7]A large empirical industrial organization literature use game-theoretic models to build structural econometric models of entry, exit and market concentration. See Berry and Reiss (2007) for a review.

[8]Manser and Brown (1980) and McElroy and Horney (1981) use divorce as the threat point while Lundberg and Pollak (1993), Haddad and Kanbur (1994), Konrad and Lommerud (2000) and Chen and Woolley (2001) use some form of non-cooperative behavior as the threat point.

observed decisions of husbands and wives. We do not impose the restriction that all couples decide their labor supply in the same way and allow for the possibility that husband–wife interactions may differ across couples.

Finally, our paper is related to recent papers in empirical labor literature that allow for heterogeneity in household decision making or household interactions. Jia (2005) analyze the labor supply decision of retiring couples in Norway and assumes that there are two type of families, cooperative and non-cooperative households. Her results show that more than half of the households are of the non-cooperative type. Similarly, Eckstein and Lifshitz (2012) considers two type of families while modeling labor supply of husbands and wives, modern and classical. They assume that classical household follows a Stackelberg leader game in which the wife's labor supply decision follows her husband's already-known employment outcome, while the modern family plays a Nash game. They estimate that 38% of families are modern type and the participation rate of women in those households is almost 80%. Different than Eckstein and Lifshitz (2013), we consider education level and educational match as the source of heterogeneity and do not assume a certain structure in decision making a priori. In addition, we provide empirical estimates of labor supply elasticities for married women.

2 Modeling Family Labor Supply

We focus on the static labor supply decisions of husbands and wives along the extensive margin. To this end, let y_h and y_w be the participation decisions of the husband and the wife, respectively. The participation decisions of the husband and the wife are defined as

$$y_h = \begin{cases} 1 \text{ if the husband works} \\ 0 \text{ otherwise} \end{cases} \quad \text{and} \quad y_w = \begin{cases} 1 \text{ if the wife works} \\ 0 \text{ otherwise.} \end{cases}$$

We assume that each spouse maximizes his or her utility. However, husband's and wife's decisions are interdependent, such that each individual's employment decision is affected by his or her spouse's decision. Let $U_h(y_h, y_w)$ denote the husband's utility of taking action y_h if his wife takes action y_w, and $U_w(y_h, y_w)$ be the wife's utility of taking action y_w if her husband takes action y_h. Following McFadden (1974, 1981) the individual utilities, $U_h(y_h, y_w)$ and $U_w(y_h, y_w)$, are treated random and decomposed into deterministic and random components. Assumption A.1 states this formally:

Assumption A.1

$$
\begin{aligned}
U_h(y_h, y_w) &= V_h(y_h, y_w) + \eta_h(y_h, y_w) \\
U_w(y_h, y_w) &= V_w(y_h, y_w) + \eta_w(y_h, y_w),
\end{aligned}
$$

where for $i = h, w$, $V_i(y_h, y_w)$ is the deterministic component and $\eta_i(y_h, y_w)$ is the random component of the individual utility. Furthermore, we make the following simplifying assumption on random components:

Assumption A.2

$$
\begin{aligned}
\eta_h(1,1) - \eta_h(0,1) &= \eta_h(1,0) - \eta_h(0,0) = \varepsilon_h \\
\eta_w(1,1) - \eta_w(1,0) &= \eta_w(0,1) - \eta_w(0,0) = \varepsilon_w,
\end{aligned}
$$

where $(\varepsilon_h, \varepsilon_w)$ are normally distributed with zero means, unit variances and correlation ρ. Assumption A.2 states that the difference in random utility that an individual derives from working versus not working when his or her spouse works equals to the difference in random utility the individual derives from working versus not working when his or her spouse does not work. Hence, we allow for unobserved heterogeneity in utility derived from working through the ε_h and ε_w. The assumption of ε_h and ε_w to be correlated implies that in a particular couple, there are common unobserved factors between spouses affecting the husband's and wife's utilities of working.

Finally, we assume that the change in individual's deterministic utility associated to a change in spouse's action is constant. This is summarized in the following assumption:
Assumption A.3

$$
\begin{aligned}
V_h(1,1) - V_h(0,1) &= \alpha_h + V_h(1,0) - V_h(0,0) \\
V_w(1,1) - V_w(1,0) &= \alpha_w + V_w(0,1) - V_w(0,0).
\end{aligned}
$$

Since, by Assumption A.1, the random utility of working versus not working is the same whether the spouse works or not, Assumption A.2 implies that the change in individual's utility associated to a change in spouse's action is also constant. Hence, we rule out the second order effects of spouse's employment on individual's utility.

For empirical implementation, the deterministic component of individual's utility is assumed to be a linear function of individual's observable characteristics, x_h and x_w, such that $V_h(1,1) - V_h(0,1) = x_h'\beta_h$ and $V_w(1,1) - V_w(0,1) = x_w'\beta_w$. Hence, together with assumptions A.1 to A.3, the model is parametrized as

$$\begin{aligned} U_h(1,1) &= x_h'\beta_h^1 + \alpha_h^1 + \eta_h^1 & U_w(1,1) &= x_w'\beta_w^1 + \alpha_w^1 + \eta_w^1 \\ U_h(0,1) &= x_h'\beta_h^0 + \alpha_h^0 + \eta_h^0 & U_w(1,0) &= x_w'\beta_w^0 + \alpha_w^0 + \eta_w^0 \\ U_h(1,0) &= x_h'\beta_h^1 \qquad + \eta_h^1 & U_w(0,1) &= x_w'\beta_w^1 \qquad + \eta_w^1 \\ U_h(0,0) &= x_h'\beta_h^0 \qquad + \eta_h^0 & U_w(0,0) &= x_w'\beta_w^0 \qquad + \eta_w^0, \end{aligned} \tag{1}$$

where $\beta_i^1 - \beta_i^0 = \beta_i$, $\alpha_i^1 - \alpha_i^0 = \alpha_i$ and $\eta_i^1 - \eta_i^0 = \varepsilon_i$ for $i = w, h$.

In family labor supply model, the utility or the payoff of working can be interpreted as the market wages and the utility or the payoff of not working as the reservation wage of the individual. Since, an individual's utility depends on spouse's employment decision, there are two pairs of wage equations describing the market and reservation wage of the individuals.

Consider first wife's decision whether to work or not, i.e. $y_w \in \{0,1\}$. For $y_w = 1$, $U_h(0,1)$ denotes the reservation wage of the husband when his wife works. Similarly, for $y_w = 0$, $U_h(0,0)$ is his reservation wage when the wife does not work. Hence, the difference between $U_h(0,1)$ and $U_h(0,0)$ captures the impact of wife's employment on husband's reservation wage and it is denoted by α_h^0. On the other hand, for $y_w = 1$, $U_h(1,1)$ is the market wage of the husband when his wife works. When the wife does not work, i.e. $y_w = 0$, $U_h(1,0)$ gives the market wage of the husband. Note that the difference between $U_h(1,1)$ and $U_h(1,0)$ implies an affect of wife's employment on husband's reservation wage and it is denoted by α_h^1. For the wife, the wage equations are written analogously. For $y_h \in \{0,1\}$, $U_w(y_h, 0)$ represents wife's reservation wage and $U_w(y_h, 1)$ is her market wage. Hence for the wife, α_w^0 and α_w^1 denote the impact of husband's employment on wife's reservation wage and market wage, respectively. Although, economic theory suggests that spouse' employment would affect individual's reservation wage, not his or her market wage, one can test the presence of both effects by including both α_i^0 and α_i^1 (for $i = h, w$) in the model and testing the significance of these parameters. Therefore, we include the impact of spouse's employment decision on the individual's market wage (α_h^1 and α_w^1) in the model without imposing any a priori restriction that this effect is equal to zero.

To complete the family labor supply model, it is crucial to determine how the observed dichotomous variables y_h and y_w are generated. A natural way to formulate the family labor supply is a model of simultaneous probit model that adapts the latent variable approach in single-person discrete choice models to accommodate the labor supply decisions of both spouses.[9] The extension of single-person discrete choice model to the multiple–person choice model suggests that the observed dichotomous variables (y_h and y_w) are generated according to the following rule:

$$y_h = \begin{cases} 1 \; if \; y_h^* \geq 0 \\ 0 \; otherwise \end{cases} \text{and} \;\; y_w = \begin{cases} 1 \; if \; y_w^* \geq 0 \\ 0 \; otherwise, \end{cases}$$

where

$$y_h^* = y_w[U_h(1,1) - U_h(0,1)] + (1 - y_w)[U_h(1,0) - U_h(0,0)],$$

and

$$y_w^* = y_h[U_w(1,1) - U_w(0,1)] + (1 - y_h)[U_w(1,0) - U_w(0,0)]. \tag{2}$$

Equation 2 states that, for a given employment decision of the spouse, the individual decides whether to work or not based on a simple utility comparison. Under the assumptions A.1 to A.3, and model parametrization in Equation 1, it follows that

$$\begin{aligned} y_h^* &= x_h^{'}\beta_h + \alpha_h y_w + \varepsilon_h \\ y_w^* &= x_w^{'}\beta_w + \alpha_w y_h + \varepsilon_w, \end{aligned} \tag{3}$$

where $(\varepsilon_h, \varepsilon_w)$, as stated above, have a bivariate standard normal distribution with correlation ρ.

Given Equation 3, husband's and wife's utility comparisons, as a result the probability of different outcomes to arise, can be written in terms of conditions on the random components ε_h and ε_w. Therefore, the probability of each four possible outcome for the joint labor supply decision of a couple –both spouses work, only husband works, only wife works or both spouses do not work– can be expressed in terms of model parameters. Table 1 presents the conditions on the husband's and wife's utility comparisons and the conditions that must be satisfied by the random components for each possible outcome to arise.

For instance, for a given employment decision of the wife y_w, the husband works if his utility of working, $U_h(1, y_w)$, is greater than his utility of not working, $U_h(0, y_w)$. Similarly, the wife works based on the comparison between $U_w(1, y_w)$ and $U_w(0, y_w)$

[9] See Maddala (1974) for alternative formulations of simultaneous equations for dummy endogenous variables based on the latent variable approach.

Table 1: Conditions for observed outcomes in simultaneous probit model

Husband's and Wife's actions	Utility Comparison	Condition
$y_h = 1$ and $y_w = 1$	$U_h(1,1) > U_h(0,1)$ and $U_w(1,1) > U_w(1,0)$	$\varepsilon_h > -x_h^{'}\beta_h - \alpha_h$ and $\varepsilon_w > -x_w^{'}\beta_w - \alpha_w$
$y_h = 1$ and $y_w = 0$	$U_h(1,0) > U_h(0,0)$ and $U_w(1,0) > U_w(1,1)$	$\varepsilon_h > -x_h^{'}\beta_h$ and $\varepsilon_w < -x_w^{'}\beta_w - \alpha_w$
$y_h = 0$ and $y_w = 1$	$U_h(0,1) > U_h(1,1)$ and $U_w(0,1) > U_w(0,0)$	$\varepsilon_h < -x_h^{'}\beta_h - \alpha_h$ and $\varepsilon_w > -x_w^{'}\beta_w$
$y_h = 0$ and $y_w = 0$	$U_h(0,0) > U_h(1,0)$ and $U_w(0,0) > U_w(0,1)$	$\varepsilon_h < -x_h^{'}\beta_h$ and $\varepsilon_w < -x_w^{'}\beta_w$

for a given employment decision of her husband y_h. Hence, for a particular couple, the probability that both spouses work, i.e. $(y_h, y_w) = (1,1)$, equals to the probability that $U_h(1,1) > U_h(0,1)$ and $U_w(1,1) > U_w(1,0)$. However, the utility comparisons, $U_h(1,1) > U_h(0,1)$ and $U_w(1,1) > U_w(1,0)$ can only arise if certain conditions on the random components ε_h and ε_w are satisfied. In particular, given Equation 3, $U_h(1,1) > U_h(0,1)$ and $U_w(1,1) > U_w(1,0)$ will only hold if $\varepsilon_h > -x_h^{'}\beta_h - \alpha_h$ and $\varepsilon_w > -x_w^{'}\beta_w - \alpha_w$. Hence, the probability that both spouses work, i.e. $(y_h, y_w) = (1,1)$ equals to the probability that $\varepsilon_h > -x_h^{'}\beta_h - \alpha_h$ and $\varepsilon_w > -x_w^{'}\beta_w - \alpha_w$. Therefore, the probability of $(y_h, y_w) = (1,1)$ can be expressed in terms of model parameters.

The multiple-person choice models differ from single-person models since they include simultaneity among individuals' decisions (Bresnahan and Reiss, 1991). A well known difficulty with the simultaneous probit model is that, the relationship between $(\varepsilon_h, \varepsilon_w)$ and (y_h, y_w) defined by the model is not one to one. In particular, the sum of the probabilities of observed outcomes either exceeds one or is less than one depending on the sign of the $\alpha_h \times \alpha_w$. Therefore, the model described in Equation 3 is *incoherent* and *incomplete.*[10] For instance, if $\alpha_h \times \alpha_w \geq 0$, there is a region $R \subset \varepsilon_h \times \varepsilon_w$, where the model delivers multiple solutions for y_h and y_w for the same set of parameter values, i.e. the model is *incomplete*. Hence, the sum of the probabilities of four mutually exclusive possible outcomes –$(1,1)$,$(1,0)$,$(0,1)$ and $(0,0)$– exceeds one. On the other hand, if $\alpha_h \times \alpha_w < 0$, the model is *incoherent* for the region $R \subset \varepsilon_h \times \varepsilon_w$, i.e. there is no solution for y_h and y_w. In this case, the sum of the probabilities of possible outcomes

[10]See Figure A.1. of Appendix A for details.

is less than one.

The simultaneous probit model to be coherent, one needs to impose the condition $\alpha_h \times \alpha_w = 0$, which essentially eliminates the simultaneity from the model (e.g. Heckman, 1978). However, simultaneity is crucial for allowing the possibility that husband's and wife's labor supply decisions affect each other. To consider the interdependence of husband's and wife's employment decisions, an alternative is to impose more structure to the model. The models developed by Bjorn and Vuong (1984, 1985) and Kooreman (1994) ensure the completeness and coherency without imposing the coherency restrictions. In this setting, instead of the rule described in Equation 2, the observed dichotomous variables y_h and y_w are assumed to be the outcome of a static discrete game played between two agents.

Bjorn and Vuong (1984) use the non-cooperative Nash concept and assume that the observed dichotomous variables are the Nash Equilibrium outcomes of a game played between players. Bjorn and Vuong (1985) propose a model that uses the Stackelberg equilibrium concept in which the outcomes of the sequential decision-making problem are generated as Stackelberg equilibrium of a game played between players. Since the game theoretical models may yield outcomes that are not Pareto optimal, Kooreman (1994) suggests an alternative approach that is based on the Nash principle but ensures that the outcome is always Pareto optimal. In our analysis, we employ the game–theoretical models suggested by Bjorn and Vuong (1984, 1985) and Kooreman (1994) in addition to the simultaneous probit model by imposing the coherency condition ($\alpha_h = \alpha_w = 0$). We compare game–theoretical models that allows for the interdependence of husband's and wife's employment decisions with the model without interactions between spouses' decisions, namely simultaneous probit model with coherency condition imposed.

2.1 Nash Model

For modeling family labor supply, we assume that each individual maximizes his or her utility given the employment decision of the spouse. Hence, a natural framework to model the family labor supply is a game played between spouses. In the Nash model, observed decisions of the husband and the wife, y_h and y_w, are assumed to be the outcomes of a non–cooperative game played between spouses.

In the Nash game, husband and wife decide their labor supply simultaneously. Hence, each possible decision of the spouse leads to a reaction function for the individual. Since there are four possible outcomes of the game –both spouses work, only husband works, only wife works or both spouses do not work– each spouse has four possible reaction functions. These reaction functions are (i) always decide not to work (ii) always take the same action as the spouse (iii) always take the opposite action of the spouse, and (iv) always decide to work. As the roles of the spouses in this game are symmetric, the reaction functions of the husband and the wife are identical. We denote the reaction functions of the husband with H_1, H_2, H_3 and H_4, and the reaction functions of the wife with W_1, W_2, W_3 and W_4. The reaction functions for the husband and the wife are summarized in the first columns of Table 2 and Table 3, respectively.

Each reaction function for an individual will arise, i.e. will be the best response, if certain conditions on utility comparisons hold. Second columns of Table 2 and Table 3, summarize the utility comparisons of the husband and the wife for their corresponding reaction functions. Each utility comparison, however, can only arise if certain conditions on the random components ε_h and ε_w are satisfied. We use model parametrization in Equation 1 to determine the conditions on the random components that must be satisfied for each reaction function to arise. These conditions are provided in the third columns of Tables 2 and 3. For instance, the reaction function H_1 says that husband always chooses not to work, whether wife works or does not work (column 1 of Table 2). The reaction function H_1 arises, if for the husband the utility of not working is greater than the utility of working for any decision of the wife, i.e. $U_h(1, y_w) < U_h(0, y_w)$ for $y_w = 0, 1$ (column 2 of Table 2). The condition on the random component ε_h for utility comparison $U_h(1,1) < U_h(0,1)$ and $U_h(1,0) < U_h(0,0)$ is $\varepsilon_h < -x_h'\beta_h - max(0, \alpha_h)$ (column 3 of Table 2).

Table 2: Husband's reaction functions

Reaction function	Utility Comparison	Condition
H_1: $y_h = 0$ if $y_w = 0$ and $y_h = 0$ if $y_w = 1$	$U_h(1,0) < U_h(0,0)$ and $U_h(1,1) < U_h(0,1)$	$\varepsilon_h < -x_h'\beta_h - max(0, \alpha_h)$
H_2: $y_h = 0$ if $y_w = 0$ and $y_h = 1$ if $y_w = 1$	$U_h(1,0) < U_h(0,0)$ and $U_h(1,1) > U_h(0,1)$	$-x_h'\beta_h - \alpha_h < \varepsilon_h < -x_h'\beta_h$ if $\alpha_h \geq 0$
H_3: $y_h = 1$ if $y_w = 0$ and $y_h = 0$ if $y_w = 1$	$U_h(1,0) > U_h(0,0)$ and $U_h(1,1) < U_h(0,1)$	$-x_h'\beta_h < \varepsilon_h < -x_h'\beta_h - \alpha_h$ if $\alpha_h < 0$
H_4: $y_h = 1$ if $y_w = 0$ and $y_h = 1$ if $y_w = 1$	$U_h(1,0) > U_h(0,0)$ and $U_h(1,1) > U_h(0,1)$	$\varepsilon_h > -x_h'\beta_h - \min(0, \alpha_h)$

Given the reaction functions of the husband and the wife, the Nash Equilibrium in

Table 3: Wife's reaction functions

Reaction function	Utility Comparison	Condition
W_1: $y_w = 0$ if $y_h = 0$ and $y_w = 0$ if $y_h = 1$	$U_w(0,1) < U_w(0,0)$ and $U_w(1,1) < U_w(1,0)$	$\varepsilon_w < -x_w^{'}\beta_w - \max(0, \alpha_w)$
W_2: $y_w = 0$ if $y_h = 0$ and $y_w = 1$ if $y_h = 1$	$U_w(0,1) < U_w(0,0)$ and $U_w(1,1) > U_w(1,0)$	$-x_w^{'}\beta_w - \alpha_w < \varepsilon_w < -x_w^{'}\beta_w$ if $\alpha_w > 0$
W_3: $y_w = 1$ if $y_h = 0$ and $y_w = 0$ if $y_h = 1$	$U_w(0,1) > U_w(0,0)$ and $U_w(1,1) < U_w(1,0)$	$-x_w^{'}\beta_w < \varepsilon_w < -x_w^{'}\beta_w - \alpha_w$ if $\alpha_w < 0$
W_4: $y_w = 1$ if $y_h = 0$ and $y_w = 1$ if $y_h = 1$	$U_w(0,1) > U_w(0,0)$ and $U_w(1,1) > U_w(1,0)$	$\varepsilon_w > -x_w^{'}\beta_w - \min(0, \alpha_w)$

pure strategies (hereinafter NE) can be defined. Table 4 presents the NE for each of the pairs of reaction functions. For instance, for the pair (H_1, W_4), there is a unique NE, that is (0,1), i.e. husband chooses not to work and wife chooses to work. As seen in Table 4, in some cases, there are multiple Nash equilibria and in some others, there is no NE in pure strategies.

Table 4: Nash Equilibria in pure strategies

Husband/Wife	W_1	W_2	W_3	W_4
H_1	(0,0)	(0,0)	(0,1)	(0,1)
H_2	(0,0)	(0,0) or (1,1)	No NE	(1,1)
H_3	(1,0)	No NE	(0,1) or (1,0)	(0,1)
H_4	(1,0)	(1,1)	(1,0)	(1,1)

Following Bjorn and Vuong (1984), we assume that one of the equilibria is chosen by the couple with equal probabilities in case of multiple equilibria. In case of no Nash equilibrium, the couple is assumed to choose one of the possible alternatives with equal probabilities. For instance, the outcome $(y_h, y_w) = (0, 1)$, i.e. husband does not work and wife works, is the NE, if the pair of husband's and wife's reaction functions is (H_1, W_3), or (H_1, W_4), or (H_3, W_4). In addition, the NE of the game will be (0,1) with a probability 1/2 if the pair of husband's and wife's reaction functions is (H_3, W_3) and with a probability 1/4 if the pair of husband's and wife's reaction functions is (H_3, W_2). Hence, the probability of the outcome $(y_h, y_w) = (0, 1)$ to be NE of the game, can be written as the sum of probabilities of husband's and wife's reaction functions pairs to arise. Given Tables 2 to 4, the probability of each four possible outcome for the joint labor supply decision of a couple –both spouses work, only husband works, only wife works or both spouses do not work– can be expressed in terms of conditions on the random components ε_h and ε_w, i.e. model parameters.[11]

2.2 Stackelberg Leader Model

The labor supply decision of couples can also be reformulated by using a different equilibrium concept, that is of Stackelberg–leader game. In this case, y_h and y_w are assumed to be the Stackelberg leader equilibrium (hereinafter SE) outcomes of a sequential game played between players. In this game, one of the players (leader) moves first and then the other player (follower) moves sequentially. Hence, the roles of players are asymmetric. The leader is assumed to maximize his or her utility anticipating the reaction of the follower. In other words, the leader takes into account the payoff of the follower in making his or her decision. Since in family labor supply, the roles of husband and wife are not known a prior, we consider two versions of Stackelberg leader game played between spouses, one husband being the Stackelberg leader (Stackelberg–husband leader) and another one wife being the Stackelberg leader (Stackelberg–wife leader). In this section, we explain briefly the Stackelberg model assuming the wife is the Stackelberg leader and her husband is the follower. The description of Stackelberg–husband leader model can be derived analogously.[12]

In Stackelberg–wife leader game, wife takes into account the four possible reaction functions of her husband, H_1, H_2, H_3, and H_4 when she makes her decision. The reaction functions of the husband are described in Table 5 (column 1). For example, the reaction function H_1 says that the husband will always choose not to work whether the wife works or not. In this case, for any possible action that wife can take, the utility of not working is greater for the husband than the utility of working, i.e. $U_h(0,1) > U_h(1,1)$ and $U_h(0,0) > U_h(1,0)$. Hence, each reaction function of the husband can only arise if certain conditions on the husband's utility rankings are satisfied. Once again, each utility comparison correspond to a condition on random components ε_h (columns 2 and 3 of Table 5).

Since in Stackelberg–wife leader game, the roles of the spouses are asymmetric, each reaction function of the husband calls a utility comparison for the wife. For each of the reaction function of the husband, the utility comparison of the wife, S_j for $j = 1, 2, 3, 4$ is given in Table 6. For example, when she makes her decision, if wife knows that the husband will always decide not to work whether she decides to work or not, the utility

[11]See Appendix B for details.

[12]See Appendix D for the description of SE in Stackelberg–husband leader game.

Table 5: Husband's reaction functions

Reaction function	Utility comparison	Condition
H_1: $y_h = 0$ if $y_w = 0$ and $y_h = 0$ if $y_w = 1$	$U_h(0,1) < U_h(0,0)$ and $U_h(1,1) < U_h(1,0)$	$\varepsilon_w < -x_h^{'}\beta_h - \max(0, \alpha_h)$
H_2: $y_h = 0$ if $y_w = 0$ and $y_h = 1$ if $y_w = 1$	$U_h(0,1) < U_h(0,0)$ and $U_h(1,1) > U_h(1,0)$	$-x_h^{'}\beta_h - \alpha_h < \varepsilon_h < -x_h^{'}\beta_h$ if $\alpha_h > 0$
H_3: $y_h = 1$ if $y_w = 0$ and $y_h = 0$ if $y_w = 1$	$U_h(0,1) > U_h(0,0)$ and $U_h(1,1) < U_h(1,0)$	$-x_h^{'}\beta_h < \varepsilon_h < -x_h^{'}\beta_h - \alpha_h$ if $\alpha_h < 0$
H_4: $y_h = 1$ if $y_w = 0$ and $y_h = 1$ if $y_w = 1$	$U_h(0,1) > U_h(0,0)$ and $U_h(1,1) > U_h(1,0)$	$-x_h^{'}\beta_h - \min(0, \alpha_h) < \varepsilon_h$

Table 6: Wife's utility comparisons

Reaction function for the husband	Utility comparison for the wife	Condition
H_1	S_1: $U_w(1,0) > U_w(0,0)$	$\varepsilon_w > -x_w^{'}\beta_w$
H_2	S_2: $U_w(1,1) > U_w(0,0)$	$\varepsilon_w > -x_w^{'}\beta_w - \alpha_w^1$
H_3	S_3: $U_w(1,0) > U_w(0,1)$	$\varepsilon_w > -x_w^{'}\beta_w - \alpha_w^0$
H_4	S_4: $U_w(1,1) > U_w(1,0)$	$\varepsilon_w > -x_w^{'}\beta_w - \alpha_w$

comparison for the wife is S_1, i.e. the wife only works if $U_w(1,0) > U_w(0,0)$ and does not work if $U_w(1,0) < U_w(0,0)$. Once again, the utility comparisons of the wife can only arise if certain conditions are satisfied by ε_w. These conditions are provided in the last column of Table 6.

Table 7: Stackelberg Equilibria

H_1 and S_1	(0,1)	H_3 and S_3	(0,1)
H_1 and $\overline{S_1}$	(0,0)	H_3 and $\overline{S_3}$	(1,0)
H_2 and S_2	(1,1)	H_4 and S_4	(1,1)
H_2 and $\overline{S_2}$	(0,0)	H_4 and $\overline{S_4}$	(1,0)

Given the husband's reaction functions and the wife's utility comparisons, the SE can be defined. Table 7 presents the SE for each pair of husband's reaction function and wife's utility comparisons. In Table 7, $\overline{S_j}$ denotes the negation of S_j for $j = 1, 2, 3, 4$. For example for the pair of husband's reaction function and wife's utility comparison

(H_1, S_1), the unique SE is (0,1), i.e. husband decides not to work and the wife decides to work. As seen in Table 7, the SE is always unique. The outcome (0,1) is SE if the pair of husband's reaction functions and wife's utility comparisons is (H_1, S_1) or (H_3, S_3). Once again, the probability of each observed outcome can be written in terms of the probabilities of pairs of the reaction function of husband and the utility comparison of husband to arise, as a result in terms of model parameters.[13]

2.3 Nash/Pareto Optimality

It is well known that the game theoretical models may yield outcomes that are not Pareto optimal. Bargaining models and collective models are based on the hypothesis that the household decisions are Pareto optimal. Considering this possibility, we employ the approach suggested by Kooreman (1994) that imposes Pareto optimality on the observed outcomes of the game played between two players.

For the model described in Equation 1, there is a large number of cases with multiple solutions. For model predictability, Kooreman (1994) suggests to use Nash principle to reduce the large number of cases with multiple solutions. In this approach, players are assumed to play a Nash game and three cases are distinguished (i) there is a unique NE, (ii) there are multiple Nash equilibria and (iii) there is no NE in pure strategies. Kooreman (1994) shows the existence of Pareto optimal allocation in each of these cases. In particular (i) if the game has a unique NE that is not Pareto optimal, there exists exactly one allocation that both players are better off as compared to the NE (ii) if the game has two Nash equilibria in pure strategies, at least one of them is Pareto optimal, and (iii) if the game has no NE in pure strategies there will be at least two Pareto optimal allocation. Therefore, we distinguish the three cases and apply the following rule to determine the outcome of the game: (i) if the game has a unique NE and if this is Pareto optimal, then that is the outcome of the game. If the unique NE is not Pareto optimal, players are assumed to choose the Pareto efficient outcome, (ii) if the game has two Nash equilibria in pure strategies and if only one of the Nash equilibria is Pareto optimal, this is assumed to be the outcome of the game. If both NE of the Nash equilibria are Pareto optimal, the players are assumed to choose one of the two Nash equilibria with equal probabilities, and (iii) if the game does not have a NE in pure strategies, then players are assumed to choose one of the Pareto optimal allocations with equal probabilities.

[13]See Appendix C for details.

To determine observed outcomes based on the Nash/Pareto optimality model, utility rankings of husband and wife are required. Since there are four possible outcomes, the number of possible utility rankings for a couple is $4!^2$. In order to reduce the number of possible cases, it is necessary to impose restrictions on the model parameters. Since, in the family labor supply framework, the restrictions on the parameters, $\alpha_h^1 > 0$, $\alpha_h^0 > 0$, $\alpha_w^1 > 0$ and $\alpha_w^0 > 0$ imply that spouse's employment has a positive effect on individual's utility, in our analysis we impose α_h^1, α_h^0, α_w^1 and α_w to be positive.

Once again, using the model parametrization in Equation 1, the utility rankings of the husband and the wife can be written in terms of conditions on the random components ε_h and ε_w. This allows us to write the expressions for each possible outcome of the joint family labor supply, in terms of model parameters.[14]

3 Identification and Estimation

We estimate the game theoretical models described in the previous section using a maximum likelihood estimation strategy by assuming that $(\varepsilon_h, \varepsilon_w)$ follow a bivariate normal distribution with zero means, unit variances and correlation ρ. The log-likelihood function for each game-theoretical model is as follows:

$$\begin{aligned} L &= \sum\nolimits_c \log \Pr_c(y_h, y_w) \\ &= \sum\nolimits_c [y_h y_w \log \Pr_c(1,1) + y_h(1-y_w)\log \Pr_c(1,0) \\ &+ (1-y_h)y_w \log \Pr_c(0,1) + (1-y_h)(1-y_w)\log \Pr_c(0,0)], \end{aligned} \tag{4}$$

where c indexes the observations, i.e. couples. To estimate a particular model, the expressions for four outcome probabilities $(\Pr(1,1), \Pr(1,0), \Pr(0,1)$ and $\Pr(0,0))$ are replaced with their corresponding terms based on model parameters.[15]

In addition to game–theoretical models, we also consider a model without interactions between spouses' decisions. In particular, we estimate simultaneous probit model described in Equation 3 by imposing the coherency condition on model parameters. In particular we impose the condition that spouses' decisions do not affect each other's decision, i.e. $\alpha_h = \alpha_w = 0$ and estimate a bivariate probit model.

[14] See Appendix E for details.

[15] See Appendices B, C, D and E for the expressions for each possible outcome probability in Nash model, Stackelberg–wife leader model, Stackelberg–husband leader model and Nash/Pareto optimality, respectively.

Table 8: Identified parameters in models

Model	**Identified Parameters**
Bivariate probit	α_h and $\alpha_w = 0$, β_h, β_w
Nash	α_h, α_w, β_h, β_w
Stackelberg–husband leader	α_h^1 and α_h^0, α_w, β_h, β_w
Stackelberg–wife leader	α_h, α_w^1 and α_w^0, β_h, β_w
Nash/Pareto optimality	α_h^1 and α_h^0, α_w^1 and α_w^0, β_h, β_w

Since the expressions for probability of observing each outcome is different in each game theoretical model, all the parameters are not identified in all the models. The identifiable parameters in each model are summarized in Table 8. In all the models, β_h and β_w are identified, but β_h^1, β_h^0, β_w^1 and β_w^0 are not identified separately. Furthermore, the impact of wife's employment decision on husband's utility of not working, α_h^1 and on husband's utility of working, α_h^0 are separately identified only in Stackelberg–husband leader model and Nash/Pareto optimality. In the remaining models, only α_h, that is $\alpha_h^1 - \alpha_h^0$ is identified. On the other hand, the impact of husband's employment decision on wife's market and reservation wage (α_w^1 and α_w^0) are separately identified only in Stackelberg–wife leader model and Nash/Pareto optimality. In other game theoretical models, only the impact of husband's employment decision on the wife's utility difference between working and not working, $\alpha_w = \alpha_w^1 - \alpha_w^0$ is identified. By construction, in bivariate probit model, the impact of spouse's employment decision on the individual's utility is zero, i.e. $\alpha_h = 0$ and $\alpha_w = 0$.

In our analysis, we allow for the behavioral parameters of the models to differ among four type of couples. Therefore, for four type of couples (homogamy–low, heterogamy–husband high, heterogamy–wife high and homogamy-high), we estimate the bivariate probit model and game–theoretical models separately. Then, given the observed employment decision of couples, we determine the way that couples decide their labor supply. In particular, for each couple in the sample, we calculate the predicted probabilities of four possible outcomes –both work, only husband works, only wife works or both do not work– from each model. Next, we determine the model that gives the highest probability for the observed joint employment decision of the couple and assign to the couple this particular model. As a result, for each type (homogamy–low, heterogamy–husband high, heterogamy–wife high and homogamy–high), we estimate the fraction of households that make their decisions with a particular rule.

Once we assign a particular decision making process for each household, we predict the marginal probabilities of working for husband and wife from the assigned model. This allows us, in the next step to calculate the labor supply elasticities. To calculate the labor supply elasticities we increment own wage of the individual, or spouse's wage or non–labor family income of each couple by one percent. Then using the model parameters, we recalculate the marginal probabilities of working for husband and wife after the increase. Comparing the marginal probability of working for each individual before and after the incrementation gives us a participation elasticity of the husband and the wife of each couple. Finally, using the labor supply elasticities of couples, we calculate the average labor supply elasticity of married men and women.

4 Data and Empirical Specification

We use the 2000 Census data for the U.S. obtained from IPUMS-USA. The sample is restricted to married individuals ages 25-54 with a 25-54 year old spouse present, not living in group quarters, not in school and not self–employed. We also exclude from the sample, individuals with allocated annual weeks worked or allocated hours worked per year.[16] Since, the proportion of nonparticipating males is very small, we focus on working husbands and model the choice between working full-time and working part-time.[17] Therefore, in our analysis the observed outcomes, y_h and y_w are defined as

$$y_h = \begin{cases} 1 \text{ if husband works at least 35 hrs/wk} \\ 0 \text{ if husband works less than 35 hrs/wk} \end{cases} \quad \text{and} \quad y_w = \begin{cases} 1 \text{ if wife works} \\ 0 \text{ if wife does not work.} \end{cases}$$

One of the key variables in our analysis is educational attainment of husbands and wives. We consider the education level as high if the individual has at least a college degree and as low otherwise. Couples with similar education level (low–low or high–high) are considered as homogamy, while couples with different education levels (high–low or low–high) considered as heterogamy.

In the next step, we specify the set of explanatory variables of the market and reservation wage equations for husbands and wives. The market wage equations of husbands

[16] IPUMS determines the missing, illegible and inconsistent observations and allocates values to these observations using different procedures. IPUMS provides Data Quality Flag variables for these variables to determine allocated observations. See https://usa.ipums.org/usa/flags.shtml for details.

[17] Although in the Fair Labor Standards Act (FLSA), for the U.S. there is no definition of full-time or part-time employment,the 35 hours cut-off point is motivated by the fact that the Bureau of Labor Statistics (BLS) defines those who work for less than 35 hours per week as part-time workers.

and wives are

$$U_h(1, y_w) = x_h^{'}\beta_h^1 + \alpha_h^1 y_w + \eta_h^1$$
$$U_w(y_h, 1) = x_w^{'}\beta_w^1 + \alpha_w^1 y_h + \eta_w^1, \quad (5)$$

where x_h and x_w consist of age, years of education, race dummies, and geographic variables including a regional dummy and a dummy for residence being in a metropolitan statistical area (MSA), and a constant term. The reservation wage equations for husbands and wives are specified as

$$U_h(0, y_w) = z_h^{'}\beta_h^0 + \alpha_h^0 y_w + \eta_h^0$$
$$U_w(y_h, 0) = z_w^{'}\beta_w^0 + \alpha_w^0 y_h + \eta_w^0. \quad (6)$$

The set of explanatory variables of the reservation wage equation for husbands, z_h includes a constant term, non labor family income (defined as the sum of interest, dividends and rent income), logarithm of his hourly wage and logarithm of his wife's hourly wage. For wives, z_w includes a constant term, non–labor family income, logarithm of her hourly wage, logarithm of her husband's wage, number of children and a dummy for the presence of 0 to 6 years old children.

Since our interest is to calculate the labor supply elasticities, including individual's and the spouse's wages to the reservation wage equations is crucial in our analysis. However, we do not observe wages for non–workers. Thus, we use the following procedure to impute wages. First, we define hourly wages as annual earnings divided by annual hours worked for wage and salary workers. Second, we consider hourly wages as invalid if they are allocated or if they are less than \$2 or greater than \$250 per hour in 1999 dollars. Third, we run a separate selectivity bias corrected wage regression for each type of couples (homogamy-low, heterogamy-husband high, heterogamy-wife high and homogamy-high) and for each spouse (husbands and wives) using the Heckman two-step method (Heckman, 1979). In particular, at the first stage, a pair of reduced form probit regressions are run separately for husband and for wife for each type of couples of the form:

$$y_h^* = \tilde{z}_h^{'}\gamma_h + \xi_h,$$

and

$$y_w^* = \tilde{z}_w^{'}\gamma_w + \xi_w,$$

where

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ 0 \; otherwise \end{cases} \quad for \; i = h, w, \tag{7}$$

where $\widetilde{z}_h$ and $\widetilde{z}_w$ include the variables that affect the participation decisions of the husbands and wives. We include in $\widetilde{z}_h$ a constant, cubic terms in age and years of education, race dummy, non-labor family income and geographic variables including regional dummies and a dummy for the size of the MSA of residence. In addition, $\widetilde{z}_h$ and $\widetilde{z}_w$ include the number of children and the presence of children younger than six. At the second stage, we run selection corrected wage regressions for each gender and for each type of couples of the form

$$\ln W_h = \widetilde{x}_h^{'} \delta_h + \omega_h,$$

and

$$\ln W_w = \widetilde{x}_w^{'} \delta_w + \omega_w, \tag{8}$$

where $\widetilde{x}_h$ and $\widetilde{x}_w$ include the inverse Mills ratios calculated from the first stage, a constant term, cubic terms in age and years of education, race and geographic variables including regional dummies and a dummy for the size of the MSA of residence. The exclusion of non-labor income and children variables for wives and non-labor income for husbands at the first stage provides identification of the inverse Mills ratio term in the second stage. The predicted values for wages obtained from selection corrected wage equations specified in Equation 7 and imputed for all women and men to minimize the effect of measurement error in wages.[18]

The sample statistics by type of couples are provided in Table 9. Of the 848,835 remaining couples after selection, 79% of them are homogamy (57.64% low type and 21.31% high type), whereas, only 11.90% of them are heterogamy–husband high and 9.14% of them are heterogamy–wife high types. As seen in Table 9, men are more likely to be full–time employed independent of whom they marry with. On the other hand, employment rate of married women in our sample is around 82% for high–educated and only 75% for low–educated. Hence, a well–known fact, that is high–educated married women are more likely be employed than low–educated ones, is also present in our sample. What is lesser known is that, as seen in Table 9, high–educated women are less likely to be employed if they are married to high–educated men. In our sample,

[18]The identification of wage coefficients in Equation 5 comes form the exclusion of higher order terms in age and education in z_h and z_w.

among low–educated women, employment rate is larger for women married to low–educated men compared to women married to high–educated men.

Not surprisingly, wages increase by education level. However, average hourly wage differs within the same education group depending on the educational similarity between spouses. Among individuals with the same level of education (low or high), the logarithm of hourly wage is higher for those married to someone with high education than those married to someone with low education. Non–labor family income also increase by the level of educational attainment. High–educated couples have on average the highest non–labor family income. Among heterogamous couples, average non–labor family income is higher for wife being the low–educated and husband being the high–educated one.

By construction, the years of education differs among different type of households. However, among the same level of educational attainment, average years of schooling is higher for the ones that are married to someone with high education. Furthermore, the sample of wives are relatively younger than husbands. Husbands and wives of heterogamous couples with the wife being the low–educated spouse, are slightly older than other types of husbands and wives. More than 82% of the couples sample consists of whites, non–whites being more likely to be homogamy–low type. The average number of children is similar among couples. Homogamy–low and heterogamy–husband high type couples have slightly more kids compared to other couples. On the other hand, homogamy–high and heterogamy–wife high type couples are slightly more likely to have 0-6 years old children.

5 Estimation Results

In this section, we start presenting our estimation results. We first provide the key parameter estimates of bivariate probit model and game–theoretical models for homogamy–low, heterogamy–husband high, heterogamy–wife high and homogamy–high type couples. Then, using the parameter estimates of each model, we determine the way that couples decide their labor supply by assigning to each couple the model that gives the highest probability of the observed joint employment decisions of the husband and the wife. Hence, we know the fraction of couples that follows of a particular decision making process. In what follows, we first look at how well the estimated model fits the observed employment rates of husbands and wives. Given that the model provides a satisfactory fit to the data, we then calculate the labor supply elasticities of married

Table 9: Summary statistics by type of couples

	Homogamy low	**Heterogamy husband-high**	**Heterogamy wife-high**	**Homogamy high**
Wife				
Employed (%)	0.75	0.70	0.89	0.79
Log Hourly wage	2.37	2.48	2.89	2.93
	(0.19)	(0.14)	(0.15)	(0.15)
Age	38.67	40.45	38.32	38.85
	(7.53)	(7.40)	(7.38)	(7.61)
Years of education	11.84	12.76	16.46	16.70
	(2.07)	(1.09)	(0.84)	(0.95)
Race (% white)	0.79	0.86	0.84	0.85
Husband				
Employed full-time (%)	0.97	0.98	0.97	0.98
Log hourly wage	2.73	3.24	2.81	3.26
	(0.22)	(0.16)	(0.18)	(0.18)
Age	40.48	42.54	39.91	40.46
	(7.58)	(7.33)	(7.56)	(7.71)
Years of education	11.81	16.53	12.68	16.86
	(2.09)	(0.88)	(1.12)	(0.99)
Race (% white)	0.79	0.86	0.84	0.86
Family non-labor income	901	3,076	2,053	5,344
(in 000 dollars per year)	(7,298)	(14,790)	(12,332)	(20,726)
Number of children	1.64	1.53	1.35	1.39
	(1.25)	(1.20)	(1.11)	(1.13)
% with 0-6 years old children	0.25	0.25	0.31	0.33
MSA (%)	0.78	0.88	0.84	0.91
Number of obs.	505,091	96,616	77,043	170,085

Data source: 5% sample of the 2000 Census IPUMS. *Notes:* Sample includes married individuals ages 25-54 with a 25-54 year old spouse present, not living in group quarters, not in school, not self-employed and do not have allocated weeks or hours. For husbands, the fraction of employed full time is over the employed husbands. Non–labor family income consists of interest, dividends and rent. Standard deviations in parenthesis.

women.

5.1 Key Parameter Estimates

Tables 10.a, 10.b, 10.c and 10.d provides the key parameter estimates for homogamy–low, heterogamy–husband high, heterogamy–wife high and homogamy–high type couples, respectively.[19] In all tables, each column represent the key parameter estimates (${\alpha_h}^1$, ${\alpha_h}^0$ α_w^1 and α_w^0), the coefficient estimates of own log wage, spouse's log wage and non–labor income for husbands and wives (β_h and β_w) from a particular model.

[19]The full set of estimates are available upon request.

We start with the estimates of β_h and β_w. As seen from each table, the coefficient estimates of own log wage, spouse's log wage and non–labor income for husbands and wives differ across models only slightly. On the other hand, there are significant differences across different types of couples. As expected, for all couples in all models, labor supply of married women is positively and significantly related to their own log wages (i.e. $\beta_w > 0$), negatively and significantly related to husband's log wages and non–labor family income (i.e. $\beta_w < 0$). For each model, the coefficient estimate of log own wage rate is highest for low–educated wives married to low education men and smallest for high–educated wives married to low educated men (Tables 10.a and 10.c). The coefficient estimates of own wage for low educated women married to high–educated men and for high–educated women married to high–educated men are similar and fall between these two extremes (Tables 10.b and 10.d). Moreover, the coefficient estimates of log husband's wage rate for married women are relatively small if they are married to low educated men (Tables 10.a and 10.c) and larger if they are married to high–educated men (Tables 10.b and 10.d). For all women, for each model, the coefficient estimates of non–labor family income is significant, but rather small.

For husbands, on the other hand the coefficient estimates, β_h, indicate that full–time employment of married men is positively and significantly related to their own log wages, negatively and significantly related to non–labor family income for all type of couples. However, for a particular model, the coefficient estimates of log wife's wage differ among types. For homogamy–low and heterogamy–husband high type couples, husband's full–time employment is positively and significantly related to wife's hourly wage. On the contrary, in homogamy–low and heterogamy–husband high type couples, husband's full–time employment is negatively and significantly related to wife's hourly wage in heterogamy–wife high type couples, whereas in homogamy–high type couples most of the models indicate no significant relation between husband's full–time employment and wife's hourly wage.[20]

Now, we turn our attention to the estimates of cross–effects. Recall that, for $i = h, w$, α_i^1 and α_i^0 denote the effect of spouse's employment on individual's market wage and reservation wage, respectively. A priori, spouse's employment is expected to increase the reservation wage of the individual ($\alpha_h^0 > 0$ and $\alpha_w^0 > 0$) and no cross effects ($\alpha_h^1 = 0$ and $\alpha_w^1 = 0$) are expected on the spouses' market wages. This implies negative estimates of the parameters $\alpha_h = \alpha_h^1 - \alpha_h^0$ and $\alpha_w = \alpha_w^1 - \alpha_w^0$. As Tables 10.a to 10.d present, the significant estimates of α_h (estimated and implied by the estimates for α_h^1

[20]The only exception is bivariate model which predicts a negative and significant relation between full–time employment and wife's hourly wage.

and α_h^0) are negative for all types.[21] In other words, participation of wife makes her husband less inclined to work full–time for all type of couples. However, for wives, the significant estimates of α_w (estimated or implied by the estimates for α_w^1 and α_w^0) are positive for all types. This implies that full–time employment of husband makes his wife more likely to work.

Next, we compare the estimates of the correlation parameter ρ. It is important to note that, ρ is not simply the correlation between omitted variables in the husband's and wife's equations. Instead, as seen in Assumption A.2, it arises from a more complicated relationship between $\varepsilon_h = \eta_h(1, y_w) - \eta_h(0, y_w)$ and $\varepsilon_w = \eta_w(y_h, 1) - \eta_w(y_h, 0)$. Recall that, ε_h and ε_w denote the difference between the random utility that the individual derives from working and not working for any given employment decision of the spouse. In families, where the division of housework is unbalanced, these terms might be negatively correlated. For instance, consider a couple that husband always chooses to work full–time given any decision of the wife. In this case, wife may take the housework responsibilities, and unless she receives a high–wage offer she may prefer not to work (i.e. her reservation wage increases). In this case, ρ will be negative. On the other hand, consider a couple that both spouses are career–oriented, and enjoy working more than staying at home. In this case, ρ will be positive. Consistent with this expectation, the significant estimates of ρ from game–theoretical models is negative for homogamy–low type couples and heterogamous couples (Tables 10.a to 10.c), whereas it is positive for homogamy–high type couples (Table 10.d).

Note that, the significant estimates of the parameter ρ from bivariate probit model and game–theoretical models have opposite signs (Tables 10.a and 10.d). In bivariate probit model, the cross-effects may be picked up by the correlation parameter ρ. In fact, for homogamy-low type (Table 10.a), the significant estimates for cross effects are positive (α_h and α_w) and in the bivariate probit model, that cross–effects are assumed to be zero, the estimate of the correlation parameter ρ turns to be positive. However, for homogamy–high type (Table 10.d) the sign of the correlation parameter estimate ρ is negative in bivariate probit model, whereas it is positive in game–theoretical models. Once again, for homogamy–high types, negative cross effects may be picked up by the correlation parameter ρ in the bivariate probit model.

[21]The only exceptions are Stackelberg–wife leader model for homogamy–low and Nash/Pareto optimality for heterogamy–wife high types.

Table 10.a: Key parameter estimates, Homogamy–low

Homogamy low		**Bivariate Probit**	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
β_w						
	log(wage)	1.920***	1.919***	1.919***	2.006***	1.918***
		(0.027)	(0.027)	(0.027)	(0.032)	(0.027)
	log(husband's wage)	-0.055***	-0.066***	-0.065***	0.028	-0.067***
		(0.015)	(0.016)	(0.016)	(0.019)	(0.016)
	non–labor income	-0.003***	-0.003***	-0.004***	-0.004***	-0.003***
	(in 000 dollars)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_h						
	log(wage)	0.710***	0.717***	0.718***	0.612***	0.721***
		(0.059)	(0.059)	(0.059)	(0.057)	(0.060)
	log(wife's wage)	0.148***	0.207***	0.195***	0.157***	0.197***
		(0.028)	(0.042)	(0.041)	(0.027)	(0.042)
	non–labor income	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(in 000 dollars)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	α_0^w				5.914	-0.290
α^w			0.288**	0.243	(26.512)	(0.179)
	α_1^w		(0.140)	(0.124)	6.112	0.035
					(26.511)	(0.095)
	α_0^h			-0.027		-0.408
α^h			-0.101	(0.132)	0.816***	(0.843)
	α_1^h		(0.053)	-0.119	(0.038)	-0.507
				(0.133)		(0.836)
ρ		0.025***	-0.039	-0.043	-0.106**	-0.068
		(0.005)	(0.051)	(0.055)	(0.045)	(0.062)
Log-likelihood		-324200.69	-324197.93	-324198.05	-324197.55	-324113.56
df		35	37	38	38	39
Number of obs.		505091	505091	505091	505091	505091

Data Source: 5% sample of the 2000 Census IPUMS.

Notes: (i) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (ii) See text for the description of the model parameters.

Table 10.b: Key parameter estimates, Heterogamy–husband high

Heterogamy husband high		**Bivariate Probit**	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
β_w						
	log(wage)	0.607***	0.583***	0.590***	0.572***	0.611***
		(0.097)	(0.097)	(0.097)	(0.118)	(0.103)
	log(husband's wage)	-0.833***	-0.820***	-0.824***	-0.842***	-0.852***
		(0.042)	(0.043)	(0.042)	(0.058)	(0.044)
	non–labor income	-0.006***	-0.005***	-0.006***	-0.005***	-0.006***
	(in 000 dollars)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_h						
	log(wage)	0.984***	0.702***	0.777***	0.068	0.741**
		(0.180)	(0.205)	(0.192)	(0.180)	(0.236)
	log(wife's wage)	0.239**	0.343**	0.348***	0.448***	0.473***
		(0.087)	(0.120)	(0.096)	(0.090)	(0.114)
	non–labor income	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***
	(in 000 dollars)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	α_0^w				2.108***	1.018***
α^w			1.258	0.761**	(0.179)	(0.298)
	α_1^w		(0.795)	(0.237)	2.990***	3.687***
					(0.160)	(0.415)
	α_0^h			0.275*		1.179***
α^h			-0.371	(0.131)	-0.781***	(0.124)
	α_1^h		(0.340)	0.010	(0.049)	0.908***
				(0.164)		(0.146)
ρ		-0.013	-0.330	-0.161	-0.226**	-0.202
		(0.012)	(0.189)	(0.101)	(0.075)	(0.114)
Log-likelihood		-65068.33	-65058.11	-65060.60	-65016.05	-65049.35
df		35	37	38	38	39
Number of obs.		96616	96616	96616	96616	96616

Data Source: 5% sample of the 2000 Census IPUMS.

Notes: (i) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (ii) See text for the description of the model parameters.

Table 10.c: Key parameter estimates, Heterogamy–wife high

Heterogamy wife high		**Bivariate Probit**	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
β_w						
	log(wage)	0.077	0.060	0.062	0.355	0.036
		(0.159)	(0.158)	(0.158)	(0.225)	(0.177)
	log(husband's wage)	-0.173**	-0.227***	-0.186**	-0.672***	-0.070
		(0.063)	(0.064)	(0.063)	(0.112)	(0.074)
	non–labor income	-0.005***	-0.005***	-0.005***	-0.006***	-0.010***
	(in 000 dollars)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
β_h						
	log(wage)	1.134***	0.991***	0.952***	0.826***	1.005***
		(0.213)	(0.227)	(0.222)	(0.192)	(0.207)
	log(wife's wage)	-0.277**	-0.233*	-0.230*	-0.254**	-0.333***
		(0.097)	(0.103)	(0.100)	(0.093)	(0.098)
	non–labor income	-0.003***	-0.004***	-0.003***	-0.003***	-0.005***
	(in 000 dollars)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	α_0^w				2.801***	7.259
α^w			2.101***	1.060**	(0.262)	(94.967)
	α_1^w		(0.336)	(0.365)	3.753***	7.219
					(0.228)	(94.976)
	α_0^h			0.518**		0.462***
α^h			-0.957**	(0.180)	-0.397***	(0.092)
	α_1^h		(0.360)	0.305	(0.029)	1.624***
				(0.272)		(0.132)
ρ		-0.005	-0.555***	-0.192	-0.266**	0.153
		(0.016)	(0.114)	(0.160)	(0.102)	(0.122)
Log-likelihood		-34748.79	-34741.43	-34741.21	-34704.29	-34726.17
df		35	37	38	38	39
Number of obs.		77043	77043	77043	77043	77043

Data Source: 5% sample of the 2000 Census IPUMS.

Notes: (i) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (ii) See text for the description of the model parameters.

Table 10.d: Key parameter estimates, Homogamy–high

Homogamy high		**Bivariate Probit**	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
β_w						
	log(wage)	0.872***	0.851***	0.865***	0.862***	0.861***
		(0.081)	(0.081)	(0.081)	(0.082)	(0.081)
	log(husband's wage)	-1.057***	-1.054***	-1.053***	-1.055***	-1.056***
		(0.035)	(0.035)	(0.035)	(0.036)	(0.035)
	non–labor income (in 000 dollars)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_h						
	log(wage)	0.942***	0.677***	0.742***	0.731***	0.715***
		(0.089)	(0.103)	(0.111)	(0.112)	(0.108)
	log(wife's wage)	-0.172**	-0.035	-0.059	-0.066	-0.059
		(0.057)	(0.063)	(0.065)	(0.067)	(0.066)
	non–labor income (in 000 dollars)	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	α_0^w				-0.587*	-2.089
α^w			0.456	-0.007*	(0.253)	(1.977)
	α_1^w		(0.307)	(0.003)	-0.196	-1.880
					(0.388)	(1.970)
	α_0^h			4.792		0.330***
α^h			-0.380***	(10.009)	-0.360***	(0.099)
	α_1^h		(0.088)	4.416	(0.063)	0.025
				(10.008)		(0.036)
ρ		-0.059***	-0.048	0.190***	0.037	0.003
		(0.010)	(0.108)	(0.051)	(0.114)	(0.148)
Log-likelihood		-96931.92	-96918.14	-96917.21	-96917.04	-96916.89
df		35	37	38	38	39
Number of obs.		170085	170085	170085	170085	170085

Data Source: 5% sample of the 2000 Census IPUMS.

Notes: (i) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (ii) See text for the description of the model parameters.

5.2 Distribution of Couples

Given the parameter estimates, we select the model that best predicts the observed joint labor supply behavior of each couple in the sample. To asses the model fit in terms of the employment rate of wives and full–time employment rate of husbands, Table 11 presents the actual and predicted employment rate of wives and full–time employment rate of different types. As shown in Table 11, the model predicts the employment rates of wives and husbands in different type of couples very closely.

Table 11: Actual and predicted employment rates

	Employment rate of wives		**Full-time employment rate of husbands**	
	Actual	**Predicted**	**Actual**	**Predicted**
Homogamy-low	0.75	0.76	0.89	0.90
Heterogamy-husband high	0.70	0.71	0.79	0.79
Heterogamy-wife high	0.89	0.90	0.97	0.97
Homogamy-high	0.79	0.79	0.98	0.98

Since, for each couple in the sample, we assign the model that best predicts the observed joint labor supply behavior, for each type of household, we know the fraction of couples that follow of a particular decision making process. The resulting distribution of couples is presented in Table 12. As seen in Table 12, for most of the highly educated husbands and wives (homogamy–high), the observed labor supply decision of the couple is best predicted by bivariate probit model. Recall that, in bivariate probit model, the cross effects of employment decisions are assumed to be zero. This implies that, most of the high–educated spouses (about 46%) make their labor supply decisions independent than each other. For these couples around 27% of household decisions can be justified as coming from a Nash game. The joint labor supply decision of remaining homogamy-high type couples are determined either by a Stackelberg leader game or Nash/Pareto optimality model.

On the other hand, for the majority of homogamy–low and heterogamy –both low and high– types, the labor supply decisions of spouses exhibit strong interactions. For the majority of homogamy–low and heterogamy types, the labor supply decisions of the spouses are best predicted by the Stackelberg–wife leader model. Hence, when wife decides whether to work or not to work, she knows the action that her husband will take, and in making her labor supply decision she must take the husband's payoff into account and optimize accordingly. For around 20% of homogamy-low and 25% of heterogamy couples, the household decisions are predicted best by Nash/Pareto optimality model. The remaining homogamy-low and heterogamy type couples make their joint labor supply decision either independently, or following a non–cooperative Nash game or a Stackelberg–husband leader game.

Table 12: Distribution of couples by type

	Bivariate Probit	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
Homogamy-low	14.3%	14.9%	0.2%	50.7%	19.9%
Heterogamy-husband high	15.9%	4.0%	2.6%	52.5%	24.9%
Heterogamy-wife high	19.2%	3.2%	3.3%	48.3%	26.1%
Homogamy-high	45.5%	26.8%	16.1%	7.5%	4.0%

At first it may be surprising that for most of the homogamy–low and heterogamous couples, the joint labor supply decision is best predicted by Stackelberg–wife leader model. In the literature of the economics of the family, there are some examples modeled as a Stackelberg game. Bolin (1997), and Beblo and Robledo (2002) both consider Stackelberg (husband) leader game to model intra-family time allocation. They suggest that the spouse with more bargaining power, gets to be the leader in the Stackelberg game. On the other hand, Kooreman (1994) finds that Stackelberg wife leader model gives the best description of household participation decisions in a sample of Dutch households. Chao (2002) also shows that Stackelberg wife leader model outperforms in predicting contraceptive choice of married couples compared to consensual approach and non–cooperative Nash game.

Earlier literature on gender identity and division of work within a household suggests that traditional gender roles may lead women to lower their labor force participation. For instance, Bertrand, Kamenica and Pan (2013) focus on the behavioral prescription that "*a man should earn more than his wife*" and show that traditional gender roles to distort labor market outcomes of women. Their analysis suggest that, since departing from the traditional gender roles increase the likelihood of divorce, married women sometimes stay out of labor force so as to avoid a situation where they would become the primary breadwinner. Similarly, Akerlof and Kranton (2000) study the relation between traditional gender roles and economic outcomes and show that gender–identity would lead to lower labor force participation of women is deviating from the prescription that "*men work in the labor force and women work in home*" is costly.

In our sample, more than 82% of the couples that are best described by the Stackelberg–wife leader game, either husband works full–time and the wife works as well, i.e. $(y_h, y_w) = (1, 1)$. Following the traditional gender roles, suppose that it is common knowledge that the husband would rather prefer to work full time and his partner to stay home than her to work, i.e. $U_h(1, 0) > U_h(1, 1)$, but would prefer working full time and his spouse to work than working part–time and his wife to work, i.e. $U_h(1, 1) > U_h(0, 1)$. Suppose further that the wife derives a lower utility from not working than working, i.e. $U_w(1, 1) > U_w(1, 0)$ and $U_w(0, 1) > U_w(0, 0)$. Then it is logical for wife to decide to work and make known to her husband this fact. Given his wife's decision, then husband will end up working full–time. Hence, the outcome will be $(y_h, y_w) = (1, 1)$. This might be particularly the case for women married to low educated husbands. In fact, the largest fraction of couples with an observed outcome $(y_h, y_w) = (1, 1)$ and follow a Stackelberg–wife leader game is among heterogamy–wife high types. In particular, about 89% of heterogamy–wife high type couples that follow a Stackelberg–wife leader game has an observed outcome $(y_h, y_w) = (1, 1)$. For heterogamy–wife high types, it is logical to think that the high–educated wife would be more attached to the market than her low–educated husband and will be willing to work.

5.3 Labor Supply Elasticities of Married Women

We now turn our attention to the labor supply estimates of married women. Table 13 presents the average own wage, cross wage and income elasticities of participation for married women by type. The average labor supply elasticities of married women varies to a great extent for different types.[22] The average participation own wage elasticity is largest (0.77) for low–educated women married to low educated men, and smallest (0.03) for high–educated women married to low educated men. The own wage elasticities for low educated women married to high–educated men and for high–educated women married to high–educated men are similar and fall between these two extremes (about 0.30). Furthermore, cross wage elasticities for married women are relatively small (less than -0.05) if they are married to low educated men and larger

[22]For all types of couples, labor supply elasticities of married men are small and the differences between the labor supply elasticities of different types are negligible. See Table F.1 of Appendix F for labor supply elasticities of married men.

(about -0.37) if they are married to high–educated men. For all types of couples, participation elasticity of non–labor family income for married women is small.

Table 13: Labor supply elasticities of married women by type of couples

	Own wage	**Husband's wage**	**Non-labor income**
Homogamy-low	0.77	-0.02	-0.001
	(0.000)	(0.000)	(0.000)
Heterogamy-husband high	0.30	-0.37	-0.012
	(0.000)	(0.001)	(0.000)
Heterogamy-wife high	0.03	-0.05	-0.004
	(0.000)	(0.000)	(0.000)
Homogamy-high	0.31	-0.38	-0.016
	(0.000)	(0.001)	(0.000)

Notes: Standard errors in parenthesis.

What about the distribution of labor supply elasticities? Since our labor supply elasticity calculations are based on the predictions of marginal probability of working for each woman before and after an incrementation of her own wage, or her husband's wage, or non–labor family income, we know the distributions of labor supply elasticities. As for all types of couples, the participation non–labor family income elasticity of married women is small, we focus on the distributions of own wage elasticities and cross wage elasticities. The distribution of own wage elasticities of married women is presented in Figure 1. First, for all types of couples, the distribution of labor supply own wage elasticity of married women is skewed right with no women having a negative elasticity. However, for all types, there exists women with labor supply own wage elasticity that is close to zero, implying that for these women, own wage increases have relatively small effects on their labor supply. Second, the dispersion of labor supply own wage elasticity distribution differ considerably across different types. In particular, the distribution is more dispersed for homogamy–low types. The long upper tail of the elasticity distribution for homogamy–low type couples implies that among these families there are women with large labor supply own wage elasticity (with a maximum about 3.36). On the other hand, the dispersion is smallest for heterogamy–wife high types. In other words, for these types, the labor supply own wage elasticities of married women are concentrated around the mean which is close to zero (about 0.03). Hence, for heterogamy–wife high types, the labor supply of all women show little responsiveness to the changes in their own wages. The dispersions of the labor supply own wage elasticity distributions for heterogamy–husband high and homogamy–high types lie between these two extremes.

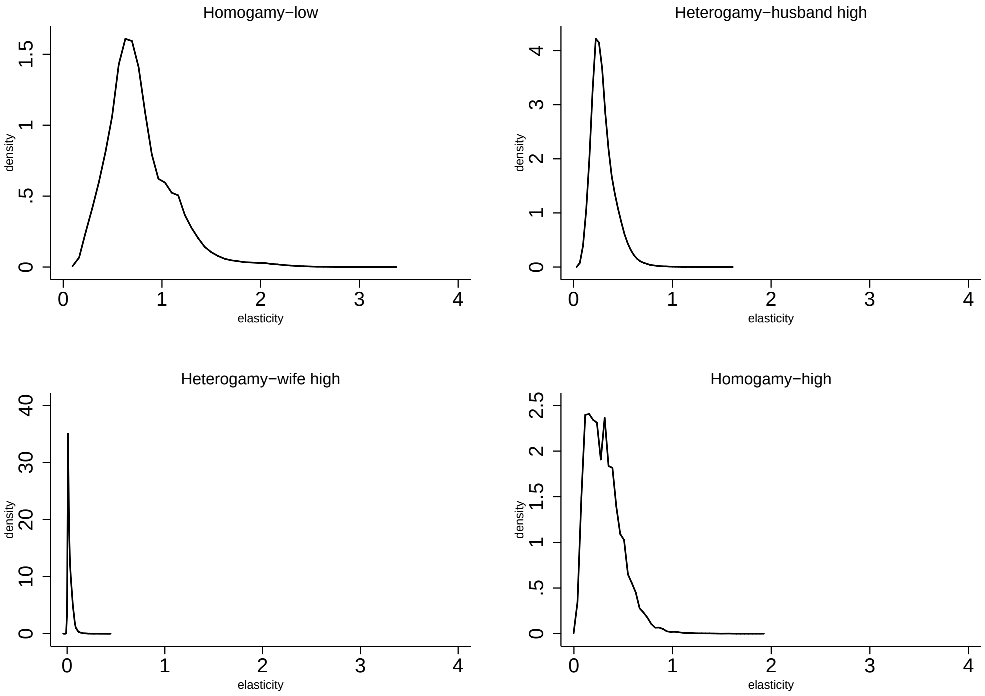

Figure 1: Kernel density of participation own wage elasticities of married women by type of couples

The distribution of cross wage elasticities of married women is presented in Figure 2. In this case, since the cross wage elasticity is negative, the responsiveness of women to the changes in their husbands' wages increases as you move to the left of the elasticity distribution. Note that, for all types of couples, the distributions of cross wage elasticities are skewed left. For all types, there are women with own wage elasticity that is close to zero, implying that for these women increases in their husbands' wages have relatively small effects on labor supply. For the majority of women in all types, the cross wage elasticities are negative. The only exception is heterogamy–wife high types. Among the heterogamy–wife high type couples, there are wives with positive cross wage labor supply elasticity (with a maximum about 0.19). As seen in Figure 2, the dispersion of labor supply cross wage elasticity differs between different types. Different than the labor supply own wage elasticity distribution, the labor supply cross wage elasticity distribution is less dispersed for homogamy–low types. For these couples, the cross wage elasticities of married women are concentrated around the mean which is close to zero (about -0.02). Similar to the dispersion of own wage elasticity distribution, the dispersion of cross wage elasticity distribution for heterogamy–wife high types is small. Therefore, for homogamy–low and heterogamy–wife high types, the labor supply of all women show little responsiveness to the changes in their husbands' wages. On the other hand, the dispersions of cross wage elasticity distributions for heterogamy–husband high and homogamy–high types are similar and larger than the other types.

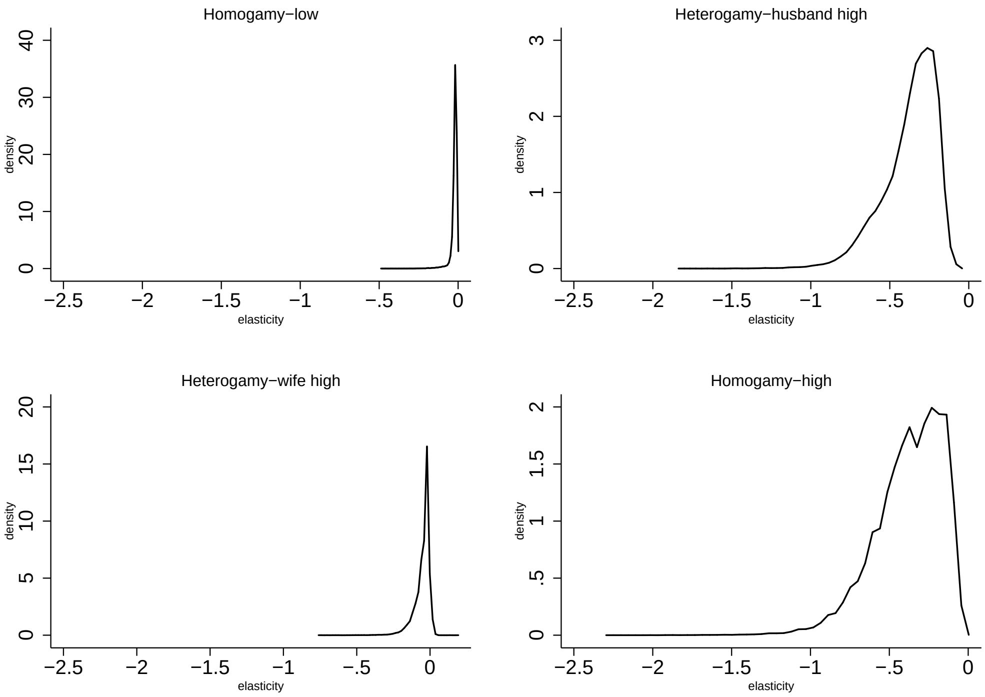

Figure 2: Kernel density of participation cross wage elasticities of married women by type of couples

What accounts for the differences between women of different types? As Heim (2007) notes, a high participation elasticity implies that the market wages must be close to the reservation wage. Therefore, a small increase in wages or a decrease in spouse's wage or income will lead women to participate. This might be the case particularly for low–educated women, since their employment and career opportunities are lower compared to high educated women (Cohen and Bianchi, 1998). On the other hand, if the employment and career opportunities vary among women of a particular type, then for this type, the distribution of labor supply elasticities of married women will be more dispersed. In fact, for homogamy–low types, unconditional distribution of the log own wage for married women exhibits the largest variation consistent with the large

Table 14: Characteristics of couples with labor supply own wage elasticities below and above the average elasticity

	Homogamy low		**Heterogamy husband-high**		**Heterogamy wife-high**		**Homogamy high**	
	Below	Above	Below	Above	Below	Above	Below	Above
Wife								
Employed (%)	0.84	0.64	0.79	0.57	0.91	0.86	0.89	0.67
Log Hourly wage	2.44	2.29	2.58	2.57	2.83	2.83	2.95	2.93
	(0.15)	(0.18)	(0.14)	(0.14)	(0.15)	(0.13)	(0.18)	(0.14)
Age	39.36	37.68	41.89	38.36	38.88	37.37	39.40	38.17
	(7.09)	(8.01)	(7.47)	(6.76)	(7.79)	(6.53)	(8.59)	(6.11)
Years of education	12.59	10.76	12.93	12.51	16.57	16.27	16.96	16.37
	(0.80)	(2.74)	(0.83)	(1.34)	(0.90)	(0.69)	(1.00)	(0.78)
Race (% white)	0.83	0.74	0.88	0.82	0.84	0.84	0.87	0.81
Husband								
Employed full-time (%)	0.97	0.97	0.98	0.98	0.96	0.99	0.97	0.98
Log Hourly wage	2.76	2.67	3.19	3.21	2.85	2.88	3.25	3.33
	(0.18)	(0.23)	(0.19)	(0.18)	(0.17)	(0.16)	(0.22)	(0.16)
Age	41.17	39.48	43.61	40.99	40.55	38.83	40.75	40.11
	(7.28)	(7.88)	(7.46)	(6.84)	(7.91)	(6.79)	(8.71)	(6.23)
Years of education	12.23	11.20	16.44	16.67	12.62	12.76	16.82	16.91
	(1.32)	(2.74)	(0.83)	(0.94)	(1.14)	(1.03)	(0.98)	(1.00)
Race (% white)	0.83	0.74	0.88	0.85	0.84	0.84	0.87	0.83
Family non-labor income	668	1,237	1,534	5,309	1,466	3,042	2,842	8,426
(in 000 dollars per year)	(4,398)	(10,095)	(4,524)	(22,299)	(8,464)	(16,912)	(8,937)	(29,033)
Number of children	1.22	2.24	0.96	2.36	0.90	2.09	0.73	2.20
	(1.04)	(1.28)	(0.92)	(1.07)	(0.96)	(0.92)	(0.82)	(0.90)
% with 0-6 years old children	0.08	0.49	0.04	0.55	0.12	0.63	0.11	0.60
MSA (%)	0.76	0.82	0.84	0.93	0.81	0.89	0.87	0.96
Number of obs.	300,239	204,852	57,466	39,150	48,712	28,331	94,580	75,505

Data source: 5% sample of the 2000 Census IPUMS. *Notes:* Sample includes married individuals ages 25-54 with a 25-54 year old spouse present, not living in group quarters, not in school, not self-employed and do not have allocated weeks or hours. For husbands, the fraction of employed full time is over the employed husbands. Non–labor family income consists of interest, dividends and rent. Standard deviations in parenthesis.

dispersion of their labor supply own wage elasticity distribution (See Table 9).

In Tables 14 and 15, we present the characteristics of different type of couples by the labor supply responsiveness of wives to the own wage changes and the changes in husband's wage, respectively. For each type, the first column (*below*) shows the characteristics of couples with wives whose labor supply elasticities are below or equal to the average labor supply elasticity. On the other hand, the second column (*above*) presents the characteristics of families with wives whose labor supply own wage elasticities are above the average. Note that, since own wage elasticity of married women is positive and cross wage elasticity is negative, in Table 14 the labor supply responsiveness of married women to the changes in their own wages is higher if their labor supply elasticities are above the average, whereas in Table 15 the labor supply responsiveness of

Table 15: Characteristics of couples with labor supply cross wage elasticities below and above the average elasticity

	Homogamy low		**Heterogamy husband-high**		**Heterogamy wife-high**		**Homogamy high**	
	Below	Above	Below	Above	Below	Above	Below	Above
Wife								
Employed (%)	0.68	0.80	0.55	0.81	0.83	0.93	0.67	0.89
Log Hourly wage	2.29	2.44	2.57	2.58	2.83	2.83	2.93	2.95
	(0.18)	(0.15)	(0.14)	(0.14)	(0.13)	(0.15)	(0.14)	(0.18)
Age	37.58	39.34	38.47	41.81	37.27	38.93	38.16	39.41
	(7.85)	(7.25)	(6.80)	(7.48)	(6.37)	(7.86)	(6.12)	(8.59)
Years of education	10.65	12.56	12.53	12.92	16.24	16.59	16.37	16.96
	(2.82)	(0.82)	(1.35)	(0.84)	(0.65)	(0.91)	(0.78)	(1.00)
Race (% white)	0.73	0.83	0.83	0.87	0.86	0.83	0.81	0.87
Husband								
Employed full-time (%)	0.97	0.97	0.98	0.98	0.97	0.97	0.98	0.97
Log Hourly wage	2.67	2.76	3.22	3.19	2.88	2.85	3.33	3.26
	(0.23)	(0.18)	(0.17)	(0.19)	(0.16)	(0.17)	(0.16)	(0.22)
Age	39.29	41.20	41.06	43.55	39.19	40.33	40.10	40.76
	(7.74)	(7.39)	(6.83)	(7.48)	(6.89)	(7.89)	(6.24)	(8.71)
Years of education	11.10	12.24	16.71	16.41	12.71	12.66	16.91	16.82
	(2.82)	(1.31)	(0.96)	(0.81)	(1.14)	(1.09)	(1.00)	(0.98)
Race (% white)	0.73	0.83	0.86	0.87	0.86	0.82	0.83	0.87
Family non-labor income	1,276	673	5,256	1,579	2,940	1,531	8,395	2,855
(in 000 dollars per year)	(10,368)	(4,484)	(22,177)	(5,065)	(16,610)	(8,858)	(28,980)	(9,005)
Number of children	2.29	1.24	2.34	0.98	2.12	0.89	2.20	0.72
	(1.28)	(1.05)	(1.08)	(0.94)	(0.96)	(0.92)	(0.90)	(0.82)
% with 0-6 years old children	0.49	0.10	0.54	0.04	0.65	0.10	0.60	0.11
MSA (%)	0.82	0.76	0.93	0.84	0.90	0.80	0.96	0.87
Number of obs.	188,959	316,132	38,925	57,691	28,058	48,985	75,687	94,398

Data source: 5% sample of the 2000 Census IPUMS. *Notes:* Sample includes married individuals ages 25-54 with a 25-54 year old spouse present, not living in group quarters, not in school, not self-employed and do not have allocated weeks or hours. For husbands, the fraction of employed full time is over the employed husbands. Non–labor family income consists of interest, dividends and rent. Standard deviations in parenthesis.

married women to the changes in their husbands' wages is higher if their elasticities are below or equal to the average. Tables 14 and 15 show that, for all types, married women whose labor supply is more responsive (to their own or their husband's wage) are less likely to be employed, less educated, younger and less likely to be white. Their husbands are also more likely to be less educated and young, and less likely to be white.

For homogamy–low types, if the labor supply of married women is more responsive, their husbands earn on average less and they are less educated. However, for other type of couples, the average hourly log wage of husbands is higher and the husbands are more educated for women whose labor supply elasticities are more responsive to the changes in their own wage and their husbands' wages. Finally, for all types, the labor supply of married women is more responsive to the changes in their own wages among families that have higher non–labor family income and more children and that are more likely to have a pre–school age child and live in a MSA.

5.3.1 The role of children

One of the striking difference between women whose labor supply elasticity is below or equal to the average elasticity and women with labor supply elasticities above the average is the difference in their likelihood of having children. Since, the labor supply elasticity of different types varies to a great extent, one can think the presence of pre–school children as the source of heterogeneity among different types of couples. In fact, Lundberg (1988) tests alternative theories of family labor supply behavior and finds that the presence of young children has a crucial effect on household interactions.

Table 16: Distribution of couples by presence of 0–6 years old children

	Bivariate Probit	**Nash**	**Stackelberg Husband leader**	**Stackelberg Wife leader**	**Nash/ Pareto optimality**
with 0–6 years old children					
Homogamy-low	7.0%	35.5%	0.0%	42.6%	14.9%
Heterogamy-husband high	2.2%	9.7%	5.3%	53.7%	29.0%
Heterogamy-wife high	3.4%	3.4%	8.5%	59.2%	25.6%
Homogamy-high	7.7%	51.7%	21.6%	12.2%	6.8%
without 0–6 years old child					
Homogamy-low	16.6%	8.2%	0.3%	53.5%	21.5%
Heterogamy-husband high	20.4%	2.2%	1.7%	52.1%	23.6%
Heterogamy-wife high	26.1%	3.1%	1.1%	43.5%	26.3%
Homogamy-high	64.0%	14.6%	13.5%	5.3%	2.7%

Although we control for the number of children and the presence of pre–school children in the reservation wage equation of wives, it is possible that household interactions might be different for couples with and without pre–school children. One possibility is that all couples with children make their decisions in a particular way, while all couples without children make theirs in a different way. However, since we allow for each couple to differ in the way they make their labor supply decisions, this should not alter our results. But if there are large differences between the labor supply elasticities of couples with and without pre–school children for some types but not for others, then differential responses of married women based on the spouses' education levels might depend on presence of children in the household. Considering this possibility, we compare the distribution of couples and the labor supply elasticities of married women of different types by the presence of 0–6 years old children. Tables 16 and 17 present these results.

Not surprisingly, the fraction of couples whose employment decisions follow the bivariate probit model is smaller for the ones with pre–school children. Thus, consistent with the findings of Lundberg (1988), labor supply decisions of spouses are more likely to be independent of each other if there are no children of pre–school age in the household. The presence of children matter most for homogamy–high couples. While without children, we do not observe any interactions for majority of households (64%), with children their employment decisions follow a non–cooperative Nash game (about 51%).

Table 17: Labor supply elasticities of married women by the presence of 0-6 years old children

	Own wage	**Husband's wage**	**Non-labor income**
with 0-6 years old children			
Homogamy-low	1.07	-0.04	-0.001
	(0.001)	(0.000)	(0.000)
Heterogamy-husband high	0.44	-0.57	-0.013
	(0.001)	(0.001)	(0.001)
Heterogamy-wife high	0.05	-0.10	-0.005
	(0.000)	(0.000)	(0.000)
Homogamy-high	0.45	-0.56	-0.020
	(0.001)	(0.001)	(0.000)
without 0-6 years old child			
Homogamy-low	0.68	-0.02	-0.001
	(0.000)	(0.000)	(0.000)
Heterogamy-husband high	0.25	-0.31	-0.011
	(0.000)	(0.000)	(0.000)
Heterogamy-wife high	0.02	-0.03	-0.003
	(0.000)	(0.000)	(0.000)
Homogamy-high	0.24	-0.29	-0.015
	(0.000)	(0.000)	(0.000)

Notes: Standard errors in parenthesis.

How do these results affect the labor supply elasticities of married women? Table 17 presents the labor supply elasticities of married women of different types by the presence of pre–school children. As expected, the elasticity estimates are larger for mothers of young children. For all type of households. The participation wage elasticity is once again highest for low–educated women married to a low–educated man and smallest for high–educated women married to someone with low–education both for mothers of pre–school children and other women. Their cross wage and income elasticities suggest little responsiveness of labor supply of those women to changes in husband's wage or changes in non–labor income. Independent of having a 0–6 years old children, once again, participation wage, cross wage and income elasticities of high–educated women is as large as low–educated women if they are married to a high–educated man. Hence, we conclude that, differential responses of married women based on the spouses' education levels are present among married women, independent of whether children are present in the household or not.

5.3.2 Aggregate Labor Supply Elasticities of Married Women

Given the average labor supply elasticities and the population shares of different types, one can calculate the aggregate participation elasticity of married women. Formally, the aggregate participation elasticity is calculated as

$$\sum_k P_k \epsilon_k = \epsilon \tag{9}$$

where P_k is the proportion of women that are of type k and ϵ_k is the estimated (own wage, or cross wage, or income) elasticity of married women of type k. It is important to note that, this formulation of the overall participation elasticity captures the heterogeneity among couples in the way they make their labor supply decisions, and as a result, differences in their labor supply responsiveness. Allowing for the heterogeneity across couples yields an average wage elasticity of 0.56, an average cross wage elasticity of -0.13, and an average income elasticity of -0.006.

How large are these elasticities? Heim (2007) and Blau and Kahn (2007) provide recent estimates of labor supply elasticities for married women in the U.S. Heim (2007) reports a participation wage elasticity of 0.03 and a participation income elasticity of -0.05 in 2003. On the other hand, different models estimated by Blau and Kahn (2007) yield participation wage elasticities between 0.27 and 0.30, cross wage elasticities between -0.13 and -0.10, and income elasticities between -0.002 and -0.004 in 2000. Our elasticity estimates are larger than these estimates.

One of the main difference between our study and these studies is that we allow for household interactions and we let these interactions differ across different types of households. To understand the role of each of these factors, we conduct several exercises. First, we ignore the heterogeneity across homogamous and heterogamous couples with different education levels and re–estimate the different models, i.e. bivariate probit, Nash, Stackelberg–husband leader, Stackelberg–wife leader and Nash/Pareto optimality, for all couples jointly. As a result, we have one set of behavioral parameter estimates from each model for all couples. Then, using these parameter estimates we consider two alternative scenarios.

In Scenario I, we ignore the differences between types but allowed for heterogeneity across couples in the way they make their labor supply decisions. In particular, given the observed employment decision of couples we calculate the predicted probabilities of four possible outcomes –both work, only husband works, only wife works or both do not work– from each model. This allows us to determine the model that gives the highest probability to the observed joint employment decision of the couple. Then, we assign to the couple this particular model and calculate the labor supply elasticities of married women.

Table 18: Labor supply elasticities of married women, alternative scenarios

	Own wage	**Husband's wage**	**Non-labor income**
Benchmark	0.56	-0.13	-0.006
Scenario I	0.25	-0.24	-0.006
Scenario II-Majority	0.29	-0.26	-0.006
Scenario II-Best-fit	0.20	-0.23	-0.007
Scenario II-No interaction	0.27	-0.23	-0.007

In Scenario II, we assign to all couples only one model as their decision making mechanism. Since the preferences of husbands and wives are not directly observed, we consider three alternatives. The first one is to assign to all couples the model that best predicts the observed outcome of the majority. Since 43% of the couples' observed decisions are best predicted by Stackelberg–wife leader model, this is the first possibility we consider (Scenario II–majority). The second alternative is comparing models based on their goodness of fit. Using Akaike and Bayesian information criteria as well as the Likelihood Dominance Criterion suggested by Pollak and Wales (1991) to compare the performance of non-nested models, Nash/Pareto optimality is the preferred model (Scenario II–best–fit). Finally, we also ignore the household interactions and estimate the labor supply elasticities of married women using the bivariate probit model parameter estimates for all couples (Scenario II-no interaction). The elasticity estimates based on different scenarios are presented in Table 18. For comparison, benchmark elasticities are shown in the last row. In all the scenarios, we find that the labor supply income elasticities for married women are small and similar to our benchmark estimates. Hence, ignoring the differences between types has no significant effect on labor supply income elasticities. However, in all scenarios, we find lower labor supply own wage elasticities and higher labor supply cross wage elasticities for married women. This is even true, when we ignore the heterogeneity among households but allow for household interactions (Scenario I). It worths noting that the labor supply own wage elasticities are similar to the ones estimated by Blau and Kahn (2007) when heterogeneity among households is ignored (in all Scenarios). Blau and Kahn (2007) without considering the household interactions and heterogeneity among couples find participation wage elasticities between 0.27 and 0.30 in 2000.

6 The Shrinking Labor Supply Elasticities of Married Women

Our results show that labor supply elasticities differ greatly among households. This raises a natural question: What is the impact of compositional changes in population on women's overall labor supply elasticities? From 1980 to 2000, the population share of couples changed considerably. Both women and men in 2000 were more educated than their counterparts in 1980. Moreover, there had been an increase in the educational resemblance of spouses in the United States (Mare, 1991; Pencavel, 1998; Schwartz and Mare, 2005).

In order to get an idea of the effect of compositional changes on the married women's labor supply responsiveness we carry out the following counterfactual exercise. We calculate what the overall labor supply elasticities would be, if the married women had the responsiveness of 2000 but the distribution of couples would be of 1980. For this purpose, we calculate the overall labor supply elasticities of married women from Equation 10, using the elasticity estimates for year 2000 and the population shares of couples in 1980.[23] The population shares of different type of couples in 1980 and in 2000 are presented in the first panel of Table 19. As noted by earlier studies, from 1980 to 2000, there had been an increase in the fraction of homogamy–high type couples. In addition, there had been an increase in the share of heterogamy–wife high types reflecting the increase in educational attainment levels of women during the recent decades.

Table 19: Labor supply elasticities under counterfactual distribution of couples

Population share	**1980**	**2000**
Homogamy-low	0.72	0.60
Heterogamy-husband high	0.12	0.11
Heterogamy-Wife high	0.04	0.09
Homogamy-high	0.12	0.20
Participation elasticity	**Benchmark**	**Counterfactual**
Own wage	0.56	0.63
Husband's wage	-0.13	-0.11
Non-labor income	-0.006	-0.004

The second panel of Table 19 presents the labor supply elasticities under the counterfactual distribution of couples. For comparison, benchmark elasticities based on the actual shares of couples in 2000 are shown in the last row of Table 19. Under the counterfactual distribution of couples, we find a participation own wage elasticity of 0.63, a participation cross wage elasticity of -0.11 and a participation non–labor income of -0.004. This implies that, although, compositional changes do not have a considerable effect on the participation cross wage and participation non–labor income elasticities of married women, changing composition of couples accounts for a decline in participation own wage elasticity of married women –from 0.63 to 0.56– between 1980 and 2000. This result suggests that the increase in their educational attainment levels during the recent decades results in a smaller responsiveness for married women to the changes in their wages. Nonetheless, for quantifying the role of compositional changes on the labor supply responsiveness of married women needs a more detailed analysis.

[23]Data for the population shares of couples in 1980 comes from 5% sample of the 1980 Census IPUMS–USA.

7 Concluding Remarks

We provide labor supply elasticity estimates of married men and women allowing for heterogeneity among couples (by educational attainments of husbands and wives) and modeling explicitly how household members interact and make their labor supply decisions. To this end, we focus on the static labor supply decision of couples along the extensive margin.

We find that the labor supply decisions of husbands and wives depend on each other, unless both spouses are highly educated. For high-educated couples, the labor supply decisions of husband and wife are jointly determined only if they have pre-school children. We also find that labor supply elasticities differ greatly among households. The participation own wage elasticity is largest for low-educated women married to low educated men, and smallest for high-educated women married to low educated men. The own wage elasticities for low educated women married to high-educated men and for higheducated women married to high-educated men are similar and fall between these two extremes. For all types of couples, participation elasticity of nonlabor family income is small. The cross-wage elasticities for married women are relatively small if they are married to low educated men and larger if they are married to higheducated men. Allowing for heterogeneity across couples yields an overall participation wage elasticity of 0.56, a cross wage elasticity of -0.13 and an income elasticity of -0.006 for married women. Our analysis show that just allowing for household interactions while ignoring heterogeneity among households generates lower labor supply wage elasticity (about 0.25) for married women.

The results of this study has important implications for policy analysis. Since, many public policies, e.g. earned income tax credit (EITC) or Temporary Assistance for Family Needs (TAFN) programs, are designed to target specific groups, it is essential to understand the potential impacts on labor supply of different individuals. Earlier studies mostly focus on the heterogeneity associated to the presence of preschool children (e.g. Lundberg, 1988). In this study, we further show that differential responses of married women based on the spouses' education levels are present among married women, independent of whether children are present in the household or not.

The analysis in this paper also provides a natural framework to study how changes in educational attainments and household structure affect aggregate labor supply elasticities. Over the last decades, there has been dramatic changes in the educational composition of population in the U.S. Not only the educational attainment levels of men and women increased, but also the resemblance of husbands and wives on educational attainment increased substantially (Pencavel 1998; Schwartz and Mare 2005). Our analysis indicate show that if the married women had the responsiveness of 2000 but the distribution of couples would have been as of 1980s, the aggregate labor supply own wage elasticity of married women would be 0.63 instead of 0.56.

We conclude by commenting on three important issues we have abstracted from and that might be important in future research. First, we have abstracted from fertility decisions, which can be viewed as a shortcoming of our analysis. Although we control for the presence of children in our analysis, earlier work suggest that the decision to have children and the labor supply decision may be interdependent (e.g. Rosenzweig and Wolpin 1980; Angrist and Evans 1998). The second issue pertains to the role of increasing assortative mating and changing composition of families and its interplay with labor supply elasticities. Our analysis in Section 6 is a preliminary first step in this direction. Finally, we have not addressed the life–cycle and dynamic issues. The dynamic extension of the family labor supply model would allow to analyze the variations in family labor supply behavior of different type of couples over the life cycle. We leave this extension for future research.

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Appendices

Appendix A. Simultaneous Probit Model

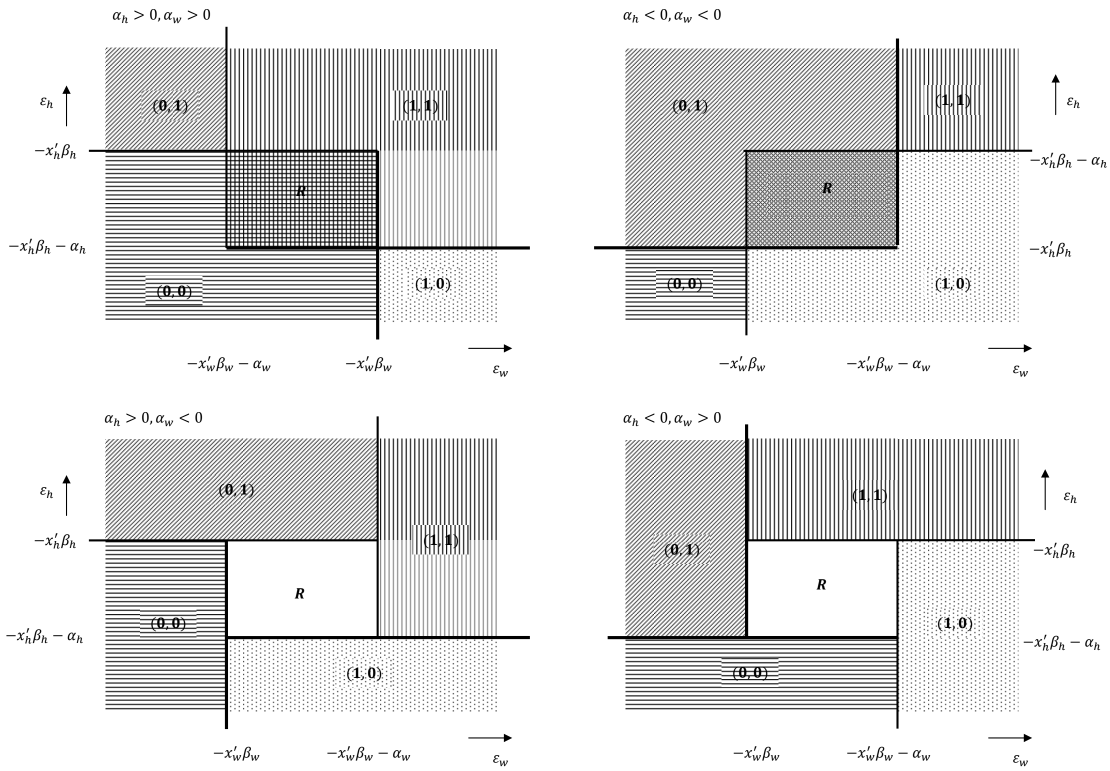

Figure A.1: This figure depicts the possible outcomes when the conditions on the random components in the simultaneous binary model are satisfied. Each panel illustrates a different case for the signs of the parameters α_h and α_w. The region R in each panel corresponds to the region where model is incoherent or incomplete. In the top left panel this region is the intersection of $(y_h, y_w) = (0, 0)$ and $(y_h, y_w) = (1, 1)$, and in the top right panel this is the intersection of $(y_h, y_w) = (1, 0)$ and $(y_h, y_w) = (0, 1)$. In the bottom panels, regions R indicate no solution for (y_h, y_w)

Appendix B. Nash Model

Outcome Probabilities in terms of Reaction Functions

$$\begin{aligned}
\Pr(0,0) &= \Pr(H_1,W_1)+\Pr(H_1,W_2)+\Pr(H_2,W_1) \\
&+ a_1\Pr(H_2,W_2)+c_1\Pr(H_2,W_3)+d_1\Pr(H_3,W_2) \\
\Pr(1,0) &= \Pr(H_3,W_1)+\Pr(H_4,W_1)+\Pr(H_4,W_3) \\
&+ b_1\Pr(H_3,W_3)+c_2\Pr(H_2,W_3)+d_2\Pr(H_3,W_2) \\
\Pr(0,1) &= \Pr(H_2,W_4)+\Pr(H_4,W_2)+\Pr(H_4,W_4) \\
&+ a_2\Pr(H_2,W_2)+c_4\Pr(H_2,W_3)+d_4\Pr(H_3,W_2) \\
\Pr(1,1) &= \Pr(H_1,W_3)+\Pr(H_1,W_4)+\Pr(H_3,W_4) \\
&+ b_2\Pr(H_3,W_3)+c_3\Pr(H_2,W_3)+d_3\Pr(H_3,W_2)
\end{aligned}$$

Outcome Probabilities in terms of Model Parameters

If $\alpha_h \geq 0$ and $\alpha_w \geq 0$, then

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h,-x_w^{'}\beta_w,\rho)-a_1I(-x_h^{'}\beta_h,-x_w^{'}\beta_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w-\alpha_w,\rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-\rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h-\alpha_h,x_w^{'}\beta_w,-\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h+\alpha_h,x_w^{'}\beta_w+\alpha_w,\rho)-a_1I(-x_h^{'}\beta_h,-x_w^{'}\beta_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w-\alpha_w,\rho)
\end{aligned}$$

If $\alpha_h \geq 0$ and $\alpha_w < 0$, then

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h,-x_w^{'}\beta_w,\rho)+c_1I(-x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w,\rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-\rho)+c_2I(-x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w,\rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h-\alpha_h,x_w^{'}\beta_w,-\rho)+c_3I(-x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w,\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h+\alpha_h,x_w^{'}\beta_w+\alpha_w,\rho)+c_4I(-x_h^{'}\beta_h,-x_w^{'}\beta_w-\alpha_w,-x_h^{'}\beta_h-\alpha_h,-x_w^{'}\beta_w,\rho)
\end{aligned}$$

If $\alpha_h < 0$ and $\alpha_w \geq 0$, then

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) + d_1 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) + d_2 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h, x_w^{'}\beta_w, -\rho) + d_3 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h, x_w^{'}\beta_w + \alpha_w, \rho) + d_4 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, \rho)
\end{aligned}$$

If $\alpha_h < 0$ and $\alpha_w < 0$, then

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) - b_2 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h, x_w^{'}\beta_w, -\rho) - b_1 I(-x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h, x_w^{'}\beta_w + \alpha_w, \rho)
\end{aligned}$$

where $\Phi(a, b, \rho)$ is the cumulative distribution function evaluated at (a, b) of a bivariate standard normal distribution with correlation ρ, $I(a, b, c, d, \rho)$ is the integral of the corresponding density over the range $a \geq \varepsilon_h$, $b \geq \varepsilon_w$ and

$$\begin{aligned}
a_1 + a_2 = 1 \quad c_1 + c_2 + c_3 + c_4 = 1 \\
b_1 + b_2 = 1 \quad d_1 + d_2 + d_3 + d_4 = 1.
\end{aligned}$$

Note that, in the text it is assumed that $a_i = 1/2$, $b_i = 1/2$ for $i = 1, 2$, and $c_i = 1/4$, $d_i = 1/4$ for $i = 1, 2, 3, 4$ (See Bjorn and Vuong, 1984).

Appendix C. Stackelberg Wife Leader Model

Outcome Probabilities in terms of Husband's Reaction Functions and Wife's Utility Comparisons

$$
\begin{aligned}
\Pr(0,0) &= \Pr(H_1, \overline{S_1}) + \Pr(H_2, \overline{S_2}) \\
\Pr(1,0) &= \Pr(H_3, \overline{S_3}) + \Pr(H_4, \overline{S_4}) \\
\Pr(0,1) &= \Pr(H_1, S_1) + \Pr(H_3, S_3) \\
\Pr(1,1) &= \Pr(H_2, S_2) + \Pr(H_4, S_4)
\end{aligned}
$$

Outcome Probabilities in terms of Model Parameters

If $\alpha_h \geq 0$, then

$$
\begin{aligned}
\Pr(0,0) &= \Phi(-x_w^{'}\beta_w, -x_h^{'}\beta_h, \rho) \\
&- I(-x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w^1, -x_h^{'}\beta_h - \alpha_h, \rho) \\
\Pr(1,0) &= \Phi(-x_w^{'}\beta_w - \alpha_w^1 + \alpha_w^0, x_h^{'}\beta_h, -\rho) \\
\Pr(0,1) &= \Phi(x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h, -\rho) \\
\Pr(1,1) &= \Phi(x_w^{'}\beta_w + \alpha_w^1 - \alpha_w^0, x_h^{'}\beta_h + \alpha_h, \rho) \\
&- I(-x_w^{'}\beta_w - \alpha_w^1, -x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w^1 + \alpha_w^0 - \alpha_w, -x_h^{'}\beta_h - \alpha_h, \rho)
\end{aligned}
$$

otherwise

$$
\begin{aligned}
\Pr(0,0) &= \Phi(-x_w^{'}\beta_w, -x_h^{'}\beta_h, \rho) \\
\Pr(1,0) &= \Phi(-x_w^{'}\beta_w - \alpha_w^1 + \alpha_w^0, x_h^{'}\beta_h, -\rho) \\
&+ I(-x_w^{'}\beta_w + \alpha_w^0, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w - \alpha_w^1 + \alpha_w^0, -x_h^{'}\beta_h, \rho) \\
\Pr(0,1) &= \Phi(x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h, -\rho) \\
&+ I(-x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w + \alpha_w^0, -x_h^{'}\beta_h - \alpha_h, \rho) \\
\Pr(1,1) &= \Phi(x_w^{'}\beta_w + \alpha_w^1 - \alpha_w^0, x_h^{'}\beta_h + \alpha_h, \rho)
\end{aligned}
$$

where $\Phi(a, b, \rho)$ is the cumulative distribution function evaluated at (a, b) of a bivariate standard normal distribution with correlation ρ, $I(a, b, c, d, \rho)$ is the integral of the corresponding density over the range $a \geq \varepsilon_w$, $b \geq \varepsilon_h$.

Appendix D. Stackelberg Husband Leader Model

Table D.1: Wife's reaction functions

Reaction function	Utility comparison	Condition
W_1: $y_w = 0$ if $y_h = 0$ and $y_w = 0$ if $y_h = 1$	$U_w(0,1) < U_w(0,0)$ and $U_w(1,1) < U_w(1,0)$	$\varepsilon_w < -x_w^{'}\beta_w - \max(0, \alpha_w)$
W_2: $y_w = 0$ if $y_h = 0$ and $y_w = 1$ if $y_h = 1$	$U_w(0,1) < U_w(0,0)$ and $U_w(1,1) > U_w(1,0)$	$-x_w^{'}\beta_w - \alpha_w < \varepsilon_w < -x_w^{'}\beta_w$ if $\alpha_w > 0$
W_3: $y_w = 1$ if $y_h = 0$ and $y_w = 0$ if $y_h = 1$	$U_w(0,1) > U_w(0,0)$ and $U_w(1,1) < U_w(1,0)$	$-x_w^{'}\beta_w < \varepsilon_w < -x_w^{'}\beta_w - \alpha_w$ if $\alpha_w < 0$
W_4: $y_w = 1$ if $y_h = 0$ and $y_w = 1$ if $y_h = 1$	$U_w(0,1) > U_w(0,0)$ and $U_w(1,1) > U_w(1,0)$	$-x_w^{'}\beta_w - \min(0, \alpha_w) < \varepsilon_w$

Table D.2: Husband's utility comparisons

Reaction function for the wife	Utility comparison for the husband	Condition
W_1	C_1: $U_h(1,0) > U_h(0,0)$	$\varepsilon_h > -x_h^{'}\beta_h$
W_2	C_2: $U_h(1,1) > U_h(0,0)$	$\varepsilon_h > -x_h^{'}\beta_h - \alpha_h^1$
W_3	C_3: $U_h(1,0) > U_h(0,1)$	$\varepsilon_h > -x_h^{'}\beta_h - \alpha_h^0$
W_4	C_4: $U_h(1,1) > U_h(0,1)$	$\varepsilon_h > -x_h^{'}\beta_h - \alpha_h$

Table D.3: Stackelberg Equilibria

W_1 and C_1	(1,0)	W_3 and C_3	(1,0)
W_1 and $\overline{C_1}$	(0,0)	W_3 and $\overline{C_3}$	(0,1)
W_2 and C_2	(1,1)	W_4 and C_4	(1,1)
W_2 and $\overline{C_2}$	(0,0)	W_4 and $\overline{C_4}$	(0,1)

Outcome Probabilities in terms of Wife's Reaction Functions and Husband's Utility Comparisons

$$\begin{aligned}
\Pr(0,0) &= \Pr(\overline{C_2}, W_2) + \Pr(\overline{C_3}, W_3) \\
\Pr(1,0) &= \Pr(C_3, W_3) + \Pr(C_4, W_4) \\
\Pr(0,1) &= \Pr(C_1, W_1) + \Pr(C_2, W_2) \\
\Pr(1,1) &= \Pr(\overline{C_1}, W_1) + \Pr(\overline{C_4}, W_4)
\end{aligned}$$

Outcome Probabilities in terms of Model Parameters

If $\alpha_w \geq 0$, then

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
&- I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h^1 + \alpha_h^0, x_w^{'}\beta_w, -\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h^1 - \alpha_h^0, x_w^{'}\beta_w + \alpha_w, \rho) \\
&- I(-x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1 + \alpha_h^0 - \alpha_h, -x_w^{'}\beta_w - \alpha_w, \rho)
\end{aligned}$$

otherwise

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) \\
&+ I(-x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h + \alpha_h^0, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h^1 + \alpha_h^0, x_w^{'}\beta_w, -\rho) \\
&+ I(-x_h^{'}\beta_h + \alpha_h^0, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h - \alpha_h^1 + \alpha_h^0, -x_w^{'}\beta_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h^1 - \alpha_h^0, x_w^{'}\beta_w + \alpha_w, \rho)
\end{aligned}$$

where $\Phi(a, b, \rho)$ is the cumulative distribution function evaluated at (a, b) of a bivariate standard normal distribution with correlation ρ, $I(a, b, c, d, \rho)$ is the integral of the corresponding density over the range $a \geq \varepsilon_h$, $b \geq \varepsilon_w$ (See Bjorn and Vuong, 1985).

Appendix E. Nash/Pareto optimality Model

Outcome Probabilities in terms of Model Parameters

If $\alpha_h^0 - \alpha_h^1 >= 0$ and $\alpha_w^0 - \alpha_w^1 >= 0$:

$$
\begin{aligned}
\Pr(1,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -\rho) \\
&- \frac{1}{2} I(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h - \alpha_h^0 + \alpha_h^1, x_w^{'}\beta_w - \alpha_w^0 + \alpha_w^1, \rho) \\
&+ I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -\rho) \\
&- \frac{1}{2} I(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
&- I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho)
\end{aligned}
$$

If $\alpha_h^0 - \alpha_h^1 >= 0$ and $\alpha_w^0 - \alpha_w^1 < 0$:

$$
\begin{aligned}
\Pr(1,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h - \alpha_h^0 + \alpha_h^1, x_w^{'}\beta_w - \alpha_w^0 + \alpha_w^1, \rho) \\
&+ I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho) \\
&+ \frac{1}{2} I(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -\rho) \\
&+ \frac{1}{2} I(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, \rho) \\
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
&- I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho)
\end{aligned}
$$

If $\alpha_h^0 - \alpha_h^1 < 0$ and $\alpha_w^0 - \alpha_w^1 >= 0$:

$$
\begin{aligned}
\Pr(1,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -\rho) \\
&+ \frac{1}{2} I(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h - \alpha_h^0 + \alpha_h^1, x_w^{'}\beta_w - \alpha_w^0 + \alpha_w^1, \rho) \\
&+ I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho) \\
&+ \frac{1}{2} I(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -\rho) \\
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
&- I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho)
\end{aligned}
$$

If $\alpha_h^0 - \alpha_h^1 < 0$ and $\alpha_w^0 - \alpha_w^1 < 0$:

$$
\begin{aligned}
\Pr(1,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h - \alpha_h^0 + \alpha_h^1, x_w^{'}\beta_w - \alpha_w^0 + \alpha_w^1, \rho) \\
&+ I(-x_h^{'}\beta_h, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho) \\
&+ I(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w + \alpha_w^0 - \alpha_w^1, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h + \alpha_h^0 - \alpha_h^1, -x_w^{'}\beta_w, -\rho) \\
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) \\
&- I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h^1, -x_w^{'}\beta_w - \alpha_w^1, \rho)
\end{aligned}
$$

where $\Phi(a, b, \rho)$ is the cumulative distribution function evaluated at (a, b) of a bivariate standard normal distribution with correlation ρ and $I(a, b, c, d, \rho)$ is the integral of the corresponding density over the range $a \geq \varepsilon_h$, $b \geq \varepsilon_w$.

Table E.1: Nash/Pareto optimality ($\alpha_h^1 > 0$, $\alpha_h^0 > 0$, $\alpha_w^1 > 0$ and $\alpha_w^0 > 0$)

Husband/Wife	$U_w(0,0) < U_w(1,0) < U_w(0,1) < U_w(1,1)$	$U_w(0,0) < U_w(0,1) < U_w(1,0) < U_w(1,1)$	$U_w(0,1) < U_w(0,0) < U_w(1,0) < U_w(1,1)$	$U_w(0,0) < U_w(0,1) < U_w(1,1) < U_w(1,0)$	$U_w(0,1) < U_w(0,0) < U_w(1,1) < U_w(1,0)$	$U_w(0,1) < U_w(1,1) < U_w(0,0) < U_w(1,0)$
$U_h(0,0) < U_h(1,0) < U_h(0,1) < U_h(1,1)$	(1,1)	(1,1)	(1,1)	(1,0)	(1,0)	(1,0)
$U_h(0,0) < U_h(0,1) < U_h(1,0) < U_h(1,1)$	(1,1)	(1,1)	(1,1)	(1,0)	(1,0)	(1,0)
$U_h(0,1) < U_h(0,0) < U_h(1,0) < U_h(1,1)$	(1,1)	(1,1)	(1,1)	(1,1) and (1,0)	(1,1)	(0,0)
$U_h(0,0) < U_h(0,1) < U_h(1,1) < U_h(1,0)$	(0,1)	(0,1)	(1,1) and (0,1)	(1,0) and (0,1)	(1,0)	(1,0)
$U_h(0,1) < U_h(0,0) < U_h(1,1) < U_h(1,0)$	(0,1)	(0,1)	(1,1)	(0,1)	(1,1)	(0,0)
$U_h(0,1) < U_h(1,1) < U_h(0,0) < U_h(1,0)$	(0,1)	(0,1)	(0,0)	(0,1)	(0,0)	(0,0)

Appendix F. Labor Supply Elasticities of Married Men

Table F.1: Labor supply elasticities of married men by type of couples

	Own wage	**Wife's wage**	**Non-labor income**
Homogamy-low	0.04	0.01	0.000
	(0.000)	(0.000)	(0.000)
Heterogamy-husband high	0.02	0.02	0.000
	(0.000)	(0.000)	(0.000)
Heterogamy-wife high	0.06	-0.02	0.000
	(0.000)	(0.000)	(0.000)
Homogamy-high	0.05	-0.01	0.000
	(0.000)	(0.000)	(0.000)
All	0.04	0.00	0.000

Notes: Standard errors in parenthesis.