Ph.D. Thesis:
Women in the Labor Markets:
Wages, Labor Supply, and Fertility Decisions

Ezgi Kaya

International Doctorate in Economic Analysis (IDEA)
Departament d'Economia i Histria Econmica
Facultat d'Economia i Empresa

Thesis Supervisor:
Prof. Dr. Nezih Guner

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To Mom and Dad

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Introduction

One of the most remarkable changes in labor markets over the last decades is the women's engagement in the labor markets. The most important development in labor markets, in all industrialized countries was the increase in the entry of women, in particular married women, into the labor force. The economic literature associates the increasing labor force participation of women with the changes in the wage structure, either in terms of the gender wage gap or the elasticity of the female labor supply to changes in their own wages or their husband's wages and with the changing fertility behavior of women. In this thesis, I study the three key aspects of the changing position of women in the labor markets: the gender wage gap, female labor supply elasticities and the interaction between labor supply of women and fertility behavior, and explore how women fare in the labor markets and how labor market institutions and policy affect their behavior.

In the first chapter of this thesis, entitled *Gender Wage Gap Trends in Europe: The Role of Occupational Allocation and Skill Prices*, I explore the recent gender wage gap trends in a sample of European countries with a new approach, that uses the direct measures of skill requirements of jobs held by men and women. Between 1968 and 1990, in the U.S., the gender wage gap declined and a part of this decline is explained by changes in male-female differences in cognitive, motor and people skill intensities, and the physical strength that occur due to the shifts in occupational allocations, as well as the changes in the prices of these skills (Bacolod and Blum, 2010). In this chapter, I revisit the findings of Bacolod and Blum (2010) for a set of European countries: three Southern Europe countries (Italy, Portugal, Spain), two Anglo-Saxon countries (Ireland and the U.K.), and Austria (as an example of Continental European countries).

The results of Chapter 1 show that, during the 1990s and 2000s, the gender wage gap declined in the majority of European countries and in the U.S. Similar to the U.S. experience, a part of this decline is explained by changes in male-female differences in brain and brawn skill intensities that occur due to the shifts in occupational allocations. However, in contrast to the U.S. experience, the changes in returns to brain and brawn skills had a widening effect on the gender wage gap. Furthermore, a substantial part of the changes in the gender wage gaps cannot be explained by the changes in the gender gaps in labor market characteristics, brain and brawn skills or changes in the wage structure. I find that the unexplained part of the gender wage gap is strongly correlated with labor market institutions, e.g. employment protection of workers and trade union density. This suggests a strong link between the changes in the labor market institutions and changes in gender wage gap trends.

In the second chapter, entitled *Heterogeneous Couples, Household Interactions and Labor Supply Elasticities of Married Women*, I study labor supply elasticities of married women and men. Estimates of labor supply elasticities have a central place in empirical labor economics. 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 the husband's and the wifes 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 do not depend on educational attainments of females, or relative education levels of husbands and wives (i.e. who is married to whom). In this chapter, I estimate labor supply elasticities of married women and men allowing for the heterogeneity among couples (in educational attainments of husbands and wives) and explicitly modeling how household members interact and make their labor supply decisions. For this purpose, I focus on static labor supply decisions of couples along the extensive margin. Using data from the 2000 U.S. Census, I estimate five models of household interactions (Nash, Stackelberg-wife leader, Stackelberg-husband leader, Nash with Pareto optimality, and a bivariate probit model without household interactions) for different type of couples (high educated husband and high educated wife, low educated husband and low educated wife, and mixed couple) using a maximum likelihood estimation strategy. Then, given the estimated parameters, I select the model that best predicts the observed labor supply behavior of a particular couple in the sample and calculate labor supply elasticities of household members using the parameter estimates of this particular model.

The results of Chapter 2 show that there is considerable variation among couples in the way they make their labor supply decisions. I find that labor supply decisions of husbands and wives depend on each other, unless both spouses are highly educated. For highly educated couples, labor supply decisions of the husband and the wife are jointly determined only if they have pre-school age children. I also find that labor supply elasticities differ greatly among households. The participation own-wage elasticity is largest (0.77) for women with low education married to men with low education, and smallest (0.03) for women with high education married to men with low education. Own-wage elasticities for women married to highly educated men is between these two extremes (about 0.30). These results imply an overall participation wage elasticity of 0.56 which is larger than the recent estimates of labor supply elasticities of married women (e.g. Blau and Kahn, 2007; Heim, 2007). The current analysis differs from these studies as I allow for household interactions and I let these interactions to differ across different types of households. My analysis shows that ignoring the heterogeneity between household types and differences between couples in the way they make their labor supply decisions yield a lower labor supply wage elasticity for married women (0.200.29). I also find that even if differences between couples in the way they make their labor supply decisions are ignored, accounting for the differences between household types already yields a higher labor participation wage elasticity for married women (0.460.49).

The third chapter is entitled *Temporary Contracts and Fertility* and is coauthored with Nezih Guner and Virginia Sánchez Marcos. In this chapter, we investigate how temporary contracts affect the fertility behavior of women in Spain. In 1984, Spanish government introduced a labor market reform which allowed employers were to contract workers on a fixed-term basis even when the nature of the job was not temporary, which relaxed the conditions for firms to hire workers under fixed term contracts. Since the reform, the vast majority of new contracts in Spain have been and still are on a fixed-term nature. In 2008, the fraction of the labor force with temporary contracts was 29.3% in Spain, while the OECD average was only 11.8%. Furthermore, the incidence of temporary contracts among women is higher than among men. More than 30% of women had a temporary contract in Spain in 2007. The conversion rate of temporary contracts to permanent contracts is very low, only about 6% per year. Hence, a large number of women move from one temporary contract to other. This clearly generates a great deal of uncertainty and can affect womens decision to have a child. In this chapter, to study the link between temporary contracts and fertility, we estimate discrete-time duration models of the first and subsequent births using data from Continuous Sample of Working Histories (Muestra Continua de Vidas Laborales in Spanish), a micro-level dataset of Spanish administrative records, and compare the probability of having a child of women working under permanent and temporary contracts, holding demographic and other variables constant.

The results of Chapter 3 suggest that job stability is an important determinant of the birth hazards. We find that childless women working under permanent contracts in a given year are 8.2% more likely to give a birth in the following year than childless women working under temporary contracts in that particular year. Moreover, the effect becomes stronger for the transitions from the first to second and even more pronounced from second to third birth.

Chapter 1

Gender Wage Gap Trends in Europe: The Role of Occupational Allocation and Skill Prices

1.1 Introduction

There was a dramatic decline in the gender wage gap in the U.S. during the 1980s. The fact that this happened despite a significant rise in overall wage inequality, shifted the attention in the literature to the relationship between the overall wage structure and the gender wage gap. The key change in the U.S. wage structure in 1980s was the rising returns to education and experience due to an increase in demand for high–skilled labor (Katz and Murphy, 1992; Juhn, Murphy and Pierce, 1993). In their seminal paper, Blau and Kahn (1997) find that the change in the U.S. wage structure should have widened the gender wage gap since women had an initial relative deficit in labor market characteristics such as education and experience. However, women were able to overcome this deficit by improving their labor market characteristics, especially their experience levels.

The existing literature attributes the increase in relative demand for high-skilled labor to the technological change, in particular to the developments in computer technology.[1] The task based approach of skill biased technological change proposed by Autor, Levy, and Murnane (2003) moves beyond traditional measures of labor market characteristics (such as education and experience) and models the relation between the skills and technological change through tasks performed at jobs. In this framework, work performed in an occupation is broken down into routine and non–routine tasks, which are substitutes and complements with computers, respectively. Therefore, with the development of

[1] See Katz and Autor (1999) for a survey.

computer technologies, a shift in the production technology occurred that favored more skilled workers who perform non-routine cognitive tasks in their jobs.

If occupations are characterized by their skill requirements, one can infer the skill intensities of workers given their occupational allocation.[2] Since there exists gender differences in occupational allocation, we expect changing relative demand for skills to have an impact on the gender wage gap.[3] Focusing on the different aspects of the skills required to perform an occupation (such as cognitive, motor, people skills and physical strength), Bacolod and Blum (2010) study how changes in the prices of various skills affected the gender wage gap in the U.S. Their results show that changes in prices of different types of skills (cognitive, motor, people skills and physical strength) contributed to narrowing the gender gap between 1968 and 1990. During this period, cognitive and people skills became relatively more valuable compared to motor skills and physical strength. Since females held occupations that require more cognitive and people skills relative to males, this narrowed the gender wage gap in the U.S. between 1968 and 1990.

This chapter of the this thesis revisits the findings of Bacolod and Blum (2010) for a set of European countries: three Southern Europe countries (Italy, Portugal, Spain), two Anglo-Saxon countries (Ireland and the U.K.), and Austria (as an example of Continental European countries).[4] The skill requirements of occupations are obtained from Occupational Information Network (O*Net) data. First, using the data from O*Net, occupations are characterized by two primary attributes, "brains" and "brawns". Then, the brain and brawn skill requirements of jobs are matched with the individual level data from European Community Household Panel (ECHP) and European Union Statistics on Income and Living Conditions (EU-SILC) given the occupational allocation of workers. As a result, skill intensities of each individual in the sample are determined and wage return to each skill is estimated.[5] Finally, the contribution of changes in skill intensities and skill prices to the gender wage gap is quantified by decomposing the gender wage gap for each country into its components using the technique developed by Juhn, Murphy and Pierce (1991). In order to explore whether the patterns in the U.S. during the 1990s and 2000s changed compared to 1970s and 1980s, we also analyze the changes in the U.S. gender wage gap for the same time period using data from Current Population Survey (CPS).

[2]This allocative process may result from different choices of individuals, discrimination in the process of recruitment or hiring or differences in comparative advantage of workers as in Roy (1951).

[3]Welch (2000) assumes that women are relatively more intensive in intellectual or brain skills while men being more physical or brawn skill intensive. Hence, an increase in the relative value of brain skills, should actually narrow the gender wage gap.

[4]The sample of countries does not include examples of the Nordic and eastern European countries due to the lack of comparable data for the analysis. See Section 1.3 for the description of data sources.

[5]See Autor et al. (2003) and Bacolod and Blum (2010) for a similar approach.

We find that, from 1993 to 2008, the U.S. gender wage gap declined (0.051 log points) and a part of the convergence in the gender gap can be explained by the change in brain and brawn skill prices, similar to the findings of Bacolod and Blum (2010) for 1970s and 1980s.[6] In particular, 11.7% of the closing gender wage gap can be explained by changing returns to brain and brawn skills.[7] During the same period, the gender wage gaps also declined in the European countries in our sample, except Spain.[8] The experience of Austria and the U.K. was similar to the U.S., i.e. brain skills became more valuable, while brawn skills became relatively less valuable. Moreover, a part of the decline in the gender wage gaps in Austria and in the U.K. can be explained by the changes in returns to brain and brawn skills. In particular, the changes in returns to brain and brawn skills account for around 15.4% of the closing gender wage gap in Austria and around 7.6% in the U.K.

In contrast, the increase in returns to brain skills and decrease to brawn skills was not a common phenomenon for the Southern European countries –Italy, Portugal and Spain– and for Ireland.[9] In contrast to the U.S. experience, in Southern European countries and in Ireland, the changes in returns to brain and brawn skills had a widening effect on the gender wage gaps. In the absence of changes in skill prices, the gender wage gap would have narrowed even further in Ireland (0.032 log points more), in Italy (0.022 log points more) and in Portugal (0.037 log points more). On the other hand, if skill prices would not have changed, the Spanish gender wage gap would have widen only around 0.025 log points instead of 0.035.

Despite these differences across European countries and the U.S. a striking fact is that, a substantial part of the changes in the gender wage gaps cannot be explained by the changes in observable gender-specific factors (i.e. labor market characteristics or brain and brawn skills) or changes in wage structure (i.e. returns to characteristics, skill prices or residual wage inequality). Of course a natural question is then why the gender wage gaps still declined during 1990s and 2000s. Other factors that may have contributed to the convergence of the unexplained gender pay gap include changes in selection to the employment, changes in gender differences in unobservable skills and labor market discrimination, as well as the changes in labor market institutions. To answer

[6] Bacolod and Blum (2010) show that 20% of the narrowing gender gap in the 1980s in the U.S. is due to change in prices of cognitive, people and motor skills as well as the physical strength.

[7] This result is similar when the decomposition analysis is performed for an earlier period. See Table A.6 of Appendix A for the decomposition results for 1979–1988.

[8] The increase in the gender wage gap in Spain from 1994 to the beginning of 2000s is documented also by Guner, Kaya and Sánchez-Marcos (2014).

[9] During the period of analysis, in Italy, Portugal, Spain and Ireland, brawn skills became relatively even more valuable. The change in skill prices in these countries are potentially affected by the period of the analysis. Ireland and Spain from the mid-1990s experienced a construction and housing boom which potentially explains the increase in returns to brawn skills.

this question, we explore the relationship between the gender wage gaps that can not be explained by changes in observable gender-specific factors and wage structure and changes in various measures that captures the labor market institutions and discrimination. We find that the changes in these measures are highly correlated with the unexplained part of the gender wage gap trends. Furthermore, we provide some evidence consistent with the role of changes in the labor market institutions, such as decline in the trade union density and increase in the employment protection of temporary workers, in explaining the gender wage gap trends even if the bias induced by non-random selection to employment is corrected.

The number of studies that focus on the skill requirements of occupations to analyze the gender wage gaps in the European labor markets is rather limited. This paper is intended to fill this gap in the literature. A recent paper that is particularly related to the current study is Black and Spitz-Oener (2010). Using self-reported measures of tasks performed within occupations, Black and Spitz-Oener (2010) employ a task-based approach to study the effect of changing tasks on the gender wage gap trends in Germany. Their results indicate that changes in the relative task and relative prices together explain more than 40 percent of the narrowing of the gender gap in West Germany despite the widening effect of changing task prices. Overall, these results are parallel to the findings of this study. In contrast to Black and Spitz-Oener (2010), this study considers skills to be required to perform an occupation and characterizes occupations by skills rather than self-reported measures of routine or non-routine tasks.

The results of the current study are also related to the findings of Borghans, ter Weel, and Weinberg (2006). Using data for Germany, for the U.S. and for the U.K., they show that occupations that require more computer usage and higher extent of team work require more people skills. Moreover women have relatively higher employment rate in occupations which require people skills. They suggest that the increased importance of people skills by the technological change and innovative work practices have raised womens relative employment in those occupations. This study complements their findings by showing the increasing representation of women in occupations which require brain skills. In addition to that, this study quantifies the role of changes in skill intensities and skill prices on the gender wage gap trends in various countries.

The remainder of the paper is organized as follows. The next section explains the details of the decomposition technique employed. Section 1.3 describes the data sources and concepts used in the analysis and presents the empirical specification. Section 1.4 analyses the gender wage gap trends, changes in brain and brawn skill intensities of male and female workers and trends in skill prices in the sample of European countries and the U.S. The main results for the decomposition of the changing gender wage gaps are presented in Section 1.5. Finally, Sections 1.6 and 1.7 discuss the role of labor market institutions and non-random selection to the labor market that might also have an impact on the gender wage gap trends and Section 1.8 concludes.

1.2 Analytical Framework

The existing literature classifies the factors affecting the gender wage gap into two groups: (i) gender specific factors and (ii) factors related to wage structure. Gender specific factors capture the relative differences of males and females in labor market characteristics (such as education, experience, brain and brawn skill intensities) as well as the gender differences in unobserved qualifications or discrimination. Returns to labor market characteristics, skill prices or the residual wage inequality are not related specifically to aspects of gender and considered as factors related to wage structure. The method developed by Juhn, Murphy and Pierce (1991), hereafter JMP, enables one to decompose the change in the gender pay gap into changes in gender specific factors and those related to the changes in wage structure. This section briefly explains the JMP decomposition technique that is employed in the analysis to quantify the role of each component on the gender wage gap trends. To this end, let the wage equation for males at time t be given by

$$lnW_t^M = X_t^M\beta_t + S_t^M\gamma_t + \sigma_t\theta_t^M, \tag{1.1}$$

where lnW_t^M is the logarithm of hourly wages, X_t^M is a matrix of labor market characteristics (including education and experience) with returns vector β_t, S_t^M is the matrix of brain and brawn skill intensities of workers determined by the skill requirements of the jobs that they hold and γ_t is the price vector for brain and brawn skills. θ_t^M is the vector of standardized residuals (with mean zero and variance one) and σ_t is the residual standard deviation of male wages for year t (i.e. unexplained level of male residual wage inequality). Given consistent estimates of Equation 1.1, the gender wage gap for year t can be decomposed as

$$\Delta lnW_t \equiv lnW_t^M - lnW_t^F = [\Delta X_t\beta_t + \Delta S_t\gamma_t] + \sigma_t\Delta\theta_t, \tag{1.2}$$

where lnW_t^M and lnW_t^F are the average log hourly wage for males and females, respectively, ΔX_t is the male-female differences in labor market characteristics, ΔS_t is the male–female differences in brain and brawn skill intensities, and $\Delta\theta_t$ is the male–female differences in the average standardized residuals. Hence, the gender wage gap for year t can be decomposed into two components, one component due to male–female differences in average labor market characteristics and in average brain and brawn skills weighted by the male prices for these characteristics and skills ($\Delta X_t \beta_t + \Delta S_t \gamma_t$), and another component due to differences in the average standardized residuals weighted by the male residual wage inequality ($\sigma_t \Delta\theta_t$).[10] Then given the gender wage gap in two years, s and t, the change in the gender wage gap from year t to s, can then be decomposed as

$$\begin{aligned} \Delta lnW_s - \Delta lnW_t &= [(\Delta X_s - \Delta X_t)\beta_s + (\Delta S_s - \Delta S_t)\gamma_s] \\ &+ [\Delta X_t(\beta_s - \beta_t) + \Delta S_t(\gamma_s - \gamma_t)] \\ &+ (\Delta\theta_s - \Delta\theta_t)\sigma_s \\ &+ \Delta\theta_t(\sigma_s - \sigma_t). \end{aligned} \tag{1.3}$$

In this four component decomposition, the first component reflects the contribution of changing gender differences in labor market characteristics as well as the skill intensities and is called "observed X effect". The second component captures the effect of changing returns to characteristics and prices of skills for males and is called "observed β effect". The two components are straightforward to calculate using the estimated coefficients from the male wage equation and sample means by gender.

The third and the forth components are called "gap effect" and "unobserved price effect", respectively, and they are calculated using the entire male and female residual distributions. In particular, the gap effect is calculated as follows. First, for each women in each year a hypothetical wage residual is computed by estimating what her wage residual would be if her labor market characteristics and skills were rewarded as they would be rewarded for men for that year (i.e. female residuals from male regression). Then, a percentile number is assigned to her corresponding to the position of her hypothetical residual in the male residual wage distribution for that year. Second, given her percentile number in year t and the male residual wage distribution in year s, her imputed wage residual is computed for year t. Similarly, her imputed wage residual for year s is the male residual in year s that corresponds to her percentile number in year s. For males, the imputed wage residual for year t is calculated by using their percentile ranking in year s and their wage residuals for year t. Finally, the gender difference between the average of the imputed wage residuals in time period t and s are used to compute the gap effect. Since both computations use the same year s distribution, this term captures the effect of changing positions of females in the male wage residual distribution. Such a change is considered as either the convergence in unobservable skills of females and males or a

[10]We follow the parametrization by Blau and Kahn (1997) by formulating the wage gap based on male's wage equation. Alternatively, the formulation could based on the female's wage equation or pooled regression. Using male's wage equation lies in the assumption that the prices from the male regression are equivalent to competitive prices. Since, male-female differences in returns can reflect discrimination, the use of male's equation is employed to simulate the wage equation in a nondiscriminatory labor market.

decline in the discrimination (Juhn et al., 1991). Analogously, the unobserved price effect is calculated by comparing the same year t individuals and by allowing only male residual wage inequality to change. Provided that $\Delta\theta_t$ is negative (since females typically earn less than the mean), a rise in male residual inequality would lead to an increase the gender wage gap.

Since the first and the third term of Equation 1.3 captures the changing male–female differential in observed and unobserved qualifications respectively, the sum of these two terms are called "gender-specific factors". On the other hand, the sum of the second and the forth component reflects the changing observed and unobserved prices and is called as "wage structure effect" (Blau and Kahn, 1997; Juhn, et al., 1991). By decomposing the changes in the residual gap into into price and quantity effects, JMP decomposition technique can be used to quantify the relative importance of gender-specific factors and wage structure in the gender pay gap trends.

There are, however, two potential drawbacks of JMP decomposition (Blau and Kahn, 1997; Kunze, 2007; Suen 1997). First, the inconsistent estimates of β_t and γ_t in Equation 1.1 may affect the interpretation of each component. Since female employment rates have changed considerably, the selection bias might be one reason that would lead inconsistent estimates (Heckman, 1979). The sign of the bias is ex-ante unpredictable, since the selected group might be positively or negatively selected in terms of their unobserved characteristics (Blau and Beller, 1988; Blau and Kahn, 1997). Selectivity bias correction (Heckman, 1979) is a common approach to overcome this problem. In our benchmark estimates we use male prices to ameliorate the problem due to changes in non-random selection into work since male employment rates are quite stable over time.[11] Moreover, changes in male prices abstracts from the change in male-female differences in returns that may be relate with discrimination. In Section 1.7, we explore the possible contribution of sample selection to the gender wage gap trends by implementing the correction for selection into work using a two-stage Heckman (1979) selection model.

Second, the residual gender wage gap can be separated to gender-specific factors and wage structure component only if the residual gap does not change over time due to sample composition, measurement error, equation misspecification or a change in the distribution of unobserved characteristics. Since the aim of this chapter is to quantify the role of brain and brawn skills on the gender wage gap trends rather than identifying the role of gender specific factors and the factors related to wage structure per se, this is less of a concern for the purpose of this study. Nonetheless, the forces that may affect the residual gender wage gap is discussed in Section 1.6 with providing descriptive evidence that residual gap attributed to gender–specific factors actually may be changes in discrimination as well

[11]See Blau and Kahn (1997) for a similar approach.

as the changes in labor market institutions such as trade union density or employment protection.

1.3 Data, Concepts and Empirical Specification

1.3.1 Wage and Employment Data

For European countries, individual level data on wages and labor market characteristics comes from two different sources, European Community Household Panel (hereinafter, ECHP) and European Union Statistics on Income and Living Conditions (hereinafter, EU-SILC) provided by Eurostat. The ECHP is a panel survey of 15 European countries from 1994 to 2001, covering a wide range of topics like income, health, education, housing, demographics and employment characteristics. From 2001 the ECHP was succeeded by the EU-SILC. EU-SILC provides cross-sectional and longitudinal data on income, poverty, social exclusion and living conditions pertaining to individual-level changes over time, observed over a four year period since 2003. As a result, there is no single data source to study the long term dynamics of the wage structure in Europe., although the differences between these two surveys, harmonizing some of the variables of the two datasets is possible.[12]

The key variable for this study is the gross hourly wage. The analysis are restricted to the countries which provide complete information on hourly wages in both surveys, namely Austria, Ireland, Italy, Portugal, Spain and the U.K. The analysis are based on the data from the initial wave of ECHP and cross-sectional component of the EU-SILC because of their representativeness.[13] Both surveys include information on demographic characteristics and employment of individuals.[14]

For the U.S., the data come from Integrated Public Use Microdata Series (IPUMS) of Current Population Survey (hereinafter, CPS) March Supplements. The CPS survey years, 1994 and 2009, were selected to match the sample period of the ECHP and EU-SILC data used. The sample is restricted to individuals of working age, between 25 and 54 years old who are working at least 15 hours per week with valid observations on all the variables used in the wage equations. Wage observations five times greater than the 99th

[12] Goos, Manning and Salomons (2009 and 2011) make use of wages from these two surveys to investigate job polarization trends in Europe.

[13] In the first wave of ECHP, in 1994, a sample of nationally represented households were interviewed in Ireland, Italy, Portugal, Spain and the U.K. Austria have joined the project in 1995. Data from EU-SILC is used from the 2009 cross-sectional component for all countries except 2008 for the U.K. due to the differences in income reference period.

[14] See Appendix A.1.1 and A.1.2 for the description of variables and procedures followed to construct samples.

percentile or lower than the half of the 1st percentile of the country wage distributions in each year are excluded from the country samples. The U.S. samples are constructed using the same rules as the ECHP and EU-SILC samples.

1.3.2 Data on Skill Requirements of Occupations

Brain and brawn skill requirements of occupations constructed using Occupational Information Network (hereinafter, O*Net) data. O*Net database developed by the U.S. Department of Labor is the most well known source for information on occupations in the U.S. labor market. It is a replacement for the Dictionary of Occupational Titles (DOT) which was extensively used in earlier research.[15] Recently, O*Net has been used to determine occupational skill requirements and task content of occupations for several European countries.[16]

O*NET database provides detailed information about worker and job characteristics for more than 1110 occupations in the U.S. labor market with a set of measurable descriptors. The descriptors that characterize the occupations are defined and classified by O*Net. A subset of the these descriptors classified under worker abilities measures and includes descriptors on cognitive abilities, psycho-motor abilities and physical abilities.[17] To construct brain skills, all the descriptors classified under cognitive abilities and to construct brawn skills all the descriptors classified under psycho-motor and physical abilities are used – twenty one different measures of cognitive ability intensity, ten measures of psycho-motor ability intensity and nine measures of physical ability intensity.[18] Appendix A.1 provides the list and the description of the variables used, organized by brain and brawn skill type.[19]

[15]See Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Bacolod and Blum, 2010.

[16]We follow the common practice in the literature on matching occupational skill requirements of the U.S. labor market with European datasets. See Amuedo-Dorantes and de la Rica (2011) for Spain; Ortega and Polavieja (2009) for 25 European countries to analyze the task specialization of immigrants and Goos, Manning and Salomons (2009, 2011) for analyzing the job polarization in 16 European countries.

[17]It is common in the literature to reduce the large number of descriptors to a relevant subset using textual definitions. See Amuedo-Dorantes and de la Rica, 2011; Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009; Peri and Sparber, 2009.

[18]We checked the consistency of this classification using principal component analysis performed among all set of descriptors under worker abilities title. Informed by this analysis, we categorized cognitive ability measures as brains and psycho-motor abilities together with physical abilities as brawns. The results of the principle component analysis performed among all set of attributes are available upon request. The details of the principle component analysis technique can be found in Appendix A.3

[19]The remaining O*NET worker ability descriptors largely pertain to sensory dimension which we do not include in the analysis. We excluded the descriptors measuring sensory abilities mainly for two reasons. First, sensory abilities include descriptors that are not clearly being classified under one of the two sets (brains and brawns) according to their textual definitions. Second, they are related with some measures of cognitive abilities and at the same time with psycho-motor and physical abilities which prevents the clear classification of skills.

1.3.3 Constructing Skill Requirements of Occupations

To construct skill requirements of occupations, first, the occupation codes used in O*Net is converted to the codes used in individual level survey data.[20] Since individual level data provide occupation information at aggregate level (eighteen occupation categories) for each category there are several jobs classified under each broad title. Hence for each category, a weighted average of all the descriptor values for the jobs classified under the broad title is calculated using the percentage of workers employed in the U.S. labor market by 2001 as weights. It is important to note that matching O*Net data with European data relies on the assumption that the occupations in the U.S. and in Europe being examined herein are not different with regards to their skill requirements.

O*Net descriptors have the importance scale where O*Net rank each descriptor as not important at all (1), somewhat important (2), important (3), very important (4) or extremely important (5) to perform an occupation. As pointed out by the earlier research, descriptor values range from one to five, but the score of each descriptor varies considerably across occupations. Peri and Sparber (2009) and Amuedo-Dorantes and de la Rica (2011) overcome this problem by rescaling the measures. Following the methodology of Amuedo-Dorantes and de la Rica (2011), we rescale O*Net descriptors to reflect the relative importance of each skill among all occupations. Formally, let s_{kj} be the value of skill descriptor k for occupation j where $j = 1, 2, ...18$; and the maximum and minimum value of the descriptor s_k among occupations be $\overline{s_k}$ and $\underline{s_k}$. Each skill descriptor value is rescaled as the following: $s^*_{kj} = (s_{kj} - \underline{s_k})/(\overline{s_k} - \underline{s_k})$. Using the rescaled descriptor values, s^*_{kj}, the measures of brain and brawn skills are constructed by taking the simple average of corresponding set of descriptors' rescaled values. Table 1.1 displays the occupations under the broad classification, as well as the brain and brawn skill summary measures for each of the occupations.

As presented in Table 1.1, occupations at the top of the brain skill measure distribution are professionals (physical, mathematical, engineering, life science, health and teaching), and legislators, senior officials and managers (corporate managers and managers of small enterprises). At the bottom of the brain skill distribution, there are laborers (in mining, construction,manufacturing and transport) and elementary occupations (sales and services). If occupations are ranked according to their brain skill requirements, the average difference in brain skill requirement between two consecutive positions in the occupational ranking is 0.05, which is equal to 1/4 standard deviation difference in brain skills (standard deviation of brawn skills is 0.2). On the other hand, occupations at the top of the brawn skill distribution are mainly blue-collar workers (extraction and building workers

[20]See Appendix A.1.4 for the details of mapping 2010 Standard Occupational Code (SOC) used in the O*NET data to ISCO-88 codes.

Table 1.1: Brain and brawn skill intensity of occupations

Occupation code	Average of Rescaled Values: Brains	Brawns	Brains/Brawns	Occupation title
1112	0.86	0.33	2.59	Physical, mathematical, engineering, life science, health professionals
1300	0.78	0.1	7.94	Managers of small enterprises
2122	0.76	0.08	9.56	Teaching professionals
2300	0.74	0.16	4.68	Legislators, senior officials, corporate managers
2400	0.71	0.11	6.24	Other professionals
3132	0.65	0.51	1.27	Physical, engineering, life science, health associate professionals
3334	0.52	0.07	7.59	Teaching and other associate professionals
4142	0.51	0.78	0.65	Agricultural, fishery and related laborers
5100	0.49	0.87	0.56	Extraction, building, other craft and related trades workers
5200	0.47	0.78	0.6	Metal, machinery, precision, handicraft, printing and related trades workers
6100	0.47	0.83	0.56	Stationary-plant and related operators, drivers and mobile-plant operators
7174	0.45	0.33	1.36	Models, salespersons and demonstrators
7273	0.42	0.22	1.97	Office and customer services clerks
8183	0.38	0.62	0.6	Personal and protective services workers
8200	0.32	0.64	0.5	Machine operators and assemblers
9100	0.28	0.8	0.35	Skilled agricultural and fishery workers
9200	0.15	0.74	0.2	Laborers in mining, construction,manufacturing and transport
9300	0.02	0.53	0.03	Sales and services elementary occupations
Mean	0.50	0.47	2.63	
Std. dev.	0.23	0.30	3.12	
Pearson correlation coefficient	-0.58			

Note: Occupation codes are based on regrouped (group B) classification of ECHP data. If the occupations are regrouped, the first and the last two digits of the occupation code corresponds to the 2-digit ISCO-88 classification of occupations.

and stationary-plant operators). Once again, if the occupations are ranked according to their brawn skill requirements, again the average difference in brawn skill requirement between two consecutive positions implies, on average, 0.05 change in brawn skill measure which corresponds to a 1/6 standard deviation change in brawn skill requirement (standard deviation of brawn skills is 0.3).

Finally, constructed skill measures are merged with the individual level data using the occupational allocation of individuals. This allocative process may result from different choices of individuals, discrimination in the process of recruitment or hiring or differences in comparative advantage of workers as in Roy (1951) which is taken as given over the time period of analysis. Moreover, the brain and brawn skill measures do not vary by worker within occupations. On the other hand, since there is no time variation in O*Net, the time variation in brain and brawn skill intensity differences between men and women comes only from the occupational differences. The results of the current analysis are valid only if the skill composition within occupations is constant over time. Throughout a long period, some skills might become idle for certain occupations possible due to change in the task content of occupations by technological progress. However, using DOT (earlier version of O*Net) Goos and Manning (2007) show that most of the overall changes in task composition of occupations in U.S. labor market happened between occupations not within occupations. Autor and Handel (2009) also provide evidence on the dominance of occupation as a predictor for the variation in the task measures using the individual level Princeton Data Improvement Initiative. Given the results of previous studies and considering the relatively recent and short length of our individual level data (from 1993 to 2008), it is reasonable to assume that any kind of progression might affect the distribution of skills and skill prices rather than the skill content of the occupations.

1.3.4 Empirical Specification

Using the matched data set, the JMP decomposition is implemented by estimating the following specification:[21]

$$\begin{aligned} \ln Wage_{ijct} &= \beta_{1ct} + \beta_{2ct} Edu_{2ijct} + \beta_{3ct} Edu_{3ijct} + \beta_{4ct} Exp_{ijct} + \\ &+ \beta_{5ct} Exp^2_{ijct} + \beta_{6ct} Brains_{jct} + \beta_{7ct} Brawns_{jct} + u_{ijct} \end{aligned} \tag{1.4}$$

where $\ln Wage_{ijct}$ is logarithm of gross hourly wage of male worker i employed in occupation j in country c at year t. Edu_2 and Edu_3 are dummies for secondary and higher levels of educational attainment leaving the low level of educational attainment as the omitted category. Exp is the proxy for labor market experience. Finally, $Brains_{jct}$ and $Brawns_{jct}$ are the skill requirements of the occupation that the worker holds at time t.

To determine the skill prices separately, hedonic price model is employed and occupations are assumed to be described by their bundle of skills, brains and brawns, and since brain and brawn skills can not be sold separately there is no market for skills. Hence, the prices of these skills are not observed independently. Then, the ordinary least squares estimates for the skill coefficients in Equation 1.4 are interpreted as the marginal contributions of brains ($\partial \ln Wage/\partial Brains$) and brawns ($\partial \ln Wage/\partial Brawns$) to the logarithm of hourly wages.

1.4 Descriptive Analysis

1.4.1 Gender Wage Gap Trends

Table 1.2 summarize the main characteristics of the variables used in the analysis. First of all, female workers on average earned less than males in all the countries in each year indicating the persistence of gender wage gaps. The unadjusted gender wage ratio in the U.S. was around 75% ($e^{(2.557-2.842)} * 100$) in 1993 and 79% ($e^{(2.665-2.899)} * 100$) in 2008. The unadjusted gender wage ratio for the European countries varied between 74%

[21] We investigated the possibility of different functional forms using higher order polynomials in brains and brawns (namely quadratic and cubic terms). In no case, these terms were statistically significant and had an effect on the ceteris paribus returns to other labor market characteristics.

Table 1.2: Summary statistics on female and male workers, 1993 and 2008

Panel A. Descriptive statistics for 1993	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Log (hourly wage)	2.184	2.461	2.107	2.346	2.125	2.200	1.382	1.509	2.066	2.146	2.111	2.408	2.557	2.842
	(0.544)	(0.435)	(0.571)	(0.532)	(0.405)	(0.367)	(0.680)	(0.597)	(0.550)	(0.518)	(0.484)	(0.517)	(0.610)	(0.630)
Primary edu(%)	23.7	14.8	22.4	34.8	38.2	49.6	66.1	76.7	39.5	52.9	43.7	35.4	3.4	5.6
Secondary edu(%)	66.8	76.8	51.1	39.7	48.6	38.2	14.0	11.9	20.8	19.5	25.7	25.9	59.0	57.4
High edu(%)	9.5	8.4	26.3	25.3	12.8	11.3	13.3	9.2	39.7	27.6	30.2	38.0	37.6	37.0
Experience (year)	17.282	16.655	15.683	18.185	14.375	16.609	15.711	19.082	13.930	17.579	18.838	17.774	18.667	18.572
	(9.672)	(9.522)	(8.960)	(9.416)	(9.370)	(9.830)	(9.585)	(9.855)	(9.716)	(10.464)	(10.382)	(9.818)	(8.510)	(8.442)
Brain skills	0.411	0.479	0.502	0.508	0.453	0.446	0.435	0.474	0.455	0.474	0.499	0.547	0.515	0.496
	(0.193)	(0.172)	(0.214)	(0.198)	(0.194)	(0.177)	(0.192)	(0.161)	(0.246)	(0.181)	(0.207)	(0.199)	(0.210)	(0.222)
Brawn skills	0.375	0.550	0.330	0.488	0.372	0.508	0.446	0.570	0.355	0.546	0.329	0.435	0.318	0.464
	(0.231)	(0.293)	(0.213)	(0.300)	(0.265)	(0.293)	(0.280)	(0.289)	(0.243)	(0.291)	(0.216)	(0.290)	(0.229)	(0.300)
Number of obs.	952	1,440	951	1,365	1,597	2,551	1,229	1538	1,276	2,551	3,132	3,357	22,062	23,172

Panel B. Descriptive statistics for 2008	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Log (hourly wage)	2.324	2.523	2.570	2.666	2.170	2.228	1.614	1.735	2.203	2.318	2.612	2.842	2.665	2.899
	(0.438)	(0.441)	(0.502)	(0.504)	(0.406)	(0.369)	(0.552)	(0.548)	(0.476)	(0.443)	(0.518)	(0.524)	(0.630)	(0.672)
Primary edu(%)	14.3	8.5	12.4	20.0	26.5	42.1	54.6	68.2	26.1	36.3	8.0	7.0	3.4	5.4
Secondary edu(%)	50.3	56.7	24.4	23.2	43.2	39.9	19.3	17.4	24.4	23.4	52.5	52.2	48.0	52.9
High edu(%)	35.4	34.7	61.7	50.5	30.3	17.9	25.2	12.9	49.4	39.9	46.7	47.0	48.6	41.7
Experience (year)	19.828	22.168	16.496	18.226	15.436	17.315	17.967	20.675	15.473	18.451	14.831	15.622	19.828	19.820
	(9.178)	(9.178)	(9.212)	(10.018)	(8.454)	(8.953)	(9.570)	(10.241)	(8.759)	(9.286)	(10.390)	(9.529)	(9.251)	(9.055)
Brain skills	0.438	0.492	0.541	0.523	0.462	0.453	0.417	0.474	0.459	0.482	0.527	0.558	0.538	0.504
	(0.208)	(0.188)	(0.210)	(0.227)	(0.200)	(0.194)	(0.233)	(0.181)	(0.237)	(0.196)	(0.188)	(0.221)	(0.211)	(0.220)
Brawn skills	0.327	0.505	0.314	0.443	0.347	0.372	0.418	0.587	0.346	0.518	0.300	0.401	0.305	0.451
	(0.220)	(0.294)	(0.211)	(0.287)	(0.249)	(0.265)	(0.252)	(0.276)	(0.220)	(0.291)	(0.206)	(0.278)	(0.223)	(0.301)
Number of obs.	1,744	1,960	1,170	1,113	5,172	6,193	1,351	1,377	3,854	4,140	2,232	2,070	31,018	31,907

Data Source: For 1993-1994 sample, European Community Household Panel (for Ireland, Italy, Portugal, Spain, U.K. 1994 and for Austria 1995) and CPS March Supplements (for the U.S. 1994). For 2008 sample, European Union Statistics on Income and Living Conditions (EU-SILC, 2009) and CPS March Supplements 2009. *Notes:* See Appendix A.1.1 for variable definitions.

(for the U.K.–$e^{(2.111-2.408)} * 100$) and 92% (for Italy–$e^{(2.125-2.200)} * 100$) in 1993. During the 1990s and 2000s, the majority of European countries experienced a decline in the gender wage gap similar to the U.S. except Spain. The decline in the gender wage gap in European countries and the U.S. varied from the lowest 0.006 log points (in Portugal–$[(1.509-1.382)-(1.735-1.614)]$ to the highest 0.143 $[(2.346-2.107)-(2.666-2.570)]$ log points (in Ireland). By 2008, the unadjusted female–male wage ratio was lowest for the U.K. and for the U.S. (about 79% for both countries). In Spain, the unadjusted gender wage gap increased from 0.080 (2.146-2.066) log points in 1993 to 0.115 (2.318-2.202) log points in 2008.[22]

One obvious reason for closing of the gender wage gaps might be the improved labor market characteristics of women. In fact, during the period of analysis, women have been catching up with men in their educational attainment levels. By 2008, the share of women at higher educational levels rose considerably as compared to 1993 in all countries in the sample. Austria and Ireland experienced the most remarkable increase. From 1993 to 2008, the share of women with higher education increased 25.9 percentage points in Austria and 35.4 in Ireland. Although there was an increase in the share of higher educated males during this period, the increase was larger for females than males in all countries, again except for Spain. In Spain the fraction of with high education increased 12.3 percentage points for males, while the increase was only around 9.7 percentage points for females. On the other hand, in 2008 women workers were more experienced than they were in 1993. In 1993, the average years of labor market experience of women in our sample was 14.31 years, while in 2008 it was 14.98 years. However, from 1993 to 2008 the experience levels of men also increased (from 15.56 years of labor market experience to 16.53 years). Hence, the male–female difference in experience levels persisted in most of the European countries to the detriment of women. From 1993 to 2008, the experience gap between males and females narrowed in Ireland, Italy, Portugal and Spain, while the gap widened in Austria and the U.K. On the other hand, as Table 1.2 presents, women in the U.S. became on average more experienced than men already at the beginning of 1990s.

1.4.2 Brain and Brawn Intensities

Besides the observed labor market characteristics (education and experience), a part of the changing gender wage gap might be explained by the changing male–female differences in

[22]See the report by Eurofound on the increase in the gender wage gap in Spain during the late 1990s: http://www.eurofound.europa.eu/eiro/studies/tn0912018s/es0912019q.htm. Using data from the ECHP and EU-SILC, Guner, Kaya and Sánchez-Marcos (2014) also show that Spanish gender wage gap increased 0.074 log points from 1994 to 2004.

brain and brawn skill intensities that occur due to the shifts in occupational allocations.[23] Table 1.2 provides the average brain and brawn skill intensities of male and female workers in each country in 1993 and in 2008.

First, similar to the U.S., in 1993 in all the European countries in the sample workers were allocated to occupations such that males were on average more brawn skill intensive than females. However, in contrast to the U.S., in Europe, males were also on average more brain skill intensive than than their female counterparts. The only exceptions are Ireland and Italy where the gender differences in brain skill intensity are not statistically different. Second, in 1993, like female workers in the U.S., European women were likely to work in occupations that require more brain than brawn skills, on average. Portugal is the only exception. In Portugal, women were working in occupations that require on average more brawn skills than brain skills. However, in contrast to the U.S., in 1993 European males were working in occupations such that their average brawn skill intensity was larger than their average brain skill intensity. The only exceptions are Ireland and the U.K. where by 1993 males were allocated to occupations such that their average brain skill intensity was higher than their average brawn skill intensity.

From 1993 to 2008, both European men and women shifted their occupational allocations to more brain skill and less brawn skill intensive occupations similar to their counterparts in the U.S. The only exception is again Portugal, where the average brain skill intensity of females slightly decreased and the average brawn skill intensity of males increased. The shifts in the occupational allocations of males and females resulted in changes in the male–female skill differences. In particular, the gap between genders in brain skill intensities increased favoring females except in Portugal and Spain, while the brawn skill intensity gap increased favoring males only in Austria and Portugal.

1.4.3 Brain and Brawn Skill Prices

How did the skill prices change during the last decades in the European labor market? To answer this question, Table 1.3 presents the male wage regression estimates.[24] In all the countries in common, brain skills were positively and significantly valued throughout the period, while the marginal contribution of brawn skills to the logarithm of hourly wages was relatively small and negative. To be concrete, as discussed in Section 1.3.3, a change in occupation associated with a 1/4 standard deviation increase in brain skill requirements such as going from having the brain skills required to be a protective service

[23]See Tables A.1 and A.2 of Appendix A for the occupational allocation of males and females in 1993 and in 2008 for the sample of countries.

[24]See Tables A.7 and A.8 of the Appendix A for the estimation results using the males and females pooled sample and using only females, respectively.

worker to be an office or service clerk. In 1993, such a skill premium was associated with the lowest 1.9 percent (for Italy, 0.384×0.05) and with the highest 4.3 percent (for Portugal, 0.866×0.05) rise in wages in the European countries in the sample. In 2008, the same occupational change was associated with the least 2.1 percent (for Italy, 0.438×0.05) and the most 3.6 percent (for the U.S., 0.715×0.05) higher wage. On the other hand, in 1993, a change in occupation that implied a 1/6 standard deviation increase in brawn skill requirements received a wage penalty, penalty being highest in Portugal (with around 3.7 percent, -0.731×0.05) and the lowest in the U.S. (with around 0.8 percent, -0.166×0.05). By 2008, this penalty was lowest in Ireland (with around 0.7 percent, -0.141×0.05) and despite highest in Portugal (with around 1.9 percent, -0.371×0.05).

From 1993 to 2008, returns to brain skills increased in Austria, Italy, the U.K. and the U.S., while in Ireland, Portugal and Spain brain skills became relatively less valuable.[25] Among European countries, the highest in increase in marginal contribution of the brain skills to the logarithm of hourly wages occurred in Italy (5.4 percentage points increase). Compared to European countries, in the U.S. the increase in marginal contribution of the brain skills to the wages was much higher with around 14.7 percentage points ($0.715 - 0.568$). During the same period, brawn skills became significantly less valuable in the U.S., as well as in Austria and in the U.K. In contrast to the U.S. experience, the brawn skill penalty declined in Southern European countries and in Ireland.

As a result, from 1993 to 2008, in all the sample of countries, there had been substantial changes in brain and brawn skill differences between genders and prices of these skills. Despite the cross-country differences in changing male–female differences in brain and brawn skills and skill prices, from 1993 to 2008 the unadjusted gender wage gap narrowed in all countries except Spain. The change in the gender wage gap may reflect several changing dynamics including the relative improvements in women's characteristics and skills and/or declines in the returns to those characteristics and prices of skills. For this purpose, Section 1.5 quantifies the role of each factor determining the trends in the gender wage gap using the decomposition analysis described above. But before, the following section considers a number of robustness checks for the estimates of the brain and brawn skill prices.

1.4.4 Robustness Checks

A range of robustness tests are carried out to check whether the estimated returns to brain and brawn skills are affected by the construction of skills discussed in Section 1.3.3 or the empirical specification (Equation 1.4). For checking whether the construction pro-

[25]For each country, the changes in brain skill prices are statistically significant at 1% significance level.

Table 1.3: Wage regression estimates

	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	1994	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008
Secondary Education	0.117 ***	0.069 ***	0.244 ***	0.102 *	0.115 ***	0.094 ***	0.142 ***	0.281 ***	0.223 ***	0.142 ***	0.118 ***	0.130 **	0.432 ***	0.315 ***
	(0.039)	(0.031)	(0.039)	(0.051)	(0.022)	(0.022)	(0.037)	(0.051)	(0.030)	(0.027)	(0.015)	(0.059)	(0.047)	(0.030)
Higher Education	0.235 ***	0.249 **	0.395 ***	0.405 ***	0.350 ***	0.243 ***	0.538 ***	0.663 ***	0.349 ***	0.270 ***	0.275 ***	0.301 ***	0.739 ***	0.673 ***
	(0.073)	(0.044)	(0.061)	(0.064)	(0.039)	(0.035)	(0.123)	(0.175)	(0.054)	(0.040)	(0.035)	(0.053)	(0.072)	(0.057)
Experience	0.002	0.022 ***	0.033 ***	0.022 ***	0.007 **	0.027 ***	0.015 ***	0.043 ***	0.014 **	0.029 ***	0.022 ***	0.014 ***	0.043 ***	0.043 ***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.003)	(0.004)	(0.009)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Experience^2	0.000	- 0.000 **	- 0.000 ***	- 0.000	- 0.000	- 0.000 ***	- 0.000 ***	-0.001 ***	- 0.000	- 0.000 ***	- 0.000 ***	- 0.000 **	-0.001 ***	-0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.595 ***	0.614 ***	0.682 ***	0.570 ***	0.384 ***	0.438 ***	0.866 ***	0.450 **	0.724 ***	0.583 ***	0.649 ***	0.680 ***	0.568 ***	0.715 ***
	(0.137)	(0.059)	(0.150)	(0.127)	(0.101)	(0.106)	(0.216)	(0.208)	(0.192)	(0.103)	(0.132)	(0.070)	(0.136)	(0.123)
Brawns	-0.188 ***	-0.260 ***	-0.307 **	-0.141	-0.314 ***	-0.204 **	-0.731 ***	-0.371 **	-0.405 ***	-0.328 ***	-0.234 *	-0.291 ***	-0.166	-0.170 **
	(0.028)	(0.036)	(0.108)	(0.089)	(0.071)	(0.075)	(0.122)	(0.141)	(0.079)	(0.085)	(0.126)	(0.072)	(0.099)	(0.074)
Constant	2.097 ***	1.918 ***	1.546 ***	1.858 ***	2.004 ***	1.746 ***	1.289 ***	1.123 ***	1.693 ***	1.715 ***	1.790 ***	2.236 ***	1.592 ***	1.688 ***
	(0.121)	(0.089)	(0.110)	(0.115)	(0.056)	(0.101)	(0.133)	(0.139)	(0.121)	(0.126)	(0.116)	(0.060)	(0.153)	(0.141)
VIF(Brains)	1.38	1.43	1.73	1.88	1.28	1.26	1.42	1.45	1.46	1.43	1.63	1.51	1.73	1.86
VIF(Brawns)	1.26	1.31	1.55	1.7	1.46	1.32	1.38	1.55	1.37	1.49	1.48	1.51	1.78	1.87
R^2	0.15	0.26	0.34	0.37	0.32	0.25	0.43	0.36	0.36	0.37	0.25	0.23	0.25	0.27
Number of obs.	1,440	1,960	1,365	1,113	2,551	6,193	1,538	1,377	2,551	4,140	3,357	2,070	23,172	31,907

Notes: i) Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies. (iv) Variance inflation factor: VIF$= 1 - (1 - {R_i}^2)$ and ${R_i}^2$ is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

cess of skill measures affects the wage equation estimates, a different technique, Principle Component Analysis is employed to generate brain and brawn skill measures. Principle Component Analysis is a data reduction technique which maximizes the amount of variation of the large number of variables explained by a smaller number of components (Jolliffe, 1986).[26] Using the brain and brawn skill measures constructed via Principle Component Analysis, the skill intensity of jobs held by females and males are determined and the empirical model specified in Equation 1.4 is re-estimated. Table A.10 in Appendix A provides the estimate of the male wage regression specified in Equation 1.4 using the skill measures constructed via Principle Component Analysis. A comparison of the returns to skills using these new measures of skills with the estimation results discussed in the previous section shows that construction process of skill measures does not alter our results.[27]

The second check for robustness focuses on the empirical specification. The empirical specification that is considered, excluding the brain and brawn skill measures, is simple but fairly standard in the literature (Blau and Kahn, 1997; Willis, 1986). However, the estimation of wage equation including brain and brawn skills simultaneously might exhibit collinearity. As presented in Table 1.1, brain and brawn skill measures are negatively correlated. The existence of collinearity would inflate the variances of the parameter estimates and can produce parameter estimates of the "incorrect sign" and of implausible magnitude (Greene, 1993). Taking into account this concern, the variance inflation factor (VIF), the collinearity diagnostic statistics is computed and presented in Table 1.3. VIF is based on the proportion of variance in the each independent variable that is not related to the other independent variables in the model. Conventionally, a variance inflation factor of ten or larger have been used as rule of thumb to indicate serious multicollinearity (Kennedy, 1992; Hair, Black, Babin and Anderson, 1995). As seen in Table 1.3 the mean variance inflation factor values for brain and brawn skill measures for each regression are

[26] Principle Component Analysis has been commonly used in the literature to construct measures from DOT or O*Net data (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009; Ortega and Polavieja, 2012). See Appendix A.3 for a brief explanation of the technique and the procedure followed to construct skill measures and summary statistics of brain and brawn skills using this method.

[27] The skill measures constructed by the Principle Component Analysis are unit free as the rescaled skill measures, but note that the scale of measurement in both technique is different. Using skill measures constructed with another process produces negligible changes in the estimated coefficients. For example, the coefficient estimate for brain skills using the measures constructed by Principle Component Analysis is around 0.143 for the U.S. in 1993. In this case, the standard deviation of brain skill measure is one by construction (See Table A.4 in Appendix A). Then one standard deviation increase in brain skills is associated with 14.3% increase in hourly wages. Once again, if occupations are ranked according their brain skill requirements, a change in occupation implies on average 0.2 increase in brain skill measure, i.e. 1/5 standard deviation increase in brain skills. This change (1/5 standard deviation increase) is associated with 2.8% ($14.3 \times 1/5$) increase in hourly wages which is the same as the main estimations presented in Table 1.3 (0.568×0.05). A similar comparison can be done for the rest of the coefficients.

much lower than ten indicating no collinearity.

As a third robustness check, we also consider an alternative specification that includes only the ratio of brain to brawn skill measures instead of the brain and brawn skill measures separately:

$$\begin{aligned} \ln Wage_{ijct} &= \beta_{1ct} + \beta_{2ct} Edu_{2ijct} + \beta_{3ct} Edu_{3ijct} + \\ &+ \beta_{4ct} Exp_{ijct} + \beta_{5ct} Exp^2_{ijct} + \beta_{6ct} (Brains/Brawns)_{jct} + u_{ijct}, \end{aligned} \quad (1.5)$$

where (Brains/Brawns) is the brain to brawn skill ratio of the job j that the individual i in country c held at time t. In this case, the coefficient estimate for brain to brawn ratio, β_6, reflects the marginal contribution of working in an occupation relatively more brain skill intensive than brawn skill. The full set of coefficient estimates from this specification is presented in Table A.9 of Appendix A. Once again, the estimation of this specification give positive and significant coefficient estimates for the brain to brawn ratio implying a positive return of working in a relatively more brain skill intensive occupation. We find that, in line with the results presented in the previous section, returns to brains to brawns ratio increased in the U.S. over time period of analysis. Among the European countries in the sample, in the U.K., return to brains to brawns ratio increased, in Austria and in Ireland did not change significantly, while in Southern European countries, the returns declined from 1993 to 2008.

1.5 Decomposition of the Changes in the Gender Wage Gap

What is the role of skills in explaining the gender wage gap trends? The decomposition analysis results presented in Panel B of Table 1.4 addresses this question. But before, several interesting descriptive findings regarding the changes in the gender wage gaps are presented in Panel A.

The first four rows of Panel A present the residual standard deviation for males and females (from own wage regressions specified by Equation 1.4) in 1993 and 2008. A higher residual standard deviation indicates a higher wage inequality within education, experience and brain–brawn skill levels. For instance, the residual wage inequality for males was higher than females in all the countries except Italy in both years and in Austria in 2008. From 1993 to 2008, the residual wage inequality increased for both genders in most of the countries. The only exceptions are Austria, Portugal and Spain where the residual wage inequality declined both for males and females. One important difference

Table 1.4: Decomposition of the change in gender wage gap, 1993 vs 2008

Panel A. Descriptive statistics	Austria	Ireland	Italy	Portugal	Spain	U.K.	U.S.
Male residual SD*							
1993	0.402	0.433	0.303	0.451	0.416	0.448	0.545
2008	0.378	0.399	0.320	0.440	0.352	0.458	0.575
Female residual SD**							
1993	0.488	0.434	0.308	0.416	0.399	0.395	0.533
2008	0.353	0.421	0.332	0.340	0.344	0.449	0.546
Mean female residual from male wage regression							
1993	-0.264	-0.274	-0.125	-0.192	-0.155	-0.272	-0.333
2008	-0.188	-0.143	-0.103	-0.218	-0.146	-0.229	-0.311
Mean female residual percentile***							
1993	31.14	32.62	38.76	35.89	39.08	30.71	32.01
2008	33.72	39.82	40.64	33.61	38.65	34.24	33.46
Panel B. Decomposition of the change in gender wage gap $\Delta\overline{lnW_{2008}} - \Delta\overline{lnW_{1993}}$							
Change in gender wage gap	**-0.078**	**-0.143**	**-0.018**	**-0.006**	**0.035**	**-0.066**	**-0.051**
Gender wage gap-1993 ($\Delta\overline{lnW_{1993}}$)	0.277	0.238	0.075	0.127	0.080	0.297	0.285
Gender wage gap-2008 ($\Delta\overline{lnW_{2008}}$)	0.199	0.096	0.057	0.121	0.115	0.231	0.234
(1) Observed X's	**0.007**	**-0.041**	**-0.042**	**-0.071**	**0.015**	**-0.013**	**-0.023**
Education variables	-0.003	-0.016	-0.030	-0.044	0.010	-0.021	-0.018
Experience variables	0.019	-0.017	-0.002	-0.009	-0.007	0.018	0.003
Brains	-0.009	-0.017	0.007	0.015	0.004	-0.011	-0.008
Brawns	-0.001	0.009	-0.017	-0.033	0.008	0.001	0.000
(2) Observed Prices	**-0.009**	**0.030**	**0.045**	**0.039**	**0.030**	**-0.010**	**-0.006**
Education variables	-0.003	0.001	0.014	-0.018	0.008	0.000	-0.001
Experience variables	0.006	0.006	0.010	0.019	0.011	-0.005	0.000
Brains	0.001	0.002	0.001	-0.024	-0.003	0.001	-0.005
Brawns	-0.013	0.022	0.021	0.061	0.013	-0.006	-0.001
(3) Unobserved Prices	**-0.003**	**-0.018**	**0.004**	**0.006**	**-0.032**	**0.010**	**0.013**
(4) Gap	**-0.073**	**-0.114**	**-0.025**	**0.020**	**0.022**	**-0.053**	**-0.034**
Sum gender-specific $(1+4)$	-0.066	-0.155	-0.067	-0.051	0.037	-0.066	-0.058
Sum wage structure $(2+3)$	-0.012	0.012	0.049	0.045	-0.002	0.000	0.007

Notes: The change in the differential is the change in the male-female log wage differentials between 1993 and 2008. * Estimated using male wage regression. ** Estimated using female wage regression. *** Computed by assigning each women a percentile ranking in the indicated year's residual male wage distribution and calculating the female mean of these percentiles.

between the European countries in the sample and the U.S. is that both male and female residual wage inequalities were much higher in the U.S. than any other European country in both years.

The mean female residual from the male wage regression and the mean female residual percentile presented in the following four rows of Panel A. The mean female residual from the male wage regression is generally interpreted as a measure of discrimination but might also capture the omitted productivity differences between males and females (Blau and Kahn, 1997). On the other hand, the mean female residual percentile show the progression of females within education, experience and skill groups similar to the change in the absolute value of the female residuals from male wage regression. The results presented in Table 1.4 indicates that the mean female residual from male wage equation of residuals are lower for the U.S. than all the European countries in the sample. In other words, after controlling for education, experience as well as the brain and brawn skills, the adjusted female–male wage ratio was lowest in the U.S. to the detriment of women in both years. By 1993, the adjusted female–male wage ratio varied from 76% (for Ireland) to 88% (for Italy) in the European countries, while it was only around 72% in the U.S. By 2008, the ratio was highest in Italy (with around 90%) and lowest in the U.K. (with around 80%) still being 7 percentage points above the U.S. ratio (with around 73%). Moreover, by 2008, the mean female residual percentile was higher compared to 1993 in all countries except Portugal and Spain. In Portugal, from 1993 to 2008, the mean female residual decreased which resulted in a lower ranking of the mean female residual percentile. On the other hand, in Spain although the the mean female residuals (from male regression) increased from -0.155 in 1993 to -0.146 in 2008, women did not move up within the residual wage distribution of males.

The unadjusted gender wage gaps in 1993 and in 2008 as well as the change in the gap between these two years is presented in Panel B. During 1990s–2000s all European countries experienced a decline in the unadjusted gender wage gap in common, except Spain. Despite the common trend in the gender wage gap in other countries, the rate of convergence varies substantially across countries, from 0.006 log points (in Portugal) to 0.143 log points (in Ireland). How did the changes in skill prices affect gender wage gap trends? In the U.S., from 1993 to 2008, 17% (0.008/0.051) of the closing gender wage gap can be explained by changes in returns to brain and brawn skills. Similar to the U.S. experience, in Austria and in the U.K. a part of the convergence in the gaps was due to changes in skill prices, about 15.4% (0.012/0.078) of the gender wage gap in the former and around 7.8% (0.005/0.066) in the later. However, in contrast to the U.S. experience, the changes in returns to brain and brawn skills had a widening effect on the gender wage gap in Ireland, Italy, Portugal and Spain. The main reason for this is that, in all Southern European countries and in Ireland, brawn skills became more valuable, skills that women had an initial deficit. Hence, if the occupational allocation of men and women had remained constant, this should have widen the gender wage gaps. Despite the decline in brain skill prices in Portugal and in Spain that favored women since women had also initial deficit in brain skills, the change in brawn skill prices reclaimed the potential gains of women from the decline in brain skill prices.

What accounts for the convergence of the gender wage gaps? We start with the contribution of "Observed X's" and "Observed Prices". "Observed X's" heading indicates the contribution of the labor market characteristics and skills to the gender wage gap trends in each country for 1990s-2000s. The "Observed Prices" captures the effect of changing returns to characteristics and prices of skills on the gender wage gap trends. We start with the only exception, Spain that experienced an increase in the unadjusted gender wage gap, around 0.035 log points. As seen in Table 1.4, the change in gender differences in labor market characteristics and skills as well as the the change in returns to these characteristics and skills were responsible for the widening gender wage gap in Spain. On the other hand, in other European countries, a substantial part of the convergence in the gender wage gaps, cannot be explained by observed factors. The part of the convergence explained by changes in characteristics and skills and returns to these characteristics and skills is only around 2.5% for Austria, 7.7% for Portugal, 18.8% for Ireland and 35% for the U.K. In Italy, however, the changes in these factors cannot explain the closing gender wage gap. However, in the U.S. the changes in "Observed X's" and "Observed Prices" accounted for more than the half (around 57%, 0.029/0.051) of the convergence in the gender wage gap.

The change in male residual wage inequality measured as "Unobserved Prices" had a widening effect on the gender wage gap in Italy, Portugal, and the U.K. as well as the U.S. Hence female workers in these countries were adversely affected from the increase of male residual inequality (see Male residual SD in Table 1.4). On contrary, the decline in the wage residual inequality in Austria and Spain favored women. However, the change in male residual wage inequality is unlikely to explain the gender wage gap trends.

Turning the attention to the last term of the decomposition, "Gap effect" reveals the importance of the unexplained factors on gender wage gap trends. In countries where females moved up in the male residual wage distribution (see Mean female residual percentile in Table 1.4), namely in Austria, Ireland, Italy, the U.K. and the U.S., the gap effect is negative. In other words, womens progression within groups had a narrowing effect on the gender wage gap from 1993 to 2008 in these countries. In Portugal and in Spain, however, the gap effect had a widening effect on the gender wage gaps. What is striking is that, the "Gap effect" accounts for a substantial part of the convergence of the gender wage gap in most of the countries. The part of the convergence gender wage gap due to unobserved factors measured as "Gap effect" is around 94% for Austria, 80% for Ireland and the U.K., and 66% for the U.S. In Spain, "Gap effect" accounts for the 63% of the widening gender wage gap. In Italy, the unexplained part reach a value greater than 100% implying if observed and unobserved prices, i.e. wage structure would not have changed, the gender wage gap would narrow even further. In Portugal, the gap effect is not able to explain the convergence in the gender wage gap.

1.6 The Role of Labor Market Institutions

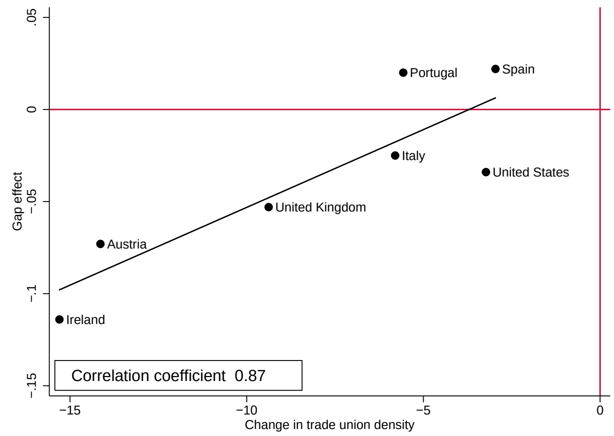
One of the results of this study arise from the fact that a substantial part of the changes in the gender wage gaps can not be explained by the changes in the gender gaps in labor market characteristics and skills or changes in the wage structure (measured as gap effect presented in Table 1.4). It is important to note that, not only the convergence in unobserved skills of males and females, but also the changes in the labor market institutions and/or the changes in discrimination would be captured by the gap effect. Indeed, Gayle and Golan (2012) develop a model of the labor supply, occupational sorting and human capital accumulation in which statistical discrimination and a wage gap arise endogenously. They use this dynamic equilibrium model to quantify the driving forces behind the decline in the gender earnings gap in the U.S. They find that for the period 1967–1997 decline in the statistical discrimination accounts for a large fraction of the decline in the gender wage gap in the U.S.

Actually, women in the U.S. advanced in the male residual distribution much more during 1980s compared to 1990s–2000s (measured as the mean female residual percentile).[28] If a part of the gap effect is due to statistical discrimination and such a sharp decline in statistical discrimination occurred in the U.S. during the 1980s, this might partially explain the larger contribution of the gap effect to the change in the gender wage gap during the 1980s as compared to the later decades. Indeed, the main bulk in women's improvement in labor market characteristics and skills and the increase in the labor market commitment of women in the U.S. occurred during the 1980s which might contributed to a reduction in statistical discrimination (Blau and Kahn, 2000). On the other hand, as shown by Pissarides, Garibaldi, Olivetti, Petrongolo and Wasmer (2005), more generous institutions that compress the wage distribution will also tend to decrease the gender wage gap. In other words, the changing positions of females in the male wage residual distribution might be not only due to the convergence in unobservable skills of females and males, but also to the decline in the discrimination or changes in the labor market institutions. Unfortunately, the harmonized data used in this study lack variables on either union status or union coverage. However, for further investigating the issue, this section provide descriptive evidence on the role of some of these factors on the changing gender wage gap via gap effect. For this purpose the relationship between the gender wage gaps

[28] See Tables A.5 and A.6 of Appendix A for the wage regression estimates and decomposition of the change in the U.S. gender wage gap from 1979 to 1988.

that can not be explained by the characteristics and skills or returns to these characteristics and skill prices (measured as gap effects presented in Table 1.4) and the changes in various measures that captures the labor market institutions and discrimination is explored. We find that the changes in these measures are highly correlated with the gap effect. In other words, the change in female's progression in each country's male residual wage distribution might be capturing the effect of changes in some of these measures or a combination of them.

The measures that capture the changes in the labor market flexibility include the change in the trade union density as well as the OECD employment protection measures for temporary and regular workers. The change in trade union density in each country is defined as the change in the percentage of employees who are members of a trade-union from 1993 to 2008. For calculating the change in employment protection of regular and temporary workers in each country, the changes in the value of two OECD indicators from 1993 to 2008 are used. These two OECD indicators are individual dismissal of workers with regular contracts and regulation of temporary contracts.[29]



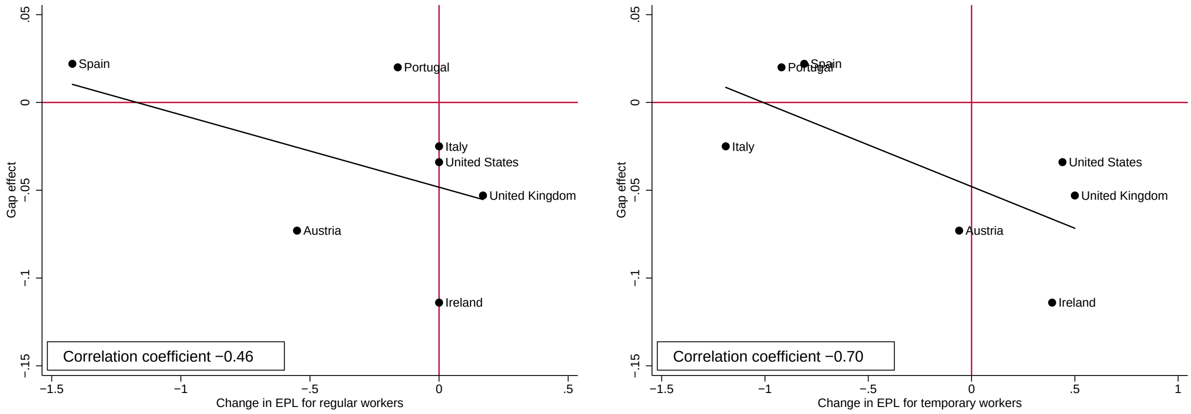
Note: The change in trade union density is defined as the change in the percentage of employees who are members of a trade-union from 1993 to 2008.

Figure 1.1: The change in trade union density and the gap effect

Figure 1.1 relates the change in trade union density from 1993 to 2008 to the gap effects presented in Table 1.4. As Figure 1.1 shows, in all countries there was a decline in trade union density from 1993 to 2008. The higher the decline in the trade union density, the larger the gap effect implying a higher rank for females within the residual wage distribution of males. This might be explained by the fact that the decline in the

[29]To find out more about the employment protection measures see www.oecd.org/employment/protection.

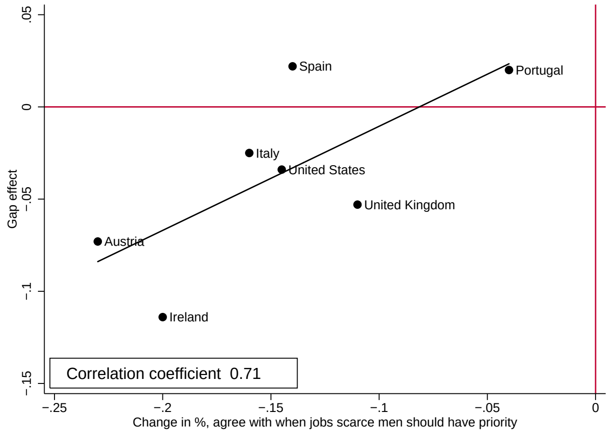
trade union membership might decrease the unionization gap between men and women given the higher trade union membership among men. Hence, the declining unionization rate had a larger negative impact on male than female workers narrowing the gender wage gap (Blau and Kahn, 2000).



Note: The change in employment protection of regular workers is defined as the change in the OECD indicator of individual dismissal of workers with regular contracts and the change in employment protection of temporary workers is defined as the change in the OECD indicator of regulation of temporary contracts from 1993 to 2008.

Figure 1.2: The change in employment protection of workers and the gap effect

Moreover, as presented in Figure 1.2 the correlation coefficient between the change in employment protection and the gap effect is high and negative. Although the change in employment protection of regular workers do not show a clear pattern, countries with higher employment protection of temporary workers in 2008 compared to 1993, are also countries in which the gap effect tends to decrease the gender wage gap. Indeed, for 25–34 years old age group, Pissarides et al. (2005), find that stricter employment legislation for temporary contracts tend to decrease the gender wage gap, while the stricter employment protection legislation for regular workers tend to increase the gap since it is designed to protect the “insiders in the labor market and have a larger a negative impact on the young. Since there is no measure of discrimination, an indirect measure is generated to capture the attitudes towards gender. Using data from World Values Surveys (WVS), the proportion of people in each country agree with the statement “When jobs are scarce, men should have more right to a job than women is computed. Although this is an imperfect measure for discrimination, the change in the proportion of people that agree with this statement would capture the change in attitudes about gender roles in work. As Figure 1.3 presents, the correlation coefficient between the change in attitudes toward gender roles from 1993 to 2008 and the gap effect is high and positive. In other words, if in 2008



Note: The change in attitudes toward gender roles is measured as the change in mean response in World Value Survey to the statement 'When jobs are scarce, men should have more right to a job than women' from 1993 to 2008 (0-1 scale: 0 indicates no agreement with the statement, 1 indicates complete agreement with the statement).

Figure 1.3: The change in attitudes toward gender roles and the gap effect

less people agree with the statement "When jobs are scarce, men should have more right to a job than women" as compared to 1993, the higher the ranking of females in the male residual distribution. This is parallel to the argument that the decline in the statistical discrimination would allow female's progression leading a decline in the gender wage gap.

1.7 The Role of Selection

A further issue to note is the substantial increase in women's employment rates over time.[30] Despite the use of male wage regression in analysis ameliorates the problem due to changes in non-random selection into work, the estimated gap effects that are attributed to the change in labor market institutions may include the impact of changes in unmeasured selectivity of women participants to the labor market. Earlier studies emphasized the importance of selection in explaining the gender wage gap trends.[31] For instance, Blau and Kahn (2006) study changes in the U.S. gender wage gap between 1979 and 1998 and find that sample selection implies that the 1980s gains in womens relative wages were overstated and that selection may also explain part of the slowdown in convergence between male and female wages in the 1990s. Mulligan and Rubinstein

[30] See Figures A.1 and A.2 of Appendix A for the trends in employment rates in the European countries and the U.S. respectively.

[31] See Olivetti and Petrongolo (2008) for how nonrandom selection into work may affect international comparisons of gender wage gaps.

(2008) also argue that in the U.S. between 1975 and 2001, selection into employment shifted from negative to positive for women, and the narrowing of the gender wage gap during this period reflects changes in female workforce composition.

The sign of the bias is ex-ante unpredictable, since the selected group might be positively or negatively selected in terms of their unobserved characteristics (Blau and Beller, 1988; Blau and Kahn, 1997). Moreover the selection process into work may be different for women compared to men and selection rule may have changed with the large changes in employment rates. For instance, if women in 1990s who were employed tend to have relatively high-wage characteristics, an increase in women's employment rates may understate the convergence of the gender wage gap may be understated since there will be more women in the labor market who tend to have relatively low-wage characteristics. On the other hand, if the market becomes more positively selective over time, the convergence in the gender wage gap will be overstated.

We explore the possible contribution of sample selection to the narrowing of the gender wage gap by re-decomposing the gender wage gap trends in the selection corrected model. Additionally, we explore whether the labor market institutions are related to unexplained part of the gender wage gap trends, i.e. gap effect, even after the selectivity correction. Correction for selection into work is implemented here using a two-stage Heckman (1979) selection model. In particular, we estimate probit participation equations for males and for females in each country for each year and reestimate the wage regressions:

$$lnW_t^M = X_t^M \beta_t + S_t^M \gamma_t + \sigma_t \theta_t^M + \psi_t \lambda_t^M, \tag{1.6}$$

where λ is the inverse Mills ratio derived from a probit participation equation and is a measure of the selection bias, and ψ is its estimated coefficient in the wage equation that measures the wage effects of selection.[32] Then, we decompose the change in the gender wage gap over time in the selection corrected model as:

$$\begin{aligned} \Delta lnW_s - \Delta lnW_t &= [(\Delta X_s - \Delta X_t)\beta_s + (\Delta S_s - \Delta S_t)\gamma_s] \\ &+ [\Delta X_t(\beta_s - \beta_t) + \Delta S_t(\gamma_s - \gamma_t)] \\ &+ (\Delta\theta_s - \Delta\theta_t)\sigma_s \\ &+ \Delta\theta_t(\sigma_s - \sigma_t) \\ &+ (\Delta\lambda_s - \Delta\lambda_t)\psi_s + \Delta\lambda_t(\psi_s - \psi_t). \end{aligned} \tag{1.7}$$

[32] The left-hand side in the probit is whether or not a person is employed and the probit is identified by including brains and brawns in the wage function but not in the probit function, and by including the non-labor family income, number of children and a dummy for the presence of 0-6 years old children in the probit function. Probit results are not reported here but are available on request.

The decomposition of the change in gender wage gaps in the selection corrected model in Equation 1.7 refines the JMP decomposition model (Equation 1.3) as it includes now two additional components, $(\Delta\lambda_s - \Delta\lambda_t)\psi_s$ and $\Delta\lambda_t(\psi_s - \psi_t)$. Neuman and Oaxaca (1998) show that wage decompositions are sensitive to the way the selection term is interpreted. Since, our interest is the unexplained part of change in the gender wage gaps after correcting for the nonrandom selection to employment, i.e. "Selectivity-corrected gap effect", we follow the simplest approach suggested by Gupta et. al. (2008), in which gender differences in the selectivity over time are treated as a separate component of the wage decomposition (the last two terms of equation 1.7).

Table 1.5: Addressing selection bias: Selectivity-corrected gender wage gaps

	Austria	Ireland	Italy	Portugal	Spain	U.K.	U.S.
Change in gender wage gap	-0.078	-0.143	-0.018	-0.006	0.034	-0.066	-0.051
Gap effect	-0.073	-0.114	-0.025	0.020	0.022	-0.053	-0.034
Selectivity corrected-gap effect	-0.030	-0.578	0.046	-0.079	-0.011	-0.334	0.183

Selectivity-corrected gap effect is based on estimating the selection corrected model using a two-stage Heckman (1979) selection model. See text for details.

The results change somewhat for the selection corrected model, particularly with respect to the gap effect.[33] Table 1.5 presents the change in the gender wage gaps from 1993 to 2008 for each country once again and the gap effect from the JMP decomposition of the selection corrected model (measured as *selectivity corrected-gap effect* in Table 1.5). For comparison, Table 1.5 also includes the gap effect estimated from the model that does not account for selection. First, for Ireland, Portugal, Spain and the U.K., even after selection correction, a substantial part of the changes in the gender wage gaps remains unexplained. Hence, in these countries due to sample selection, the gains in womens relative wages were understated. Moreover, the unexplained part of the gender wage gap trends becomes negative for Portugal and Spain in the selection corrected model, going from 0.020 log points to -0.079 log points for Portugal and from 0.022 log points to -0.011 log points for Spain. Correcting for selection reveals the convergence in the unexplained part of the gender wage gap in Portugal and Spain from 1993 to 2008. On the other hand, for Italy and the U.S. the unexplained part of the gender wage gap trends becomes positive in the selection corrected model indicating that controlling for the inverse Mills ratio, the gender wage gap widened slightly in these countries. In Austria, the convergence in

[33] Table A.11 in Appendix A provides the contribution of each component to the change in gender wage gaps from 1993 to 2008 based on the selection corrected model.

the gender wage is overstated due to selection, however about 38%(-0.030/-0.078) of the slowdown in the narrowing of the gender wage gap cannot be explained neither by labor market characteristics and skills or changes in the wage structure nor selection.

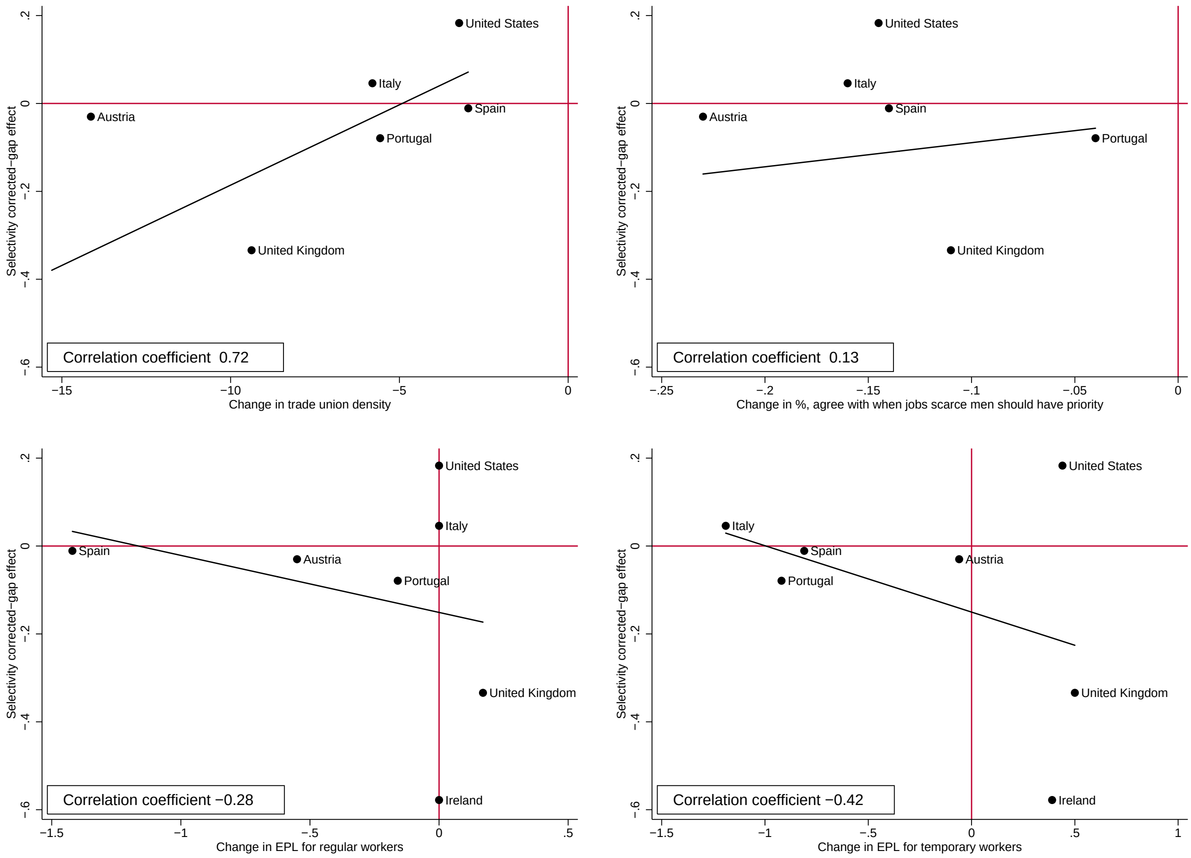


Figure 1.4: The change in labor market institutions, discrimination and the selectivity-corrected gap effect

In Figure 1.4, we present again the relationship between the unexplained part of the gender wage gap trends, "Selectivity-corrected gap effect and the change in labor market institutions. The correlation coefficient between the gap effect and changes in measures that captures the labor market institutions and discrimination decrease when selection bias is corrected. In particular the correlation between the gap effect and the change in proportion of people that agree with the statement "when jobs are scarce, men should have more right to a job than women" decreases from 0.62 to 0.13. This is not surprising, considering that selection into work and the changes in attitudes towards gender roles may be altered together. However, despite the decline in correlation coefficients, the change in the trade union density and the change in employment protection of regular workers are still strongly correlated with the selectivity corrected-gap effect. This evidence confirms that, to the extent that labor market institutions are an important component in explaining the degree of overall gender wage gap trends.

1.8 Concluding Remarks

The recent literature focusing on the U.S. emphasizes the role of various skills required by occupations and changing prices of those skills on the closing gender wage gap. In this chapter, we explore the recent gender wage gap trends in various European countries as well as in the U.S. using the direct measures of skill requirements of jobs.

Our findings reveal that, although in Austria and in the U.K., similar to the U.S. experience, a part of the closing gender wage gap can be explained by the changes in brain and brawn skill prices, the increase in returns to brain skills and decrease to brawn skills was not a common phenomenon for the Southern European countries Italy, Portugal and Spain and for Ireland. In contrast to the U.S. experience, in Southern European countries and in Ireland, the changes in returns to brain and brawn skills had a widening effect on the gender wage gaps. Nevertheless, from 1993 to 2008 the gender wage gaps declined in the sample of European countries, except Spain. However, a substantial part of the changes in the gender wage gaps cannot be explained by the changes in observable gender-specific factors (i.e. labor market characteristics or brain and brawn skills) or changes in wage structure (i.e. returns to characteristics, skill prices or residual wage inequality).

Other factors that may have contributed to the convergence of the unexplained gender pay gap include changes in selection to the employment, changes in gender differences in unobservable skills and labor market discrimination, as well as the changes in labor market institutions. The results of this study reveal the relation between the changing attitudes toward gender and/or the labor market flexibility and the unobservable gender specific factors that contribute to closing gender wage gap even after the non-random selection to employment is corrected.

Chapter 2

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

2.1 Introduction

Estimates of labor supply elasticities have a central place in empirical research in labor economics.[1] This is not surprising given the key role labor supply elasticities play in policy analysis (e.g. taxation) and in models of macroeconomic fluctuations.[2] With few notable exceptions, e.g. Lundberg (1988), however, the empirical literature studies labor supply elasticities of males or females without allowing for 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, depend neither on educational attainment of females nor on the relative education levels of husbands and wives (i.e. who is married to whom).

While there are few empirical studies on labor supply elasticities which contemplate interactions between household members, there is, on the other hand, a growing theoretical and empirical literature on household decision-making which emphasizes the importance of modeling households as a collection of individuals, each with his or her own utility function. The conventional unitary model, which considers the family as a single decision unit, has received little empirical support and its theoretical foundations have been questioned.[3] Several papers have proposed alternative models of the family labor supply

[1] Blundell and MaCurdy (1999) and Keane (2011) provide extensive surveys of this literature.

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

[3] For a more detailed discussion see Lundberg and Pollak (1997).

decision to incorporate the 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).

In this chapter, we estimate labor supply elasticities of married women and men allowing for heterogeneity between couples in terms of educational attainment 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?

We focus on the static labor supply decisions of couples along the extensive margin. Couples differ in the education levels of husbands and wives, as well as in the way they make their labor supply decisions. In particular, we consider two educational categories: less than college and college graduates and above, corresponding to low and high education. As there are two spouses, we distinguish four types of couples: (i) husband and wife with low education (homogamy-low) (ii) husband with high education and wife with low education (heterogamy-husband high) (iii) husband with low education and wife with high education (heterogamy-wife high), and (iv) husband and wife with high education (homogamy-high). Now that we have moved away from the standard unitary model and allow for the interaction between husbands and wives to affect the labor supply decision of each, we need to specify the way that these separate decisions are made. 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 household using a maximum likelihood estimation strategy. Then, given the parameter estimates, we select the model that best predicts 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 is observed as following a particular decision-making process. Once we assign a particular decision-making process to each household, we calculate labor supply elasticities for household members.

Our results show that there is considerable variation among different couples in the way they make their labor supply decisions. In particular, the labor supply decisions of husbands and wives exhibit strong interactions unless both of the spouses have a high level of education. For more than 48% of homogamy-low and heterogamy couples, the joint labor supply decisions of husbands and wives are most consistent with the Stackelberg-wife leader game, whereas the decisions of 20% of these couples are best predicted by the Nash/Pareto optimality model. For homogamy-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 are best explained as the result of a Nash game. 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 matters most for homogamy-high couples. While without children we do not observe any interactions for a majority of households, with children the majority of household employment decisions are consistent with a non-cooperative Nash game.

Apart from the observed variation in decision-making processes across different types of couples, we also observe that labor supply elasticities of married women of different types vary to a great extent. The participation own-wage elasticity is largest (0.77) for women with low education married to men with low education, and smallest (0.03) for highly educated women married to men with low education. The own-wage elasticities of women with low education married to highly educated men and for women with high education married to highly educated men are similar and fall between these two extremes (about 0.30). We also find that participation cross-wage elasticities for married women are relatively small (less than −0.05) if they are married to men with low education and larger (−0.37) if they are married to men with high education. For all types of couples, the participation non-labor family income elasticity is small.

Allowing for heterogeneity across couples yields an aggregate participation wage elasticity of 0.56, a cross-wage elasticity of −0.13 and an income elasticity of −0.006 for married women. Our participation own-wage elasticity estimate is larger than the recent estimates of labor supply elasticities of married women (e.g. Blau and Kahn, 2007; Heim, 2007).[4] The current analysis differs from these studies in that we allow for household interactions and we let these interactions differ across different types of households. Our analysis shows that ignoring the heterogeneity between household types and differences between couples in the way they make their labor supply decisions generate a lower labor supply wage elasticity for married women (0.20–0.29). We find that even if differences between couples in the way they make their labor supply decisions are ignored, accounting for the differences between household types already yields a higher labor participation wage elasticity for married women (0.46–0.49).

The results of this study have important implications for policy analysis. Since many

[4]Heim (2007) shows that married women's participation wage elasticity declined from 0.66 to 0.03 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.

policies are designed to target specific groups, it is essential to understand the potential differential impact on the labor supply of individuals. For instance, U.S. income transfer and tax policies — such as the Earned Income Tax Credit (EITC) or Temporary Assistance for Needy Families (TANF) programs — are targeted to encourage work among low–income families or families with children.[5] The differences in labor supply elasticities of married women depending on spouses' education levels is a dimension that has been overlooked by the literature. Furthermore, while earlier studies have focused on heterogeneity arising from the presence of pre-school age children, e.g. Del Boca (1997), Lundberg (1988), we further show that the variation in the responses of married women depending on the spouses' education levels is present, independent of whether children are present in the household or not.

The variation in labor supply elasticities of married women raises a natural question: What is the impact of compositional changes in the population on women's overall labor supply elasticities? Over the past several decades there have been dramatic changes in the educational composition of the population in the U.S. Not only have the educational attainment levels of men and women increased, but also the similarity between husbands and wives in their educational attainment has increased substantially (Mare 1991; Pencavel 1998; Schwartz and Mare 2005).[6] In order to get an idea of the effect of these compositional changes on married women's labor supply responsiveness, we carry out a counterfactual exercise. We calculate what the overall labor supply elasticities would be if married women had the responsiveness of 2000 but the distribution of couples would have been that 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 elasticity 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, the 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 chapter of the thesis 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 for married women. Heim (2007) and Blau and Kahn (2007) are recent

[5]Since estimates of labor supply elasticities are of key interest to policymakers, a substantial 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 (2012).

[6]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, as well as the differential fall in marriage and rise in divorce for individuals with different levels of educational attainment 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.

examples of papers in this group. Both studies find a decline in women's labor supply elasticities over the past several decades. The decline in the labor supply elasticities of married women has been attributed to the increase in marriage instability and increasing work opportunities for women (Goldin, 1990; Blau and Kahn, 2007). However, marriage instability and the work opportunities available to women depend on their educational attainment and also their educational similarity with their spouses.[7] Since factors that might affect the labor supply responsiveness of married women differ by the level of educational attainment as well as the educational similarity of spouses, it is natural to think that labor supply responsiveness does so as well. In addition, Heim (2007) and Blau and Kahn (2007) abstract from the interactions between household members.

There are a few empirical studies which have estimated joint labor supply of husbands and wives as opposed to individual labor supply, such as Apps and Rees (1996), Blundell, Chiappori, Magnac and Meghir (2007), Chiappori, Fortin and Lacroix (2002), Fortin and Lacroix (1997), Hausmand and Ruud (1984), Kooreman and Kapteyn (1990), and Ransom (1987a, 1987b). Hausman and Ruud (1984), and Ransom (1987a, 1987b) account for the interdependent nature of family labor supply decisions in a unitary framework. On the other hand, Apps and Rees (1996), Blundell, Chiappori, Magnac and Meghir (2007), Chiappori, Fortin and Lacroix (2002), Fortin and Lacroix (1997), and Kooreman and Kapteyn (1990) test the unitary model and find that restrictions implied by the unitary framework are rejected by the data. As a further step, these studies estimate the labor supply equations of husbands and wives from a collective specification. However, all these studies assume that within-household allocations are efficient for all couples. Del Boca (1997) and Lundberg (1988) also test alternative theories of family labor supply behavior. Additionally, they consider the possibility that couples are heterogeneous in the way that they make their labor supply decisions. However, both studies consider the presence of young children as the only source of heterogeneity, former between Italian couples, and the later between low income families in the U.S. In this chapter, we consider the heterogeneity in educational attainments of husbands and wives and show that the variation in the responses of married women depending on the spouses' education levels is present, independent of whether children are present in the household or not.

Second, this chapter of the thesis is related to the literature that studies household

[7]Earlier studies show that women with high education 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).

interactions. The models that we employ to estimate the labor supply elasticity of women are include both non-cooperative and cooperative models. In non-cooperative models, as developed by Konrad and Lommerud (1995), each individual within a household maximizes his or her own utility, relative to his or her own budget constraint, taking the actions of other household members as given. The cooperative approach includes collective models developed by Chiappori (1988, 1992), as well as cooperative bargaining models suggested by Manser and Brown (1980) and McElroy and Horney (1981). The collective approach assumes that household decisions are Pareto-efficient. Cooperative bargaining models, which are a particular case of collective models, represent household allocations as the outcome of some specific bargaining process and the cooperative allocation reached depends crucially on the threat point, i.e. what happens in case of disagreement among couples.[8] Following the literature that studies household interactions, we consider alternative equilibrium concepts, including the non-cooperative Nash game and Stackelberg leader game, and the approach which imposes Pareto optimality on the observed decisions of husbands and wives. However, 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, this chapter is related to recent papers in the empirical labor literature that allow for heterogeneity in household decision-making or household interactions. Jia (2005) analyzes the labor supply decision of retiring couples in Norway and assumes that there are two types of families, cooperative and non-cooperative. 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 the 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 of the modern type and the participation rate of women in those households is almost 80%. Differing from Eckstein and Lifshitz (2012), we consider the education level and relative education levels of spouses as the source of heterogeneity. In addition we do not assume a certain structure of the decision-making a priori.

The remainder of this chapter is organized as follows. The next section describes the family labor supply models that are employed in our analysis. Section 2.3 discusses the identification issues and explains the estimation strategy. Section 2.4 presents the data source and the empirical specification. The main estimation results for the family labor supply models and labor supply elasticities of married women are presented in Section

[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.

2.5. Finally, Section 2.6 discusses the role of changes in the educational composition of the population composition on declining labor supply elasticities of married women and Section 2.7 concludes.

2.2 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. These decisions are defined as

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

Since there are two individuals and two possible actions for each of the spouse, there are four possible outcomes of the family labor supply decision, (y_h, y_w): (i) both spouses work, (ii) only husband works, (iii) only wife works, or (iv) both spouses do not work. We assume that each spouse maximizes his or her utility. However, the decisions of husbands and wives 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 as 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 For a given labor supply decision of the spouse, y_i for $i = h, w$,

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

where $(\varepsilon_h, \varepsilon_w)$ are normally distributed with zero means, unit variances and correlation ρ. Assumption A.2 states that the random component of utility does not depend on the labor supply decision of the spouse. Hence, we allow for unobserved heterogeneity in utility derived from working through the ε_h and ε_w. Allowing ε_h and ε_w to be correlated reflects the fact that for a particular couple there may be common, unobserved factors affecting both spouses' 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 by the following assumption:

Assumption A.3

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

Combined with Assumption A.2, this implies that the change in an individual's overall utility associated with a change in their spouse's action is also constant. In other words, we rule out the second order effects of spouse's employment on individual's utility.

For empirical implementation, the deterministic component of an individual's utility is assumed to be a linear function of individual's observable characteristics, x_h and x_w. Hence, together with assumptions A.1 to A.3, the model is parametrized as

$$\begin{aligned} U_h(1,1) &= x_h'\beta_h^1 + \alpha_h^1 + \eta_h^1 \quad & U_w(1,1) &= x_w'\beta_w^1 + \alpha_w^1 + \eta_w^1 \\ U_h(0,1) &= x_h'\beta_h^0 + \alpha_h^0 + \eta_h^0 \quad & U_w(1,0) &= x_w'\beta_w^0 + \alpha_w^0 + \eta_w^0 \\ U_h(1,0) &= x_h'\beta_h^1 \qquad\quad + \eta_h^1 \quad & U_w(0,1) &= x_w'\beta_w^1 \qquad\quad + \eta_w^1 \\ U_h(0,0) &= x_h'\beta_h^0 \qquad\quad + \eta_h^0 \quad & U_w(0,0) &= x_w'\beta_w^0 \qquad\quad + \eta_w^0. \end{aligned} \tag{2.1}$$

In the family labor supply model, the utility or the payoff of working can be interpreted as the market wage. The utility or the payoff of not working can be interpreted as the reservation wage of the individual.

For example, consider the 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, $U_h(0,1) - U_h(0,0) = \alpha_h^0$ captures the impact of the wife's employment on the husband's reservation wage. 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 $U_h(1,1) - U_h(1,0) = \alpha_h^1$ is the effect of the wife's employment on the husband's reservation wage. For the wife, the wage equations are written analogously.

Although, economic theory suggests that the spouse's employment would affect an individual's reservation wage but not his or her market wage, one can test the presence of both effects by including α_i^0 and α_i^1 (for $i = h, w$) in the model and testing the significance of these parameters. Therefor, we include the impact of the spouse's employment decision on the individual's market wage (α_h^1 and α_w^1) in the model without imposing the restriction that the effect is 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. The simultaneous probit model is a natural choice to extend the single-person discrete choice model to accommodate the labor supply decisions of both spouses.[9] In the simultaneous probit model, the observed dichotomous variables (y_h and y_w) are assumed to be 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

$$y_w^* = y_h[U_w(1,1) - U_w(0,1)] + (1 - y_h)[U_w(1,0) - U_w(0,0)]. \tag{2.2}$$

Equation 2.2 states that, for a given employment decision of the spouse, an individual decides to work or not based on a simple utility comparison. Under assumptions A.1 to A.3, and model parametrization in Equation 2.1, it follows that

$$\begin{aligned} y_h^* &= x_h^{'}\beta_h + \alpha_h y_w + \varepsilon_h \\ y_w^* &= x_w^{'}\beta_w + \alpha_w y_h + \varepsilon_w, \end{aligned} \tag{2.3}$$

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 $i = w, h$.

Given Equations 2.2 and 2.3, utility comparisons of the husband and the wife, and as a result the probability of each of the four possible outcomes of the joint labor supply decision of a couple can be written as conditions on random components ε_h and ε_w, i.e. model parameters. For each possible outcome of the family labor supply decision, Table 2.1 presents conditions on the husband's and the wife's utility comparisons and conditions that must be satisfied by the random components.

For example, 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,

[9] See Maddala (1974) for details.

Table 2.1: 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 $U_w(1,1) > U_w(1,0)$	$\varepsilon_h > -x_h^{'}\beta_h - max(0, \alpha_h)$ and $\varepsilon_w > -x_w^{'}\beta_w - max(0, \alpha_w)$
$y_h = 1$ and $y_w = 0$	$U_h(1,0) > U_h(0,0)$ and $U_w(1,1) < U_w(1,0)$	$\varepsilon_h > -x_h^{'}\beta_h - min(0, \alpha_h)$ and $\varepsilon_w < -x_w^{'}\beta_w - max(0, \alpha_w)$
$y_h = 0$ and $y_w = 1$	$U_h(1,1) < U_h(0,1)$ and $U_w(0,1) > U_w(0,0)$	$\varepsilon_h < -x_h^{'}\beta_h - max(0, \alpha_h)$ and $\varepsilon_w > -x_w^{'}\beta_w - min(0, \alpha_w)$
$y_h = 0$ and $y_w = 0$	$U_h(1,0) < U_h(0,0)$ and $U_w(0,1) < U_w(0,0)$	$\varepsilon_h < -x_h^{'}\beta_h - min(0, \alpha_h)$ and $\varepsilon_w < -x_w^{'}\beta_w - min(0, \alpha_w)$

the wife works based on the comparison between $U_w(1, y_w)$ and $U_w(0, y_w)$ 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 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, $U_h(1, 1) > U_h(0, 1)$ and $U_w(1, 1) > U_w(1, 0)$ will only hold if $\varepsilon_h > -x_h^{'}\beta_h - max(0, \alpha_h)$ and $\varepsilon_w > -x_w^{'}\beta_w - max(0, \alpha_w)$. Hence, the probability that both spouses work, i.e. $(y_h, y_w) = (1, 1)$ equals to the probability that $\varepsilon_h > -x_h^{'}\beta_h - max(0, \alpha_h)$ and $\varepsilon_w > -x_w^{'}\beta_w - max(0, \alpha_w)$.

The multiple-person choice model differs from the single-person model in that it allow for the possibility of simultaneity between 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 $\alpha_h \times \alpha_w$. This means that, the model described in Equation 2.3 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 is less than one.

In order for the simultaneous probit model to be coherent, one needs to impose the

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

coherency condition $\alpha_h \times \alpha_w = 0$ (Heckman, 1978). However, imposing the parameter restriction $\alpha_h \times \alpha_w = 0$ essentially eliminates the simultaneity from the model, which 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 completeness and coherence of the model without imposing $\alpha_h \times \alpha_w = 0$. In this setting, instead of the rule described in Equation 2.2, the observed dichotomous variables y_h and y_w are assumed to be the outcomes 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 pure-strategy Nash equilibrium outcomes of a game played between agents. Bjorn and Vuong (1985) propose a similar game theoretical model using the Stackelberg equilibrium concept. Since 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 these game theoretical models, which allow for the interdependence of the employment decisions of the husband and the wife, with the simultaneous probit model where the coherency restriction is imposed.

2.2.1 Nash Model

In the Nash game, the husband and the 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 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 column of Table 2.2 and Table 2.3, respectively.

Each reaction function for an individual will arise, i.e. will be the best response, if certain conditions on utility comparisons hold. The second columns of Table 2.2 and Table 2.3 summarize the utility comparisons of the husband and the wife for their corresponding

Table 2.2: 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 $U_h(1,1) > U_h(0,1)$	$\varepsilon_h > -x_h^{'}\beta_h - \min(0,\alpha_h)$

reaction functions. Each utility comparison, however, can only arise if certain conditions for the random components ε_h and ε_w are satisfied. We use the model parametrization in Equation 2.1 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 column of Tables 2.2 and 2.3.

For instance, the reaction function H_1 says that the husband always chooses not to work, whether the wife works or not (column 1 of Table 2.2). 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 2.2). The corresponding 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 2.2).

Table 2.3: 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 $U_w(1,1) > U_w(1,0)$	$\varepsilon_w > -x_w^{'}\beta_w - \min(0,\alpha_w)$

Given the reaction functions of the husband and the wife, the Nash equilibrium in pure strategies (hereafter NE) can be defined.[11] Table 2.4 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 2.4, in some cases, there are multiple Nash equilibria and in others, there is no NE in pure strategies.

Once again, existence of multiple Nash equilibria and no NE in pure strategies correspond to the *incompleteness* and *incoherency* of the model. In order to ensure coherence and completeness, we follow the approach proposed by Bjorn and Vuong (1984) and include an equilibrium selection mechanism to the model.[12] Modeling the equilibrium selection mechanism requires additional assumptions, however, it does not require eliminating the simultaneity from the model as required by the simultaneous probit model.

We include the equilibrium selection mechanism to the model following the approach suggested by Bjorn and Vuong (1984). We assume that each equilibrium has an equal probability to be chosen by the couple when there are multiple equilibria.[13] In case of no Nash equilibrium, the couple is assumed to choose from one of the possible alternatives with equal probabilities.

Table 2.4: 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)

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.

[11] The equilibrium concept adopted here is Nash in pure strategies. For a similar approach, see applications by Bresnehan and Reiss (1990) for a firm entry model in automobile retail market, and by Bjorn and Vuong (1994) for a model of household labor supply. For a review of alternative equilibrium concepts see De Paula (2013).

[12] For alternative strategies to identify model parameters see Tamer (2003) and Ciliberto and Tamer (2009).

[13] Alternative equilibrium selection mechanisms are suggested by Bresnahan and Reiss (1990, 1991), who treat the multiple outcomes as one event. However, this approach limits the model predictability (Tamer, 2003).

Given Tables 2.2 to 2.4, the probability of each of the four possible outcomes for the joint labor supply decision of a couple can be expressed in terms of conditions on the random components ε_h and ε_w, and therefore in terms of model parameters.[14]

2.2.2 Stackelberg Leader Model

The labor supply decision of couples can also be reformulated by using a different equilibrium concept, that of the Stackelberg-leader game. In this case, y_h and y_w are assumed to be the Stackelberg leader equilibrium (hereafter SE) outcomes of a sequential game. In this game, one of the players (the leader) moves first and then the other player (the follower) moves after observing the action of the leader. 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. In the family labor supply, the roles of husband and wife are not known a priori, so we consider two versions of a Stackelberg leader game played between spouses: first, assuming that the husband is the Stackelberg leader, and second, assuming that the wife is the Stackelberg leader. In this section, we briefly explain the Stackelberg model assuming that the wife is the Stackelberg leader and her husband is the follower. The Stackelberg-husband leader model is analogous.[15]

In a Stackelberg-wife leader game, the 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 the same as the ones in the Nash model, which are described in Table 2.2. As, in the Stackelberg-wife leader game the roles of the spouses are asymmetric, so each reaction function of the husband corresponds to a utility comparison for the wife. For each reaction function of the husband, the utility comparison of the wife, S_j for $j = 1, 2, 3, 4$ is given in Table 2.5. For example, if the wife knows that the husband always decides not to work, independently of her working or not, the corresponding utility comparison of 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 2.5.

Given the husband's reaction functions and the wife's utility comparisons, the SE can be defined. Table 2.6 presents the SE for each pair of husband's reaction function and wife's utility comparisons. In Table 2.6, $\overline{S_j}$ denotes the negation of S_j for $j = 1, 2, 3, 4$. As seen in Table 2.6, the SE is always unique. 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. the

[14]See Appendix B.2 for details.

[15]See Appendix B.4 for the description of SE in Stackelberg-husband leader game.

Table 2.5: Wife's utility comparisons

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

Table 2.6: 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)

husband decides not to work and the wife decides to work. The outcome (0,1) is a SE if the pair of the 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 that each pair of the reaction function of the husband with the utility comparison of the wife, and hence in terms of model parameters.[16]

2.2.3 Nash/Pareto Optimality

It is well known that game theoretical models may yield outcomes that are not Pareto optimal. Bargaining models and collective models are based on the hypothesis that 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 2.1, there is a large number of cases with multiple solutions. For model predictability, Kooreman (1994) suggests using the Nash principle to reduce the large number of cases with multiple solutions. In this approach, the husband and the wife are assumed to play a Nash game. If the game has a unique NE and it is Pareto optimal, then it is assumed to be the outcome of the game. If the unique NE is not Pareto optimal, players are assumed to choose the Pareto efficient outcome. If the game has two Nash equilibria in pure strategies and if only one of the Nash equilibria is

[16]See Appendix B.3 for details.

Pareto optimal, it 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 them with equal probabilities. 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. [17]

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. In the family labor supply model the restrictions on 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, so in our analysis we impose that α_h^1, α_h^0, α_w^1 and α_w must be positive.

Once again, using the model parametrization in Equation 2.1, the utility rankings of the husband and the wife can be written in terms of conditions for 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.[18]

2.3 Identification and Estimation

We estimate the game theoretical models described in the previous section using a maximum likelihood estimation strategy 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:

$$\begin{aligned} L &= \sum_c \log \Pr_c(y_h, y_w) \\ &= \sum_c [y_h y_w \log \Pr_c(1,1) + y_h(1-y_w)\log \Pr_c(1,0) \\ &+ (1-y_h)y_w \log \Pr_c(0,1) + (1-y_h)(1-y_w)\log \Pr_c(0,0)], \end{aligned} \tag{2.4}$$

where c is the index for each observation, i.e. a couple. To estimate a particular model, expressions for the four outcome probabilities, given in terms of model parameters, are substituted in.[19]

In addition to the game theoretical models, we also consider a model without interactions between spouses' decisions. In particular, we estimate the simultaneous probit

[17] Kooreman (1994) shows the existence of the Pareto optimal allocation in each of these cases.

[18] See Appendix B.5 for details.

[19] See Appendices B.2, B.3, B.4 and B.5 for the expressions for each possible outcome probability in Nash model, Stackelberg-wife leader model, Stackelberg-husband leader model and Nash/Pareto optimality, respectively.

model described in Equation 2.3 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.[20]

Table 2.7: 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

Because the expressions for probability of observing a given 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 2.7. β_h and β_w are identified in all the models,but β_h^1, β_h^0, β_w^1 and β_w^0 cannot be identified separately. Furthermore, the impact of the wife's employment decision on the husband's utility of not working, α_h^1 and on husband's utility of working, α_h^0 are separately identified only in the Stackelberg-husband leader model and the Nash model when Pareto optimality is imposed. In the remaining models, only $\alpha_h = \alpha_h^1 - \alpha_h^0$ is identified. On the other hand, the impact of the husband's employment decision on the wife's market and reservation wages (α_w^1 and α_w^0) are separately identified only in the Stackelberg-wife leader model and the Nash model when Pareto optimality is imposed. In the 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 the bivariate probit model, the impact of the spouse's employment decision on an 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 types of couples (homogamy-low, heterogamy-husband high, heterogamy-wife high and homogamy-high). Therefore, for each type, we estimate the bivariate probit model and the 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

[20]This approach is similar to the one suggested by Del Boca (1997) where she models the labor supply decisions of the husband and the wife using a bivariate probit model.

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 compute the fraction of households whose observed decisions are most consistent with a particular model.

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

2.4 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 aged 25-54 with a 25- to 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.[21] 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.[22] Therefore, in our analysis of the observed outcomes, y_h and y_w are defined as

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

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 to be homogamous, while couples with different education levels (high-low or low-high) are considered to be heterogamous.

[21] 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.

[22] 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.

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

$$\begin{aligned} U_h(1, y_w) &= x_h^{'}\beta_h^1 + \alpha_h^1 y_w + \eta_h^1 \\ U_w(y_h, 1) &= x_w^{'}\beta_w^1 + \alpha_w^1 y_h + \eta_w^1, \end{aligned} \tag{2.5}$$

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 (hereafter MSA), and a constant term. The reservation wage equations for husbands and wives are specified as

$$\begin{aligned} U_h(0, y_w) &= z_h^{'}\beta_h^0 + \alpha_h^0 y_w + \eta_h^0 \\ U_w(y_h, 0) &= z_w^{'}\beta_w^0 + \alpha_w^0 y_h + \eta_w^0. \end{aligned} \tag{2.6}$$

The set of explanatory variables for 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), his log hourly wage and his wife's log hourly wage. For wives, z_w includes a constant term, non-labor family income, her log hourly wage, her husband's log hourly wage, number of children and a dummy for the presence of 0- to 6-year-old children.

Since our main interest is to calculate the labor supply elasticities, including own wage and spouse's wage in the reservation wage equations is crucial for our analysis. We do not observe wages for non-workers, however, so 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 couple (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 the husband and for the wife for each type of couple of the form:

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

and

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

where

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ 0 \; otherwise \end{cases} \quad for \; i = h, w, \tag{2.7}$$

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, a 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 couple of the form

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

and

$$\ln W_w = \widetilde{x}_w' \delta_w + \omega_w, \tag{2.8}$$

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 child variables for wives and non-labor income for husbands at the first stage ensures identification of the inverse Mills ratio term in the second stage. The predicted values for wages obtained from the selection corrected wage equations specified in Equation 2.8 are imputed for all women and men to minimize the effect of measurement error in wages.[23]

Sample statistics by type of couple are provided in Table 2.8. Of the 848,835 remaining couples after selection, 79% of them are homogamy type (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 2.8, men are more likely to be full-time employed independently of whom they are married to. On the other hand, the employment rate of married women in our sample is around 82% for those with high education and only 75% for those with low education. Hence, a well-known fact is also present in our sample, that women with high education are more likely to be employed than women with low education. What is less known is that, highly educated women are less likely to be employed if they are married to highly educated men. In our sample, among highly educated women, employment rate is lower for women married to men with high education compared to women married to men with low education.

[23]The identification of wage coefficients in Equation 2.5 comes form the exclusion of higher order terms in age and education in z_h and z_w.

Table 2.8: 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 thousands of 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. *Note:* 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.

Not surprisingly, wages increase by education level. However, the 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 hourly wage is higher for those married to someone with high education than those married to someone with low education. The average non-labor family income also increases by the level of educational attainment. Highly educated couples have the highest non-labor family income. Among heterogamous couples, non-labor family income is higher when the wife is the spouse with low education one and the husband is the highly educated one.

By construction, years of education differ among different types of households. However, within the same level of educational attainment, average years of schooling is higher for individuals that are married to someone with high education. Furthermore, the wives are relatively younger than the husbands. Husbands and wives of heterogamous couples where the wife is the spouse with low education, are slightly older than other types of husbands and wives. More than 82% of the couples in the sample consist of whites, with non-whites being more likely to be of the 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 children aged 0 to 6 years.

2.5 Estimation Results

In this section, we present our estimation results. We first provide the key parameter estimates of the bivariate probit model and of the 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. In particular, we assign to each couple the model that gives the highest probability of the observed joint employment decisions of the husband and the wife. This, in turn, allows us to compute the fraction of couples that follow 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 women.

2.5.1 Key Parameter Estimates

Tables 2.9, 2.10, 2.11 and 2.12 provide the key parameter estimates for homogamy-low, heterogamy-husband high, heterogamy-wife high and homogamy-high type couples, respectively.[24] In all tables, each column represents the key parameter estimates (${\alpha_h}^1$, ${\alpha_h}^0$ α^1_w and α^0_w), 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.

We start with the estimates of β_h and β_w. As is evident from Tables 2.9 to 2.12, coefficient estimates for own-wage, spouse's wage and non-labor income are similar across models. This implies that, for each type of couple, the impact of own-wage, or spouse's wage, or non-labor income on the individual's reservation wage is independent of the way that household members make their labor supply decisions. For all couples in all models, the labor supply of married women is positively and significantly related to their own wage (i.e. $\beta_w > 0$), and it is negatively and significantly related to the husband's wage

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

and the non-labor family income (i.e. $\beta_w < 0$). On the other hand, there are significant differences across different types of couples. By comparing the first row of Tables 2.9, 2.10, 2.11 and 2.12, we conclude that the coefficient estimate for own-wage is highest for wives with low education married to men with low education and smallest for wives with high education married to men with low education (Tables 2.9 and 2.11). Coefficient estimates for own-wage for women with low education married to highly educated men and for women with high education married to highly educated men are similar and fall between these two extremes (Tables 2.10 and 2.12). Moreover, comparing the second row of Tables 2.9, 2.10, 2.11 and 2.12 shows that coefficient estimates for the husband's wage are relatively small if women are married to men with low education (Tables 2.9 and 2.11) and they are large if women are married to men with high education (Tables 2.10 and 2.12). For all women, for each model, the coefficient estimate for the non-labor family income is significant, but it is small compared to coefficient estimates of the own-wage and the spouse's wage (third row of Tables 2.9, 2.10, 2.11 and 2.12).

For husbands, on the other hand, coefficient estimates, β_h, indicate that full-time employment of married men is positively and significantly related to their own-wage, and negatively and significantly related to non-labor family income for all types of couples. However, for a particular model, the coefficient estimate for the wife's wage is different between different types of couples. For homogamy-low and heterogamy-husband high types, the full-time employment of the husband is positively and significantly related to the wife's wage. On the contrary, for heterogamy-wife high types, the full-time employment of the husband is negatively and significantly related to the wife's wage. Finally, for homogamy-high types there is no significant relation between the husband's full-time employment and the wife's wage.[25]

Now we turn our attention to estimates of cross-effects. Recall that, for $i = h, w$, α_i^1 and α_i^0 denote the effect of the spouse's employment on the individual's market wage and the reservation wage, respectively. A priori, the 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 are expected on spouses' market wages ($\alpha_h^1 = 0$ and $\alpha_w^1 = 0$). This implies negative estimates of parameters $\alpha_h = \alpha_h^1 - \alpha_h^0$ and $\alpha_w = \alpha_w^1 - \alpha_w^0$. As Tables 2.9 to 2.12 present, significant estimates of α_h (estimated and implied by the estimates of α_h^1 and α_h^0) are negative for all types.[26] In other words, the employment of the wife makes her husband less likely to work full-time for all types of couples. However, for wives, significant estimates of α_w (estimated or implied by estimates for α_w^1 and α_w^0) are positive for all types. This implies

[25] The only exception is the bivariate probit model which predicts a significant negative relation between the husband's full-time employment and the wife's wage.

[26] Only exceptions are Stackelberg-wife leader model for homogamy-low types and the Nash/Pareto optimality for heterogamy-wife high types.

that the full-time employment of the husband makes his wife more likely to work.

Table 2.9: 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.

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

Table 2.10: 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.

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

Table 2.11: 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 thousand 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.

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

Table 2.12: 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	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(in 000 dollars)	(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	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***
	(in 000 dollars)	(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.

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

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 is implied by Assumption A.2, the correlation ρ 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 in which the husband always chooses to work full-time given any decision of the wife. In this case, the wife may take the housework responsibilities, and unless she receives a high-wage offer, she may prefer not to work since 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 explanation, the significant estimates of ρ from game theoretical models is negative for homogamy-low type couples and heterogamous couples (Tables 2.9 to 2.11), whereas it is positive for homogamy-high type couples (Table 2.12).

Note that the significant estimates of the parameter ρ from the bivariate probit model and game theoretical models have opposite signs (Tables 2.9 and 2.12). In the bivariate probit model, the cross-effects may be picked up by the correlation parameter ρ. In fact, for the homogamy-low type (Table 2.9), the significant estimates of α_h and α_w are positive. Then, for these couples, the estimate of the correlation parameter ρ from the bivariate probit model turns to be positive. However, for the homogamy-high type (Table 2.12) the sign of the correlation parameter estimate ρ is negative in the 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.

2.5.2 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 assess the model fit in terms of the employment rate of wives and full-time employment rate of husbands, Table 2.13 presents the actual and the predicted values for different types. As shown in Table 2.13, the model performs well at predicting the employment rates of wives and husbands for different types of couples.

Because we assign each couple in the sample the model that best predicts the observed joint labor supply behavior, we know the fraction of couples that follow a particular

Table 2.13: 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

decision-making process. The resulting distribution of couples is presented in Table 2.14. As Table 2.14 shows, for most of the homogamy high couples, the observed labor supply decisions of couples is best predicted by the bivariate probit model. Recall that in the bivariate probit model, the cross effects of employment decisions are assumed to be zero. This implies that most of the highly educated spouses (about 46%) make their labor supply decisions independent of each other. For these couples around 27% of household decisions can be justified as coming from a Nash game.

On the other hand, for the majority of homogamy-low and both heterogamy types, the labor supply decisions of spouses exhibit strong interactions. The decisions of a majority of these couples are best predicted by the Stackelberg-wife leader model. Hence, when the wife decides whether to work or not, she knows the action that her husband will take given her choice, and in making her labor supply decision she takes the husband's payoff into account and optimizes accordingly. For around 20% of homogamy-low and 25% of heterogamy couples, the household decisions are best predicted by the Nash/Pareto optimality model.

Table 2.14: 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 both heterogamy types, the joint labor supply decision is best predicted by Stackelberg-wife leader model. In the empirical literature, there are some examples that model the household decisions as the outcome of a Stackelberg game played between spouses. For instance, Bolin (1997), and Beblo and Robledo (2002) 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 the 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 the consensual approach and of a non-cooperative Nash game.

The 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 distort labor market outcomes of women. Their analysis suggest that, since departing from the traditional gender roles increases the likelihood of a divorce, married women sometimes stay out of the labor force in order 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. They argue that if deviating from the prescription — "*men work in the labor force and women work in home*" — is costly then women are less likely to participate to the labor force.

These studies suggest that a woman's labor force participation decision might depend on her perception of how her husband will react if she decides to work. Then, taking her husband's reaction into account, the wife will decide how to proceed. Indeed, in our sample, in more than 72% of the couples that are best described by the Stackelberg-wife leader game, the 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 a husband prefers working full time while his wife stays home to working full time while she works, i.e. $U_h(1, 0) > U_h(1, 1)$, but prefers working full time while his wife works to working part time while his wife works, i.e. $U_h(1, 1) > U_h(0, 1)$. Hence from the man's perspective the ideal outcome is him working full-time and his wife not working. Suppose on the other hand that the wife derives a lower utility from not working than working, i.e. $U_w(1, 1) > U_w(1, 0)$ and $U_w(0, 1) > U_w(0, 0)$, i.e. she prefers to work. Then it is logical for the wife to decide to work and make it known to her husband. Given his wife's decision, then the husband will end up working full-time. Hence, the outcome will be $(y_h, y_w) = (1, 1)$.

While these particular gender roles might be relevant for all types of couples, it is particularly relevant for the case of highly educated women married to men with low education. In fact, the largest fraction of couples with an observed outcome $(y_h, y_w) = (1, 1)$ that 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 highly educated wife would be more attached to the market than her husband who has low education.

2.5.3 Labor Supply Elasticities of Married Women

We now turn our attention to the labor supply estimates of married women. Table 2.15 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.[27] The average participation own-wage elasticity is largest (0.77) for women with low education married to men with low education, and smallest (0.03) for women with high education married to men with low education. The own-wage elasticities for women with low education married to men with high education and for women with high education married to men with high education are similar and fall between these two extremes (0.30 and 0.31 respectively). Furthermore, cross-wage elasticities for married women are relatively small (less than -0.05) if they are married to men with low education and larger (about -0.37) if they are married to men with high education. For all types of couples, participation elasticity of non-labor family income for married women is small.

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 increment of her own wage, or her husband's wage, or non-labor family income, we know the distributions of labor supply elasticities. Since 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 2.1. First, for all types of couples, the distribution of labor supply own-wage elasticity of married women is right-skewed with no women having a negative elasticity. However, for all types, there exist 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 differs considerably across different types. In particular, the distribution is more dispersed

[27] 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 B.5 of Appendix B.6 for labor supply elasticities of married men.

Table 2.15: 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)

Note: Standard errors in parenthesis.

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 of 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.

The distribution of cross-wage elasticities of married women is presented in Figure 2.2. In this case, since the cross-wage elasticity is negative, the responsiveness of women to 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 left-skewed. For all types, there are some women for which the cross-wage elasticity is close to zero, implying that, for these women, increases in their husbands' wages have relatively small effects on their labor supply. For the majority of women in all types, the cross-wage elasticities are negative. The only exceptions to this general trend can be found in heterogamy-wife high types. Among heterogamy-wife high type couples, there are wives with positive cross-wage labor supply elasticity (with a maximum of 0.19). As seen in Figure 2.2, the dispersion of labor supply cross-wage elasticity differs between different types. Contrary to 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

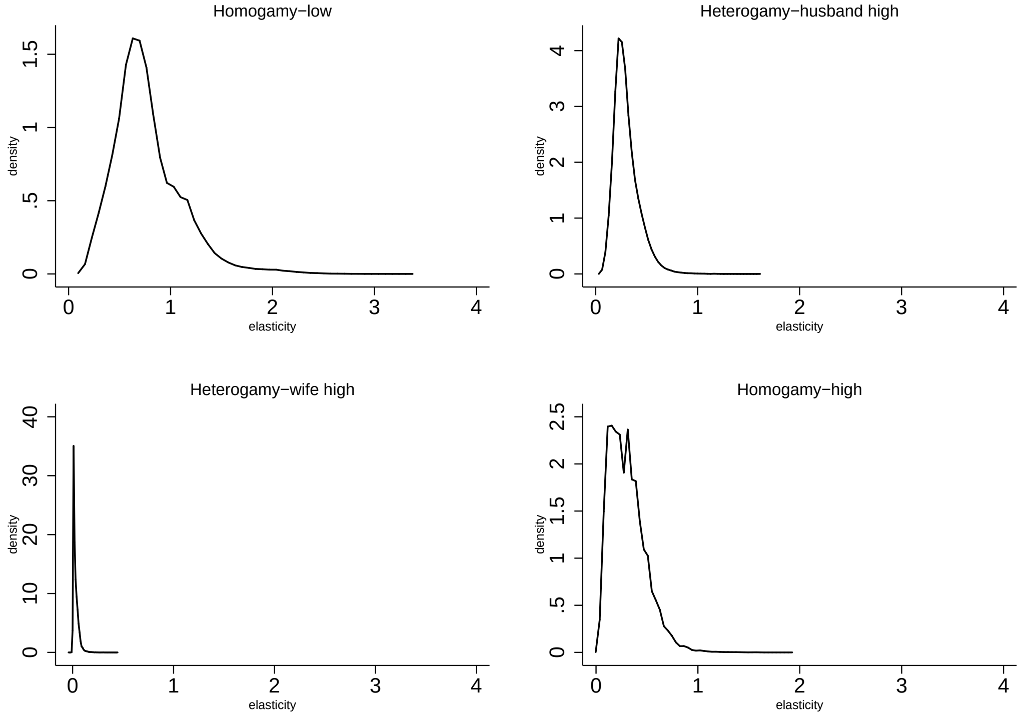


Figure 2.1: Kernel density of participation own-wage elasticities of married women by type of couples

which is close to zero (about -0.02). Similar to the dispersion of the own-wage elasticity distribution, the dispersion of the 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 shows little responsiveness to 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 those of other 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. Particularly, this might be the case for women with low education, since their employment and career opportunities are lower compared to women with high education (Cohen and Bianchi, 1998). On the other hand, if 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, the unconditional distribution of own-wage for married women exhibits the largest variation, which is consistent with the large dispersion of their labor supply own-wage elasticity distribution (See Table 2.8).

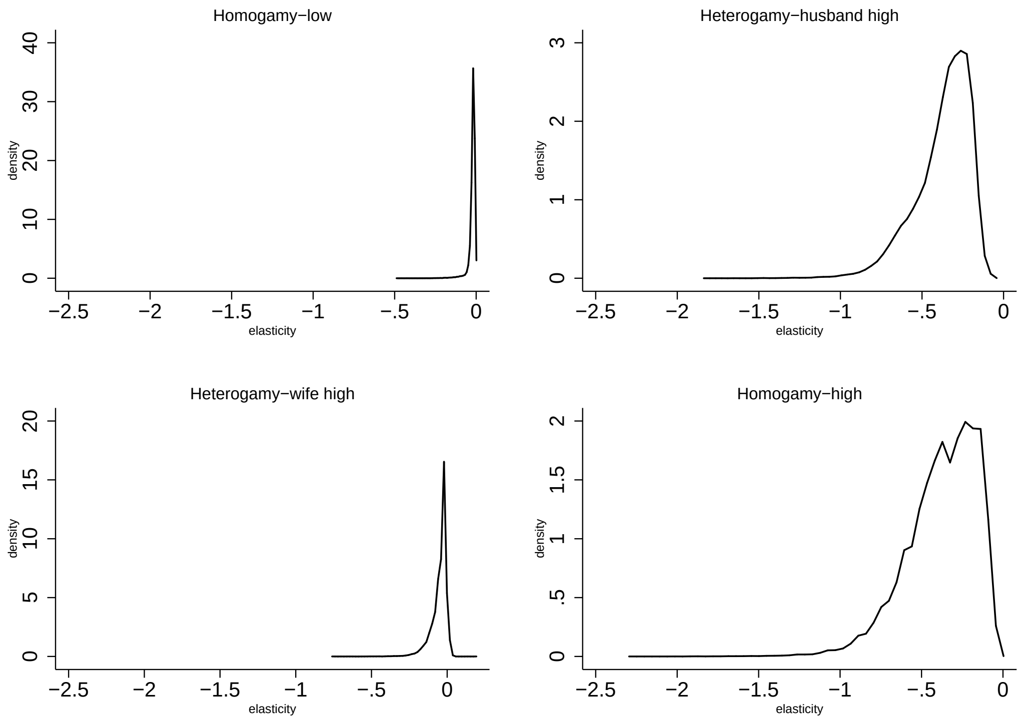


Figure 2.2: Kernel density of participation cross-wage elasticities of married women by type of couples

In Tables 2.16 and 2.17, we present the characteristics of different types of couples by the labor supply responsiveness of wives to changes in their own wages and to changes in their husbands' wages, 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 the own-wage elasticity of married women is positive and the cross-wage elasticity is negative. This implies that in Table 2.16, the labor supply responsiveness of married women to changes in their own wages is higher if their labor supply elasticities are above average. In Table 2.16, on the other hand, the labor supply responsiveness of married women to changes in their husbands' wages is higher if their elasticities are below or equal to average. Tables 2.16 and 2.17 show that, for all types, married women whose labor supply is more elastic (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 young and less likely to be white. For homogamy-low types, if the labor supply of married women is more elastic, their husbands earn on

Table 2.16: 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. *Note:* 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.

average less and they are less educated. However, for other types of couples, the average hourly log wage of husbands is higher and the husbands are more educated for women whose labor supply is more elastic. For all types, the labor supply of married women is more elastic if they have more children and a pre-school age child.

2.5.4 The role of children

A 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 considerably, one can think of the presence of pre-school age children as the source of heterogeneity among different types of couples. In fact, Del Boca (1997),

Table 2.17: 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. *Note:* 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.

as well as Lundberg (1988) test alternative theories of family labor supply behavior and find that the presence of young children has a crucial effect on household interactions.

Although we control for the number of children and the presence of pre-school age children in the reservation wage equation of wives, it is possible that household interactions are different for couples with and without pre-school age children. One possibility is that children affect the way a couple makes its labor supply decisions. However, since we allow for each couple to differ in the way they make their labor supply decisions, this should not alter our results. Still, if there are large differences between the labor supply elasticities of couples with and without pre-school age 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

Table 2.18: 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%

types by the presence of 0–6 years old children. Tables 2.18 and 2.19 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 age 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 matters most for homogamy-high couples. While without children, we do not observe any interactions for the majority of households (64%). However, those with children take their employment decisions following a non-cooperative Nash game (51%).

How do these results affect the labor supply elasticities of married women? Table 2.19 presents the labor supply elasticities of married women of different types by the presence of pre-school age children. As expected, the elasticity estimates are larger for mothers of young children. This pattern is true for all types of households. The participation wage elasticity is once again highest for women with low education married to men with low education and smallest for women with high education married to men with low education both for mothers of pre-school age children and other women. Their cross-wage and income elasticities suggest little responsiveness of labor supply of those women to changes in the husband's wage or changes in non-labor income. As before, independently of whether or not they have 0- to 6-year-old children, own-wage, cross-wage and income elasticities of women with high education are as large as women with low education if they are married to men with high education. Hence, we conclude that differential responses

Table 2.19: 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)

Note: Standard errors in parenthesis.

of married women based on spouses' education levels are present among married women, independent of whether children are present in the household or not.

2.5.5 Aggregate Labor Supply Elasticities of Married Women

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

$$\sum_k P_k \epsilon_k = \epsilon \tag{2.9}$$

where P_k is the proportion of women that are of the type k and ϵ_k is the estimated (own-wage, or cross-wage, or income) elasticity for married women of the type k. We find that the aggregate wage elasticity is 0.56, the cross-wage elasticity is -0.13, and the non-labor family income elasticity is -0.006 for married women. 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.

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 own-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.

One of the main differences 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.

In one scenario, Scenario I, we ignore differences between couples. Hence we assume that all couples make their labor supply decisions in the same way and there are no differences between types. We re-estimate all models for all couples ignoring types, obtaining one set of behavioral parameter estimates for each model for all couples. Then, we assign to all couples one particular model as their way of decision-making and calculate labor supply elasticities using parameter estimates of this model. As the preferences of husbands and wives are not directly observed, we consider three alternatives for assigning all couples the same decision-making mechanism. The first alternative is assigning couples the model that best predicts the observed outcome of the majority. We find that 43% of the couples' observed decisions are best predicted by Stackelberg-wife leader model. Hence the first possibility we consider is assigning to all couples Stackelberg-wife leader model as the way of their decision-making, and calculating labor supply elasticities using parameter estimates of this model (Scenario I-majority). The second alternative is assigning couples the model that best performs based on the goodness of fit. To compare model performances of all models, we use Akaike and Bayesian information criteria, as well as the Likelihood Dominance Criterion suggested by Pollak and Wales (1991). According to these criteria, Nash/Pareto optimality is the model that performs better compared to other models. Hence we assign couples the Nash/Pareto optimality model as their decision-making mechanism and recalculate labor supply elasticities using parameter estimates of this model (Scenario I-best-fit). Finally, we assume that all couples make their labor supply decisions independently. Hence, we use the simultaneous probit model parameter estimates for all couples to calculate labor supply elasticities (Scenario I-no interaction).

In an alternative scenario, Scenario II, we account for differences between types, but assume that couples of a particular type are the same in the way that they make labor supply decisions. For this purpose, we assign couples of a particular type one decision-making model. Then, using parameter estimates of the model for this type, we calculate labor supply elasticities. Finally, using population shares and elasticity estimates of types, we calculate aggregate labor supply elasticities. As in Scenario I, we consider three alternatives for assigning models to couples. First, we consider assigning couples of each type the model that best predicts the behavior of the majority of this type (Scenario II-majority). For this purpose, we use the information presented in Table 2.14, and assign homogamy-low and heterogamy types the Stackelberg-wife leader model and homogamy-high types the bivariate probit model. Second, we consider assigning couples of each type, the model that performs better compared to other models based on Akaike and Bayesian information criteria, as well as the Likelihood Dominance Criterion (Scenario II-majority). Comparing the goodness-of-fit in terms of these criteria, we find that the Stackelberg-wife leader model performs better than other models for each type. Therefore, we assign all types the Stackelberg-wife leader model. Finally, we assume that husbands and wives make their labor supply decisions independent from each other and use the simultaneous probit model parameter estimates for each type to calculate labor supply elasticities of different types and calculate the aggregate labor supply elasticity (Scenario II-no interaction).

Table 2.20: 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-Majority	0.29	-0.26	-0.006
Scenario I-Best-fit	0.20	-0.23	-0.007
Scenario I-No interaction	0.27	-0.23	-0.007
Scenario II-Majority	0.46	-0.22	-0.093
Scenario II-Best-fit	0.46	-0.22	-0.094
Scenario II-No interaction	0.48	-0.23	-0.097

The elasticity estimates based on different scenarios are presented in Table 2.20. For comparison, benchmark elasticities are shown in the first row. In both scenarios, we find that the labor supply own-wage elasticity for married women is smaller than our benchmark estimates. Ignoring the differences between types has a significant effect on labor supply own-wage elasticities. When we ignore the heterogeneity among couples in educational attainments of husbands and wives, we find participation own-wage elasticities between 0.20 and 0.29. Note that the elasticity calculated in Scenario I-no interaction is similar to the elasticity estimates of Blau and Kahn (2007) who without considering the household interactions and heterogeneity among couples find participation wage elasticities between 0.27 and 0.30 in 2000. Furthermore, under Scenario II, we find elasticities between 0.46 and 0.48 which are much higher than elasticities under Scenario I, but smaller than our benchmark estimates. In other words, not taking into account the heterogeneity among couples in the way that they make their labor supply decisions underestimates the labor supply elasticities (0.56 versus 0.48). However, ignoring the differences between different types underestimates the labor supply elasticities even more (0.27 versus 0.56). This suggests the crucial role of considering differences between couples in education levels of spouses for estimating labor supply elasticities of married women.

2.6 Declining Labor Supply Elasticities

Our results show that labor supply elasticities differ greatly among households. This raises a natural question: What is the impact of compositional changes in the 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 married women's labor supply responsiveness, we carry out the following counterfactual exercise. We calculate what the aggregate labor supply elasticities would be, if married women had the responsiveness of 2000 but the distribution of couples had been that of 1980. For this purpose, we calculate the overall labor supply elasticities of married women from Equation 2.9, using the elasticity estimates for year 2000 and the population shares of couples in 1980.[28] The population shares of different types of couples in 1980 and in 2000 are presented in the first panel of Table 2.21. As noted by earlier studies, from 1980 to 2000, there was an increase in the fraction of homogamy-high types. In addition, there was an increase in the share of heterogamy-wife high types reflecting the increase in educational attainment levels of women during the recent decades.

The second panel of Table 2.21 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 2.21. Under the counterfactual distribution of couples, we find a participation own-wage elasticity of 0.63,

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

Table 2.21: Labor supply elasticities under counterfactual distribution of couples

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

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 on the participation non-labor income elasticities of married women, the change in the composition of couples accounts for a decline in the participation own-wage elasticity of married women from 0.63 to 0.56. This result suggests that the increase in the educational attainment level of married women during the recent decades has resulted in reduced responsiveness to changes in their wages. Nonetheless, quantifying the role of compositional changes on the labor supply responsiveness of married women requires a more detailed analysis.

2.7 Concluding Remarks

In this chapter, we focus on the static labor supply decision of couples along the extensive margin. Using data from the 2000 U.S. Census, we estimate labor supply elasticities for married women and men by allowing for the heterogeneity among couples in educational attainments of husbands and wives and by modeling the way that household members make their labor supply decisions.

We find that labor supply decisions of husbands and wives depend on each other, unless both spouses are highly educated. For highly educated couples, labor supply decisions of the husband and the wife are jointly determined only if they have preschool age children. We also find that labor supply elasticities differ greatly among different types of households. Allowing for heterogeneity among couples yields an overall participation wage elasticity of 0.56, a cross-wage elasticity of -0.13 and a non-labor income elasticity of -0.006 for married women. Our analysis shows that ignoring the heterogeneity among couples results in a smaller estimate for labor supply own-wage elasticity for married women (about 0.27). We show that taking into account heterogeneity among couples in educational attainments of husbands and wives has an important impact on the elasticity estimates. We find that by only taking into account the heterogeneity among couples in spouses' educational attainments results in a larger elasticity estimate for married women (about 0.48).

The results of this study have important implications for policy analysis. Since many public policies are designed to target specific groups, it is essential to understand potential impacts of policies on the labor supply of different individuals. While earlier studies have focused on heterogeneity associated with the presence of pre-school age children, we show that the variation in the responses of married women depending on the spouses' education levels is present, independent of whether children are present in the household or not. The analysis in this chapter also provides a natural framework to study how changes in educational attainments and household structure affect aggregate labor supply elasticities. Our analysis indicates that if married women had the responsiveness of 2000 but the distribution of couples was the same as in 1980, the overall 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 which might be important for 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 the increase in assortative mating and the changing composition of families and their interplay with labor supply elasticities. Our analysis in Section 2.6 is a preliminary first step in this direction. Finally, we have not addressed life-cycle and dynamic issues. The dynamic extension of the family labor supply model would make it possible to analyze variations in the family labor supply behavior of different types of couples over the life cycle. We leave this extension for future research.

Chapter 3

Temporary Contracts and Fertility

(joint with Nezih Guner and Virginia Sánchez Marcos)

3.1 Introduction

The last decades witnessed unprecedented changes in family lives in OECD countries. Since 1980s the total fertility rate (TFR) declined dramatically in most of the OECD countries, reaching below replacement levels (OECD, 2011). Demographers labeled this pattern as "lowest-low fertility" (Kohler et al 2002, Billari and Kohler 2004). The fertility decline in Spain was quite remarkable. The TFR declines from 2.9 children per women in 1970 to 1.4 children in 2009, making Spain one of the lowest fertility countries in OECD. The last decades was also a period of dramatic change in labor markets. While only about 28% of women between ages of 25 and 54 worked in 1977, more than 61% of them did so in 2013 (Guner, Sanchez-Marcos and Kaya, 2014). Furthermore, the fraction of temporary (fixed-term) workers has grown since the end of the 1980s. In 2008 the fraction of the labor force with temporary contracts was 29.3% in Spain, while the OECD average was only 11.8% (OECD, 2010). Furthermore, the incidence of temporary contracts among women is higher than among men. In 2007, just before the recent crisis, the share of temporary workers was 29.1% among male workers and 31.7% among female workers (Guner, Sanchez-Marcos and Kaya, 2014).

In this chapter, we investigate how temporary contracts affect the fertility behavior of women in Spain. To this end, we estimate discrete-time duration models of the first and subsequent births using data from the data from Continuous Sample of Working Histories (Muestra Continua de Vidas Laborales in Spanish), a micro-level dataset of Spanish administrative records, and compare the probability of having a child of women working under permanent and temporary contracts. Our results suggest that job stability is an important determinant of birth hazards. We find that, holding demographic and other variables constant, women with permanent contracts in a given year are 8.2% more likely to have a first birth in the following year than woman working with temporary contract. The effect of holding a permanent contract with respect to temporary contract on the estimated transition rates becomes stronger for the transition from the first to the second birth, and even more for the transition from the second to the third birth. Women working under permanent contracts are 1.22 times more likely to have the second child and 2.97 times more likely to have the third child with respect to women working under temporary contracts.

Delayed childbearing is one of the key factors behind low fertility rates in Spain (OECD, 2011). Existing literature, e.g. Morgan and Rindfuss (1999) shows that that delaying the first birth to later ages is associated with a reduction of completed fertility. With a delay in first birth, even if women have high fertility intentions and the available evidence by Morgan and King (2001) show that they indeed do, they simply do not have time to have more children. In fact, Kohler, Skytthe and Christiansen (2001), find that for every year by which the first birth is deferred, there is a reduction of completed fertility by between 2.9% and 5.1% for Spain. Delayed childbearing also contributes to large number of women who never have children and remain childless. In 2008, about 36% of women between ages 25 and 49 was childless in Spain (OECD, 2011).

The low fertility rate in Spain is in part explained by a relatively high proportion of women remaining childless (over 20%) and by an increase in age of childbearing (OECD, 2011). With a delay in first birth, even if women have high fertility intentions (and the available evidence by Morgan and King (2001) show that they do), they simply do not have time to have more children. Empirical studies confirm the evidence that delaying the first birth to later ages is associated with a reduction of completed fertility (Morgan and Rindfuss, 1999). In fact, Kohler, Skytthe and Christiansen (2001), find that for every year by which the first birth is deferred, there is a reduction of completed fertility by between 2.9% and 5.1% for Spain.

The increasing opportunity cost of children, due to higher female labor force participation and the narrowing of the gender wage gap, is often seen as one of the main causes of fertility decline (Hotz, Klerman, Willis, 1997). Alba, Alvarez and Carrasco (2009), however, analyze the effect of female labor market status on fertility for Spain and find a positive but a non-significant effect of participation and employment on the probability of having the first child, once the endogeneity is accounted for. On the other hand, high unemployment rates, difficulties of combining market work with family responsibilities and the family policies, such as parental leaves, child benefits and child care subsidies, can distort fertility decisions.[1] In fact, Gutiérrez-Doménech (2008) analyze the effects of labor market stability on fertility behavior of Spanish women and finds that the increase in the incidence of unemployment among men tends to delay marriage and as a result fertility. Ahn and Mira (2001) also show that male unemployment is an important factor of the timing of marriages. Furthermore, González (2013) explore the impact of a universal child benefit in Spain in 2007 by employing a regression discontinuity design approach. Her findings show that the child benefit significantly increased the fertility, in part through decreasing the incidence of abortions.

In this chapter, we emphasize the effect of job stability, in particular the difference between the fertility behavior of women working with permanent and temporary contracts. As we mentioned above, the fraction of temporary (or fixed-term) workers has grown since the end of the eighties as a result of a series of labor market reforms that were introduced to combat unemployment and the incidence of temporary contracts among women is higher than among men. Low firing costs and fragile attachment to the employer of temporary workers brought a high degree of uncertainty to Spanish households, which presumably affect fertility decisions. Indeed, there is some evidence that fertility suffers when women are on temporary contracts (Adsera, 2006; Bellani and Esping-Andersen, 2013; De la Rica and Iza (2005); Fernàndez-Kranz and Lacuesta, 2009). Our chapter contributes to this strand of the literature by quantifying the impact of working under a permanent contract with respect to temporary contract on the birth hazards of Spanish women.

This chapter is organized as follows. Section 3.2 briefly describes both the recent fertility trends in Spain and provides descriptive evidence on the relationship between fertility and labor markets. Section 3.3 presents the data used in the analysis, describes the empirical models and selection of covariates, and Section 3.4 reports the empirical results. Section 3.5 contains a discussion of the results and our conclusions.

3.2 Background

In this section we document the recent fertility trends in Spain and explore the relationship between fertility and labor markets across countries. As we mentioned above, all OECD countries experienced a decline in fertility during the 1970s and 1980s, but the drop in total fertility rate in Spain is remarkable (Figure 3.1). Total fertility rate in Spain was 2.90 in 1970, which was above the OECD average (2.67). From the beginning of the 1980s, however, the fertility rate in Spain fell below the OECD average. The OECD average was 1.69 in 1995, while the total fertility rate in Spain was only around 1.17. Between 2002

[1] The childcare cost in Spain for a two-year old in 2004 was about 30% of average wages, a figure surpassed only by Luxembourg and Switzerland among OECD countries (OECD, 2007).

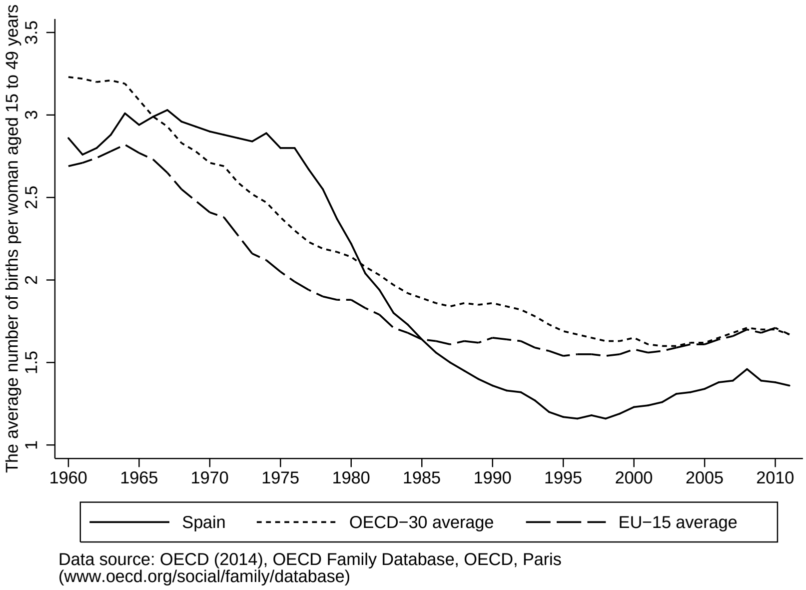


Figure 3.1: Total fertility rate, 1960-2010

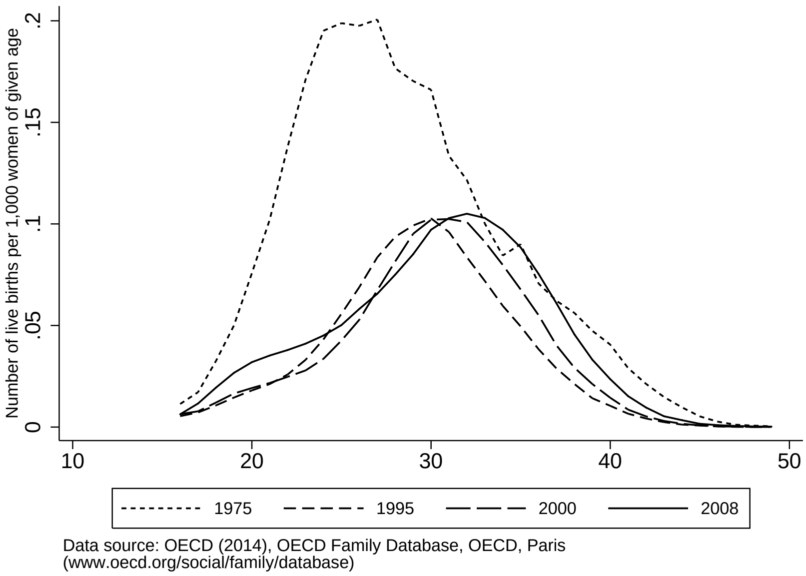


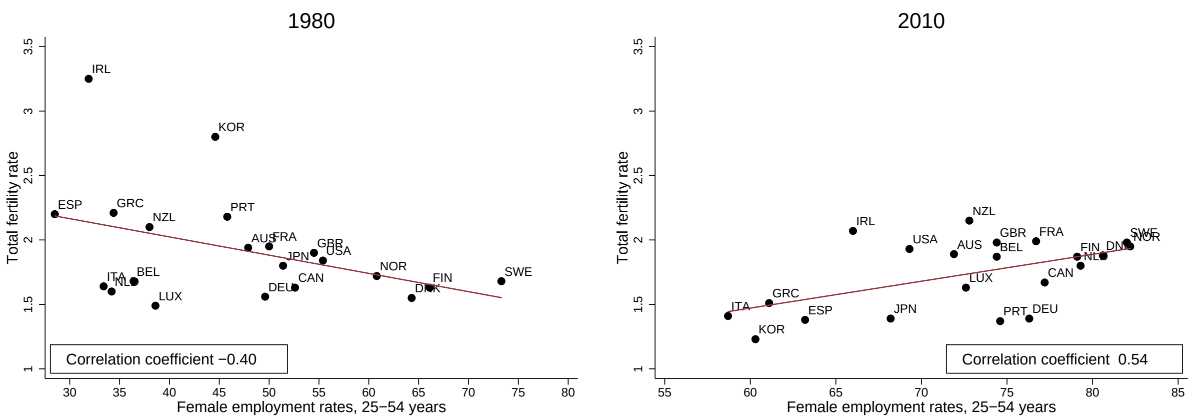
Figure 3.2: Age-specific fertility rates, 1975-2008

and 2008, the total fertility rate increased by 0.2 children per woman. Since 2002, the total fertility rate increased by 0.2 children per woman in Spain up to 2008. However, in contrast to the most of the OECD countries, since the beginning of the economic crisis in 2008 the total fertility rate in Spain has fallen again. By 2011, the total fertility rate in Spain was around 1.36, much below the OECD average that was 1.70.

The decline in fertility is closely related with the delaying the transition to motherhood.

With a delay in first birth, the age-interval in which women have their children becomes narrower and as a results they have fewer children overall even if they want to have more children. In fact, the desired number of children in Spain in 2000 was 2.32, while the actual number of children was only around 1.82 (OECD, 2014). Moreover, the mean age at first birth in Spain increased significantly from 1970 to the mid-1990s and late 2000s, from 26.6 years of age to 28.4 in 1995 and to 29.7 in 2009 (OECD, 2014). Figure 3.2 presents how fertility has moved to older ages over time by the evolution of age-specific fertility rates. As seen in Figure 3.2, from 1975 to 2008, both younger and older women experienced a decline in fertility rates and there had been a shift in the peak of childbearing.

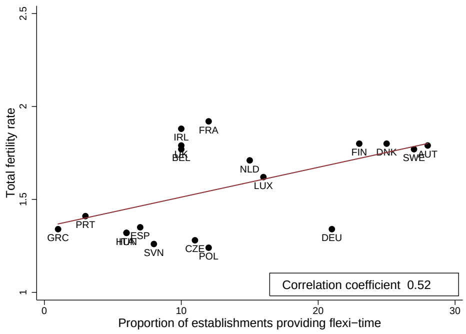
Earlier literature emphasizes the role of increasing employment rates on fertility trends. Figure 3.3 illustrates the relationship between the total fertility rate and employment rate of females aged 25–54 for OECD countries. As seen in Figure 3.3, this relationship has changed from 1980 to 2010. While the correlation between the total fertility rate and the employment rate of women was strongly negative in 1980, in 2010 this relationship is reversed–an empirical fact that has been stressed by several authors (Ahn and Mira, 2002; Del Boca, Pasqua and Pronzato, 2003). The reversal of this relationship has been attributed to the changing social norms towards working mothers, and the role of labor market institutions as well as policies that reconcile work and family are factors (Ahn and Mira, 2002; Brewster and Rindfuss, 2000; Da Rocha and Fuster, 2006).



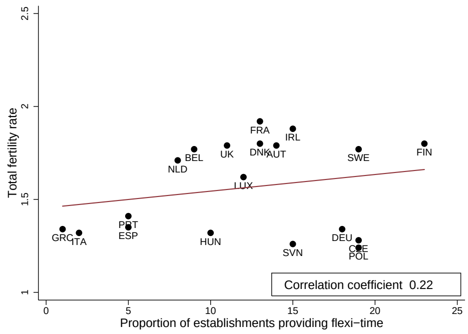
Data source: OECD (2014), OECD Family Database, OECD, Paris (www.oecd.org/social/family/database).

Figure 3.3: Cross-country relationship between employment rates of females and total fertility rate

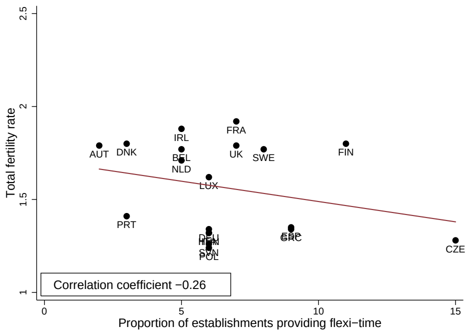
A growing empirical literature that studies the relationship between the fertility and the labor market institutions and policies shows that high rates of unemployment, instability in the labor markets, inflexible labor markets and lack of family-friendly policies.[2] Figure 3.4 shows the relation between the total fertility rate and labor market flexibility in working time. Not surprisingly, as seen in Figure 3.4, flexible working time arrangements are positively associated with fertility, if these arrangements allow accumulating hours for long periods of leave or taking full days off are positively associated with fertility. Flexible working time arrangements varies considerably across countries and the control of working time by employees is limited in Spain where more than 70% of employees report that working time is entirely fixed by the company (OECD, 2014).



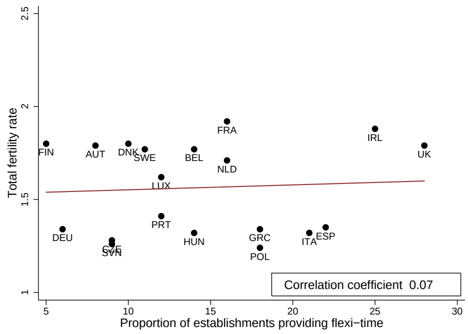
(a) accumulate hours for longer periods of leave



(b) accumulate hours for full days off



(c) accumulate hours, but no accumulation of full day off



(d) vary the start and end of daily work, but no accumulation of hours

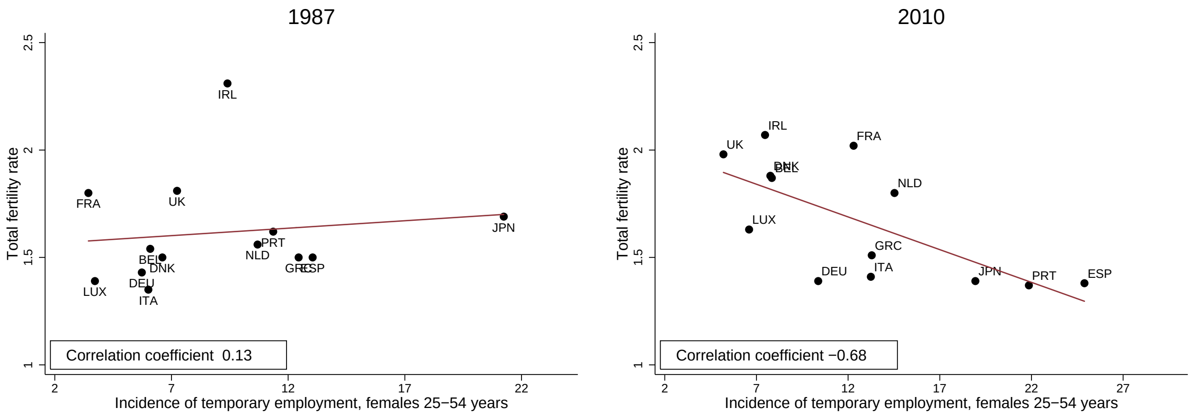
Data source: OECD Family Database (www.oecd.org/social/family/database).

Figure 3.4: Cross-country relationship between labor market flexibility and total fertility rate, 2005

The other labor market regularities that are related with fertility includes part-time schedules, public sector employment or temporary contracts. It has been shown that being employed in the public sector raises fertility (Esping-Andersen, 2002; De la Rica

[2]See Thévenon and Gauthier (2011) for the effects of family-friendly policies on fertility and Adserá (2004) for the effects of different labor market arrangements.

and Iza, 2005). On the other hand, the impact of part-time schedules on fertility is rather complex. Ariza, de la Rica and Ugidos (2003) study the relationship between part-time schedules and fertility rates, and show that for working women, the part-time schedule affects fertility positively in Belgium, Germany, Ireland, Italy and The Netherlands, but the effect is negative in some other European countries including Spain. The relationship between the incidence of temporary contracts and the total fertility rate is illustrated in Figure 3.5. Figure 3.5 shows that this relationship became more pronounced from 1987 to 2010 and by 2010 the cross-country correlation was negative.



Data source: OECD (2014), OECD Family Database, OECD, Paris (www.oecd.org/social/family/database).

Figure 3.5: Cross-country relationship between incidence of temporary employment and total fertility rate

The impact of the incidence of temporary contracts is particularly important for the Spanish case. In 1984, Spanish government introduced a labor market reform which allowed employers to contract workers on a fixed-term basis even when the nature of the job was was not temporary, which relaxed the conditions for firms to hire workers under fixed term contracts. Since the reform, the vast majority of new contracts in Spain have been and still are on a fixed-term nature. In 2008 the fraction of the labor force with temporary contracts was 29.3% in Spain, while the OECD average was only 11.8% (OECD, 2010).

The temporary contracts can last between 6 months to 3 years with compulsory conversion to a permanent contract afterwards. In practice temporary contracts are often much shorter than 3 years and the conversion rate of temporary contracts to permanent ones is about 6% per year (Bentolila, Dolado and Jimeno, 2012). As a result, a large fraction of labor force face very uncertain labor market prospects as they move from one temporary job to the next one. The main difference between temporary (fixed-term) and permanent contracts is in cost of firing a worker. Workers with permanent contracts are entitled to severance pay of 20 days wages per year of service (up to a maximum of 12 months' wages) in fair dismissals and to 45 days' (up to a maximum of 42 months') wages in unfair dismissals. Firing costs for fixed-term employees is only 12 days' wages per year of service. There has been several reform attempts that aim to to lower the prevalence of temporary employment, but without much success.

3.3 Data and Empirical Models

3.3.1 Data Description

We use data from the Muestra Continua de Vidas Laboral (hereafter MCVL) issued for the years 2005-2010. The MCVL is a random sample of 4% of the population of the individuals registered to the Spanish Social Security during the reference year. An individual can be in MCVL if she is employed, receives unemployment insurance or social security benefits. In addition to demographic characteristics of individuals (such as sex, date of birth, education level, place of residence and country of birth), MCVL provides rich information on the labor trajectory of workers. This information includes part-time or full-time, qualification, and the type of contract of each employment spell as well as the dates the employment spell started and ended. As a result, other variables such as labor market experience and tenure can be easily calculated. If an individual is included in MCVL, then her entire work history, as long as she has a relation with the Spanish Social Security System, is also available.

It is important to note that, individuals without a relationship with the Social Security at any time during the reference year are not included in the MCVL. We recovered the information for individuals that were not registered to Social Security using the earlier waves. Since, MCVL provides reliable information on type of contract only after the year 1996, we focus on work histories from 1996 to 2010. For labor market experience, we use information back to 1980. Note that individuals can hold more than one contract per year. Indeed, in 2010 more than 25.95% of our sample hold more than one job (see Table 3.1). We define the main job of an individual in a given year in the case of multiple jobs as in Fernández-Kranz and Lacuesta (2009). The main job of the individual who has multiple jobs in a given year is defined as the job under a permanent contract, if there is one, and in the case of multiple jobs with the same type of contract the job that the individual worked the largest number of days. Since, our focus is the relation between employment related variables and fertility, we disregard women that are working but their type of contract information is missing or not working one year before the childbearing.

Information on the household composition (date of birth and the sex of each individual living in the household at the time of interview) at the time of the interview is available in the Padrón Municipal de Habitantes (Spanish Municipal Registry of Inhabitants, hereinafter Padrón) and it is possible to match this information at the person level with the Social Security records. Although, Padrón does not specify the relationships between members of the household. To construct family relations we follow the approach suggested by we follow the algorithm suggested by Alba-Ramírez and Cáceres-Delpiano (2013). To link children with their mother, we restrict the sample to households where there is at least one adult woman and discard households with two or more adult women when their ages make it difficult to identify the mother of the children in the household.[3] We assume that a man living in the same household with a five years age difference with respect to the woman is the potential husband.

We restrict our analysis to native women born between 1965 and 1975 who were childless at the beginning of the analysis period and exposed to birth risk.[4] Our final sample includes 17,974 women with 269,610 total number of observations.

Table 3.1 shows the descriptive statistics if sample used in the analysis by childbearing status. Out of 17,974 women 23.78% had at least one child during 1996-2010, 10.39% had two children and only around 1% women had three children.[5] The mean age of women at the birth of their first child is 33.8 and the mean age at subsequent births are 35.84 and 37, respectively.[6] Table 3.1 indicates that mothers are more likely to hold a permanent contract before the third birth compared to the second, and before the second birth compared to the first birth. Moreover, women working under a temporary contract are more like to be mothers at earlier ages compared to women working with temporary contract.

[3]More precisely, if there are two or more adult women in the household, we disregard households with two or more adult women when the age difference between adult women to be more than five years.

[4]In our sample, women are 35 to 45 years old in 2010. By this way, we ensure that childless women in our sample are unlikely to be mothers even after 2010. See Anderson, Binder and Krause (2003), and Fernández-Kranz, Lacuesta and Rodríguez- Planas (2012) for a similar strategy.

[5]In our sample, the fraction of mothers are small mainly because we focus on native women who are working. Using Encuesta de Población Activa (Economically Active Population Survey, EPA), we compare the fertility rates of this particular group and all women to investigate the representativeness of our sample. For Spain using data from the EPA, it is possible to generate consistent statistics on total fertility and age-specific fertility rates (See Appendix C, Figures C.1 and C.2). In Appendix C Figures C.1 and C.3, we illustrate the total fertility rate and age-specific fertility rates of working-native women. For the time period of our analysis, lower fertility rates of this group of women compared to all women supports the representativeness of our sample.

[6]According to OECD (2014), in 2009, the mean age of women at the birth of their first child was 29.7 for Spain, while in our sample it is 33.8. This difference is potentially due to exclusion of women who do not have any Social Security Record, i.e. out of labor force, immigrants and age restriction.

Table 3.1: Descriptive statistics by childbearing status

Childless women		Mothers	
Total individuals	13,699	Total individuals	4,275
Total observations	205,485	Total observations	64,125
		% with only one child	23.78
		% with two children	10.38
		% with three children	0.99
Mean age	32.93	Mean age	33.05
Mean age in 2010	39.93	Mean age in 2010	40.05
		Mean age at n^{th} childbirth	
		1^{st} birth	33.80
		2^{nd} birth	35.84
		3^{rd} birth	37.00
% with below secondary education	28.44	% with below secondary education	25.66
% with secondary education	50.75	% with secondary education	50.57
% with higher education	20.81	% with higher education	23.77
% Full-time employed in 2010	74.49	*% Full-time employed one year before the n^{th} birth*	
		1^{st} birth	81.03
		2^{nd} birth	81.40
		3^{rd} birth	81.46
% with permanent contract in 2010	84.05	*% with permanent contract one year before the n^{th} birth*	
		1^{st} birth	78.81
		2^{nd} birth	84.72
		3^{rd} birth	93.14
		Mean age at n^{th} birth (with permanent contract one year before)	
		1^{st} birth	34.35
		2^{nd} birth	35.96
		3^{rd} birth	37.13
		Mean age at n^{th} birth (with temporary contract one year before)	
		1^{st} birth	31.76
		2^{nd} birth	35.21
		3^{rd} birth	35.50

Data source: Muestra Continua de Vidas Laborales (MCVL) 2005-2010.
Notes: Sample includes native women born between 1965 and 1975 who were childless in 1996 and exposed to birth risk. See text for variable definitions and further sample restrictions.

3.3.2 Single-Spell Discrete-Time Duration Models

We employ a discrete-time duration model to study the transition to the motherhood. [7] In other words, we estimate the conditional probability that individual i where $i = 1, ..., n$ will have the first birth at a specific age t, given that she was childless at age $(t-1)$, where age is measured in years. Formally, we define this conditional probability p_{it}, i.e. the discrete-time hazard rate as follows:

$$p_{it} = Pr[T_i = t | T_i \geq t, x_{it}] \tag{3.1}$$

[7] Since we measure the age of women at childbirth in years, we consider a discrete-time instead of a continuous-time duration model. For other examples of discrete-time duration models to study timing of the childbearing, see Nicoletti and Tanturri (2008) and Ahn and Mira (2001).

where T is the discrete random variable giving the uncensored time of first birth and x_{it} is a vector of observed variables (time-varying or constant over time). We assume that the hazard rate in Equation 3.1 is a logistic regression function of age t and the observed variables x_{it}:

$$p_{it} = 1/[1 + exp(-\alpha_t - \beta^{'} x_{it})], \tag{3.2}$$

which can be written as

$$log[p_{it} - (1 - p_{it})] = \alpha_t - \beta^{'} x_{it}. \tag{3.3}$$

We introduce the state dependence of the discrete hazard rate by specifying α_t as quadratic polynomial in t:

$$\alpha_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2. \tag{3.4}$$

For the model described in Equation 3.1, the likelihood function of a sample can be written as:

$$L = \prod_{i=1}^{n} [Pr(T_i = t_i)]^{\delta_i} [Pr(T_i > t_i)]^{1-\delta_i} \tag{3.5}$$

where δ_i equals to 1 if woman i gives birth to her first child at the age t, i.e. the observation is uncensored and 0 otherwise. It can be shown that substituting the expressions for probabilities in Equation 3.5 and taking the logarithm yields the following log-likelihood function:[8]

$$logL = \sum_{i=1}^{n} \delta_i log[o_{it_i}/(1 - o_{it_i})] + \sum_{i=1}^{n} \sum_{j=1}^{t_i} log(1 - o_{ij}). \tag{3.6}$$

We estimate discrete hazard model by employing a maximum likelihood estimation strategy. The single-spell discrete-time model described above, however, does not incorporate the presence of unobserved heterogeneity across women, i.e. unobserved individual-specific factors that may affect the hazard rate. The importance of controlling for unobservables in the analysis of life cycle birth processes has been shown by Heckman, Hotz and Walker (1985). Moreover, ignoring the unobserved heterogeneity can result in bias, inefficiency, and inconsistent standard errors (Allison, 1982; Singer and Willett, 1993). Therefore, we consider also a modified version of the model takes into account the unobserved hetero-

[8] See Allison (1982) for details.

geneity, by introducing an individual specific random component to the hazard function:

$$p_{it} = 1/[1 + exp(-\alpha_t - \beta^{'} x_{it})] + u_i, \tag{3.7}$$

where u_i has a normal distribution with a mean of 1 and a constant variance σ_u^2.

3.3.3 Multiple-Spell Discrete-Time Duration Models

The single-spell discrete-time models work well for non-repeatable events like first births, but cannot be directly applied to repeatable events, like subsequent births. To also consider the transitions from first birth to second birth, from second birth to third birth, the discrete-time model can be generalized to multiple-spell model. In this case, let T_k where $k = 1, 2, 3$ be a set of random variables denoting the time at which the k^{th} birth occurs to some individual with realized value t_k. The discrete-time hazard rate for the k^{th} event is defined as

$$p_k(t) = Pr[T_k = t | T_k \geq t, T_1 = 1, ..., T_{k-1} = t_{k-1}, x_t]. \tag{3.8}$$

In case of multiple births, one needs to take into account the possibility that transitions to subsequent births from the same individual are dependent. Moreover, processes affecting the occurrence of the first, second and third birth may not be the same. In multiple-duration model, we take into account the former by introducing the time interval between two subsequent births $(t - t_{k-1})$ and for the later we allow β to differ the first, second and third birth. Hence, we define the hazard rate for the k^{th} event as

$$p_k(t) = 1/exp[-\alpha(t - t_{k-1})) - \beta_k^{'} x_t - (t_{k-1} - t_{k-2})\gamma_1] \quad k = 1, 2, 3. \tag{3.9}$$

Therefore, the hazard rate for the k^{th} event depends on the duration between the last two events $(t_{k-1} - t_{k-2})$. Once again, to incorporate the presence of unobserved heterogeneity between individuals due to time invariant omitted variables, we introduce an individual specific random component to the model such that the hazard rate is

$$p_k(t) = 1/exp[-\alpha(t - t_{k-1}) - \beta_k^{'} x_t - (t_{k-1} - t_{k-2})\gamma_1 - u] \quad k = 1, 2, 3. \tag{3.10}$$

In our empirical analysis we first present the estimates for the models with and without controlling for unobserved heterogeneity. In doing so, we discuss the implications of introducing unobserved heterogeneity in the life cycle birth processes of Spanish women.

3.3.4 Selection of Covariates

In our analysis, the duration variables are defined as the duration of the first birth in years since woman's fifteenth birthday, the duration in years from first birth until the second birth and the duration in years from second birth until the third birth.

The covariates included are education level (three categories: (i) below secondary, (ii) secondary, and (iii) high education), a dummy that takes value of 1 if there is a potential husband living in the household and 0 otherwise (lagged), years of actual labor market experience (lagged), qualification of the main job (lagged, five categories: (i) high, (ii) medium-high, (iii) medium, (iv) medium-low, and (v) low), a dummy variable that takes value of 1 if the woman had a full-time main job and 0 otherwise (lagged), and a dummy variable if the main job was under a permanent contract and 0 otherwise (lagged).[9]

In the analysis of second and third birth intervals, we also included the variables related to previous births. These variables include the duration of previous birth intervals and gender composition of children. The previous birth intervals may proxy some of the unobservable characteristics of women such as preferences for children or fecundity (Ahn and Mira, 2001). The gender composition of the previous children may also affect the decision of a woman to have a second or third child if she has preferences for gender of the children or preferences for a balanced gender composition. Indeed, using data from the Encuesta Sociodemografica (Sociodemographic Survey) of 1991, Ahn and Mira (2001) show that Spanish parents with the same sex two children have a 30% higher hazard in the third birth interval. Hence, for the timing to the second child, we add the duration between the first birth and since woman's 15th birthday and a dummy variable equal to 1 when the first child was a girl to control for gender preferences. For third birth, the extra variables are the duration of the previous spell and a dummy variable that take a value of 1 if the first two children were the same sex to incorporate preferences for a balanced gender composition.

3.3.5 Empirical Survival Functions and Hazard Rates

Before we turn to the empirical results, we first start with a descriptive analysis of the relationship between the type of employment contract and the timing of the first and subsequent births. For this purpose, we first provide a graphic overview of the empirical

[9] One of the drawbacks of using the MCVL data is that it does not provide information on employment related variables for the spouses. The employment of the spouse may also affect the birth hazard. To explore this possibility, we use the data from European Community Household Panel (ECHP, 1994-2001). ECHP provides information on the spouses, however, sample sizes are relatively small. Using ECHP data, we estimate a simple linear probability model of giving birth to a child conditional on type of spouse's employment contract and income, however, the coefficient estimates of these variables turn to be insignificant. These results are presented in Appendix C, Table C.1.

estimates of the survivor function and hazard rates by type of contract using life-table methods. Life-table methods make no prior assumptions about the shapes of the survival and hazard functions, and they are informative about the pattern of duration dependence. The empirical estimates of survival functions show the fraction of women who remained childless by the end of each time period. On the other hand, empirical estimates of hazard functions provide the unconditional probability of a birth.

Figure 3.6 provides the empirical estimates of the survival functions and hazard rates of first, second and third birth by type of contract. We start with the first birth. As seen in panel (a), more than 90% of the women in our sample who were employed one year before the child birth (holding a permanent or temporary contract) remained childless even after 30 years since the 15th birthday. This fraction is slightly larger for women who were holding a temporary contract. Panel (b) shows that women with permanent contract have a significantly higher hazard than those with temporary contract, and hence enter childbearing earlier. The Likelihood-ratio test statistic and Log-rank test for equality of survivor functions for equality of survivor functions reject the null hypothesis of no differences between workers with temporary and workers with permanent contract in survivor functions for the first birth.[10] This is also true for second birth and third birth, although the difference is not statistically significant for the second birth (panels (d) and (f)). As expected, the probability of transition to first birth increases by age, until 40s and then starts to decline, while the probability of subsequent births decreases by years since the previous birth.

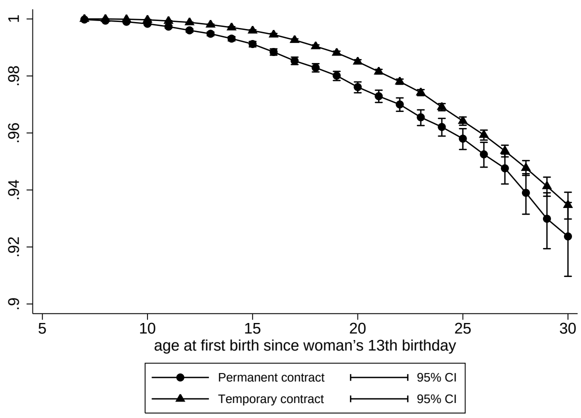
It is important to note that, the observed patterns in empirical hazards in Figure 3.6 are partly due to the aggregation of individuals with different characteristics that may affect their probability of having a child. In the next section, we present the estimates of conditional hazards and try to separate out effects on the hazards due to observed heterogeneity from those due to state dependence and unobserved heterogeneity.

3.4 Empirical Results

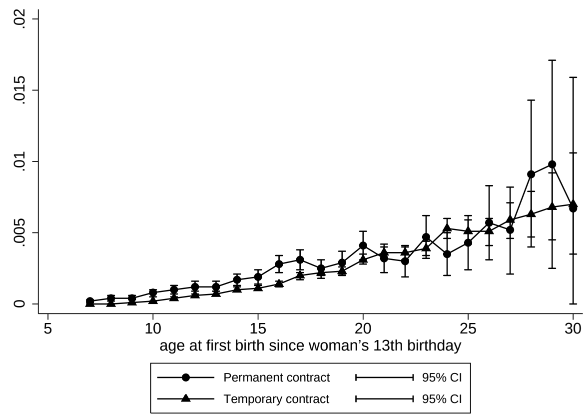
We now turn to the influence on the hazard of first, second and third birth of individual characteristics, including the type of employment contract, while controlling for duration dependence. We first start with the empirical estimates of the parameters of the statistical model that does not control for unobservables, and then follow with the results allowing for unobserved heterogeneity. The estimation results are reported in Table 3.2.

As expected, the hazard rates of first and subsequent births are first increasing and

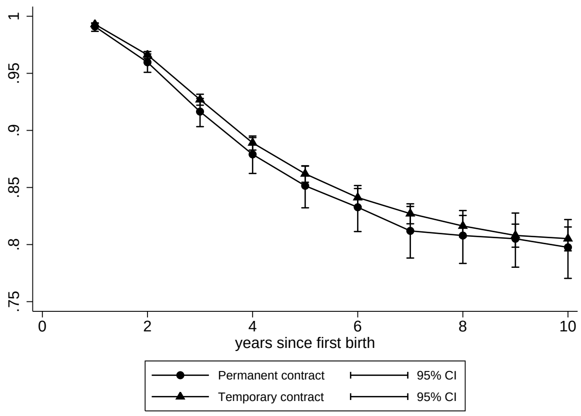
[10] χ^2 value for the Likelihood-ratio test statistic of homogeneity is 5.21 (p-value= 0.022) and χ^2 value for the Log-rank test for equality of survivor functions 101.26 (p-value= 0.000).



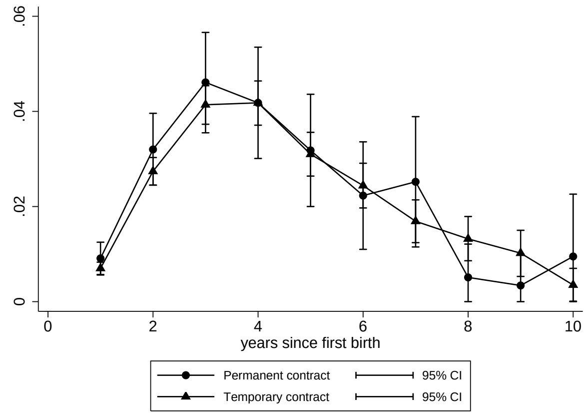
(a) Survivor function estimates, first birth



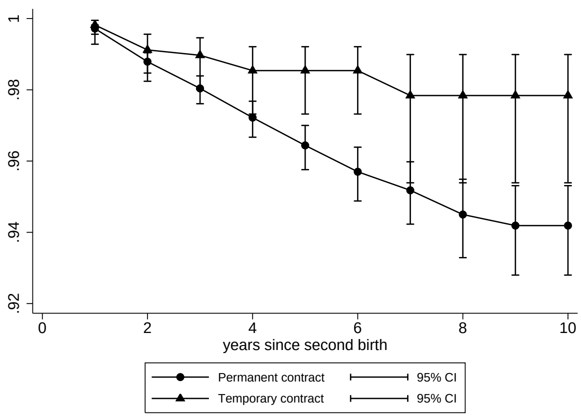
(b) Hazard rate estimates, first birth



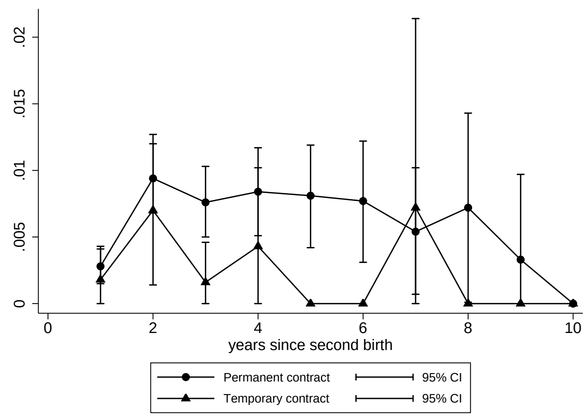
(c) Survivor function estimates, second birth



(d) Hazard rate estimates, second birth



(e) Survivor function estimates, third birth



(f) Hazard rate estimates, third birth

Data source: Muestra Continua de Vidas Laborales (MCVL) 2005-2010.

Figure 3.6: Empirical survival and hazard functions

Table 3.2: Estimates for birth process hazard rates, not controlling for unobserved heterogeneity

	Age 15 to first birth		First birth to second birth		Second birth to third birth	
	Coeff.	Robust s.e.	Coeff.	Robust s.e.	Coeff.	Robust s.e.
Constant	-6.788***	(0.228)	-6.266***	(0.317)	-4.329***	(1.076)
Duration	0.218***	(0.023)	1.106***	(0.088)	1.103***	(0.145)
Duration^2	-0.005***	(0.001)	-0.013***	(0.001)	-0.151***	(0.024)
Duration 1st birth			0.922***	(0.087)		
Duration 2nd birth					-0.292***	(0.072)
Age at 2nd birth					-0.029	(0.030)
Permanent contract	**0.079***	**(0.043)**	**0.198****	**(0.083)**	**1.052*****	**(0.361)**
Full-time	0.022	(0.041)	0.075	(0.074)	0.216	(0.225)
Medium-high qualification	0.015	(0.065)	-0.169	(0.117)	0.121	(0.309)
Medium qualification	0.029	(0.053)	-0.076	(0.096)	0.007	(0.278)
Medium-low qualification	0.017	(0.054)	0.016	(0.096)	-0.109	(0.285)
Low qualification	0.132**	(0.064)	-0.001	(0.119)	0.351	(0.326)
Labor market exp	-0.009*	(0.005)	-0.014	(0.010)	-0.021	(0.028)
Married	1.201***	(0.030)	0.586***	(0.063)	-0.142	(0.175)
Secondary education	0.078**	(0.039)	-0.064	(0.075)	-0.096	(0.211)
High education	0.204***	(0.051)	0.025	(0.097)	0.049	(0.268)
1st child female			0.021	(0.058)		
1st & 2nd children same sex					0.184	(0.184)
Observations	218,347		45,684		9,035	

*Notes:*Individual level clustered robust standard errors are in parenthesis. See text for variable definitions.
*Data source:*Muestra Continua de Vidas Laborales (MCVL) 2005-2010.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

then decreasing in age (the coefficients for the variables duration and duration squared are positive and negative, repetitively and statistically significant). The length of the previous birth interval is positively associated with the transition rate to the next child for the second child and negatively associated for the third child duration. In other words, women that had their first child in later ages have higher probability to have a second child, however, they are less likely to have a third child. This difference is probably due to the decline in the natural age-related decline in fertility since women who wait longer for having the first child would be older and less likely to have a third child. Once the duration of the second birth is controlled, the age at second birth does not have a significant effect on the probability of having a third child.

It is quite evident from Figure 3.6 that holding a permanent contract increases the hazard of having a child. Moreover, the coefficient on the permanent contract variable is one of the most significant estimated effects and the effect increases from first to second,

Table 3.3: Estimates for birth process hazard rates, controlling for unobserved heterogeneity

	Age 15 to first birth		First birth to second birth		Second birth to third birth	
	Coeff.	Robust s.e.	Coeff.	Robust s.e.	Coeff.	Robust s.e.
Constant	-6.788***	(0.234)	-3.488***	(0.315)	-3.517***	(1.038)
Duration	0.218***	(0.024)	0.424***	(0.091)	0.669***	(0.181)
Duration^2	-0.005***	(0.001)	-0.007***	(0.001)	-0.100***	(0.024)
Duration 1^{st} birth			0.479***	(0.091)		
Duration 2^{nd} birth					-0.291***	(0.061)
Age at 2^{nd} birth					-0.030	(0.029)
Permanent contract	**0.079***	**(0.046)**	**0.121**	**(0.080)**	**1.052*****	**(0.353)**
Full-time	0.022	(0.044)	0.081	(0.070)	0.215	(0.217)
Medium-high qualification	0.015	(0.071)	-0.099	(0.110)	0.124	(0.316)
Medium qualification	0.029	(0.059)	-0.038	(0.091)	0.012	(0.279)
Medium-low qualification	0.017	(0.059)	0.066	(0.091)	-0.109	(0.292)
Low qualification	0.132*	(0.070)	0.026	(0.112)	0.357	(0.338)
Labor market exp	-0.009	(0.006)	-0.014	(0.009)	-0.0215	(0.027)
Married	1.201***	(0.034)	0.446***	(0.057)	-0.137	(0.169)
Secondary education	0.078*	(0.044)	-0.050	(0.069)	-0.094	(0.213)
High education	0.204***	(0.057)	0.041	(0.091)	0.049	(0.273)
1^{st} child female			0.006	(0.053)		
1^{st} & 2^{nd} children same sex					0.183	(0.164)
$\ln\sigma_u^2$	-12.16	(3.785)	-11.39	(10.048)	-9.766	(13.524)
σ_u	0.002	(0.004)	0.003	(0.017)	0.007	(0.051)
ρ	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
prob. $\geq \bar{\chi}^2$	0.474		0.491		0.497	
Observations	218,347		17,663		7,469	

*Notes:*Individual level clustered robust standard errors are in parenthesis. See text for variable definitions.
*Data source:*Muestra Continua de Vidas Laborales (MCVL) 2005-2010.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and second to third birth. In particular, childless women working with a permanent contract in a given year are 8.2% ($(e^{0.079} - 1) * 100$) more likely to have a first birth in the following year than woman working with temporary contract. Moreover, women with a permanent contract are 1.22 ($e^{0.198}$) times more likely to have the second child and 2.97 ($e^{1.052}$) times more likely to have the third child.

The other labor market related variables, such as working full-time or labor market experience do not affect the hazards significantly. The only exception is working in low-qualified occupations in the estimation of likelihood of having a first child. Woman working in occupations that only require low qualification increases the hazard of the first birth, which presumably reflects the selection into motherhood.

The estimated effects of other personal characteristics are quite intuitive. Being married (measured as living with a man with a five years age difference in the same household) makes a woman more like to become a mother, and more likely to have a second child. A secondary or a higher education degree raise the hazard of first birth significantly, while the effects are not significant for the subsequent births. Last, the gender composition of previous children do not raise the hazards significantly.

In Table 3.3, we present the estimates of the models of duration of the first, second and third birth intervals controlling for unobserved heterogeneity. Regarding the hazard of giving a birth, the results with and without unobserved heterogeneity are quite consistent. A comparison of Tables 3.2 and 3.3 reveals that there are no substantial differences between the parameter estimates between two models, the model with and the model without unobserved heterogeneity.[11] All coefficients in Table 3.3 have the same sign as the corresponding ones in Table 3.2 and they are of a similar magnitude. In Table 3.3, however, the standard errors are somewhat larger which results in permanent contract variable coefficient to become insignificant. In each model of the corresponding birth interval, the Likelihood-ratio test rejects the presence of unobserved heterogeneity or random effect.

3.5 Concluding Remarks

In this chapter, we investigate the influence of job instability on the timing of childbearing in Spain. We do so by exploiting a large and rich longitudinal data set. We estimate a discrete-time duration models of the first and subsequent births and compare the probability of having a child of women working under permanent and temporary contracts, holding demographic and other variables constant.

Our results show that job instability plays a role in fertility decisions. Women with permanent contracts in a given year are 8.2% more likely to have a first birth in the following year than woman working with temporary contract. The effect of holding a permanent contract with respect to temporary contract on the estimated transition rates becomes stronger for the transition from the first to the second birth, and from the second to the third birth.

One of the shortcoming of our analysis is that we do not consider the potential endogeneity of the contract type. Moreover, the employment and fertility decisions are likely to be mutually determined. We believe that a model can be useful to understand the joint

[11] This result is not uncommon in the literature. For instance, Bover, Arellano, and Bentolila (2002), for the hazard of unemployment find that there are no substantiation differences between discrete-time models with and without unobserved heterogeneity.

determination of timing of childbearing decisions together with employment decisions. We leave this and other extensions for future research.

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Appendix A

Appendix for Gender Wage Gap Trends in Europe: The Role of Occupational Allocation and Skill Prices

A.1 Data Appendix

A.1.1 Variables

Gross hourly wage: Gross hourly wages from ECHP and EU-SILC are constructed by dividing gross monthly wages for the previous year by monthly hours worked in the main job in that year. The income reference period in the ECHP and in EU-SILC is the calendar year preceding the year of data collection in all countries except the U.K. and Ireland. In Ireland it is the 12 months prior to the interview, and in the United Kingdom it refers to the period around the date of interview. Hence ECHP data on wages refers to the year 1993 except for Austria to the year 1994 since Austria joined the survey in 1995. EU-SILC data refers to the year 2008. Wages are converted in 2005 PPP units using the purchasing power parity (PPP) exchange rates and then deflated by using the harmonized consumer price index (HCPI=2005). Both surveys include supplementary information on PPP exchange rates and HCPI is extracted from OECD Main Indicators database. In March CPS the annual earnings are top-codded. Following Katz and Murphy (1992) and Blau and Kahn (1997) procedure, the top-codded values are multiplied by 1,45. Then, the hourly wage from March CPS is constructed using the annual gross wages for the previous year divided by the product of weeks worked and average hours worked per week in that year. Wages are deflated by using the consumer price index (CPI=2005).

Occupation: The occupation information in ECHP and EU-SILC is defined using the International Standard Classification of Occupations (ISCO-88) and codded at the two-digit level. Occupation variable from March CPS is reclassified based on European classification using the ISCO-SOC crosswalk made available by the Center for Longitudinal Studies in the U.K. at http://www.cls.ioe.ac.uk/text.asp?section=000100010005000160002.

Education: The education variable from ECHP and EU-SILC is harmonized by using the International Standard Classification of Education (hereinafter, ISCED) categories. High educational qualifications are defined as ISCED categories 5-7, and include recognized third level education. Secondary education is defined by ISCED categories 3 and 4, and includes all second stage of secondary level education. Low education is defined as having no qualifications or only qualifications below the secondary education level, and corresponds to ISCED categories 0-2. Educational attainment variable from March CPS is reclassified based on the ISCED categories using the mapping provided by UNESCO Institute for Statistics (UIS) http://www.uis.unesco.org/education/ISCEDmappings.

Labor Market Experience: EU-SILC, provides the exact number of years spent in paid work with two exceptions; Ireland and the U.K. For Ireland and the U.K. the missing information on experience in EU-SILC is proxied using the years passed after the highest level of education was attained. On the other hand, ECHP lacks the information on actual labor market experience. However it provides information about the age of individuals at the highest level of education completed and at the beginning of the working life as well as the number of continuous months of unemployment before current job. Using these variables we generate a proxy for labor market experience. To proceed more formally, let y_t denote the year of the survey, y_s the year when the individual attained the highest education level, y_w the year when the individual began working life and m_u the number of continuous months of unemployment before current job ($y_u = m_u/12$ in years). The measure for labor market experience for individuals who completed their education earlier than starting to the working life (if $y_s >= y_w$) is computed as $exp = y_t - y_w$ and for the ones who started the working life before completing their highest education degree (if $y_s > y_w$) as $exp = y_t - y_s$. Then, the measure for labor market experience is partially corrected by subtracting the continuous months of unemployment before current job ($exp^* = exp - y_u$). Since March CPS does not provide information about the actual labor market experience, we use potential labor market experience variable that is age–years of schooling–6. Values for years of schooling is imputed using the educational attainment levels suggested by Jaeger (1997).

A.1.2 Sample

ECHP samples come from the initial wave of each country which is representative for the corresponding year. Although the ECHP aims at being both cross-sectionally and longitudinally representative, due to non random attrition and demographic changes arising from the arrival of new waves of immigrants, its cross-sectional representativeness tends to fade away over time (See Peracchi (2002) for an overview of ECHP data). On the other hand, EU-SILC is a four-year rotated panel and provides two types of annual data: cross-sectional data and longitudinal data observed periodically over a four-year period. The analysis are based on the cross-sectional component of EU-SILC which is representative for the corresponding year.

The ECHP and EU-SILC samples are restricted to individuals of working age, between 25 and 54 years old. In ECHP age is top-coded at 85 years in wave 1, 86 years in wave 2, and so on, for all countries, whilst age at first job is top coded for all countries and waves at 60 years. As we are mostly concerned with working age population, these top-coding rules are relatively unimportant. The sample is further restricted to individuals who are working at least 15 hours per week with valid observations on all the variables used in the wage equations. As suggested by Commission of the European Communities, gender wage gap "ought to be based on data covering the whole economy, including all sectors and firm sizes, including possibly also those working less than 15 hours per week" (CEC, 2003). However, the restriction of working at least 15 hours per week is necessary because of the nature of ECHP, since ECHP does not distinguish individuals regularly working less than 15 hours from those out-of the labor force in the first two waves. Finally, wage observations five times greater than the 99th percentile of the country wage distributions in each year or lower than 1$ per hour are excluded from the sample.

The U.S. samples are constructed using the same rules as the ECHP and EU-SILC samples. In particular, sample is restricted to workers 25-54 aged, not living in group quarters, not in school, not working without pay, working at least 15 hours per week and with positive number of years of potential labor market experience with non-missing variable responses. Finally, wage outliers five times greater than 99th percentile of the U.S. wage distributions in each year or lower than 1$ per hour are dropped.

A.1.3 Descriptors Comprising the Skill Measures

Variables comprising BRAIN SKILLS measure

O*Net Descriptor	Description
oral comprehension	listening and understanding information and ideas presented through spoken words and sentences.
written comprehension	reading and understanding information and ideas presented in writing.
oral expression	communicating information and ideas in speaking so others will understand.
written expression	communicating information and ideas in writing so others will understand.
fluency of ideas	coming up with a number of ideas about a topic.
originality	coming up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
problem sensitivity	telling when something is wrong or is likely to go wrong.
deductive reasoning	applying general rules to specific problems to produce answers that make sense.
inductive reasoning	combining pieces of information to form general rules or conclusions.
information ordering	arranging things or actions in a certain order or pattern according to a specific rule or set of rules.
category flexibility	generating or using different sets of rules for combining or grouping things in different ways.
mathematical reasoning	choosing the right mathematical methods or formulas to solve a problem.
number facility	adding, subtracting, multiplying, or dividing quickly and correctly.
memorization	remembering information such as words, numbers, pictures, and procedures.
speed of closure	quickly making sense of, combining, and organizing information into meaningful patterns.
flexibility of closure	identifying or detecting a known pattern that is hidden in other distracting material.
perceptual speed	quickly and accurately comparing similarities and differences among sets of letters, numbers, objects, pictures, or patterns.
spatial orientation	knowing the location in relation to the environment.
visualization	imagining how something will look after it is moved around or when its parts are moved or rearranged.
selective attention	concentrating on a task over a period of time without being distracted.
time sharing	shifting back and forth between two or more activities or sources of information.

Variables comprising BRAWN SKILL measure

O*Net Descriptor	Description
arm-hand steadiness	keeping hand and arm steady while moving arm or while holding arm and hand in one position.
manual dexterity	quickly moving hand, hand together with arm, or two hands to grasp, manipulate, or assemble objects.
finger dexterity	making precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
control precision	quickly and repeatedly adjusting the controls of a machine or a vehicle to exact positions.
multi limb coordination	coordinating two or more limbs while sitting, standing, or lying down.
response orientation	choosing quickly between two or more movements in response to two or more different signals.
rate control	timing movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
reaction time	quickly responding to a signal when it appears.
wrist-finger speed	making fast, simple, repeated movements of the fingers, hands, and wrists.
speed of limb movement	quickly moving the arms and legs
static strength	exerting maximum muscle force to lift, push, pull, or carry objects.
explosive strength	using short bursts of muscle force to propel oneself, or to throw an object.
dynamic strength	exerting muscle force repeatedly or continuously over time.
trunk strength	using abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.
stamina	exerting physically over long periods of time without getting winded or out of breath.
extent flexibility	bending, stretching, twisting, or reaching with body, arms, and/or legs.
dynamic flexibility	quickly and repeatedly bending, stretching, twisting, or reaching out with body, arms, and/or legs.
gross body coordination	coordinating the movement of arms, legs, and torso together when the whole body is in motion.
gross body equilibrium	keeping or regaining body balance or stay upright when in an unstable position.

A.1.4 Mapping of O*Net-SOC Occupational Codes to ISCO Codes

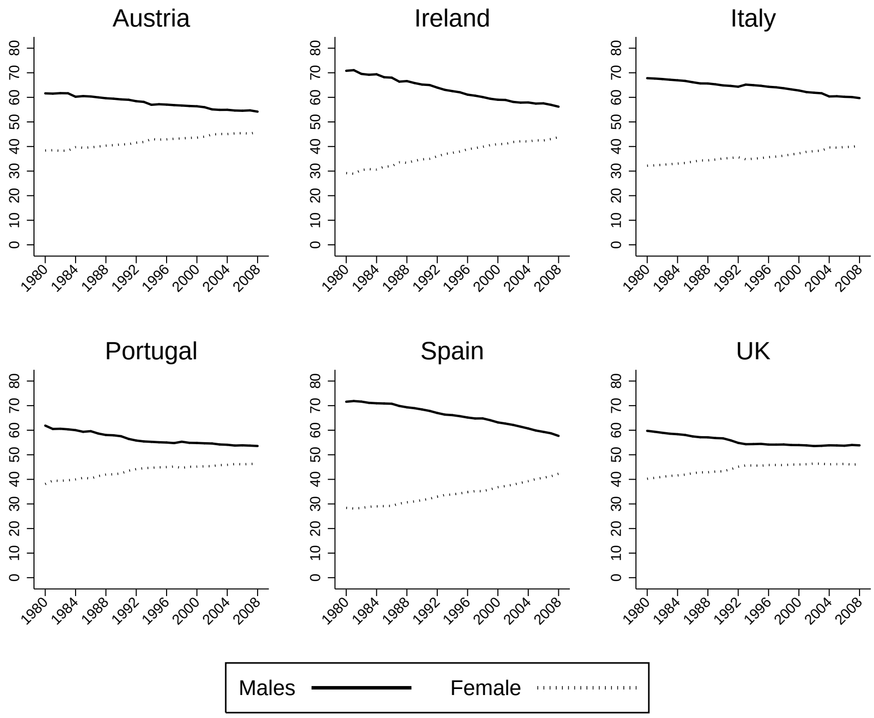
15th edition of O*Net occupational coding is based on SOC 2010, but there exist differences between two occupation codes. O*Net splits up several SOC 2010 occupations into multiple separate occupations. O*Net includes 1110 occupations with detailed information in the database for 974 of them, while SOC 2010 includes 840 detailed occupations. 667 occupations in 15th edition of O*Net are at SOC level which we have the ability requirements and employment shares of these occupations in the 2001 U.S. labor market. However, 37 SOC level occupations are divided into multiple categories at O*Net level. For instance, SOC 2010 code 11-3031 is Financial Managers, which O*Net provides information on ability requirements, but divides up this category into further two categories 11-3031.01, Treasurers and Controllers; and 11-3031.02 Financial Managers, Branch or Department. For these two categories, we have their ability requirements separately but we do not have their employment shares separately. We have dealt with these O*NET categories by simply taking the descriptor values for the main 37 occupation titles (for this example the values for 11-3031, Financial Managers are taken into account). For 269 occupations in 15th edition O*Net do not exist in SOC 2010 separately. For instance, SOC code 13-2011 is Accountants and Auditors. O*NET divides it into 13-2011.01 Accountants; and 13-2011.02 Auditors and provides the ability requirements of detailed categories (for 13-2011.01 and 13-2011.02) but does not provide the ability requirements of the main category (13-2011). Since we do not have the employment shares of detailed categories, we deal with these categories by taking a simple mean of the descriptor values to determine the skill requirement of the main title (for this example we took the simple average of descriptor values for occupations 13-2011.01 and 13-2011.02 to determine the skill requirement of 13-2011 Accountants and Auditors). There is one exceptional case in O*Net classification 19-1020.01 Biologists which does not exist in SOC classification, which we excluded from the analysis. Information on abilities is collected for 854 occupations among those 1100.

After determining the descriptor values of all SOC 2010 level occupations we proceed as follows: First, we matched ISCO codes with SOC 2000 codes using the ISCO-SOC 2000 made available by the Center for Longitudinal Studies in the U.K. at

http://www.cls.ioe.ac.uk/text.asp?section=000100010005001600002. Then, using SOC 2000-SOC 2010 crosswalk provided by Integrated Public Use Microdata Series (IPUMS-USA) we matched ISCO codes with SOC 2010 codes. O*Net codes are matched with ISCO codes using these two crosswalks. Finally, using the employment shares of SOC 2010 occupations for 2001 derived from Occupational Employment Statistics Survey 2010 by Bureau of Labor Statistics, we determine the descriptor values of broader occupational titles. In total 849 O*Net occupations are classified under broad categories of ISCO level occupations with total employment share 97% in 2001 in the U.S. labor market.

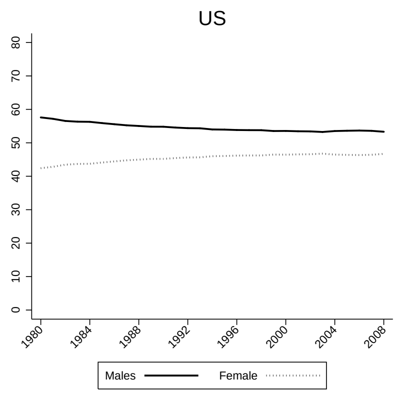
For Portugal, EU-SILC does not differentiate two occupational categories: 1112, Legislators, senior officials and corporate managers and 1300, Managers of small enterprises. Only for Portugal, these two occupations are aggregated while determining the descriptor values of broad level occupations.

A.2 Selected Labor Market Statistics



Source: OECD Employment Statistics, 2011.

Figure A.1: Employment rates in the European countries, % of labor force ages 15-64: 1980-2008



Source: OECD Employment Statistics, 2011.

Figure A.2: Employment rate in the U.S., % of labor force ages 15-64: 1980-2008

Table A.1: Female share and concentration in occupations, 1993

	Austria		Ireland		Italy		Portugal		Spain		UK		US	
	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F
Legislators, senior officials and corporate managers	0.14	1.46	0.12	1.22	0.15	0.83	0.27	1.03	0.09	0.60	0.30	7.11	0.51	0.27
Managers of small enterprises	0.21	1.08	0.20	1.88	0.00	0.00	0.15	0.18	0.26	0.21	0.34	2.15	0.40	9.19
Physical, mathematical, engineering, life science and health professionals	0.40	2.19	0.51	10.52	0.29	1.91	0.31	2.08	0.38	6.24	0.34	5.30	0.51	6.02
Teaching professionals	0.52	2.31	0.57	9.95	0.69	9.46	0.67	5.81	0.63	13.26	0.62	7.45	0.70	7.33
Other professionals	0.42	0.62	0.32	3.16	0.33	0.82	0.44	2.16	0.46	3.43	0.57	4.72	0.54	8.45
Physical, engineering, life science and health associate professionals	0.25	4.82	0.34	3.65	0.48	5.64	0.39	15.44	0.26	2.94	0.57	6.31	0.62	5.64
Teaching and other associate professionals	0.46	11.60	0.37	6.95	0.44	9.19	0.57	11.88	0.42	11.39	0.45	5.84	0.50	5.02
Office and customer services clerks	0.69	29.46	0.67	28.33	0.50	36.20	0.61	18.88	0.49	18.22	0.71	27.97	0.74	30.14
Personal and protective services workers	0.57	12.11	0.44	10.04	0.39	3.73	0.70	14.20	0.45	11.02	0.65	11.61	0.61	11.92
Models, salespersons and demonstrators	0.79	10.41	0.76	7.23	0.41	2.89	0.38	3.71	0.43	6.37	0.83	6.59	0.42	3.17
Skilled agricultural and fishery workers	0.10	0.27	0.00	0.00	0.23	0.81	0.41	2.10	0.06	0.21	0.13	0.16	0.18	0.49
Extraction, building, other craft and related trades workers	0.11	2.90	0.05	0.76	0.26	7.15	0.38	13.63	0.12	3.91	0.22	1.53	0.06	0.38
Metal, machinery, precision, handicraft, printing and related trades workers	0.08	1.79	0.07	1.00	0.18	4.65	0.11	1.71	0.04	1.08	0.05	0.75	0.06	0.68
Stationary-plant and related operators, drivers and mobile-plant operators	0.05	0.77	0.02	0.35	0.07	0.83	0.03	0.47	0.01	0.10	0.04	0.37	0.11	0.94
Machine operators and assemblers	0.36	1.88	0.47	7.36	0.08	0.26	0.43	4.50	0.24	2.05	0.41	3.99	0.46	0.50
Sales and services elementary occupations	0.72	11.83	0.56	5.40	0.48	9.56	0.73	10.46	0.65	15.59	0.68	6.18	0.46	2.49
Agricultural, fishery and related laborers	0.34	0.21	0.07	0.24	0.52	3.61	0.54	1.89	0.25	1.36	0.23	0.20	0.00	0.00
Laborers in mining, construction,manufacturing and transport	0.30	4.28	0.16	1.94	0.22	2.44	0.21	1.12	0.15	2.00	0.35	1.77	0.35	7.37
Dissimilarity Index	47.64		41.86		29.30		34.79		42.28		39.93		34.06	

Note: F_i/T_i = female employees in occupation i as percentage of total employees in occupation i. F_i/F = female employees in occupation i as a percentage of female employees. The dissimilarity index (ID) is calculated as follows: $ID = [1/2 \sum[F_i/F - M_i/M]] * 100$. The ID has a minimum value 0 when there is same percentage of female and male in each occupation and a maximum value of 100 when each occupation is completely male or female.

Table A.2: Female share and concentration in occupations, 2008

	Austria		Ireland		Italy		Portugal		Spain		UK		US	
	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F	F_i/T_i	F_i/F
Legislators, senior officials and corporate managers	0.26	2.18	0.42	12.17	0.32	0.90			0.24	0.80	0.35	10.31	0.45	1.00
Managers of small enterprises	0.30	0.83	0.52	2.52	0.38	0.80	0.26	1.63	0.29	0.32	0.36	1.60	0.41	9.45
Physical, mathematical, engineering, life science and health professionals	0.36	2.40	0.50	8.14	0.39	3.16	0.49	4.91	0.48	7.61	0.23	3.38	0.58	6.13
Teaching professionals	0.56	6.03	0.62	8.08	0.64	5.29	0.69	4.34	0.61	9.08	0.67	8.14	0.72	9.41
Other professionals	0.55	3.64	0.59	8.52	0.54	3.36	0.72	5.86	0.52	4.38	0.64	6.18	0.52	11.40
Physical, engineering, life science and health associate professionals	0.23	4.13	0.43	3.10	0.39	7.85	0.22	2.15	0.39	4.04	0.62	9.08	0.64	5.74
Teaching and other associate professionals	0.57	14.75	0.46	4.08	0.65	20.52	0.69	9.99	0.47	8.44	0.54	9.01	0.49	3.38
Office and customer services clerks	0.70	26.16	0.73	19.64	0.56	19.41	0.63	15.62	0.67	24.96	0.79	25.74	0.72	26.60
Personal and protective services workers	0.64	11.99	0.62	16.27	0.54	8.87	0.70	15.89	0.53	10.97	0.72	14.51	0.60	13.23
Models, salespersons and demonstrators	0.73	9.57	0.76	8.75	0.67	6.48	0.76	6.32	0.68	8.31	0.74	4.99	0.42	3.31
Skilled agricultural and fishery workers	0.50	0.61	0.10	0.05	0.15	0.39	0.23	0.80	0.13	0.29	0.04	0.06	0.12	0.30
Extraction, building, other craft and related trades workers	0.05	0.78	0.03	0.26	0.19	4.09	0.29	8.47	0.12	2.19	0.06	0.32	0.09	0.66
Metal, machinery, precision, handicraft, printing and related trades workers	0.03	0.36	0.04	0.33	0.13	1.74	0.04	0.51	0.04	0.46	0.04	0.26	0.04	0.37
Stationary-plant and related operators, drivers and mobile-plant operators	0.02	0.29	0.03	0.18	0.07	0.98	0.04	0.53	0.05	0.54	0.06	0.34	0.13	1.01
Machine operators and assemblers	0.38	1.23	0.43	1.15	0.37	3.88	0.46	4.26	0.26	1.47	0.28	1.30	0.53	0.24
Sales and services elementary occupations	0.73	11.71	0.47	3.17	0.64	10.60	0.73	17.33	0.71	13.45	0.46	4.01	0.55	3.37
Agricultural, fishery and related laborers	0.36	0.26	0.13	0.09	0.41	1.29	0.34	0.15	0.37	0.69	0.31	0.21	0.12	0.00
Laborers in mining, construction,manufacturing and transport	0.25	3.07	0.24	3.53	0.09	0.38	0.38	1.25	0.23	2.02	0.12	0.55	0.26	4.40
Dissimilarity Index	46.57		32.35		36.28		44.50		37.97		42.18		34.06	

Note: F_i/T_i = female employees in occupation i as percentage of total employees in occupation i. F_i/F = female employees in occupation i as a percentage of female employees. The dissimilarity index (ID) is calculated as follows: $ID = [1/2 \sum[F_i/F - M_i/M]] * 100$. The ID has a minimum value 0 when there is same percentage of female and male in each occupation and a maximum value of 100 when each occupation is completely male or female.

A.3 Constructing Skill Requirement of Occupations by Principle Component Analysis

Principle Component Analysis (PCA) is a variable reduction technique which maximizes the amount of variance accounted for in the observed variables by a smaller group of variables called components. The components are not latent factors. PCA is not a model based technique and involves no hypothesis about the substantive meaning of or relationships between latent factors. Technically, let the random vector $\mathbf{X}' = [X_1, X_2, ..., X_p]$ be our observable measures with the covariance matrix $\sum$ with eigenvalues $\lambda_1 \geqslant \lambda_2 \geqslant ...\lambda_p \geqslant 0$. The linear combinations:

$$\begin{aligned} Y_1 &= \mathbf{a}_1'\mathbf{X} = \mathbf{a}_{11}X_1 + a_{12}X_2 + ... + a_{1p}X_p \\ Y_2 &= \mathbf{a}_2'\mathbf{X} = \mathbf{a}_{21}X_1 + a_{22}X_2 + ... + a_{2p}X_p \\ &... \\ Y_p &= \mathbf{a}_p'\mathbf{X} = \mathbf{a}_{p1}X_1 + a_{p2}X_2 + ... + a_{pp}X_p \end{aligned}$$

with $Var(Y_i) = \mathbf{a}_i' \sum \mathbf{a}_i$ and $Cov(Y_i, Y_k) = \mathbf{a}_i' \sum \mathbf{a}_k, i, k = 1, 2, ..., p$ are the principle components i.e. components are uncorrelated linear combinations $Y_1, Y_2, ..., Y_p$ whose variances are as large as possible. Principle components are then defined by:

$$\begin{aligned} \text{First principle component} &= \text{linear combination } \mathbf{a}_1'\mathbf{X} \\ \text{that maximizes } Var(\mathbf{a}_1'\mathbf{X}) \text{ st. } \mathbf{a}_1'\mathbf{a}_1 = 1 & \\ \text{Second principle component} &= \text{linear combination } \mathbf{a}_2'\mathbf{X} \\ \text{that maximizes } Var(\mathbf{a}_2'\mathbf{X}) \text{ st. } \mathbf{a}_2'\mathbf{a}_2 = 1 & \quad \text{and } Cov(\mathbf{a}_1'\mathbf{X}, \mathbf{a}_2'\mathbf{X}) = \mathbf{0} \\ & \quad ... \\ i^{th} \text{ principle component} &= \text{linear combination } \mathbf{a}_i'\mathbf{X} \\ \text{that maximizes } Var(\mathbf{a}_i'\mathbf{X}) \text{ st. } \mathbf{a}_i'\mathbf{a}_i = 1 & \quad \text{and } Cov(\mathbf{a}_i'\mathbf{X}, \mathbf{a}_k'X) = 0 \\ \text{for } k \neq i & \end{aligned}$$

PCA can be also performed based on the correlation matrix instead of variance-covariance matrix. If the correlation matrix is used, the variables are standardized and the total variance will equal the number of variables used in the analysis since each standardized variable has a variance equal to one. The use of correlation-matrix is necessary when the variables have different scales of measurement or not measured in a natural scale. The number of principle components is decided based on the cumulative variance explained by the components. As a rule of thumb, the first components that explains at least 50% - 70% of the cumulative variance are taken. Kaiser criterion also suggests not to keep components with an eigenvalue of less than 1, since these components account for less variance than the original variable does. Scree plots can be used to represent the ability of principle components in explaining the variation in data by showing the eigenvalues, and hence the variance explained by each component. Moreover, component loadings of each variable involved in the analysis help to interpret the constructed components since they show the weight of each variable in forming the components' scores.

Principle Component Analysis (PCA) based on the correlation matrix has been widely used in the early research to construct task or skill measures from the various descriptors of DOT or O*Net data (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009; Ortega and Polavieja, 2012). A common approach is performing separate PCAs for different sets of selected standardized descriptors (mean zero and variance one) and using the first principle component of each analysis as the summary measure for that particular set of descriptors (Autor, Levy and Murnane, 2003; Bacolod and Blum, 2010; Goos, Manning and Salomons, 2009). An alternative way is constructing the measures using a joint PCA performed using all standardized descriptors and selecting the components that explain the substantial part of the variance. However, in the case of jointly performed PCA, by construction, principle components will be orthogonal to each other. Building skill measures using a principle component analysis of the all O*Net descriptors will be ruling out the possible complementary or substitution, i.e. correlation between skill measures a priori.

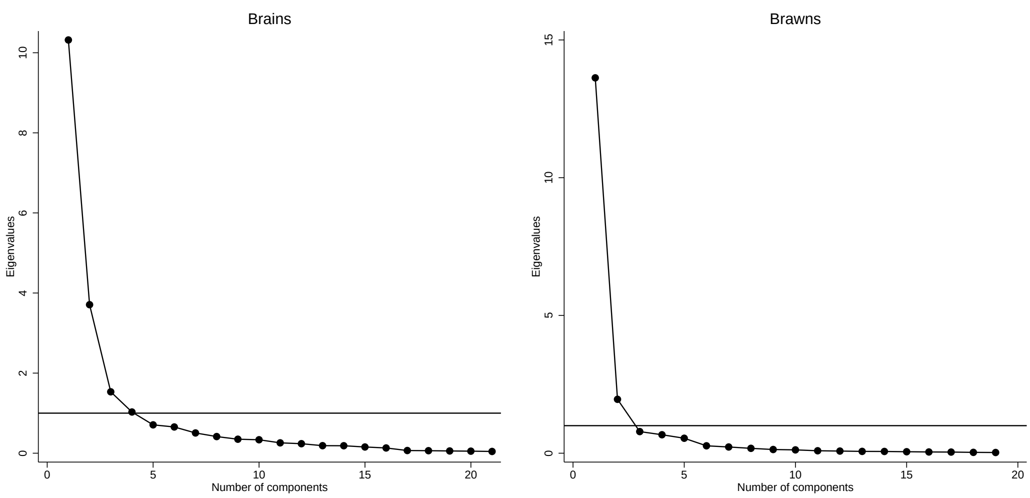


Figure A.3: Scree plot of eigenvalues after separate PCA

Following the earlier literature, we also construct alternative skill measures via PCA.

First, we performed two separate PCAs using the O*Net ability descriptors of O*Net occupations (using the 849 O*Net occupations, those are matched with ISCO level occupations as explained in Appendix A.1.4). One PCA is performed among the cognitive ability descriptors and the other among psycho-motor ability descriptors together with physical ability descriptors. The first component of the first PCA explains around 50% of the variation among the cognitive ability descriptors, while most of the variation among the psycho-motor and physical ability descriptors are explained by first principal component (around 72% of the variation). Figure A.3 visually presents the ability of first principle components of each analysis to explain the variation in corresponding descriptor values. Principal components based on transformation of correlation matrix to eigen-basis coordinates are unit free. If the loadings of all descriptors related to the same skill in the corresponding component is positive, then a higher component score implies a higher intensity in that skill. Table A.3 presents the component loadings of each descriptor involved in the analysis. All the cognitive ability descriptors have positive weights on the first principle component of the former PCA analysis (with one exception: Spatial Orientation), while all psycho-motor and physical ability descriptors have positive loadings on the first component of the later PCA without any exception. Hence we call the first and the second components as “brains” and “brawns”, respectively.

Table A.3: Principal component loadings

Brains		Brawns	
Descriptor	Component Loading	Descriptor	Component Loading
Oral Comprehension	0.219	Arm-Hand Steadiness	0.241
Written Comprehension	0.245	Manual Dexterity	0.241
Oral Expression	0.202	Finger Dexterity	0.177
Written Expression	0.240	Control Precision	0.233
Fluency of Ideas	0.258	Multilimb Coordination	0.258
Originality	0.243	Response Orientation	0.238
Problem Sensitivity	0.242	Rate Control	0.235
Deductive Reasoning	0.278	Reaction Time	0.241
Inductive Reasoning	0.270	Wrist-Finger Speed	0.214
Information Ordering	0.249	Speed of Limb Movement	0.241
Category Flexibility	0.251	Static Strength	0.257
Mathematical Reasoning	0.213	Explosive Strength	0.123
Number Facility	0.198	Dynamic Strength	0.250
Memorization	0.235	Trunk Strength	0.240
Speed of Closure	0.229	Stamina	0.246
Flexibility of Closure	0.216	Extent Flexibility	0.252
Perceptual Speed	0.143	Dynamic Flexibility	0.140
Spatial Orientation	-0.050	Gross Body Coordination	0.244
Visualization	0.092	Gross Body Equilibrium	0.234
Selective Attention	0.183		
Time Sharing	0.173		

Then again, to determine the brain skill and brawn skill requirement of broad classification of occupations we make use of the employment shares of SOC 2010 codded occupations for 2001 are derived from Occupational Employment Statistics Survey 2010 by Bureau of Labor Statistics. Basically, we took the weighted average of the component scores of occupations under the broad title where the weights are employment shares. Finally, we standardized the skill measures (mean 0, standard deviation 1). Table A.4 presents the summary statistics of brain and brawn skill measures constructed by this procedure.

Table A.4: Brain and brawn skill intensity of occupations, using skill measures constructed by PCA

Occupation	Principle Component Values		Occupation
code	Brains	Brawns	title
1112	1.11	-1.05	Legislators, senior officials and corporate managers
1300	1.14	-1.27	Managers of small enterprises
2122	1.62	-0.57	Physical, mathematical, engineering, life science and health professionals
2300	1.29	-1.28	Teaching professionals
2400	1.06	-1.22	Other professionals
3132	0.64	0.08	Physical, engineering, life science and health associate professionals
3334	0.27	-1.35	Teaching and other associate professionals
4142	-0.19	-0.86	Office and customer services clerks
5100	-0.52	0.46	Personal and protective services workers
5200	-0.13	-0.44	Models, salespersons and demonstrators
6100	-1.04	1.10	Skilled agricultural and fishery workers
7174	-0.19	1.22	Extraction, building, other craft and related trades workers
7273	-0.22	0.99	Metal, machinery, precision, handicraft, printing and related trades workers
8183	-0.44	1.29	Stationary-plant and related operators, drivers and mobile-plant operators
8200	-0.81	0.61	Machine operators and assemblers
9100	-1.97	0.24	Sales and services elementary occupations
9200	-0.11	1.11	Agricultural, fishery and related laborers
9300	-1.52	0.93	Laborers in mining, construction,manufacturing and transport
Mean	0	0	
Std. dev.	1	1	
Pearson correlation coefficient	-0.68		

Note: Occupation codes are based on regrouped (group B) classification of ECHP data. If the occupations are regrouped, the first and the last two digits of the occupation code corresponds to the 2-digit ISCO-88 classification of occupations.

A.3.1 Wage Regression Estimates, Decomposition Results and Robustness Checks

Table A.5: Wage regression estimates, U.S.

	1979	1988	1993	2008
Secondary Education	0.319 ***	0.351 ***	0.432 ***	0.315 ***
	(0.034)	(0.044)	(0.047)	(0.030)
Higher Education	0.478 ***	0.586 ***	0.739 ***	0.673 ***
	(0.061)	(0.060)	(0.072)	(0.057)
Experience	0.043 ***	0.049 ***	0.043 ***	0.043 ***
	(0.006)	(0.003)	(0.005)	(0.004)
Experience^2	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.471 ***	0.599 ***	0.568 ***	0.715 ***
	(0.126)	(0.129)	(0.136)	(0.123)
Brawns	-0.013	-0.110	-0.166	-0.170 **
	(0.083)	(0.100)	(0.099)	(0.074)
Constant	1.941 ***	1.683 ***	1.592 ***	1.688 ***
	(0.142)	(0.141)	(0.153)	(0.141)
VIF(Brains)	1.73	1.77	1.73	1.86
VIF(Brawns)	1.82	1.86	1.78	1.87
R^2	0.17	0.23	0.25	0.27
Number of obs.	22,691	20,446	23,172	31,907

Notes: i) Occupational level clustered standard errors are in parentheses. (ii)*, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies. (iv) Variance inflation factor: VIF= $1-(1-{R_i}^2)$ and ${R_i}^2$ is the coefficient of determination of the regression equation where each explanatory variable regressed on all the other explanatory variables.

Table A.6: Decomposition of the changes in gender wage gap, U.S.

Panel A. Descriptive statistics	1979 vs 1988	1993 vs 2008
Male residual SD*		
year t	0.496	0.545
year s	0.533	0.575
Female residual SD**		
year t	0.488	0.533
year s	0.521	0.546
Mean female residual from male wage regression		
year t	-0.499	-0.333
year s	-0.385	-0.311
Mean female residual percentile***		
year t	22.01	32.01
year s	29.03	33.46
Panel B. Decomposition of the change in the gender wage gap		
Change in gender wage gap	-0.138	-0.051
(1) Observed X's	-0.012	-0.023
Education variables	-0.001	-0.018
Experience variables	-0.001	0.003
Brains	-0.010	-0.008
Brawns	0.000	0.000
(2) Observed Prices	-0.012	-0.006
Education variables	0.002	-0.001
Experience variables	0.000	0.000
Brains	-0.001	-0.005
Brawns	-0.013	-0.001
(3) Unobserved Prices	0.026	0.013
(4) Gap effect	-0.140	-0.034
Sum gender-specific (1+4)	-0.152	-0.058
Sum wage structure (2+3)	0.014	0.007

Notes: Year t and year s refer to the years 1979 and 1988 for the second column, and 1993 and 2008 for the third column, respectively. The change in the differential is the change in the male-female log wage differentials between two corresponding years.* Estimated using male wage regression. ** Estimated using female wage regression. *** Computed by assigning each women a percentile ranking in the indicated year's residual male wage distribution and calculating the female mean of these percentiles.

Table A.7: Wage regression estimates 1993-2008, pooled

	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	1994	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008
Secondary Education	0.125 *	0.124 ***	0.195 ***	0.075	0.129 ***	0.098 ***	0.149 *	0.244 ***	0.200 ***	0.128 ***	0.129 ***	0.132 *	0.354 ***	0.267 ***
	(0.045)	(0.022)	(0.041)	(0.056)	(0.025)	(0.019)	(0.056)	(0.030)	(0.025)	(0.027)	(0.023)	(0.053)	(0.032)	(0.020)
Higher Education	0.297 ***	0.331 ***	0.480 ***	0.321 ***	0.360 ***	0.241 ***	0.457 ***	0.656 ***	0.347 ***	0.306 ***	0.300 ***	0.347 ***	0.702 ***	0.630 ***
	(0.061)	(0.038)	(0.076)	(0.051)	(0.040)	(0.029)	(0.114)	(0.091)	(0.052)	(0.039)	(0.035)	(0.055)	(0.052)	(0.037)
Experience	0.005	0.018 ***	0.030 ***	0.020 **	0.007 **	0.026 ***	0.019 **	0.039 ***	0.017 ***	0.026 ***	0.017 ***	0.014 **	0.032 ***	0.031 ***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.002)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Experience^2	0.000	- 0.000	- 0.000 **	- 0.000	- 0.000	- 0.000 ***	- 0.000 *	-0.001 ***	- 0.000	- 0.000 ***	- 0.000 ***	- 0.000 **	-0.001 ***	-0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.787 ***	0.743 ***	0.832 ***	0.802 ***	0.437 ***	0.530 ***	1.059 ***	0.630 ***	0.797 ***	0.751 ***	0.823 ***	0.859 ***	0.763 ***	0.830 ***
	(0.085)	(0.052)	(0.148)	(0.130)	(0.106)	(0.085)	(0.225)	(0.135)	(0.156)	(0.103)	(0.135)	(0.134)	(0.139)	(0.149)
Brawns	-0.094	-0.114 *	-0.127	-0.009	-0.321 ***	-0.187 **	-0.886 ***	-0.318 *	-0.338 ***	-0.197 *	-0.105	-0.122	0.075	0.040
	(0.070)	(0.042)	(0.125)	(0.107)	(0.075)	(0.061)	(0.147)	(0.128)	(0.070)	(0.081)	(0.120)	(0.096)	(0.127)	(0.105)
Constant	1.822 ***	1.675 ***	1.335 ***	1.703 ***	1.926 ***	1.653 ***	1.146 ***	0.938 ***	1.558 ***	1.511 ***	1.601 ***	1.955 ***	1.435 ***	1.576 ***
	(0.087)	(0.073)	(0.117)	(0.120)	(0.069)	(0.082)	(0.117)	(0.124)	(0.100)	(0.112)	(0.101)	(0.100)	(0.126)	(0.113)
R^2	0.15	0.30	0.32	0.32	0.33	0.27	0.50	0.45	0.38	0.41	0.27	0.23	0.22	0.23
Number of obs.	2,392	3,704	2,316	2,283	4,148	11,365	2,767	2,728	3,827	7,994	6,489	4,302	45,234	62,925

Notes: i) Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies.

Table A.8: Wage regression estimates 1993-2008, females

	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	1994	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008
Secondary Education	0.008	0.114***	0.164*	0.070	0.127***	0.109***	0.095	0.206***	0.118*	0.113*	0.087**	0.108	0.282***	0.215***
	(0.081)	(0.026)	(0.060)	(0.070)	(0.024)	(0.020)	(0.098)	(0.024)	(0.052)	(0.044)	(0.030)	(0.076)	(0.044)	(0.053)
Higher Education	0.262**	0.353***	0.568***	0.268***	0.337***	0.263***	0.375*	0.712***	0.348***	0.342***	0.276***	0.361***	0.612***	0.576***
	(0.090)	(0.056)	(0.119)	(0.044)	(0.038)	(0.024)	(0.158)	(0.054)	(0.067)	(0.052)	(0.047)	(0.089)	(0.053)	(0.046)
Experience	0.014	0.013**	0.035***	0.023*	0.007*	0.024***	0.015**	0.039***	0.023***	0.019***	0.006	0.005	0.021***	0.017***
	(0.007)	(0.004)	(0.008)	(0.009)	(0.003)	(0.005)	(0.005)	(0.007)	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)
Experience^2	-0.000	-0.000	-0.001***	-0.000	-0.000	-0.000**	-0.000	-0.001***	-0.000***	-0.000	-0.000*	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.479**	0.564***	0.698***	0.910***	0.457*	0.485***	0.954**	0.423**	0.669**	0.741***	0.592***	0.756***	0.713***	0.739***
	(0.122)	(0.089)	(0.129)	(0.189)	(0.158)	(0.102)	(0.317)	(0.118)	(0.176)	(0.150)	(0.115)	(0.136)	(0.156)	(0.151)
Brawns	-0.660***	-0.321**	-0.456*	-0.046	-0.518***	-0.355***	-1.310***	-0.575***	-0.541***	-0.278**	-0.443***	-0.308**	-0.168	-0.160
	(0.125)	(0.090)	(0.191)	(0.166)	(0.101)	(0.065)	(0.177)	(0.118)	(0.115)	(0.092)	(0.078)	(0.098)	(0.178)	(0.166)
Constant	2.030***	1.788***	1.410***	1.635***	1.926***	1.682***	1.336***	1.036***	1.593***	1.518***	1.854***	2.032***	1.600***	1.732***
	(0.104)	(0.083)	(0.126)	(0.183)	(0.108)	(0.100)	(0.171)	(0.120)	(0.137)	(0.145)	(0.079)	(0.111)	(0.112)	(0.122)
R^2	0.195	0.351	0.423	0.294	0.420	0.332	0.626	0.622	0.473	0.479	0.333	0.247	0.236	0.249
Number of obs.	952	1,744	951	1,170	1,597	5,172	1,229	1,351	1,276	3,854	3,132	2,232	22,062	31,018

Notes: i) Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies.

Table A.9: Robustness checks: Wage regression estimates, returns to brains/brawns, 1993-2008

	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	1994	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008
Secondary Education	0.175**	0.138**	0.300***	0.126*	0.160***	0.125***	0.273***	0.344***	0.275***	0.176***	0.155***	0.169*	0.479***	0.363***
	(0.048)	(0.043)	(0.048)	(0.047)	(0.018)	(0.030)	(0.051)	(0.055)	(0.045)	(0.035)	(0.021)	(0.063)	(0.057)	(0.037)
Higher Education	0.367**	0.394***	0.547***	0.475***	0.421***	0.328***	0.785***	0.775***	0.500***	0.392***	0.382***	0.412***	0.843***	0.781***
	(0.099)	(0.065)	(0.099)	(0.060)	(0.052)	(0.061)	(0.114)	(0.172)	(0.100)	(0.075)	(0.046)	(0.065)	(0.091)	(0.082)
Experience	0.001	0.022***	0.034***	0.022**	0.006*	0.028***	0.011	0.041***	0.014*	0.028***	0.022***	0.016**	0.043***	0.043***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.003)	(0.004)	(0.010)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Experience^2	0.000	-0.000*	-0.000**	-0.000	-0.000	-0.000***	-0.000	-0.001***	-0.000	-0.000**	-0.000**	-0.000*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains/Brawns	0.035**	0.035**	0.044**	0.043***	0.045***	0.029**	0.080***	0.050*	0.052***	0.042**	0.038*	0.048*	0.037**	0.046***
	(0.011)	(0.010)	(0.015)	(0.011)	(0.011)	(0.008)	(0.013)	(0.017)	(0.012)	(0.012)	(0.016)	(0.018)	(0.009)	(0.011)
Constant	2.166***	1.926***	1.555***	1.928***	1.912***	1.750***	1.136***	1.033***	1.650***	1.684***	1.891***	2.267***	1.630***	1.764***
	(0.069)	(0.059)	(0.081)	(0.079)	(0.033)	(0.049)	(0.098)	(0.073)	(0.059)	(0.055)	(0.054)	(0.057)	(0.086)	(0.070)
R^2	0.109	0.203	0.298	0.345	0.309	0.220	0.361	0.342	0.308	0.324	0.197	0.159	0.230	0.243
Number of obs.	1,440	1,960	1,365	1,113	2,551	6,193	1,538	1,377	2,551	4,140	3,357	2,070	23,172	31,907

Notes: i) Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies.

Table A.10: Robustness checks: Returns to skills using measures constructed by PCA, 1993-2008

	Austria		Ireland		Italy		Portugal		Spain		U.K.		U.S.	
	1994	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008	1993	2008
Secondary Education	0.114**	0.065	0.234***	0.104	0.120***	0.095***	0.141**	0.260***	0.222***	0.143***	0.112***	0.124*	0.432***	0.316***
	(0.039)	(0.032)	(0.038)	(0.051)	(0.024)	(0.021)	(0.037)	(0.042)	(0.030)	(0.026)	(0.016)	(0.058)	(0.046)	(0.029)
Higher Education	0.230**	0.242***	0.375***	0.401***	0.358***	0.243***	0.533***	0.608***	0.345***	0.269***	0.264***	0.293***	0.733***	0.669***
	(0.072)	(0.046)	(0.056)	(0.064)	(0.042)	(0.032)	(0.122)	(0.147)	(0.054)	(0.038)	(0.033)	(0.053)	(0.070)	(0.056)
Experience	0.002	0.022**	0.033***	0.022**	0.007*	0.027***	0.015	0.043***	0.014*	0.029***	0.022***	0.014**	0.043***	0.043***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.003)	(0.004)	(0.009)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Experience^2	0.000	-0.000*	-0.000**	-0.000	-0.000	-0.000***	-0.000	-0.001***	-0.000	-0.000**	-0.000***	-0.000*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brains	0.146***	0.150***	0.177***	0.142***	0.086**	0.105***	0.206***	0.128**	0.174**	0.140***	0.165***	0.164***	0.143***	0.178***
	(0.033)	(0.014)	(0.033)	(0.031)	(0.024)	(0.025)	(0.051)	(0.041)	(0.046)	(0.025)	(0.030)	(0.018)	(0.033)	(0.032)
Brawns	-0.037**	-0.058***	-0.067	-0.022	-0.081**	-0.045	-0.192***	-0.124**	-0.099**	-0.079*	-0.047	-0.067**	-0.032	-0.030
	(0.011)	(0.010)	(0.035)	(0.029)	(0.025)	(0.026)	(0.040)	(0.032)	(0.029)	(0.027)	(0.038)	(0.022)	(0.031)	(0.024)
Constant	2.305***	2.102***	1.750***	2.074***	2.041***	1.864***	1.372***	1.190***	1.861***	1.846***	2.005***	2.441***	1.798***	1.962***
	(0.067)	(0.076)	(0.090)	(0.100)	(0.036)	(0.050)	(0.080)	(0.108)	(0.050)	(0.068)	(0.045)	(0.044)	(0.096)	(0.083)
R^2	0.147	0.266	0.344	0.373	0.313	0.247	0.429	0.365	0.356	0.367	0.253	0.235	0.254	0.269
Number of obs.	1,440	1,960	1,365	1,113	2,551	6,193	1,538	1,377	2,551	4,140	3,357	2,070	23,172	31,907

Notes: i) Occupational level clustered standard errors are in parentheses. (ii) *, ** and *** significant at 1, 5 and 10 % significance level respectively. (iii) The omitted category is taken as low level for education dummies.

Table A.11: Addressing selection bias: selectivity-corrected gender wage gaps

Decomposition results	Austria	Ireland	Italy	Portugal	Spain	U.K.	U.S.
Change in gender wage gap	-0.078	-0.143	-0.018	-0.006	0.034	-0.066	-0.051
(1) Observed X's	0.012	-0.062	-0.039	-0.078	0.015	-0.022	-0.003
(2) Observed prices	-0.027	0.091	0.044	0.046	0.029	-0.021	-0.011
(3) Unobserved prices	-0.005	-0.013	0.002	0.008	-0.022	0.007	0.012
(4) Gap effect	-0.030	-0.578	0.046	-0.079	-0.011	-0.334	0.183
(5) Selection	-0.028	0.420	-0.071	0.096	0.023	0.303	-0.232

Selectivity-corrected gap effect is based on estimating the selection corrected model using a two-stage Heckman (1979) selection model. See text for details.

Appendix B

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

B.1 Simultaneous Probit Model

Figure B.1 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 the 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)

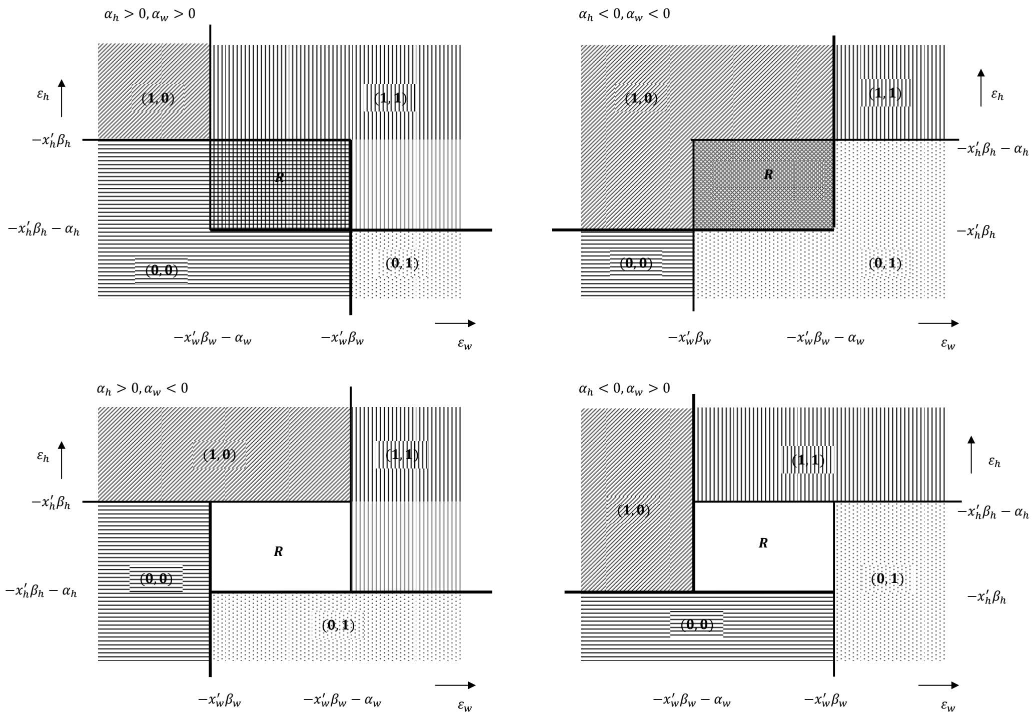


Figure B.1: Simultaneous probit model

B.2 Nash Model

Outcome Probabilities in terms of Reaction Functions

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

Outcome Probabilities in terms of Model Parameters

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

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) - a_1 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w - \alpha_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h, x_w^{'}\beta_w, -\rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h, x_w^{'}\beta_w + \alpha_w, \rho) - a_1 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w - \alpha_w, \rho)
\end{aligned}$$

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

$$\begin{aligned}
\Pr(0,0) &= \Phi(-x_h^{'}\beta_h, -x_w^{'}\beta_w, \rho) + c_1 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,0) &= \Phi(x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -\rho) + c_2 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, \rho) \\
\Pr(0,1) &= \Phi(-x_h^{'}\beta_h - \alpha_h, x_w^{'}\beta_w, -\rho) + c_3 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, \rho) \\
\Pr(1,1) &= \Phi(x_h^{'}\beta_h + \alpha_h, x_w^{'}\beta_w + \alpha_w, \rho) + c_4 I(-x_h^{'}\beta_h, -x_w^{'}\beta_w - \alpha_w, -x_h^{'}\beta_h - \alpha_h, -x_w^{'}\beta_w, \rho)
\end{aligned}$$

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).

B.3 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 $a \geq \varepsilon_w$, $b \geq \varepsilon_h$.

B.4 Stackelberg Husband Leader Model

Table B.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 B.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 B.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

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

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).

B.5 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 B.4: 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)

B.6 Labor Supply Elasticities of Married Men

Table B.5: 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

Note: Standard errors in parenthesis.

Appendix C

Appendix for Temporary Contracts and Fertility

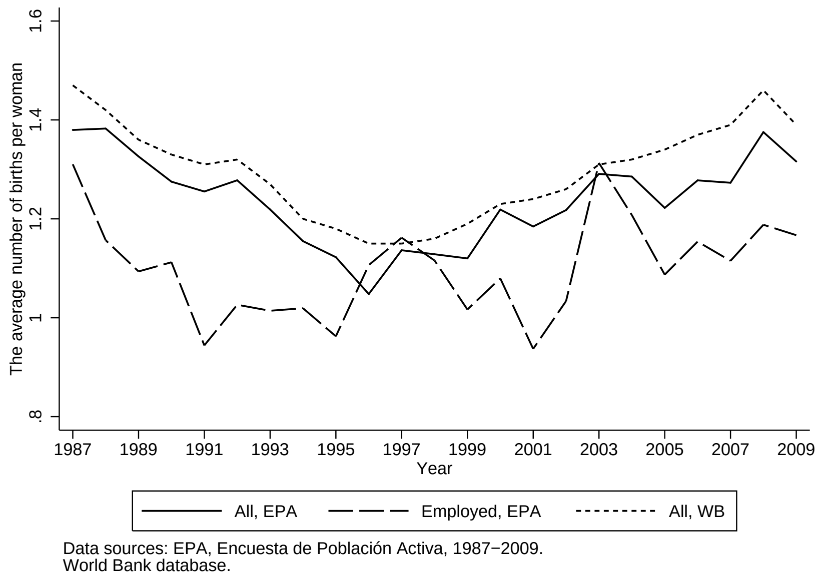


Figure C.1: Total fertility rate, 1987-2009

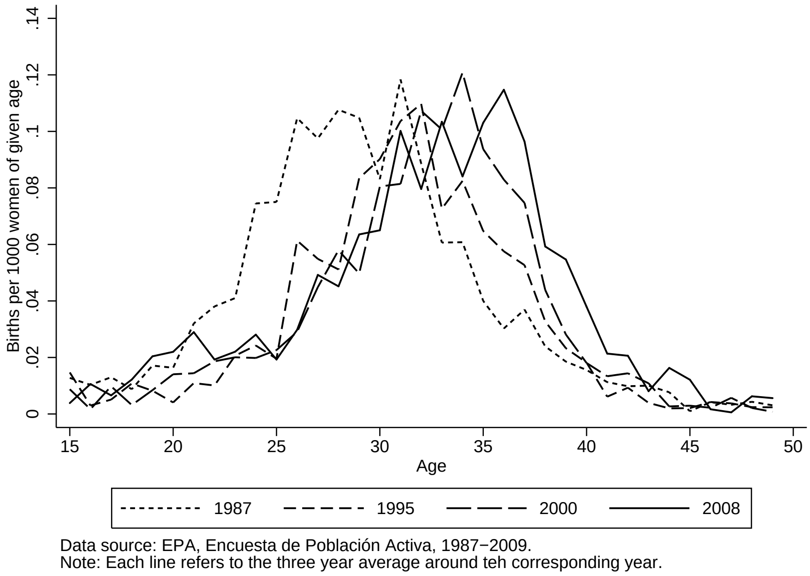


Figure C.2: Age-specific profiles of fertility rates (per 1,000 women), 1987-2008

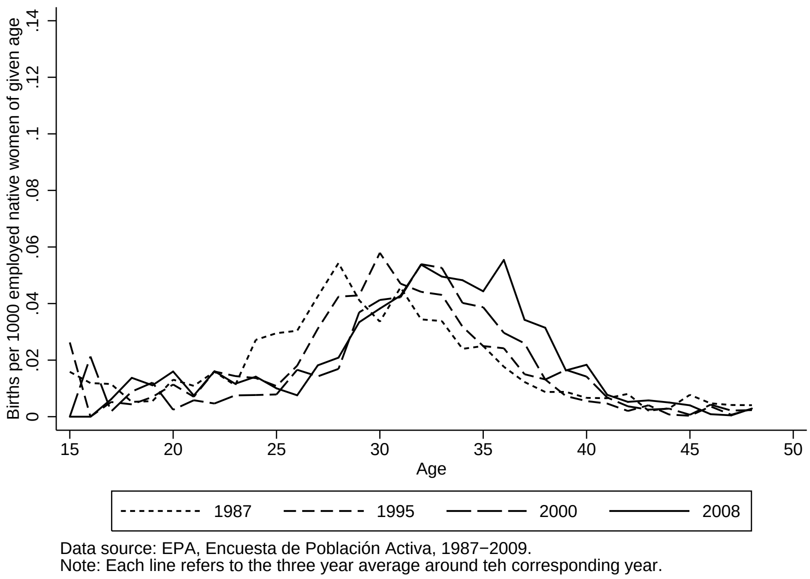


Figure C.3: Age-specific profiles of fertility rates (per 1,000 employed native women), 1987-2008

Table C.1: Linear probability model of giving birth to first child

	(1)	(2)	(3)	(4)	(5)
Indefinite contract	0.099***	0.092***	0.130***	0.130***	0.126***
	(4.19)	(3.83)	(4.84)	(4.84)	(4.67)
Age		0.006	0.004	0.004	0.003
		(1.77)	(1.19)	(1.01)	(0.77)
Indefinite contract, spouse			0.017	0.013	0.013
			(0.60)	(0.45)	(0.43)
Income, spouse (in 10 000 Euros)				0.012	0.007
				(0.53)	(0.29)
Secondary education					-0.042
					(-1.26)
Higher education					-0.040
					(-1.22)
Constant	0.126***	-0.029	-0.021	-0.019	0.038
	(7.07)	(-0.33)	(-0.21)	(-0.19)	(0.35)
Adjusted R^2	0.015	0.017	0.029	0.028	0.029
Number of obs.	1087	1087	845	845	845

Data source: ECHP, 1994-2001. Sample includes 20-40 years old employed women.

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$