TESIS DE LA UNIVERSIDAD DE ZARAGOZA

2021

76

Jorge Velilla Gambó

# Population behaviors and labor supply of the employed and the self-employed: Efficiency wages and time use, intrahousehold commitment, and intergenerational transmission

Director/es
Molina Chueca, José Alberto
Gimenez Nadal, José Ignacio



ISSN 2254-7606

Prensas de la Universidad
Universidad Zaragoza

ISSN 2254-7606

Universidad Zaragoza
1542

Tesis Doctoral

# POPULATION BEHAVIORS AND LABOR SUPPLY OF THE EMPLOYED AND THE SELF-EMPLOYED: EFFICIENCY WAGES AND TIME USE, INTRAHOUSEHOLD COMMITMENT, AND INTERGENERATIONAL TRANSMISSION

Autor

Jorge Velilla Gambó

Director/es

Molina Chueca, José Alberto
Gimenez Nadal, José Ignacio

**UNIVERSIDAD DE ZARAGOZA**
**Escuela de Doctorado**

Programa de Doctorado en Economía

2020

Universidad Zaragoza

Faculty of Economics and Business Studies
Department of Economic Analysis

THESIS:

# Population behaviors and labor supply of the employed and the self-employed: Efficiency wages and time use, intrahousehold commitment, and intergenerational transmission

## Theory, evidence and policy implications for Aragón, Spain, Europe and the US

Thesis supervisors: José Alberto Molina Chueca
José Ignacio Giménez Nadal

**Jorge Velilla Gambó**

May 30, 2020

*To my grandparents*

# Abstract

The main purpose of this Thesis is the theoretical and empirical study of a range of population behaviors, from the point of view of the supply side of the labor market, including urban efficiency wages in the United States (US) and Spain, household labor supply decisions, intrahousehold intertemporal commitment in the US and Europe, and intergenerational correlation of employment and self-employment decisions in Europe. The Thesis is divided into three essays.

Chapter 1 studies commuting, time use, and employment outcomes of workers in the US and Spain, within an urban efficiency wages theoretical framework, where commuting is considered a shock to time endowments. Leisure time and shirking at work are assumed to be substitutes so, ultimately, commuting has a negative impact on leisure time, and a positive impact on shirking at work. However, that substitution hypothesis leads to an ambiguity that, to now, had not been analyzed. The model is estimated using data from the American Time Use Surveys for years 2001-2014, and the Spanish Time Use Survey for years 2009-2010. The case of Aragón is also investigated, and a model for self-employed workers is proposed. Results show a negative elasticity between leisure time and shirking at work in the US and Spain, providing empirical support to the main hypothesis of the model. Findings also show a negative correlation between commuting and leisure, a positive correlation between commuting and shirking at work, and a positive correlation between commuting time and wages. Furthermore, results suggest that employed workers tend to reside farther from employment cores than the unemployed, with the self-employed workers lying between them. These results are in line with the predictions of the model, thus suggesting the existence of urban efficiency wages in the US and Spain.

Chapter 2 studies intertemporal collective behaviors on the basis of collective models. It first develops an intertemporal collective model of labor supply, with the main objective of distinguishing the different models that characterize the ability of spouses to cooperate: the full commitment model, the non-commitment, and the limited commitment model. Under full commitment, workers' wage shocks cannot affect their labor supply, while under non-commitment, only current shocks should determine current household labor supply. However, under limited commitment, wage shocks must have a semi-permanent effect on labor supply decisions, as both current and past shocks should determine spouses' bargaining power. The model is estimated using data from the US Panel Study of Income Dynamics from years 2001-2015, and from the European Union Statistics on Income and Living Conditions from years 2003-2016. The case of Spain is more closely investigated, with a focus on Aragón and other regions. Results reject the full- and non-commitment models, as past shocks play the role predicted by the limited commitment model. Specifically, when a spouse performed better than expected in the past, (s)he works less, suggesting that (s)he attracts a larger fraction

of household resources. This result is maintained for the countries studied, suggesting that the limited commitment version of the collective model is an excellent candidate for future theoretical and empirical models of intrahousehold dynamics.

Chapter 3 addresses intergenerational transmission of employment and self-employment, using data from the longitudinal European Union Statistics on Income and Living Conditions for the years 2003-2016. Fixed effect estimates show a significant short-term correlation between the current employment status of parents and that of their children. On the other hand, the intergenerational correlation of self-employment seems to be limited to father-to-son correlations, as it is not significant for females, in general terms. However, these intergenerational correlations may be reflecting short-term household labor supply decisions, and not transmissions, which are often related to long-term effects. To overcome this issue, we use the 2011 special module on Intergenerational Transmissions of the European Union Statistics on Income and Living Conditions (in its cross-sectional version), where respondents provide information about the labor status of their parents when they themselves were 14 years old. Thus, we can estimate whether parents' employment status when young has any significant impact on their current employment status. Estimates show a strong and significant correlation between current respondents' self-employment status, and that of their parents when the respondents were 14 years old. This suggests that self-employment decisions are not only related to short-term family labor supply decisions, but also to long-term intergenerational transmissions.

# Resumen en español

El objetivo principal de esta Tesis es analizar, tanto teórica como empíricamente, diferentes comportamientos de la población desde el punto de vista de la oferta de trabajo, incluyendo los llamados salarios de eficiencia urbanos y la distribución del tiempo disponible de los trabajadores en Estados Unidos y España, la oferta laboral de las familias y el compromiso intrafamiliar en un contexto intertemporal en Estados Unidos y Europa, y la existencia de transmisiones intergeneracionales de la actividad laboral y el auto-empleo en Europa.

En el Capítulo 1 se estudia el tiempo que emplean los trabajadores en sus desplazamientos de ida y vuelta a su puesto de trabajo (tiempo de "*commuting*"), así como su relación con otros usos del tiempo de los trabajadores, sus salarios, y su actividad laboral en Estados Unidos y España. El análisis se desarrolla en un marco teórico basado en los modelos de salarios de eficiencia urbanos, de acuerdo a los cuales el tiempo de "*commuting*" es un *shock* que afecta a la distribución del tiempo de que disponen los trabajadores. El modelo asume que el tiempo de ocio y el tiempo que los trabajadores emplean en eludir su trabajo son sustitutos y, por tanto, el tiempo de "*commuting*" tiene un impacto negativo en el tiempo de ocio y un impacto positivo en el tiempo de elusión del trabajo. Sin embargo, los resultados del modelo dependen de esta hipótesis de sustitución entre tiempo de ocio y tiempo de elusión del trabajo que, hasta la fecha, no ha sido analizada empíricamente. En dicho contexto, estimamos el modelo de salarios de eficiencia urbanos empleando la Encuesta de Uso del Tiempo de Estados Unidos de los años 2001-2014, y la Encuesta de Uso del Tiempo Española de los años 2009-2010. El caso de Aragón es estudiado de forma singular. Asimismo, el marco teórico de salarios de eficiencia urbanos es extendido a los trabajadores auto-empleados. Los resultados muestran cómo el tiempo de ocio y el tiempo de elusión del trabajo están relacionados negativamente tanto en Estados Unidos como en España, proporcionando validez empírica a la principal hipótesis del marco teórico. Asimismo, también se encuentra una correlación negativa entre el tiempo de "*commuting*" y el tiempo de ocio, una relación positiva entre el tiempo de "*commuting*" y el tiempo de elusión del trabajo, y una relación positiva entre el tiempo de "*commuting*" y los salarios de los trabajadores, tal y como predice el modelo teórico. Finalmente, los resultados sugieren que los trabajadores empleados residen más lejos de los núcleos de empleo que los trabajadores auto-empleados, que a su vez residen más lejos que los desempleados. Estos resultados, por tanto, avalan las predicciones del modelo teórico, sugiriendo la existencia de mecanismos de salarios de eficiencia urbanos en Estados Unidos y España.

En el Capítulo 2 se analizan comportamientos de las familias, partiendo de un modelo colectivo. En primer lugar, se plantea y desarrolla un modelo colectivo intertemporal de oferta de trabajo, cuyo objetivo principal es distinguir teóricamente los tres modelos diferentes que caracterizan la habilidad de los individuos para cooperar

con sus cónyuges a lo largo del tiempo: el modelo de compromiso total, el modelo de ausencia de compromiso, y el modelo de compromiso limitado. De acuerdo al modelo de compromiso total, las decisiones familiares relativas a la oferta laboral no pueden verse afectadas por los *shocks* salariales que experimenten los individuos, mientras que de acuerdo al modelo de ausencia de compromiso la oferta laboral de los individuos en un periodo concreto queda determinada exclusivamente por los *shocks* salariales que se experimenten en dicho periodo. Por otro lado, el modelo de compromiso limitado predice que los *shocks* salariales que experimentan los individuos tienen un impacto semi-permanente en su oferta de trabajo, de forma que en un periodo dado, tanto los *shocks* actuales como los *shocks* pasados (o una acumulación de los mismos) determinan la oferta laboral de las familias. En segundo lugar, estimamos la forma reducida del modelo teórico empleando los datos *Panel Study of Income Dynamics* de Estados Unidos, para el periodo 2001-2015, y los datos *European Union Statistics on Income and Living Conditions* de Europa, para los años 2003-2016. El caso de España y Aragón se estudia, asimismo, en detalle. Los resultados, para todos los países analizados, rechazan los modelos de compromiso total y de ausencia de compromiso, ya que las estimaciones sugieren que los *shocks* salariales que experimentan los individuos juegan el papel que predice el modelo de compromiso limitado. En particular, cuando un cónyuge experimentó en el pasado un *shock* salarial positivo, dicho *shock* tiene un impacto positivo y semi-permante en su poder de negociación intrafamiliar, lo cuál queda reflejado en una disminución de sus horas de trabajo. Estos resultados sugieren que el modelo de compromiso limitado es un candidato preferible, frente a los modelos de compromiso total y de ausencia de compromiso, para el futuro desarrollo de modelos de comportamiento intrafamiliar.

Finalmente, en el Capítulo 3 estudiamos la existencia de transmisiones intergeneracionales, de padres y madres a hijos e hijas, de la actividad laboral y el auto-empleo en Europa, usando primero los datos *European Union Statistics on Income and Living Conditions* de los años 2003-2016. Empleando el estimador de efectos fijos, los resultados muestran una correlación positiva y significativa entre el hecho de que los individuos estén empleados en un momento concreto, y que también lo estén sus padres en dicho momento. Por otro lado, las estimaciones no muestran una transmisión clara del auto-empleo, ya que el hecho de que los padres sean auto-empleados no parece estar correlacionado con la actividad como auto-empleadas de sus hijas en dicho periodo de tiempo. Sin embargo, estos resultados pueden estar reflejando decisiones de las familias respecto a su oferta laboral en el corto plazo, y no transmisiones intergeneracionales, que en general se asocian más con efectos de a largo plazo. En consecuencia, y para analizar estas transmisiones en el largo plazo, empleamos en segundo lugar el módulo especial sobre Transmisiones Intergeneracionales de los datos *European Union Statistics on Income and Living Conditions*, en su versión transversal del año 2011. Dicho módulo incluye información sobre los hogares de los individuos entrevistados de forma retrospectiva, cuando estos tenían 14 años de edad, incluyendo diversas características de los padres, tales como su edad o su empleo. De esta forma, estimamos con estos datos la correlación entre el hecho de que un individuo esté empleado, o auto-empleado, en el año 2011, y que sus padres fuesen trabajadores empleados, o auto-empleados, cuando dicho individuo tenía 14 años. Los resultados muestran una correlación positiva y estadísticamente significativa entre la actividad laboral de los hijos en el año 2011, y la de sus padres durante la juventud de los hijos. Esto sugiere que las decisiones laborales de los individuos relativas al auto-empleo, aunque no parecen estar fuertemente ligadas a decisiones familiares intergeneracionales en el corto plazo, sí que quedan determinadas por transmisiones intergeneracionales en el largo plazo.

# Acknowledgement

I am extremely grateful to Thesis supervisors José Alberto Molina and José Ignacio Giménez-Nadal for their excellent guidance and useful comments. I am also especially indebted to Professor Pierre André Chiappori, of Columbia University (US), for his invaluable expertise, assistance, and generosity with his time. Comments from three anonymous referees from the Department of Economic Analysis of the University of Zaragoza (Spain) are also gratefully acknowledged.

I would like to acknowledge the facilities provided by the Department of Economic Analysis of the University of Zaragoza (Spain), and by the Department of Economics of Columbia University (US). Financial support from the Government of Aragón grants (Program FSE Aragón 2014-2020), the *Cátedra Emprender* grants (University of Zaragoza), and the Research Group "*Economía de la población, mercado de trabajo y economía industrial*" (Government of Aragón, Project S32-17R, co-financed by FEDER 2014-2020) is gratefully acknowledged. I am also thankful to various travel grants awarded by Georgia State University (US), the University of Zaragoza (Spain), the AEET (Spain), and the ALdE (Spain).

Finally, I want to express my thanks to all my University colleagues during this 5-year period, to my "academic big bro" Juan Carlos Campaña, to my closest friends, and to my mates from the swimming team. Last but not least, I cannot fail to express my most sincere gratitude to Ciara, for all her patience and love, and to my family and my parents, for teaching me from an early age the importance of education.

Previous versions of Chapter 1 have been presented at the XX Applied Economics Meeting (Valencia, Spain), and the XII *Jornadas de Economía Laboral* (Valladolid, Spain). Chapter 1 is an extensive revision of a paper published in the Journal of Regional Science (vol. 58, n. 1, pp. 141-158). I would like to express my thanks to co-authors (J.I. Giménez-Nadal, J.A. Molina), to Yves Zenou, to the editors of the journal, and to two anonymous referees. The contents of this Chapter are, however, the result of the extensive work of the author.

Previous versions of Chapter 2 have been presented at the 2018 BIFI Conference (Zaragoza, Spain), the 2018 Meeting of the SEHO (Paris, France), the 32nd ESPE Conference (Antwerp, Belgium), the EEA-ESEM 2018 Congress (Cologne, Germany), the 30th EALE Conference (Lyon, France), and the 2019 SAEe (Alicante, Spain). Chapter 2 is an extensive revision of a working paper (IZA Discussion Paper n. 12353). I would like to express my thanks to co-authors (P.-A. Chiappori, J.I. Giménez-Nadal, J.A. Molina), to Alex Theloudis, and to Elena del Rey. The contents of this Chapter are, however, the result of the extensive work of the author.

Previous versions of Chapter 3 were accepted to be presented at the 2020 Meeting of the SEHO (Venice, Italy), and the 34th ESPE Conference (Barcelona, Spain), both canceled due to the Covid-19. Chapter 3 is a revision of a Working Paper (IZA

Discussion Paper n. 12933). I would like to express my thanks to co-authors (J.I. Giménez-Nadal, J.A. Molina). The contents of this Chapter are, however, the result of the extensive work of the author.

Neither the individuals nor the institutions mentioned above bear any responsibility for the analyses and conclusions presented in this Thesis.

# Contents

**Abstract** **i**

**Resumen en español** **iii**

**Acknowledgement** **vii**

**Introduction** **1**

**1 Urban efficiency wages** **11**

1.1 Introduction . . . . . . . . . . 11
1.2 Theoretical background . . . . . . . . . . 13
1.3 ATUS data and variables . . . . . . . . . . 18
1.4 Econometric analysis . . . . . . . . . . 26
1.4.1 Shirking at work and leisure . . . . . . . . . . 26
1.4.2 Leisure, shirking at work and commuting time . . . . . . . . . . 28
1.4.3 Employment, wages and commuting time . . . . . . . . . . 30
1.5 Conclusions . . . . . . . . . . 35
Appendix 1.A: Additional results . . . . . . . . . . 39
Appendix 1.B: The case of Spain . . . . . . . . . . 43
Appendix 1.C: The case of the self-employed . . . . . . . . . . 57

**2 Intertemporal intrahousehold commitment** **71**

2.1 Introduction . . . . . . . . . . 71
2.2 The limited commitment model . . . . . . . . . . 75
2.2.1 Implementation of the model . . . . . . . . . . 79
2.2.2 Parametrization . . . . . . . . . . 82
2.3 PSID Data . . . . . . . . . . 84
2.4 Results in the US . . . . . . . . . . 87
2.5 EU-SILC data . . . . . . . . . . 94
2.6 Results in Europe . . . . . . . . . . 97
2.7 Conclusions . . . . . . . . . . 106
Appendix 2.A: Static collective models . . . . . . . . . . 109
Appendix 2.B: Additional results for the US . . . . . . . . . . 111
Appendix 2.C: Additional results for Europe . . . . . . . . . . 117
Appendix 2.D: The case of Spanish regions . . . . . . . . . . 131

**3 Intergenerational employment and self-employment** **135**
3.1 Introduction . . . . . . . . 135
3.2 Literature review . . . . . . . . 138
3.3 Data and variables . . . . . . . . 141
3.3.1 Descriptive results . . . . . . . . 147
3.4 Short-term correlations . . . . . . . . 151
3.4.1 Empirical strategy . . . . . . . . 151
3.4.2 Results . . . . . . . . 153
3.5 Long-term correlations . . . . . . . . 154
3.5.1 Empirical strategy . . . . . . . . 154
3.5.2 Results . . . . . . . . 156
3.6 Discussion of results . . . . . . . . 158
3.7 Conclusions . . . . . . . . 160
Appendix 3.A: Additional results . . . . . . . . 163
Appendix 3.B: Single-parent individuals . . . . . . . . 167

**Conclusions** **171**

**Conclusiones en español** **175**

**References** **181**

**List of Figures** **199**

**List of Tables** **201**

# Introduction

This Thesis analyzes urban efficiency wages in the US and Spain, and the theory's implications for worker's time endowments; household labor supply decisions on the basis of an intertemporal collective model, and the link with intrahousehold commitment in the US and Europe; and intergenerational correlation of employment and self-employment between parents and children in Europe, both in the short- and long-term. In each of these essays, the main focus is the supply side of the labor market, where a range of perspectives are adopted.

This Thesis presents new results relative to prior research, as three original topics are studied:

1. Time endowments of workers in an urban efficiency wage setting. This represents the first analysis of time use in such a scenario in the literature.

2. Intertemporal collective models of labor supply. The model developed allows us to study intertemporal intrahousehold commitment, which represents an original contribution with respect to prior research.

3. Intergenerational correlation of employment and self-employment in Europe. As most of the prior research has focused on single countries, the use of international, harmonized data presents a significant contribution.

## Urban efficiency wages and time endowments

The time (or distance) between residences and workplace is called commuting, and its analysis has gained presence in the literature in recent decades, as it measures the interdependence between locations of employment and residence of workers.[1] The study of commuting behavior is important for several reasons. Commuting is a daily activity that can hardly be avoided in modern societies.[2] Kahneman et al. (2004) and Kahneman and Krueger (2006) show that time spent in commuting ranks among the lowest activities in terms of the "instant enjoyment" obtained by individuals, and there are increased stress and absenteeism, and psychological, health, and well-being costs associated with travel to and from work (see Evans et al., 2002; Jansen et al., 2003; Wener et al., 2003; Gottholmseder et al., 2009; Hämmig et al., 2009; Hansson et al., 2011; Roberts et al., 2011; Van Ommeren and Gutiérrez-i-Puigarnau, 2011). Recent studies have shown that the time devoted to commuting has increased in developed countries such as Germany, the Netherlands, and the US, leading to commuting time being a significant part of the total time devoted to the labor market (Susilo and Maat, 2007; Kirby and LeSage, 2009; McKenzie and Rapino, 2011; Giménez-Nadal and Molina, 2016).

The commuting behavior of individuals has been extensively analyzed and incorporated into a range of theoretical models. According to job search models, commuting is considered a source of labor mobility that allows workers to access geographically-dispersed labor markets without the need for migration (Van Ommeren, 1998; Rouwendal and Nijkamp, 2004). From the point of view of transport economics, commuters choose a mode of transport to minimize the monetary and opportunity costs of travel. In urban economics, the focus is on household location, where commuting is generally assumed to confer disutility, and households are located to maximize the utility obtained from housing and all other goods. These models include, for instance, the monocentric model (Alonso, 1964; Mills, 1967; Muth, 1969), the polycentric model (Muller, 1981; Garreau, 1991), the literature of "excess" or "wasteful" commuting (Hamilton, 1982), and the spatial mismatch hypothesis (Kain, 1968; Gobillon et al., 2007).

Commuting behaviors have been studied from different scenarios, including aggre-

[1] The term commuting has its origin in the XIX century in the United States, where workers who lived in suburbs on the outskirts of big cities and daily worked in urban cores were usually called "commuters".

[2] One exception is the practice of teleworking, or telecommuting, which has been studied by the authors in Giménez-Nadal et al. (2019).

gated flows, linear optimization problems, and microeconomic models. One microeconomic approach is that of urban efficiency wages (Ross and Zenou, 2008; Zenou, 2009) which provides a theoretical framework to study, simultaneously, the different relationships between commuting, wages, employment and unemployment, and other time endowments. According to the efficiency wages theory, (salaried) workers are paid by their employers a higher wage than that of market equilibrium in order to promote their efficiency and discourage them from shirking behaviors at work. Urban efficiency wages theory incorporates spatial trends, often associated with commutes, with the purpose of studying employment and unemployment, and its distribution across urban and employment cores.

Chapter 1 describes Ross and Zenou (2008)'s urban efficiency wages model, and studies different aspects that, so far, were considered benchmark hypotheses and had remained as theoretical ambiguities. In particular, Ross and Zenou (2008) claimed that shirking and leisure are substitutes. In developing their model, they assume that commuting time is a shock to time endowments and, specifically, longer commutes should have a negative impact on leisure time of workers, leading to increased shirking behaviors. However, that substitution assumption had not been empirically studied, and so the results of the model were subject to some degree of theoretical ambiguity. Our primary goal is, then, to directly analyze the empirical relationship between shirking at work and leisure, and thus identify a key parameter that is necessary to test the efficiency wage hypothesis. Data is taken from both the American Time Use Surveys from 2001 to 2014, and from the Spanish Time Use Survey from 2009 to 2010. These databases allow us to observe individual hours of work, and to determine whether (and to what extent) non-work activities are performed during working hours, which is a key dimension of shirking.[3] Additionally, we investigate whether or not estimates are compatible with the predictions of the model, as we analyze the elasticity between commuting time and shirking time, commuting time and leisure time, commuting time and wages, and "expected" commuting time and workers' employment status.

Estimates point to the validity of the substitution hypothesis between leisure time and shirking at work in the US and in Spain, as the elasticity between leisure and shirking is estimated to be negative and significant. Furthermore, estimates are compatible with the predictions of the model, as we find a negative correlation between commuting time and leisure time, and a positive correlation between commuting time and shirking

[3] Another key dimension of shirking is absenteeism; see Van Ommeren and Gutiérrez-i-Puigarnau (2011).

at work, which is especially relevant for workers in non-supervised occupations. To sum up, the empirical results suggest that urban efficiency wages operate in both the US and the Spanish labor markets. However, estimates suggest that supervision mechanisms are not as effective in Spain as in the US, which may be especially important for planners and policy makers.

Finally, urban efficiency wages are limited to salaried workers, that is to say, employees, as the self-employed are not paid a wage by a firm and, as a consequence, cannot be included in the efficiency wages theory. However, the substitution hypothesis between leisure time and shirking at work may well operate for them, leading to different relationships between commuting time and other time endowments. Based on the Ross and Zenou (2008)'s model, we propose an urban model for the self-employed, assuming that leisure time and shirking at work are substitutes for these workers, to find that there is no clear mechanism between self-employment outcomes and commuting time. However, the model suggests that self-employed workers commute shorter distances by placing their residence nearer employment cores than their employee counterparts. We then estimate the model empirically and find that the elasticity between leisure time and shirking time for the self-employed is negative, in line with the substitution hypothesis. Furthermore, results also suggest that self-employed workers reside nearer their respective job places, as they are found to have shorter commutes than employees.

## Intertemporal labor supply and intrahousehold commitment

The study of the family was first addressed many years ago (Aristotle, Politics, Book 1, Part 2, according to Browning et al., 2014). However, it was as a result of the work of Gary Becker (summarized in Becker, 1991) that the study of the household gained importance in Microeconomics. Family Economics is now defined as "the economic analysis of household decisions, including decisions regarding consumption, labor supply, and other uses of time, household formation and dissolution, demand for health and other forms of human capital, fertility and investment in children's human capital, demand for environmental and other public goods, migration, demand for religiosity, and decisions by agricultural households".[4]

The classical framework with which to analyze household economic behaviors is the so-called "unitary" model. The unitary model considers the household as a single decision-making unit, with a homogeneous set of preferences and a unique utility

[4]See https://sites.google.com/view/seho2018/.

function. This unitary approach has certain deficiencies and has come under heavy criticism in recent decades.[5]

Since the 1980s, and given the deficiencies of the unitary approach, various authors have developed different theories with the objective of reconciling the theory, and modeling household behaviors more accurately (Manser and Brown, 1980; Ashworth and Ulph, 1981; McElroy and Horney, 1981; Apps, 1981, 1982; Apps and Jones, 1986; Ulph, 1988; Woolley, 1988). In that context, Chiappori (1988, 1992) proposed the first general framework to study intrahousehold decisions, the collective model, assuming that there exists some type of cooperation among household members that leads to Pareto-efficient outcomes.

However, most of the theories and empirical works have been proposed in static frameworks, given the difficulty of developing bargaining theories in an intertemporal setting. That scenario prevents researchers from providing accurate answers to a range of intrahousehold decisions and different policies that have intertemporal dimensions (Chiappori and Mazzocco, 2017). To take but one example, consider a concrete policy based on wealth transfers to households with children. Is it relevant who receives the transfer in a two-member household, namely the husband, the wife, or the household as a unit? This question can be answered using a static collective model. On the other hand, one could ask whether this policy is expected to have a permanent or semi-permanent impact on household behaviors. However, this cannot be evaluated - and therefore fully answered - using a static collective model, as a dynamic (or intertemporal) model is required for the task. Furthermore, the key to responding to that question is the assumptions made regarding the ability of spouses to commit in the long term, a key dimension of intrahousehold bargaining that is straightforward in static models, while different assumptions would lead to different results in an intertemporal setting. From a theoretical point of view, there are three alternative models for intertemporal intrahousehold commitment: the full commitment model, which assumes full risk sharing; the non-commitment model, that assumes period by period efficiency but agents cannot commit to any future allocation; and the limited commitment model (Mazzocco, 2004), which lies between the two. However, so far these models have not been fully evaluated from an empirical point of view, as the existing literature is scarce and has exclusively rejected the full commitment model against the "non-full" commitment counterparts in the US and Japan.

[5]It has to be noted that sometimes the unitary model has been wrongly attributed to Becker (1974b). However, Becker's work included several nonunitary theories (Becker, 1973, 1974a).

In that context, Chapter 2 proposes an intertemporal collective model of labor supply with the main objective being to study intrahousehold commitment. The model allows us to distinguish among the full commitment model, the non-commitment model, and the limited commitment model by examining, first, whether or not household labor supply decisions are affected by present observables that were not anticipated at the beginning of the marriage. This strategy, proposed by Mazzocco (2007), allows us to reject the full commitment model. Second, according to the model, we distinguish between the non-commitment and limited commitment models by studying whether the past history of those observables has any impact on household labor supply decisions, as such impact should be negligible in the non-commitment model, but significant in the limited commitment version of the collective model. Specifically, the limited commitment model predicts that a spouse's unobserved bargaining power should increase if they performed better than expected in the past, leading to a semi-permanent reduction in their labor supply, whereas this impact should be immediately forgotten in the non-commitment model.

We then propose a reduced form empirical specification to analyze unobservable intertemporal commitment issues through observable household labor supply behaviors. The intuition is as follows: assume that household members are hit by an unexpected productivity shock that affects their wages. According to the full commitment model, these unexpected shocks, whether past or current, have a negligible effect on household labor supply decisions. According to the non-commitment model, only current shocks affect spouses' current labor supply behaviors, while past history should be forgotten. Finally, according to the limited commitment model, past shocks (or an accumulation of them) should have a semi-permanent and persistent effect on household labor supply.

The model is estimated using longitudinal data from the US Panel Study of Income Dynamics, from the years 2001 to 2015, and from the European Union Statistics on Income and Living Conditions, for the years 2003 to 2016, including information for Austria, Belgium, France, Greece, Italy, Luxembourg, Spain and Sweden. This represents the first empirical analysis of intertemporal intrahousehold commitment in Europe. Results reject the non- and full commitment models, and also the unitary model, as estimates are not compatible with the dynamics generated under those models. However, the estimated labor supply equations fit the predictions of the limited commitment model, as even controlling for present and future wages, unexpected wage shocks have a lasting impact on spouses' labor supply. Moreover, results suggest that when a spouse did better than expected, (s)he works less, suggesting that (s)he attracts a larger fraction of household resources. The results of this Chapter highlight how crucial it is to understand intrahousehold allocations in evaluating different public policies that mainly affect households, as different models can lead to different evaluations and, thus, to different conclusions. Within this context, the development of a dynamic framework for collective behaviors is needed, and our main conclusion is that the limited commitment model is an excellent candidate, compared to the full- and non-commitment models.

## Intergenerational transmission of employment and self-employment

The study of intergenerational transmission is especially important, as it investigates how and to what extent certain factors may be transmitted from parents to children, beyond pure selection theories (Black et al., 2005). Those factors include, for instance, income and poverty, human capital, human development, and occupational choices, among others (Becker and Tomes, 1979; Altonji and Dunn, 2000; Black and Devereux, 2011; Doepke and Zilibotti, 2017; Giménez-Nadal et al., 2018a). Despite the fact that prior research has identified the existence of intergenerational transmissions of employment and self-employment, the literature is scarce, and there is no consensus on the channels or the extent of these transmissions (Mäder et al., 2015; Galassi et al., 2019). Therefore, the use of an international harmonized database supposes a significant contribution to the literature, as cross-country analyses are very limited.

Understanding intergenerational transmission is of key relevance for planners and policy makers, as it may help in understanding the characteristics transmitted from generation to generation. For instance, policies aiming to reduce poverty and inequality of opportunity could be more efficiently implemented if the factors that determine such sources were known to be transmitted from parents to children. Hence, intergenerational transmissions are of special importance for children, given that they may determine future socio-economic behaviors. In this context, transmission of employment and self-employment are of special interest in Europe, given that during the recent economic crisis the levels of unemployment have been very high. Furthermore, the largest impact has been on youth, with percentages of unemployment above 40% in Greece and Spain, and between 20% and 40% in Italy, France, Belgium and Finland, according to Eurostat.

Entrepreneurship and self-employment are labor alternatives to salaried employment for those workers who do not want or cannot find an employer.[6] Consequently, self-employment has been actively promoted by institutions at a range of stages, including international, national, and regional initiatives, as a way of overcoming some of the devastating effects of the recent economic crisis (Minniti and Naudé, 2010; Naudé, 2015).[7] For example, in the case of Spain, a country whose structural unemployment rate is high and, besides, has suffered significant increases during the crisis, reaching up to the 24.6% of working age individuals being unemployed (Rocha and Aragon, 2012), several programs have appeared, including the Programa Emprendedores, the Programa España Emprende, and the laws 14/2013 (September 27th) and 6/2017 (October 24th). These programs have the main objective of fostering employment and economic growth, although their effectiveness should not be taken for granted (Naudé, 2015). Some authors have analyzed the intergenerational transmission of employment in different countries, trying to find both conditional correlations and causal links between the employment status of parents and their children. However, despite the fact that prior studies have found a significant correlation, the evidence so far is scarce, inconclusive, and most of the existing research is limited to single-country cross-sectional studies (Mäder et al., 2015; Galassi et al., 2019; Morales, 2019).

In this context, Chapter 3 explores the existence of intergenerational correlation of employment and self-employment within families, in Austria, Belgium, Denmark, Greece, Spain, Finland, France, Italy, Luxembourg, the Netherlands, Sweden, and the UK. Europe is a particularly important region in which to study these transmissions, given the large impact of the recent economic crisis on unemployment in European countries, and the moderating role of family background on that impact (Mascherini, 2019). We first provide a literature review on the transmission of employment and self-employment. Second, we use the longitudinal European Union Statistics on Income and Living Conditions data, for the period 2003-2016, to study whether or not the current labor status of interviewed individuals is correlated with the current labor status of their interviewed parents. Using fixed effects models, we estimate a positive and significant correlation between respondents' current employment status, and the current employment status of their parents. However, the self-employed status of parents appears to be correlated only with that of male workers. As we use fixed effect panel data models, these results may, however, reveal family labor supply decisions, suggesting that parents' employment is a strong predictor of children's short-term de-

[6]Entrepreneurship and self-employment are often considered as synonyms, despite the fact that self-employment might be considered a more general definition than entrepreneurship.

[7]For example, the Entrepreneurship 2020 Action Plan of the European Commission.

cisions.

Third, we investigate the existence of long-term intergenerational transmission of employment and self-employment, by analyzing the correlation between the current employment and self-employment status of interviewed individuals, and the corresponding status of the parents of interviewees when they were teenagers. In doing so, we use the special module on Intergenerational Transmissions of Disadvantages of the 2011 cross-sectional sample of the European Union Statistics on Income and Living Conditions. This module includes information about respondent parents' labor attributes when the respondents were around 14 years old, which allows us to analyze the long-term intergenerational correlation of employment and self-employment. To the best of our knowledge, this represents the first empirical comparison of short- and long-term intergenerational correlation of employment and self-employment. Unfortunately, the longitudinal and cross-section samples are not linkable at the micro level, as the surveyed individuals are different. Therefore, information from the 2011 special module on transmissions cannot be matched with the 2003-2016 longitudinal sample. OLS estimates show that the (employment) self-employment status of workers is strongly correlated with their parents being (employed) self-employed in the past. This suggests that there exists a significant channel of self-employment arising from intergenerational correlations that is not driven by short-term family labor supply decisions, but rather from long-term transmissions.

The results may be important for planners and policy makers, as they can help to anticipate which workers may be employed and become self-employed in the future, in terms of their parents economic and sociodemographic characteristics. For instance, we suggest that transmissions of employment are driven by short-term family labor supply decisions, and by long-term correlations, while intergenerational transmissions of self-employment are determined more strongly by long-term correlations, rather than by short-term decisions. Further research should focus on studying the different channels that may drive these transmissions, such as culture, social norms, and the transmission of certain managerial skills, entrepreneurial spirit, and human capital related to self-employment.

# Chapter 1

# Spatial distribution of employment in an urban efficiency wage setting

This Chapter analyzes whether efficiency wages operate in urban labor markets, within the framework proposed by Ross and Zenou (2008), in which shirking at work and leisure are assumed to be substitutes. It is used unique data from the American and Spanish time use surveys that allows us to analyze the relationships between leisure, shirking, commuting, employment, and earnings. Estimates confirm that shirking and leisure are substitutes, representing the only empirical test of the relationship between a worker's time endowment and shirking at work. Findings point to the existence of efficiency wages in the US urban labor market. Furthermore, estimates on time endowments and wages are also consistent with the theory in Spain.
Keywords: urban efficiency wages, leisure, shirking at work, commuting, ATUS, STUS

## 1.1 Introduction

In this Chapter, we analyze the spatial distribution of US employment, using data for the United States for the period 2003-2014.[1] Employment and wages have been studied in a variety of frameworks, with one approach being the theory of efficiency wages, in which firms are willing to pay workers more than expected to promote efficiency and discourage shirking at work (Shapiro and Stiglitz, 1984). However, these authors identify the problem of setting efficiency wages when workers' time endowment is unobserved, since the value of shirking depends upon the time endowments. Following

[1]The case of Spain is shown in the Appendix 1.B, using the Spanish Time Use Survey from years 2009-2010. The case of Aragón is particularly studied. The particular case of the self-employed workers is additionally shown in the Appendix 1.C.

this approach, Ross and Zenou (2008) use expected commuting time as a shock to the time endowments to indirectly test the Shapiro and Stiglitz (1984) phenomena, which is the only test of this phenomena to date. Specifically, Ross and Zenou (2008) develop a model to examine the effects of commuting on employment and wages, in which the behavioral substitution between leisure time and effort at work is allowed. According to this model, employees who devote comparatively more time to commuting have comparatively less time to devote to leisure activities, and thus have incentives to shirk at work, which decreases their effort at work. However, a key theoretical ambiguity emerges from this model, as it is not known whether shirking at work and leisure are complements or substitutes and the authors derive all their results from the assumption that leisure and shirking at work are, indeed, substitutes.

Our primary goal is to directly analyze the empirical relationship between shirking at work and leisure, and thus identify a key parameter that is necessary to test the efficiency wage hypothesis, using employment, wages, and leisure. To that end, we use the American Time Use Survey (ATUS) for the years 2003-2014, which allows us to observe the hours of work, and also to determine whether (and to what extent) non-work activities are performed during work hours. Such non-work activity during work hours is a key dimension of shirking, that is emphasized by Ross and Zenou (2008) as being especially sensitive to commuting time. We analyze how much time workers spend in non-work activities during their work schedules, and whether shirking at work (i.e., non-work activities done in the work place, such as Internet shopping, managing household finances, or Internet use on social networks) and leisure are complements or substitutes. We find evidence of substitutability between leisure and shirking at work, a critical assumption made in the current framework.

Following the theoretical framework, the negative relationship between leisure and shirking at work implies that commuting time has a negative relationship with leisure, while commuting has a positive relationship with shirking at work. We find that commuting time and leisure have a negative relationship for both supervised and non-supervised occupations. We also find that the positive relationship between commuting time and shirking time is only found in non-supervised occupations, which may indicate that the payment of efficiency wages, in concert with supervision, reduces the incentives to shirk in supervised occupations. Thus, our results are consistent with the theoretical model. Furthermore, we analyze the relationship between commuting time, unemployment, and wages, and find that commuting time presents positive and statistically significant correlations with unemployment and wages.

Our contribution to the literature is twofold. First, we analyze the relationship between shirking at work and leisure, which is our main contribution. The Ross and Zenou (2008) model identifies a key theoretical ambiguity in this relationship, and no empirical analyzes have been done, so far, to determine the direction and magnitude of this relationship. We offer a precise estimation of the magnitude of this relationship, providing empirical support to Ross and Zenou (2008). Second, we complement prior results for employment and wages. Our results show positive relationships between commuting time, on the one hand, and unemployment and wages, on the other, which is consistent with urban efficiency wage theories. Thus, we offer updated evidence of the spatial distribution of US wage employment and individual earnings.

The rest of the Chapter is organized as follows. Section 1.2 shows a literature review and briefly describes the theoretical background. Section 1.3 describes the ATUS data, and Section 1.4 contains the empirical results. Section 1.5 presents our main conclusions. The Appendix 1.A shows additional results and robustness checks, the Appendix 1.B shows the case of Spain, and the Appendix 1.C shows an application to self-employment.

## 1.2 Theoretical background

The relationship between employment, earnings, and commuting has been widely studied. Examples of analyses of employment and commuting can be found in White (1977); Zax and Kain (1991); Clark and Withers (1999) or Rouwendal and Meijer (2001), where the importance of housing/residential decisions is highlighted.[2] The Spatial Mismatch Theory (Kain, 1968) argues that poor labor market outcomes are partly the result of spatial separation between work and places of residence, and its effects on unemployment have been studied in Brueckner and Zenou (2003) and Gobillon et al. (2007). Patacchini and Zenou (2007) show the growing spatial dependence of unemployment rates, and Picard and Zenou (2015) find that minority groups have higher unemployment rates, independently of where they are located.

The effect of commuting on wages has also been studied, finding positive and robust associations. For instance, Leigh (1986) was one of the first to study compensating

[2] Renkow and Hoover (2000) empirically study urban change following the regional restructuring hypothesis and the deconcentration hypothesis, supporting the latter in opposition to the former. The regional restructuring hypothesis holds that employment opportunities have been dominant over spatial employment changes, while the deconcentration hypothesis proposes that such changes are due to consumer preferences.

wages due to commuting, finding positive evidence especially for white workers. Other authors analyzing the effects of commuting on wages are Zax (1991); White (1999); Ruppert et al. (2016); Fu and Ross (2013) and Mulalic et al. (2014). Brueckner et al. (1997) study the location of individuals in cities by income, finding that the availability of amenities in the various areas of the city is related to the location of the wealthy.

Among the different frameworks established to analyze these economic outcomes, the theory of urban efficiency wages is a common approach. According to efficiency wage models, salaried workers receive higher wages than expected from the labor market equilibrium, as firms are willing to pay workers more to promote efficiency and discourage shirking at work. However, firms do not pay enough to eliminate all shirking at work if they do not observe individual time endowments (Shapiro and Stiglitz, 1984). The urban efficiency wage models include a spatial pattern, where place of work and place of residence play an important role in determining how employment and unemployment are spatially distributed. One important factor in this framework is the distance from the place of residence to the workplace, which determines the time devoted to commuting. Thus, a key factor in urban wage efficiency models is commuting, which affects employment and wages.

We take the model of Ross and Zenou (2008) as our reference theoretical framework, where workers' residential locations are chosen and then remain fixed as they enter and leave unemployment. Assume that there is a continuum of employed or unemployed workers in a monocentric, linear and closed city. Employment is concentrated in the city center so that all firms (i.e., the Business District, $BD$) are exogenously located there. Workers can decide about their effort at work ($e$) and their residential location ($x$) between $BD$ and the city fringe ($x_f$), and consume the same amount of land, which is normalized to 1 and owned by landlords. Population is normalized to 1 so that unemployment ($u$) levels are equal to unemployment rates.

Workers can be employed at a wage $w$, or unemployed getting a benefit $b$ (normalized to 0). Changes in employment status are governed by continuous-time Markov processes. Transitions from unemployment to employment occur at a rate $\theta > 0$, and transitions from employment to unemployment occur at a rate $\delta > 0$. Therefore, the expected durations of employment and unemployment are $1/\delta$ and $1/\theta$, respectively, and workers remain a fraction $\theta/(\theta+\delta)$ employed, and a fraction $\delta/(\theta+\delta)$ unemployed. For instance, in the steady state the unemployment rate must be:

$$u = \frac{\delta}{\theta + \delta},$$

which is equivalent to the probability of being unemployed.

Authors establish an instant utility function of workers, $z_1 + V$, that depends on the quantity of a non-spatial composite good ($z_1$) consumed by the employed, and a function ($V(.)$). This function depends on leisure ($l$) and effort at work ($e$), $\partial V/\partial l > 0, \partial V/\partial e < 0$, and considers that effort and leisure are not independent, such that:[3]

$$\frac{\partial^2 V}{\partial l \partial e} > 0.$$

In this sense, the authors' key assumption is that shirking at work (i.e., the opposite to $e$) and leisure are substitutes. The intuition behind this hypothesis is as follows: low leisure at home may imply that the worker has less time for rest and relaxation and is more pressed for time at home, and thus the benefit of taking leisure (or conducting home production) while at work increases.[4] However, no empirical analyses have been done, to date, to test this assumption. Following this assumption, and setting a budget and a time constraint, Ross and Zenou (2008) find the following indirect utility of employed workers:

$$I_1(x, e) = wT - R(x) - \tau x + V(1 - T - tx, e),$$

where $T$ denotes paid work time (exogenous), $\tau x$ and $tx$ represents commuting monetary cost and time from distance $x$, respectively, and $R(x)$ is defined as the rent paid per unit of land at a distance $x$ from the $BD$.

Using a similar strategy for the unemployed, who consume a quantity $z_0$ of the composite good and are assumed to commute for job interviews, they find the following indirect utility of unemployed workers:

$$I_0(x) = -R(x) - \tau x + V_0.$$

[3]Two studies are relevant in this context. Van Ommeren and Gutiérrez-i-Puigarnau (2011) analyze the effect of the length of the worker's commute on productivity, by examining whether the commute has a positive effect on absenteeism, considering absenteeism as the opposite to productivity. The authors find that absenteeism in Germany would be 15% to 20% less if all workers had a negligible commute, which is consistent with urban efficiency wage models. Burda et al. (2015) study shirking ("not working at job", or loafing) and unemployment, in a setting robust to the operation of efficiency wages, where wage compensations discourage workers from loafing.

[4]It is also theoretically possible that leisure and shirking are complementary concepts. Changes in commuting time (and thus in leisure) may distort social life and thus the more time devoted to commuting, the less quality of social life and benefits from leisure, implying fewer planned activities at home. This decline makes the demand for personal time activities decline, including the benefits derived from personal activities at work. Since there is less time for planned activities at home, there is more time available for relaxing, so relaxing time at work also declines. However, Ross and Zenou (2008) argue that the case where effort and leisure are complements is not consistent with the results shown in their paper (footnote 7).

Therefore, the indirect utility of a worker over the job cycle is given by:

$$I = uI_0 + (1-u)I_1 = (1-u)(wT + V(1-T-tx, e)) - R(x) - \tau x + uV_0.$$

In that context, workers are assumed to be classified in two groups: shirkers ($S$), exerting a level of effort at work $e^S > 0$, and non-shirkers ($NS$), providing an effort $e^{NS} > e^S$. These differentiation has an implication on employment and unemployment, given that there is assumed to be a monitoring technology $m$ implemented by firms that represents the probability of detecting shirking behaviors, so that:

$$u^{NS} = u < u^S = \frac{\delta + m}{\delta + \theta + m}, \ \ \delta, \theta, m > 0.$$

These different unemployment rates have a consequence on bid rents (i.e., the amount that workers are willing to pay to landlords for a unit of land, which results from clearing $R(x)$ in the indirect utility function over the job cycle), that will differ from shirkers to non-shirkers, and reflect the influence of commuting time and commuting cost, pondered by the probabilities of being employed or unemployed:

$$\psi^i(x, I^{eq}) = (1-u^i)(wT + V(1-T-tx, e)) - \tau x + u^i V_0 - I^{eq}, \ \ i = S, NS,$$

where $I^{eq}$ is the indirect utility obtained in the equilibrium, which must be the same for all (shirking and non-shirking) workers. It is straightforward that bid rent functions fulfill the usual hypothesis, as they are decreasing in $x$.

Then, two scenarios are considered. The first refers to a situation where firms do not observe worker's location, and the authors establish three propositions. Proposition 1 considers that workers who reside close to their jobs will choose not to shirk (i.e. will provide more effort), whereas workers located farther away will shirk (i.e. will provide less effort). The intuition behind this proposition is as follows: if shirking and leisure are substitutes, workers residing close to jobs will provide more effort than those residing further away from jobs because they have lower commuting time and thus more leisure time at home. If $\widetilde{x}$ represents the unit of land where workers are indifferent between high or low levels of $e$, so that $\psi^{NS}(\widetilde{x}) = \psi^S(\widetilde{x})$, then it can be proven that non-shirkers are willing to pay more to landlords for living between the $BD$ and $\widetilde{x}$.

Proposition 2 establishes that higher wages reduce the fraction of shirkers in the city, in the sense that, when wages are higher, fewer workers will shirk since there are more incentives not to do so. Authors take the equality $\psi^{NS}(\widetilde{x}) = \psi^S(\widetilde{x})$, and find that:

$$\frac{\partial \widetilde{x}}{\partial w} > 0,$$

which allows them to conclude that wages affect the border between shirkers and non-shirkers. For instance, if wages are higher, less workers shirk as the fraction $1 - \widetilde{x}$ decreases due to increases in the income difference between shirkers and non-shirkers, $wT(u^S - u^{NS})$.

In the equilibrium, authors conclude that employment is lower when commuting times are longer (i.e., unemployment and commuting times should have a positive relationship). This labor market equilibrium is compatible with the existence of a certain degree of shirking at work, as firms will always want to allow some degree of shirking at work (Proposition 3). That is to say, firms cannot discriminate in terms of wages as they do not know workers' residential location, and therefore they will pay wages acknowledging its effect on $\widetilde{x}$, i.e., on the fraction of shirkers and non-shirkers at work. Authors proof that the wage that firms pay to workers such that maximizes firms' profit is consistent with the theory (Appendix A), and leads to an equilibrium where there are shirker workers, who locate their residential locations far away from jobs.

The second scenario of the model considers that firms observe workers' locations.[5] In this scenario, firms can know the commuting time of workers, and thus it is optimal for firms to wage-discriminate in terms of location and not allow shirking at work in equilibrium. As a consequence, unemployment and bid-rents in the equilibrium are only defined for non-shirkers. Imposing that the bid-rent evaluated in the city fringe equals 0, firms set a wage that equates shirking and non-shirking indirect utilities to prevent shirking behaviors. In that context, Ross and Zenou (2008) find the following expression of such wage:

$$w = w(x) = \frac{(1-u^S)V(1-T-tx, e^S) - (1-u^{NS})V(1-T-tx, e^{NS})}{T(u^S - u^{NS})} + \frac{V_0}{T},$$

for $x \in [0,1] = [BD, x_f]$, and prove that $w'(x) > 0 \; \forall x$ (Proposition 4). That is to say, authors find that wages are higher when commuting times are longer, given that if leisure and effort are substitutes, wages must compensate workers who live farther away to prevent shirking behaviors, since they commute more and thus have less time for leisure at home.

[5] An intermediate scenario considers that firms partially observe workers' locations. In this scenario, commuting time is only partially observed, in the sense that firms may observe residential location, but it is too costly to determine the true commutes of workers. Firms will pay efficiency wages to reduce shirking, but they will not know the exact premium needed to compensate workers and eliminate shirking. Within this framework, some workers will shirk, and the relationships between commuting, unemployment, and wages will hold with the existence of shirking.

In summary, three aspects of the model are to be tested:

1. A negative relationship between shirking and leisure time (i.e., shirking and leisure are substitutes, a key assumption of the model).

2. A negative association between commuting and leisure time, and positive associations between commuting time, shirking time, and wages (longer commuting times imply less leisure time, which induces shirking at work, encouraging firms to pay higher wages).

3. A positive association between unemployment rates and (expected) commuting time, as shirking incentives increase in the (expected) commuting time.

## 1.3 ATUS data and variables

We use the American Time Use Survey (ATUS) for the period 2003-2014 to analyze the relationship between shirking at work and leisure, along with the links between commuting time, on the one hand, and shirking time, leisure time, employment, and wages, on the other.[6] Respondents fill out a diary, and the ATUS thus provides us with information on individual time use, including information that can be used to compute the time devoted to shirking at work, leisure, and commuting time. The database also includes certain personal, family, demographic, and labor variables. The ATUS is administered by the Bureau of Labor Statistics, and is considered the official time use survey of the United States.[7] The advantage of our data over surveys based on stylized questions is that diary-based estimates are more accurate (Juster and Stafford, 1985; Robinson, 1985; Bianchi et al., 2000; Bonke, 2005; Yee-Kan, 2008).

The sample consists of employed and unemployed respondents between 16 and 65 years of age, in order to minimize the role of time-allocation decisions that have a strong intertemporal component over the life cycle (Aguiar and Hurst, 2007; Giménez-Nadal and Sevilla, 2012). For employed individuals, we restrict the analysis to working days, defined as days individuals spend more than 60 minutes working (excluding commuting), which allows us to avoid computing zero minutes of commuting for any worker who filled out the time use diary on a non-working day.[8] One of the relationships to

[6]2014 was the last wave available when this Chapter was written.

[7]More information at http://www.bls.gov/tus/.

[8]We have repeated the analysis without restricting by working days, but controlling for weekdays, and results are qualitatively the same. Results are available upon request. For the restriction to

be tested is between commuting and unemployment, and in this analysis we include in our sample both the employed and the unemployed. For the analysis of the relationship between shirking and leisure time, and between commuting, shirking, leisure, and wages, we restrict the sample to workers only.[9] The final sample consists of 33,360 employed individuals, and 4,945 unemployed individuals.

According to Ross and Zenou (2008), workers can be divided into "white collar" workers and "blue collar" workers; that is, slightly supervised workers and heavily supervised workers, respectively. Ross and Zenou (2008) base their classification on Levenson and Zoghi (2006), who identify a clear break in the pattern of supervision, with all major white collar occupations having a predicted supervision level between 0.62 and 0.66, and all major blue collar occupations having a predicted level of supervision between 0.34 and 0.45, on a scale between 0 and 1, where 1 implies independence from supervision. The ATUS includes information on occupations, with a ten-category classification: 1) Production, 2) Construction and extraction, 3) Installation and maintenance, 4) Transportation and materials, 5) Farming, fishing, and forestry, 6) Office and administrative, 7) Services, 8) Professional and related, 9) Sales, and 10) Management and business. Within this framework, we consider slightly supervised occupations (i.e., non-supervised) to be the following: "Management, business and financial", "Professional and related", "Service", and "Sales and related". This leaves us with "Office and administrative support", "Farming, fishing, and forestry", "Construction and extraction", "Installation, maintenance, and repair", "Production" and "Transportation and material moving" as heavily supervised occupations (i.e., supervised).[10]

The fact that we have information on the 24 hours of the day allows us to compute the total time devoted to shirking at work and to leisure, and discern the relationship

working days, we define the variable "market work time" as the time devoted to the sum of "work, main job (at home/not at home)", "working nec (at home/not at home)", "work-related activities nec (at home/not at home)", "work & related activities nec (at home/not at home)" and "waiting work related activities (at home/not home)".

[9]Since there is no point in talking about efficiency wages in self-employment, as they do not receive wages but self-employment outcomes instead, I restrict the sample of workers to those who are employees. A complete modeling and analysis of the relationship between commuting and self-employment can be found in the Appendix 1.C.

[10]We must highlight that the ATUS is not intended as a labor survey. Thus, information on occupation is only available for those who are employed, while there is no information on previous occupation for those who are not employed (i.e., inactive, unemployed, retired). That way, the type of supervision of individuals is only known for employed individuals, while it is not known for the unemployed. For this reason, in the analysis of unemployment, we cannot divide the analysis by the level of supervision, and we run the analysis for the employed vs. the unemployed. For the rest of the analysis (commuting, shirking, leisure, and wages), given that we focus on workers only, we divide the sample into supervised and non-supervised occupations.

between these two uses of time. We compute the time devoted to leisure by workers in our sample using the definition of Giménez-Nadal and Sevilla (2012) and Aguiar and Hurst (2007): activities such as watching television, sports, general out-of-home leisure, gardening and pet care, and socializing, not at work. For the time devoted to shirking at work (i.e., non-work activities), the data structure of the ATUS allows us to ascertain the time workers report not working while in the work place. We define shirking time as the total time spent at the workplace, but which is not defined as market work. For instance, time spent on leisure, personal care, or housework (e.g., online shopping) done at the workplace (location code, "place of work") is included in the definition of shirking time.[11] This definition of shirking time is related to the "loafing" time described in Burda et al. (2015), defined as the time spent by workers in non-work activities while on the job.

Table 1.1 shows a descriptive analysis of leisure and shirking time, for all workers and by group of supervision. It can be observed that average leisure and shirking times are 88.78 and 27.54 minutes per day, with standard deviations of 87.78 and 34.78, respectively. Thus, workers in the US spend around 30 minutes per working day in shirking activities. By group of workers, we find that workers in occupations with supervision spend 86.21 and 35.66 minutes in leisure and shirking activities, while workers in occupations without supervision spend 90.21 and 23.05 minutes in these activities, respectively. Thus, in comparison to workers in occupations without supervision, those in occupations with supervision spend 4 fewer minutes per day in leisure activities and 12.61 more minutes per day in shirking activities, with this difference being statistically significant at the 99% level ($p$-values of the differences in characteristics are based on a $t$-type test). Table 1.2 shows the means and standard deviations of the time devoted to shirking by workers, according to their occupation. By occupation, we find that workers in production occupations spend the most time (42.25 daily minutes) in shirking at work, while workers in management and business, and sales occupations spend the least time (17.83 and 20.45 daily minutes, respectively) in shirking at work.

The ATUS also includes information on labor earnings, which allows us to compute the hourly wage of workers. We have defined "hourly earnings" directly as earnings per hour, if this data was available from ATUS; in other cases, we have defined it as earnings per week divided by the usual weekly working hours. For workers in our

[11] In a previous version, we also included the time devoted to work breaks and meals at work in the definition of shirking time. However, breaks and time for meals may be a standard part of work and it may be considered odd to mark these activities as shirking behavior. Results are consistent to the inclusion of these activities in our definition of shirking, and are available upon request.

sample, Table 1.1 shows that the average hourly earnings are \$19.59, and the standard deviation is \$17.60.

We define other variables in order to control for the observed heterogeneity of individuals in the econometric analysis done in Section 1.4. We consider the gender of respondents (male), potential years in the labor market (age minus number of education years and minus a fixed value, taken as 3), education level, being white, and being American, Asian, or Pacific Islander, living in couple, partner's labor force status (a dummy variable that indicates whether or not the partner works), having children, and the number of individuals in the household. We consider three levels of education: "basic education" (less than high school diploma), "secondary education" (high school diploma), and "university education" (more than high school diploma), defining each as a dummy variable. We have also included "years in labor market squared" (Ross and Zenou, 2008), in order to measure non-linear effects.

Table 1.1 shows a descriptive analysis of the variables, by group of supervision. In comparison with the unemployed, the employed have a higher probability of being women (52.7% vs 45.4%), have greater experience in the labor market (20.45 vs 19.27 years); a higher proportion of them have University education (63.3% vs 46.7%), and they are more likely to be white (82.4% vs 71.4%), although there is a higher proportion of Asian employees than unemployed (4.1% vs 2.7%). Regarding the variables related to household composition, we can observe that, in comparison with the unemployed, employed workers have a greater probability of living in couple (60.4% vs 46.1%) and that their partners have a greater probability of being employed (45% vs 33.3%), have fewer children (53.6% of the employees have children, vs 56.9% of the unemployed), and thus their households are smaller (2.9 members of the employees vs 3.1 of the unemployed). When we compare workers in occupations with and without supervision, we find that the former earn \$5.90/hour less than the latter (\$15.77/hour vs. \$21.70/hour). Furthermore, workers in occupations with supervision show lower rates of University education, have longer experience in the labor market, and have a lower probability of having children, in comparison with workers in occupations without supervision.

Table 1.1: Summary statistics

| | Employed | | Unemployed | | Difference | | Supervised | | Non-supervised | | Difference | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | Diff. | *p*-value | Mean | S.D. | Mean | S.D. | Diff. | *p*-value |
| Leisure time | 88.782 | 87.778 | - | - | - | - | 86.208 | 85.526 | 90.208 | 88.972 | -4.000 | (<0.001) |
| Shirking time | 27.543 | 34.784 | - | - | - | - | 35.657 | 36.322 | 23.049 | 33.057 | 12.608 | (<0.001) |
| Commuting time | 38.682 | 40.782 | - | - | - | - | 39.554 | 40.923 | 38.198 | 40.696 | 1.356 | (0.004) |
| Hourly earnings | 19.588 | 17.597 | - | - | - | - | 15.772 | 9.625 | 21.702 | 20.429 | -5.931 | (<0.001) |
| Being male | 0.527 | 0.499 | 0.454 | 0.498 | 0.073 | (<0.001) | 0.623 | 0.485 | 0.473 | 0.499 | 0.150 | (<0.001) |
| Years working | 20.454 | 11.546 | 19.275 | 12.704 | 1.179 | (<0.001) | 21.844 | 11.621 | 19.685 | 11.432 | 2.159 | (<0.001) |
| Years working squared | 55.169 | 51.140 | 53.289 | 54.184 | 1.880 | (<0.001) | 61.218 | 53.316 | 51.817 | 49.578 | 9.401 | (<0.001) |
| Primary education | 0.081 | 0.273 | 0.192 | 0.394 | -0.111 | (<0.001) | 0.120 | 0.326 | 0.060 | 0.237 | 0.061 | (<0.001) |
| Secondary education | 0.286 | 0.452 | 0.340 | 0.474 | -0.055 | (<0.001) | 0.426 | 0.495 | 0.208 | 0.406 | 0.218 | (<0.001) |
| University education | 0.633 | 0.482 | 0.467 | 0.499 | 0.166 | (<0.001) | 0.453 | 0.498 | 0.733 | 0.443 | -0.279 | (<0.001) |
| Being white | 0.824 | 0.381 | 0.714 | 0.452 | 0.111 | (<0.001) | 0.835 | 0.371 | 0.818 | 0.386 | 0.017 | (<0.001) |
| Being American | 0.824 | 0.381 | 0.820 | 0.385 | 0.005 | (0.393) | 0.815 | 0.389 | 0.830 | 0.376 | -0.015 | (<0.001) |
| Being Asian | 0.041 | 0.197 | 0.027 | 0.161 | 0.014 | (<0.001) | 0.022 | 0.148 | 0.051 | 0.219 | -0.028 | (<0.001) |
| Being Pacific Islander | 0.002 | 0.044 | 0.003 | 0.055 | -0.001 | (0.120) | 0.002 | 0.047 | 0.002 | 0.043 | 0.000 | (0.525) |
| Living in couple | 0.604 | 0.489 | 0.461 | 0.499 | 0.143 | (<0.001) | 0.609 | 0.488 | 0.601 | 0.490 | 0.008 | (0.136) |
| Partner's labor status | 0.450 | 0.498 | 0.333 | 0.471 | 0.117 | (<0.001) | 0.438 | 0.496 | 0.457 | 0.498 | -0.019 | (0.001) |
| Have children | 0.536 | 0.499 | 0.569 | 0.495 | -0.033 | (<0.001) | 0.526 | 0.499 | 0.541 | 0.498 | -0.015 | (0.009) |
| Family size | 2.941 | 1.486 | 3.098 | 1.600 | -0.157 | (<0.001) | 2.975 | 1.527 | 2.922 | 1.463 | 0.053 | (0.002) |
| Observations | 33,360 | | 4,945 | | | | 11,893 | | 21,467 | | | |

Note: The sample (ATUS 2003-2014) is restricted to employees who work the diary-day, or to unemployed individuals. Commuting, leisure and shirking times are measured in daily minutes. Working time is measured in weekly hours. Employed group collects salaried workers in private sector. Hourly earnings are measured in US dollars. Gender takes the value 1 for men and 0 for women. Years working squared is defined as the square of years working, divided into 10. Differences are defined as the mean value of the correspondent variable for private sector employees (supervised employees), minus the corresponding value for the unemployed (non-supervised employees). $T$-test $p$-values for the mean differences in parentheses.

Table 1.2: Leisure and shirking by occupation

| | Leisure | | Shirking | | Obs. |
|---|---|---|---|---|---|
| OCCUPATIONS | Mean | S.D. | Mean | S.D. | |
| Management and business | 91.838 | 86.989 | 17.828 | 28.894 | 8,581 |
| Professional and related | 92.475 | 87.111 | 21.441 | 31.264 | 11,117 |
| Services | 89.119 | 94.595 | 25.919 | 37.277 | 6,848 |
| Sales | 93.719 | 91.443 | 20.455 | 30.535 | 4,936 |
| Office and administrative | 85.481 | 83.106 | 30.735 | 34.494 | 5,498 |
| Farming, fishing, and forestry | 90.306 | 88.244 | 32.387 | 37.638 | 346 |
| Construction and extraction | 91.260 | 92.711 | 34.813 | 41.479 | 2,141 |
| Installation and maintenance | 89.344 | 84.108 | 33.099 | 33.993 | 1,637 |
| Production | 87.896 | 86.176 | 42.254 | 36.742 | 2,768 |
| Transportation and materials | 89.918 | 93.660 | 32.480 | 39.955 | 2,399 |

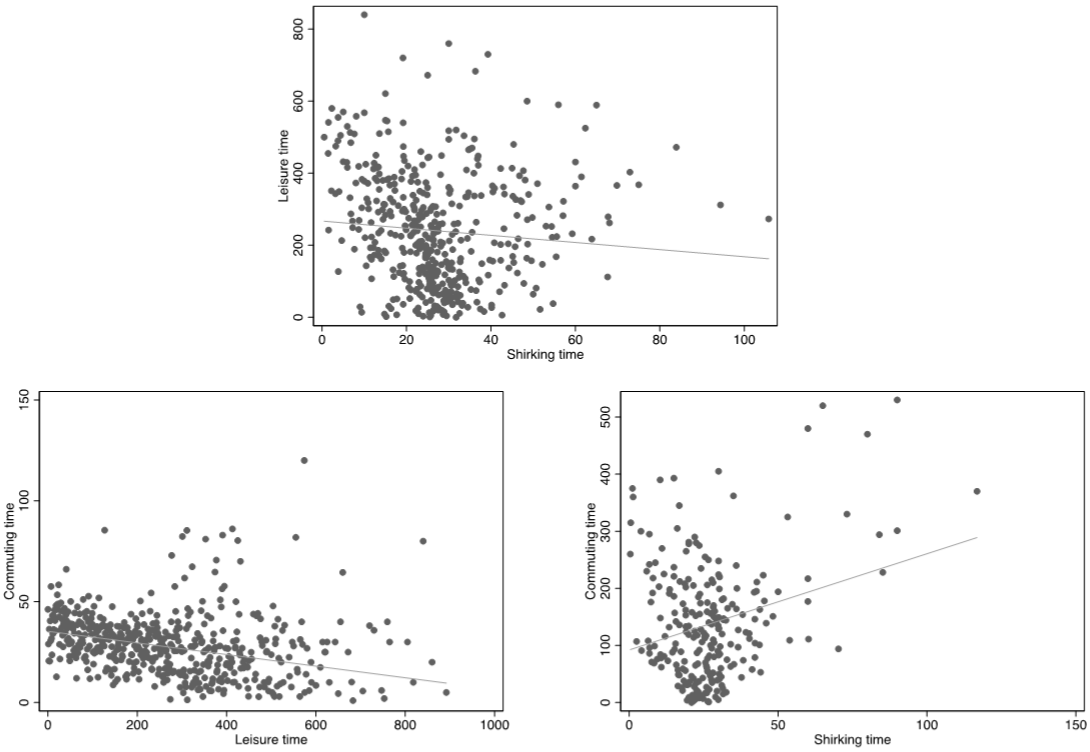
Note: The sample (ATUS 2003-2014) is restricted to employees who work the diary-day. Leisure and shirking times are measured in daily minutes.

### Descriptive evidence

From the evidence presented in Tables 1.1 and 1.2, we can determine that the higher the shirking time the lower the leisure time, which points to leisure and shirking at work being substitutes. To test this relationship, we have directly analyzed the raw correlation between leisure and shirking time. Figure 1.1 plots the average time devoted to leisure, for each time devoted to shirking at work; that is, for all those diaries with the same amount of time devoted to shirking at work, we average the time devoted to leisure. We plot mean leisure time ($Y$-axis) on the time devoted to shirking at work ($X$-axis). We have also added a linear fit of leisure time on shirking time. The linear fit shows a negative slope between leisure and shirking time, with the correlation between them being -0.242. Therefore, we find positive evidence of the substitutability of leisure and shirking at work, which complements Ross and Zenou (2008) as, a priori, they do not know whether shirking at work and leisure are complements or substitutes.

If shirking at work and leisure are substitutes, it follows that commuting and shirking at work should be positively related, while commuting and leisure should be negatively related. Thus, we now analyze the relationships between commuting time, on the one hand, and leisure and shirking time, on the other. Commuting time is the time devoted to the activity “commuting to/from work”, coded as “180501” in the ATUS. Table 1.1 shows the time devoted to commuting by workers in our sample. It can be seen that workers devote an average of 38.68 minutes per day to commuting, with workers in supervised and non-supervised occupations devoting 39.55 and 38.20 minutes per day, respectively.

Figure 1.1: Relationship between commuting, leisure and shirking

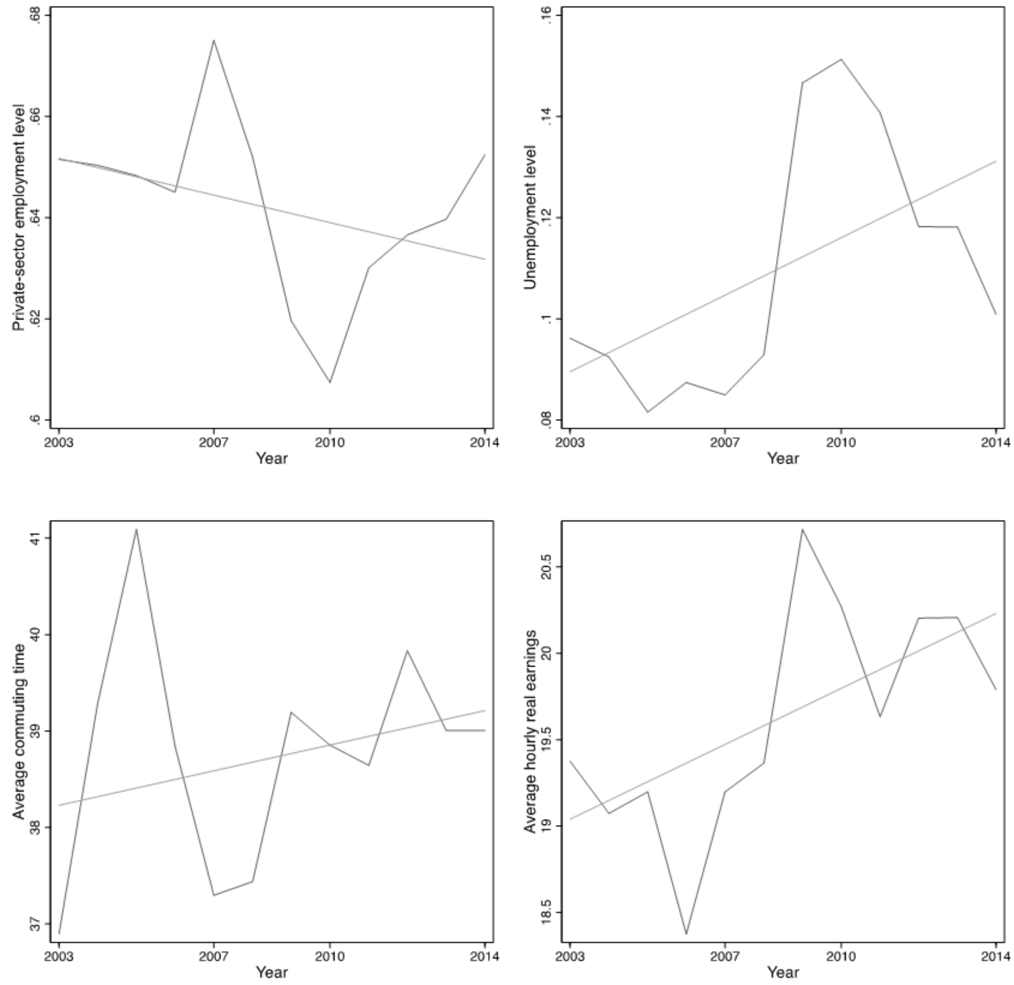



Note: The sample (ATUS 2003-2014) is restricted to employed individuals who work the diary-day. Commuting, leisure, and shirking are measured in daily minutes.

From Table 1.1, we find that workers in supervised occupations devote more time to commuting, which results in less time in leisure and more time in shirking at work, in comparison with workers in occupations without supervision. To test these relationships, we directly analyze the raw correlation between commuting, leisure, and shirking time. Figure 1.1 plots the average time devoted to commuting, for each time devoted to leisure, on the one hand, and for each time devoted to shirking at work, on the other. We plot mean leisure time, and mean shirking time ($X$-axis), on the time devoted to commuting ($Y$-axis). We have also added a linear fit of leisure and shirking times on commuting time. We observe a negative slope between commuting and leisure times (the correlation between them is -0.169) on the one hand, and a positive slope between commuting and leisure times (the correlation between them is 0.154) on the other. We conclude that there is a negative association between commuting and leisure, and a positive association between commuting and shirking at work, consistent with Ross and Zenou (2008).

Figure 1.2 shows the evolution of employment and unemployment rates, hourly wages, and commuting time in the US, from the ATUS. We observe that the employ-

Figure 1.2: Evolution of employment, commuting, and hourly earnings




Note: The sample (ATUS 2003-2014) is restricted to employees who work the diary-day. Commuting time is measured in daily minutes.

ment rate has decreased, while the unemployment rate, hourly wages, and commuting time have increased over the period. The increase in commuting time in recent years is consistent with the findings of Kirby and LeSage (2009); McKenzie and Rapino (2011); Giménez-Nadal and Molina (2014, 2016). Apart from economic conditions, which influence employment and unemployment rates, among the explanations for these trends we can find the increase in commuting time, leading to increases in unemployment rates and hourly wages.

In summary, we find that the relationship between leisure and shirking at work is negative. Accordingly, the relationship between commuting and leisure is negative, and commuting has positive relationships with shirking time, unemployment, and wages, giving empirical support to the model of Ross and Zenou (2008). However, in this analysis we do not control for other factors that may be affecting these relationships, and the evidence presents a first descriptive analysis. In the following Section, we analyze these relationships, controlling for other factors.

## 1.4 Econometric analysis

### 1.4.1 Shirking at work and leisure

According to the theoretical framework, the key assumption in the model is that leisure and shirking at work are substitutes, and thus we should find a negative relationship between them. Hence, we analyze the relationship between leisure and shirking time, once we control for other observed factors that may condition this relationship. To that end, we limit the sample to employed individuals only, and estimate Equation 1.1 using Ordinary Least Squared (OLS), as follows:

$$S_{is} = \alpha_0 + \alpha_1 L_{is} + \alpha_2 X_{is} + \alpha_3 W_{is} + \alpha_s + \varepsilon_{is} \tag{1.1}$$

where $S_{is}$ represents the (log) of shirking time of a given individual $i$ living in Metropolitan Statistical Area (MSA) $s$, and $L_{is}$ represents the (log) of leisure time of that individual. This specification of the model resembles that of Ross and Zenou (2008). $X_{is}$ includes the set of sociodemographic characteristics described in Section 1.3, $W_{is}$ represents housing attributes, $\alpha_s$ represents MSA fixed effects, and $\varepsilon_{is}$ represents random variables capturing unmeasured factors and measurement errors.[12] Given that the ability to shirk across occupations and industries may vary, we also include occupation and industry fixed effects in our estimates. Regarding the information on the attributes of the household unit ($W_{is}$), we consider the information on whether the housing unit is owned or not, with the following options: "Owned or being bought by a household member"; "Rented for cash", and "Occupied without payment of cash rent" (reference category). Given the theoretical framework, we should expect that $\alpha_1 < 0$.

Columns (1) and (2) of Table 1.3 show the results of estimating Equation 1.1 for both supervised and non-supervised workers, respectively. We find that the time workers devote to leisure is negatively related to the time they devote to shirking at work, with this correlation being statistically significant at the 90% level in the case of the

[12] The information about the MSA of residence follows the US Census Bureau's categorization of metropolitan areas. Despite that the Census Bureau's terminology for metropolitan areas, and the classification of specific areas, changes over time, the general concept is consistent: a metropolitan area consists of a large population center and adjacent communities that have a high degree of economic and social interaction. The geographic information included in the ATUS includes the metropolitan area of residence of individuals.

Table 1.3: Shirking-leisure relationship

| | Log-shirking | |
|---|---|---|
| | Supervised | Non-supervised |
| VARIABLES | (1) | (2) |
| Log-leisure | -0.032* | -0.114*** |
| | (0.018) | (0.015) |
| Being male | 0.157** | -0.010 |
| | (0.074) | (0.049) |
| Years working | 0.000 | -0.018*** |
| | (0.006) | (0.005) |
| Years working sq. | 0.001 | 0.004*** |
| | (0.001) | (0.001) |
| Secondary ed. | -0.036 | -0.066 |
| | (0.051) | (0.063) |
| University ed. | -0.262*** | -0.366*** |
| | (0.056) | (0.058) |
| Being American | -0.356*** | -0.266*** |
| | (0.072) | (0.053) |
| Being Asian | -0.235 | 0.013 |
| | (0.158) | (0.127) |
| Being Pacific Isl. | -0.723* | 0.212 |
| | (0.402) | (0.367) |
| Being White | -0.271*** | -0.266*** |
| | (0.052) | (0.055) |
| Living in couple | -0.047 | -0.041 |
| | (0.039) | (0.037) |
| Couple's labor status | -0.068 | 0.041 |
| | (0.043) | (0.036) |
| Have children | -0.004 | -0.164*** |
| | (0.040) | (0.034) |
| Family size | 0.011 | 0.033** |
| | (0.018) | (0.015) |
| Constant | 0.155 | -9.837 |
| | (12.020) | (18.836) |
| MSA FE | Yes | Yes |
| Ind. and Occ. FE | Yes | Yes |
| Housing FE | Yes | Yes |
| Observations | 11,893 | 21,467 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-MSA level. The sample (ATUS 2003-2014) is restricted to employees who work the diary-day in supervised (Column 1) and non-supervised (Column 2) occupations. The dependent variable is the logarithms of daily minutes devoted to shirking. * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

supervised workers, and at the 99% level in the case of the non-supervised workers. Specifically, we find that a decrease of 10% in leisure time is related to increases of 0.32% and 1.11% in the time that employees devote to shirking activities at work. Then, the less time devoted to leisure activities, the more time workers devote to shirking at work, which points to the validity of the main assumption of Ross and Zenou (2008).

Furthermore, the negative relationship between shirking and leisure time is stronger for workers in non-supervised occupations, given its larger coefficient and higher level of significance. This difference may indicate that workers in non-supervised occupations find it easier to shirk at work, in comparison with supervised workers; once they are paid efficiency wages, workers in non-supervised occupations do not risk being fired when they shirk, while workers in supervised occupations may find it more difficult to shirk, due to monitoring.

### 1.4.2 Leisure, shirking at work and commuting time

We then analyze the relationship between leisure and commuting time, and between shirking at work and commuting time, which supposes the first empirical test on these relationships to the authors' knowledge. From the theoretical framework, if leisure and shirking at work are substitutes, we would expect to find a negative relationship between commuting and leisure time, and a positive relationship between commuting and shirking time. We limit the sample to employed individuals only, and estimate Equation 1.2 by OLS:

$$T_{is} = \alpha_0 + \alpha_1 C_{is} + \alpha_2 X_{is} + \alpha_3 W_{is} + \alpha_s + \varepsilon_{is} \tag{1.2}$$

where $T_{is}$ represents the (log) leisure or shirking time of a given individual $i$ living in MSA $s$, and $C_{is}$ represents the (log) commuting time of that individual. The vectors $X_{is}$, $W_{is}$ and $\alpha_s$ are the same as in Equation 1.1. We also include occupation and industry fixed effects in our estimates.

Columns (1) and (3) in Table 1.4 show the results of estimating Equation 1.2 on leisure and shirking time for workers in supervised occupations, and Columns (2) and (4) in Table 1.4 show the results of estimating Equation 1.2 on leisure and shirking time for workers in non-supervised occupations. We find that commuting time has a negative relationship with leisure for workers in both supervised and non-supervised occupations, with this relationship being statistically significant at the 99% level. An increase of

Table 1.4: Leisure- and shirking-commuting relationships

| | Log-leisure | | Log-shirking | |
|---|---|---|---|---|
| | Supervised | Non-supervised | Supervised | Non-supervised |
| VARIABLES | (1) | (2) | (3) | (4) |
| Log-commuting | -0.096*** | -0.135*** | 0.003 | 0.207*** |
| | (0.009) | (0.006) | (0.023) | (0.036) |
| Being male | 0.091*** | 0.159*** | 0.154** | -0.053 |
| | (0.034) | (0.023) | (0.070) | (0.048) |
| Years working | -0.014* | -0.027*** | 0.001 | -0.015*** |
| | (0.008) | (0.003) | (0.006) | (0.005) |
| Years working sq. | 0.003* | 0.006*** | 0.001 | 0.003** |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| Secondary ed. | 0.056 | 0.031 | -0.038 | -0.074 |
| | (0.041) | (0.074) | (0.051) | (0.065) |
| University ed. | 0.064 | 0.153** | -0.264*** | -0.371*** |
| | (0.045) | (0.065) | (0.057) | (0.062) |
| Being American | 0.135*** | 0.009 | -0.360*** | -0.226*** |
| | (0.040) | (0.031) | (0.073) | (0.054) |
| Being Asian | 0.286** | 0.245*** | -0.244 | 0.001 |
| | (0.125) | (0.059) | (0.163) | (0.127) |
| Being Pacific Islander | -0.373 | 0.453*** | -0.711* | 0.170 |
| | (0.302) | (0.131) | (0.406) | (0.349) |
| Being White | 0.099*** | 0.136*** | -0.274*** | -0.272*** |
| | (0.037) | (0.027) | (0.052) | (0.055) |
| Living in couple | 0.182*** | 0.179*** | -0.052 | -0.074** |
| | (0.058) | (0.041) | (0.040) | (0.036) |
| Couple's labor status | -0.059 | -0.030 | -0.067 | 0.048 |
| | (0.047) | (0.043) | (0.043) | (0.036) |
| Have children | -0.172*** | -0.137*** | 0.002 | -0.121*** |
| | (0.039) | (0.025) | (0.041) | (0.037) |
| Family size | 0.050*** | 0.041*** | 0.009 | 0.024 |
| | (0.013) | (0.011) | (0.018) | (0.017) |
| Constant | -3.495 | 1.258 | 0.273 | -12.674 |
| | (6.091) | (3.833) | (11.977) | (18.504) |
| MSA FE | Yes | Yes | Yes | Yes |
| Ind. and Occ. FE | Yes | Yes | Yes | Yes |
| Housing FE | Yes | Yes | Yes | Yes |
| Observations | 11,893 | 21,467 | 11,893 | 21,467 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-MSA level. The sample (ATUS 2003-2014) is restricted to employees who work the diary-day in supervised occupations (Columns 1 and 3), and non-supervised occupations (Columns 2 and 4). The dependent variable is the logarithms of the daily minutes devoted to leisure (Columns 1 and 2) and to shirking (Columns 3 and 4). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

10% in the time devoted to commuting by workers is related to decreases in leisure time of 0.96% and 1.35% for workers in supervised and non-supervised occupations, respectively. A $t$-type test of the equality of coefficients does not allow us to reject the null hypothesis of the equality of coefficients, and thus we cannot conclude that the magnitude of the relationship differs by the level of supervision. The negative relationship between commuting and leisure time contained in the model is confirmed by our results.

One important ambiguity in the Ross and Zenou (2008) model is that they do not know the magnitude of the negative relationship between commuting and leisure. Time use data allows for the minimization of measurement error in both commuting and leisure time, and thus we can estimate the magnitude of this relationship by analyzing partial correlations. Results indicate that this relationship is less than 1, since the elasticity is lower than unity, and the confidence intervals at the 95% confidence level all include values lower than one (e.g., -0.114, -0.775 and -0.147, -0.122 for workers in supervised and non-supervised occupations, respectively). This evidence indicates that, as commuting time increases, workers adjust their hours of work to limit the reduction in their leisure.

Focusing on the relationship between commuting and shirking time, we find mixed results, depending on the type of occupation. The conditional correlation between commuting and shirking time is positive and statistically significant at the 99% significance level for workers in non-supervised occupations, while it is not statistically significant in those occupations that can be considered as not supervised. For workers in non-supervised occupations, an increase of 10% in the time devoted to commuting is associated with an increase of 2.07% in the shirking time of workers. However, the correlation between commuting and shirking time for workers in supervised occupations indicates that an increase of 10% in the time devoted to commuting is associated with an increase of only 0.3% in shirking time. We find evidence that is consistent with Ross and Zenou (2008) regarding the relationship between commuting and shirking time, and our results indicate that workers in non-supervised occupations find it easier to shirk at work, in comparison with supervised workers.

### 1.4.3 Employment, wages and commuting time

We next focus on the relationship between commuting time and the hourly wages of employed workers. According to Ross and Zenou (2008), we should expect to find a positive relationship between commuting time and wages. These relationships are set in equilibrium under different scenarios (i.e., no observation, or observation of worker's location, respectively), and hence the estimation of conditional correlations between commuting and earnings is sufficient to test the existence of efficiency wages.[13] We estimate by OLS Equation 1.3, as follows:

$$\omega_{is} = \alpha_0 + \alpha_1 C_{is} + \alpha_2 X_{is} + \alpha_3 W_{is} + \alpha_s + \varepsilon_{is} \tag{1.3}$$

where $\omega_{is}$ represents the (log) hourly wage of a given individual $i$ living in MSA $s$, and $C_{is}$ represents the (log) time devoted to commuting by that individual. The vectors $X_{is}$, $W_{is}$ and $\alpha_s$ are the same as in Equations 1.1 and 1.2. We also include occupation and industry fixed effects in our estimates. Given the theoretical framework, the relationship between commuting and wages is expected to be positive, $\alpha_1 > 0$, consistent with the existing literature (Van Ommeren et al., 2000; Ross and Zenou, 2008; Rouwendal and Nijkamp, 2004; Dargay and Van Ommeren, 2005; Susilo and Maat, 2007; Ruppert et al., 2016; Giménez-Nadal et al., 2018c,b).

Columns (1) and (2) of Table 1.5 show the results of estimating Equation 1.3 for the sample of workers in supervised and non-supervised occupations, respectively. We find that commuting time is positively related to hourly wages for both supervised and non-supervised occupations, with this relationship being statistically significant at the 95% level. In particular, we find that an increase of 10% in commuting time is related to an increase in wages of 0.19% and 0.16% for workers in supervised and non-supervised occupations, respectively. A $t$-type test of the equality of coefficients does not allow us to reject the null hypothesis of the equality of coefficients, and thus we cannot assume that the magnitude of the relationship differs by the level of supervision of the occupations. This evidence is consistent with the existence of efficiency wages in the US, as firms can discriminate wages in an attempt to avoid shirking, although shirking is not fully eliminated, as workers still devote time to shirking activities.

Our results differ from those presented in Ross and Zenou (2008) because they find that efficiency wages only operate for occupations with high levels of supervision (e.g.,

[13]An alternative approach would be to estimate the causal effect of commuting on wages, where worker characteristics that affect commuting time, but not wages, are needed to identify such effect. Despite that we cannot talk about causality, Ross and Zenou (2008) establish that the analysis of conditional correlations is also valid in the current context. Prior research analyzing the causal effect of commuting on wages includes Mulalic et al. (2014) and Freund et al. (2015). We estimate the transformation to logarithms because the distribution of the variable does not follow a normal distribution (see Figure 1.A1 in the Appendix 1.A) and thus we try to normalize the variable by applying a log transformation.

Table 1.5: Wages- and employment-commuting relationships

| | Log-wage | | Employment | |
|---|---|---|---|---|
| VARIABLES | Supervised (1) | Non-supervised (2) | General (3) | Pred. commuting (4) |
| Log-commuting | 0.019** | 0.016** | - | -0.059** |
| | (0.009) | (0.007) | - | (0.029) |
| Being male | 0.218*** | 0.183*** | 0.027*** | 0.031*** |
| | (0.036) | (0.017) | (0.004) | (0.003) |
| Years working | 0.037*** | 0.037*** | 0.005*** | 0.005*** |
| | (0.003) | (0.002) | (0.001) | (0.001) |
| Years working sq. | -0.007*** | -0.007*** | -0.001*** | -0.001*** |
| | (0.001) | (0.000) | (0.000) | (0.000) |
| Secondary ed. | 0.212*** | 0.274*** | 0.095*** | 0.096*** |
| | (0.039) | (0.040) | (0.010) | (0.008) |
| University ed. | 0.330*** | 0.586*** | 0.138*** | 0.135*** |
| | (0.045) | (0.056) | (0.010) | (0.007) |
| Being American | 0.072*** | 0.039* | -0.050*** | -0.035*** |
| | (0.024) | (0.021) | (0.006) | (0.005) |
| Being Asian | 0.088 | 0.232*** | 0.091*** | 0.083*** |
| | (0.098) | (0.041) | (0.012) | (0.010) |
| Being Pacific Islander | -0.306 | 0.248* | 0.043 | 0.020 |
| | (0.223) | (0.140) | (0.044) | (0.044) |
| Being White | 0.157*** | 0.150*** | 0.105*** | 0.091*** |
| | (0.034) | (0.019) | (0.008) | (0.006) |
| Living in couple | 0.104*** | 0.171*** | 0.055*** | 0.058*** |
| | (0.025) | (0.027) | (0.007) | (0.006) |
| Couple's labor status | 0.076** | -0.014 | 0.000 | -0.001 |
| | (0.030) | (0.026) | (0.005) | (0.005) |
| Have children | 0.059* | 0.075*** | -0.008 | -0.003 |
| | (0.031) | (0.023) | (0.007) | (0.005) |
| Family size | -0.058*** | -0.060*** | -0.014*** | -0.018*** |
| | (0.008) | (0.009) | (0.002) | (0.002) |
| Constant | 21.429*** | 72.535*** | 0.662*** | 0.858*** |
| | (3.921) | (11.964) | (0.028) | (0.101) |
| MSA FE | Yes | Yes | Yes | Yes |
| Ind. and Occ. FE | Yes | Yes | No | No |
| Housing FE | Yes | Yes | Yes | Yes |
| Observations | 11,893 | 21,467 | 38,305 | 38,305 |

Note: Robust standard errors clustered at the Occupation-MSA level in parentheses of Columns (1) and (2). Bootstrapped (n=500) standard errors in parentheses of Columns (3) and (4). The sample (ATUS 2003-2014) is restricted to employees who work the diary-day in supervised occupations (Column 1) and non-supervised occupations (Column 2); unemployed individuals are included in Columns (3) and (4). The dependent variable is the logarithm of hourly wages in US dollars (Columns 1 and 2), and the dummy being employed (Columns 3 and 4). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

blue collar workers). However, Ross and Zenou (2008) argue that results for lightly-supervised occupations (e.g., white collar workers) are not robust, as their estimates may suffer from a weak instrument problem that biases their IV estimates towards OLS estimates. Within this framework, we choose OLS, given that the dataset allows for a more accurate measure of commuting time in comparison with prior research, and the use of predicted commuting would make this benefit marginal. Given that these relationships are obtained in the market equilibrium, we do not attempt to estimate causal effects, but rather we am interested in equilibrium relationships, and the estimation of conditional correlations using OLS is sufficient to test for the relationships predicted by the model. Furthermore, a firm can choose between more supervision and higher wages to compensate for the commuting-induced incentives to shirk. Accordingly, commuting should induce higher wages in occupations where firms cannot supervise. In contrast, in occupations where supervision is possible, firms can partly offset the necessary wage increases by increased offshoring. Thus, theoretically, there is no reason to think that commuting may have a stronger effect on wages in supervised occupations compared to occupations where supervision is not feasible.

Finally, we analyze the relationship between employment and commuting time, where a negative relationship is expected. One important issue is that commuting time is not observed for the unemployed, which leads to selection bias. Thus, we must predict the commuting time of unemployed individuals and, to that end, we follow Ross and Zenou (2008) and apply an approach based on the identification of the effect of location on outcomes, using cross-metropolitan variations (Cutler and Glaeser, 1997). This approach has been applied in a variety of studies, including Evans et al. (1992); Cutler and Glaeser (1997); Hoxby (2000), and Card and Rothstein (2007). Ross and Zenou (2008) identify the effect of commuting time by the exclusion from the labor market equation of certain factors that can explain commuting time differences. With this approach, the source of variation for identification comes from cross-metropolitan area differences in commuting times.

However, we cannot estimate specific models of commuting time for each MSA individually, as there are several MSAs with less than 30 observations and we must be cautious in making estimates for specific metropolitan areas. Alternatively, we interact the housing stock variables with region variables included in the ATUS, exploiting systematic differences between the structure of metro areas in different regions of the country. In particular, we interact the information regarding ownership (i.e., owned, rented, other) with the information on census region of residence (i.e., Northeast, Mid-west, South, West), and thus the model is identified by the exclusion from the labor market equation of the interaction of region fixed effects with the housing stock variables. we estimate by OLS a linear model on (log) commuting time, and we then predict (log) commuting times for both the employed and the unemployed.[14]

For the relationship between commuting and employment, we estimate by OLS the following linear model:[15]

$$E_{is} = \beta_0 + \beta_1 \hat{C_{is}} + \beta_2 X_{is} + \beta_3 W_{is} + \alpha_s + \varepsilon_{is} \tag{1.4}$$

where, for a given individual $i$ living in MSA $s$, $E_{is}$ is the dummy variable "employed" that takes value 1 if he/she is an employed worker, and value 0 if he/she is unemployed. $\hat{C_{is}}$ represents the log of commuting time of individual $i$ living in MSA $s$, predicted using the commuting model described in the previous paragraph. The vectors $X_{is}$, $W_{is}$ and $\alpha_s$ are the same as in Equations 1.1, 1.2 and 1.3. Given the theoretical framework, we expect commuting time to have a negative relationship with employment, i.e., $\beta_1 < 0$. We bootstrap the standard errors of the regressions, given that we are using generated variables in the model (Pagan, 1984; Murphy and Topel, 1985). We produce 500 replications, where a random sample with replacement is drawn from the total number of observations.

Column (3) of Table 1.5 shows the results of the key explanatory variables when we estimate Equation 1.4 for the employment regression without including commuting time, while Column (4) shows the results for employment when we include predicted commuting time. We find that commuting time presents a negative and statistically significant correlation with the probability of being employed.[16] Specifically, we find that an increase in commuting time of 10% is associated with a decrease in the probability of employment of 0.6%. These results are consistent with Ross and Zenou (2008), and can be interpreted as that employed workers are located closer to work places, compared to the unemployed from their potential work places.

[14]Summary statistics of the housing and census region variables, and the results of the commuting model, can be found in Tables 1.A1 and 1.A2 in the Appendix 1.A, respectively.

[15]We have alternatively estimated a Logit model on the probability of employment, and results are robust to the use of different econometric models. We thus rely on Equation 1.4, given that coefficients can be interpreted directly, and results for the Logit model are available upon request.

[16]Results may, in principle, be affected by sample selection issues, as the selection of employed and unemployed individuals may lead to the existence of subgroups with low labor market attachment. Thus, we have estimated the employment model with an alternative subsample, to minimize the share of individuals with a low labor market attachment. We have considered unemployed individuals who report looking for a job during the four weeks prior to the survey. Besides, we have predicted the time devoted to commuting separately by gender, and by the level of education. Results are robust and are shown in Table 1.A3 of the Appendix 1.A.

Regarding the consistency of our results, when we compare the coefficients from Columns (3) and (4), we can observe that the introduction of an imputed variable does not significantly bias the estimated coefficients, as coefficients for the other explanatory variables do not vary much, and their statistical significance remains. However, the limitation of the data regarding housing attributes may mean that these variables do not contain sufficient variation to identify the coefficients of commuting, leading to a problem analogous to the weak instrument problem.[17] Ross and Zenou (2008) acknowledge that they suffer from a weak instruments problem, and thus commuting time estimates trend toward zero, as estimates with weak instruments are biased towards the OLS estimates (Bound et al., 1995; Zivot et al., 1998). Thus, we have reasons to believe that results are also biased toward zero, and we are offering a lower bound of the relationship.

## 1.5 Conclusions

Analyses of employment and earnings and their spatial distribution are common, and a rich literature on the interactions with commuting time has emerged, where efficiency wage theory represents an important strand in this field of research. In this Chapter, we use a framework based on the model of Ross and Zenou (2008) on efficiency wages, where behavioral substitution between leisure time and effort at work is allowed. The relationship between leisure and shirking at work has not been previously analyzed, and we shed light on this relationship. We find positive evidence of the substitutability between leisure and shirking at work, and thus we offer a precise estimation of the magnitude of this relationship and provide empirical support to the Ross and Zenou (2008) assumption. Furthermore, our results confirm all the relationships derived from the model. We find that commuting time has a negative relationship with leisure, while it has a positive relationship with shirking time. Additionally, we find that commuting time presents positive relationships with unemployment and wages, which can be interpreted as evidence of efficiency wages, as firms can discriminate wages in

[17] We have tested the extent to which the instrument can be explained by observed predetermined attributes (e.g., gender, education), which would imply a source of bias. We have regressed predicted commuting time on the set of sociodemographic ($X_{is}$) variables used to predict commuting time (e.g., region fixed effects and type of ownership), and we then run an $F$-test for whether the demographics can explain expected commuting. We obtain that the $F$-test is significant. Thus, predicted commuting can be explained by observed predetermined attributes and so is likely to be correlated with unobserved attributes, which implies a source of bias. This is also the case in Ross and Zenou (2008), who argue that cross-metropolitan differences in the spatial distribution of owner-occupied housing is not clearly exogenous, and we acknowledge that results for employment may be biased.

terms of location in an attempt to deter shirking.

Furthermore, the shirking time of non-supervised occupations is affected by commuting time, perhaps because they do not risk being fired if they shirk. If workers are not supervised, with longer commuting times they have less leisure time and should thus be more likely to shirk (as shirking and leisure are substitutes). Being non-supervised, they do not risk their jobs, so they are not deterred from shirking. On the contrary, the shirking time of supervised occupations is not affected by commuting time, which is consistent with the fact that, if workers are paid efficiency wages, then firms would pay higher wages when commuting distance increases, to discourage shirking. Due to the higher wages, workers' incentives to shirk decline, so there is no net effect on shirking time.

Other authors have analyzed commuting and wages, such as in the Fu and Ross (2013) model of agglomeration economies. These authors find that wage premia arise from location differences (both agglomeration and productivity), finding a positive association between workplace agglomeration and wages, robust to residential location fixed effects. Their model implies that commuting should correlate with wages, in order to ensure that similar individuals have the same utility across different work locations, even though wages differ across these locations. The efficiency wage model has a different implication, because real wages vary based on individual commutes. The results presented in this paper regarding commuting, shirking, and leisure provide empirical support to the Ross and Zenou (2008) model on efficiency wages. Further analysis of the existence of efficiency wages in other countries is proposed as a promising line of research.

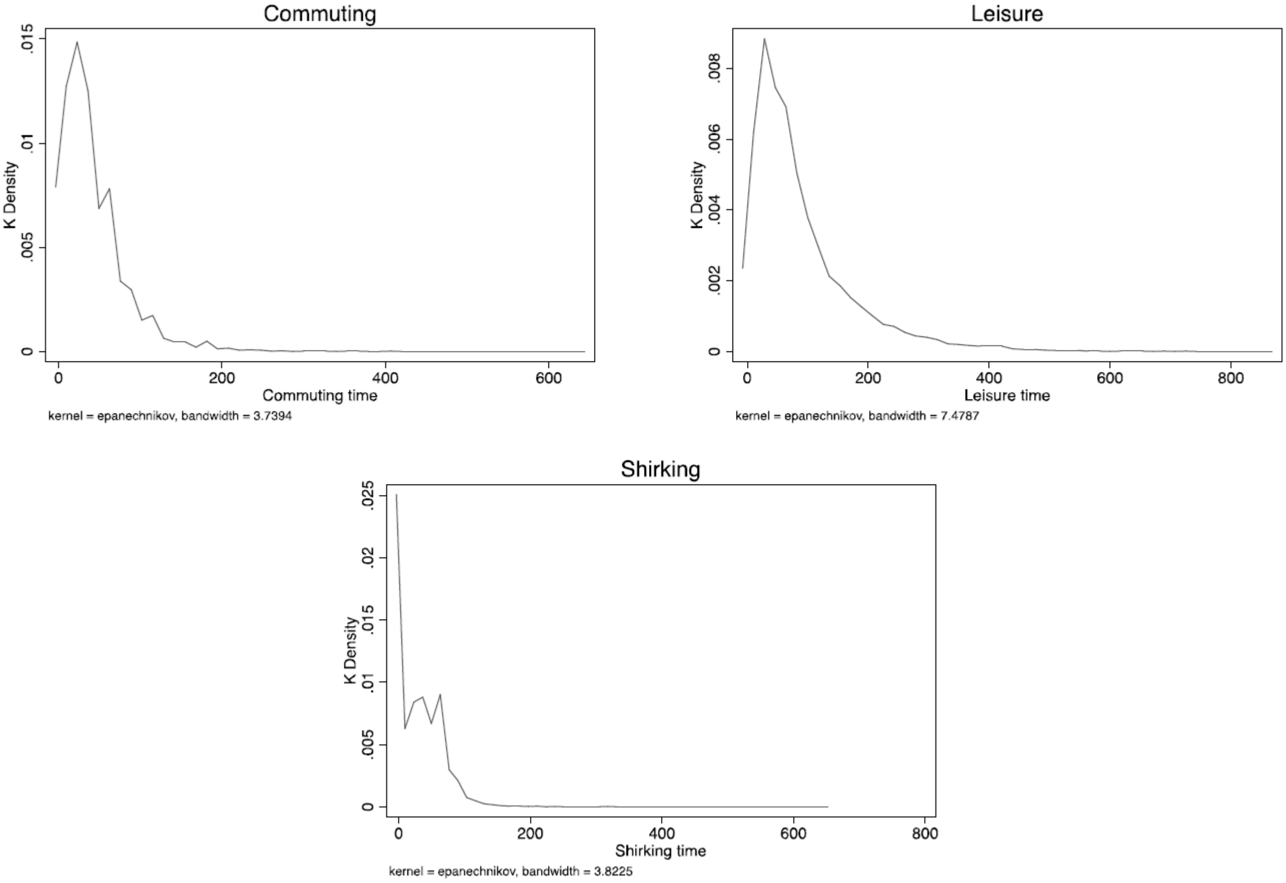
Despite that we do not deal with causality, which may represent a limitation in the current context, the theoretical framework allows us to analyze conditional correlations, in order to test the model and determine whether efficiency wages operate in labor markets. However, in our analysis, we only consider the supply side of the job market, in the sense that only worker decisions are analyzed, and the demand side of job positions is not considered. This limitation is important in the current context, as for instance, the availability of jobs is important in determining whether individuals remain unemployed or prefer to be employed. Further analysis should extend our results by incorporating the supply side of the market.

Finally, one limitation of the paper is that we have considered the amount of time devoted to non-work activities in the work place as a measure of shirking behavior.

However, we must acknowledge that this is an incomplete measure of effort at work. Becker (1985) assumes that firms buy a package of time and effort (i.e., intensity of work) from each worker, and payments to workers are according to these two components. Thus, the first component refers to the amount of time devoted to work, while the second component refers to the intensity of workers while doing their work tasks. According to this definition of effort at work (amount of time and intensity of worked hours), shirking behavior could well affect the hours of work, the intensity of worked hours, or both. In the current context, we are only considering shirking behavior referred to hours of work, but the intensity of work is not taken into account, which may help to explain our result that, for workers in supervised occupations, shirking time is not affected by commuting time. Monitoring practices in supervised occupations imply that such workers risk their jobs if they shirk, and they may find it more beneficial to modify the intensity of their work tasks. Further analysis should extend our results by incorporating this aspect.

# Appendix 1.A: Additional results

Figure 1.A1: K-density of commuting, leisure and shirking




Note: The sample (ATUS 2003-2014) is restricted to employed individuals. Commuting, leisure, and shirking are measured in daily minutes.

Table 1.A1: Summary statistics - Commuting model

| | Employed | | Unemployed | | Difference | |
|---|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | Diff. | $p$-value |
| Type of tenure | | | | | | |
| Owned | 0.704 | 0.457 | 0.560 | 0.496 | 0.144 | (<0.001) |
| Rented | 0.284 | 0.451 | 0.422 | 0.494 | -0.138 | (<0.001) |
| Other | 0.012 | 0.107 | 0.018 | 0.131 | -0.006 | (<0.001) |
| Region of residence | | | | | | |
| North-East | 0.181 | 0.385 | 0.177 | 0.381 | 0.004 | (0.005) |
| Mid-West | 0.261 | 0.439 | 0.231 | 0.421 | 0.030 | (0.009) |
| South | 0.345 | 0.475 | 0.348 | 0.476 | -0.003 | (0.014) |
| West | 0.213 | 0.213 | 0.244 | 0.429 | -0.031 | (<0.001) |
| Observations | 33,360 | | 5,651 | | | |

Note: The sample (ATUS 2003-2014) is restricted to employees who work the diary-day, or to unemployed individuals. Differences are defined as the mean value of the correspondent variable for private sector employees (supervised employees), minus the corresponding value for the unemployed (non-supervised employees). $T$-test $p$-values for the mean differences in parentheses.

Table 1.A2: Commuting model

| VARIABLES | Commuting time (1) |
|---|---|
| Owned* | |
| North-East | 14.952*** |
| | (4.812) |
| Mid-West | 6.385 |
| | (4.758) |
| South | 9.837** |
| | (4.756) |
| West | 11.305** |
| | (4.790) |
| Rented* | |
| North-East | 15.824*** |
| | (4.940) |
| Mid-West | 3.806 |
| | (4.841) |
| South | 8.788* |
| | (4.813) |
| West | 10.064** |
| | (4.872) |
| Rest of tenure* | |
| Mid-West | -8.018 |
| | (6.042) |
| South | -1.161 |
| | (5.500) |
| West | -3.229 |
| | (9.554) |
| Constant | 31.340*** |
| | (4.721) |
| Observations | 33,360 |

Note: Robust standard errors in parentheses. The sample (ATUS 2003-2014) is restricted to private sector employees who work the diary-day. The dependent variable is the daily minutes devoted to commuting. * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

Table 1.A3: Alternative employment models

| VARIABLES | Searching (1) | Gender (2) | Education (3) |
|---|---|---|---|
| Log-commuting | -0.059** | -0.050** | -0.067*** |
| | (0.028) | (0.024) | (0.026) |
| Being male | 0.031*** | 0.040*** | 0.031*** |
| | (0.003) | (0.006) | (0.003) |
| Years working | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) |
| Years working sq. | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Secondary ed. | 0.096*** | 0.096*** | 0.095*** |
| | (0.008) | (0.008) | (0.008) |
| University ed. | 0.135*** | 0.135*** | 0.145*** |
| | (0.008) | (0.008) | (0.009) |
| Being American | -0.035*** | -0.035*** | -0.035*** |
| | (0.006) | (0.005) | (0.006) |
| Being Asian | 0.083*** | 0.083*** | 0.083*** |
| | (0.010) | (0.010) | (0.010) |
| Being Pacific Islander | 0.020 | 0.019 | 0.020 |
| | (0.045) | (0.043) | (0.046) |
| Being White | 0.091*** | 0.091*** | 0.091*** |
| | (0.006) | (0.006) | (0.006) |
| Living in couple | 0.058*** | 0.058*** | 0.058*** |
| | (0.006) | (0.006) | (0.006) |
| Couple's labor status | -0.001 | -0.001 | -0.001 |
| | (0.005) | (0.005) | (0.005) |
| Have children | -0.003 | -0.003 | -0.003 |
| | (0.005) | (0.005) | (0.006) |
| Family size | -0.018*** | -0.018*** | -0.018*** |
| | (0.002) | (0.002) | (0.002) |
| Constant | 0.858*** | 0.822*** | 0.875*** |
| | (0.096) | (0.080) | (0.087) |
| MSA FE | Yes | Yes | Yes |
| Housing FE | Yes | Yes | Yes |
| Observations | 38,305 | 38,305 | 38,305 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (ATUS 2003-2014) is restricted to employees and unemployed individuals. Column (1) shows the results when we restrict the sample of unemployed individuals to those who were actively searching for a job in the last 4 weeks prior to the survey. Column (2) shows the results of estimating the model when we predict the commuting time separately by gender, and Column (3) the results of estimating the model when we predict the commuting time separately by education (university education vs. non-university education). The dependent variable is the dummy "Being employed". * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

# Appendix 1.B: The case of Spain

This Appendix 1.B analyzes the existence of efficiency wages in the Spanish labor market, under the Ross and Zenou (2008) urban efficiency wage theoretical framework. Using data from the Spanish Time Use Survey from years 2009-2010, results support the main hypothesis of urban efficiency wage models. In particular, among the findings are that leisure and shirking at work are substitutes, there is a negative relationship between commuting and leisure, and positive relationships between commuting-shirking at work and commuting-wages. Furthermore, supervision mechanisms at work have an effect on the ability of workers to shirk, although shirking cannot be fully eliminated. The contribution of the Appendix is, then, twofold. First, we analyze the benchmark hypothesis of substitution between leisure and shirking in Spain. This represents the second test of this relationship in the literature. Second, we study whether urban efficiency wages operate in Spain by testing the different implications of the model in terms of time endowments and wages. To the best of the authors' knowledge, this constitutes the first empirical analysis of urban efficiency wages in Spain using time use data.

## Literature review

Most of the literature about urban efficiency wages is either theoretical or focused on countries such as the US, China, and the UK, and the particular case of Spain has not appeared in the literature, to the best of our knowledge. Existing research has analyzed commuting, wages, and employment in Spain, within different urban and regional frameworks. For instance, Casado-Díaz (2000) analyzed the regionalization of local labor markets in Spain. Romani et al. (2003) analyzed commutes and residential moves in the period 1986-1996. Royuela and Vargas (2009) addressed the relationship between commutes and housing market regions. Mohíno et al. (2017) described the evolution of commuting and urban structures in regions that had transformed from rural to metropolitan. Sebastian (2018) studied employment polarization and employment share growths in terms of wages.

### Time use surveys in Spain

In this Appendix, we use data from the Spanish Time Use Survey (STUS) to study the different relationships that emerge from the Ross and Zenou (2008) model. Time use surveys are based on diaries where respondents report their activities through a period of time (a day in the case of the American Time Use Survey, or a week in other surveys, such as the Dutch and Latin American time use surveys), and have been reported to have some advantages over other surveys using stylized questionnaires. Specifically, diary-based surveys provide more accurate measures of time allocations, and lead to fewer measurement errors, more accurate measurement of patterns of activities, and more reliable estimates (Bianchi et al., 2000; Bonke, 2005; Yee-Kan, 2008; Harms et al., 2019). Several studies have appeared in the literature in recent years exploiting time use surveys for different purposes and have become one of the preferred tools to study time use decisions regarding leisure, paid work, unpaid work, and childcare, among others (Hamermesh, 1999; Aguiar and Hurst, 2007; Guryan et al., 2008; Hamermesh and Stancanelli, 2015; Jara-Díaz and Rosales-Salas, 2015; Stone and Schneider, 2016).

Time use surveys were introduced in Spain in the year 2002, and again in the years 2009-2010.[18] Both surveys belong to the Harmonized European Time Use Surveys (HETUS) of the Eurostat, corresponding to the 2000 and 2010 waves of the HETUS, respectively. However, contrarily to other countries, such as the United States, where the American Time Use Survey is conducted every year, these two waves constitute the only time use data available for Spain.

Several authors have used the STUS for different purposes. For instance, Ateca-Amestoy (2010) studied participation in cultural activities in Spain to discuss resource allocations. Gutiérrez-Domènech (2010) analyzed the allocation of childcare time across gender, employment and other sociodemographic and economic characteristics, finding that childcare is determined by whether working days end by 6pm. García et al. (2011) examine the allocation of individual time to physical activity and sport, finding gender-driven differences based on different decision-making processes. Álvarez and Miles-Touya (2012) and Giménez-Nadal et al. (2017) studied intergenerational transmissions of housework within families. Giménez-Nadal and Sevilla (2014) analyzed changes in time-allocation decisions, with a focus on labor supply, of the Spanish population between the 2002-2003 and the 2009-2010 STUS. Giménez-Nadal and Molina (2014) studied the relationship between time allocations of unemployed workers and regional unemployment rates. Gracia (2014) tackled child development and gender equity to show how fathers' and mothers' education, employment, and childcare time have an impact on children's educational development. Finally, Gracia and Kalmijn (2016)

[18] The Basque Country Time Budget Survey represents the first time-use survey available in Spain, although it is limited to the Basque Country and is not representative of the Spanish population as a whole.

analyzed the relationships between work schedules and different forms of leisure, including leisure with the family, with couples, time spent with children, and non-family leisure.

## STUS data and variables

We use data from the Spanish Time Use Survey (STUS, or "*Encuesta de Empleo del Tiempo*"), for the years 2009-2010. The STUS is conducted by the Spanish Institute of Statistics ("*Instituto Nacional de Estadística*", INE), with the goal of providing information about time allocation decisions of Spanish households. The STUS is intended to cover a representative sample of Spanish individuals, covering the 24 hours of one day (from 6am to 6am of the next day), and all the days of the week.

The STUS is based on diaries, so it can be used to compute the time devoted to different activities in 10-minute bands. Specifically, the STUS includes a series of main activities reported by respondents, along with secondary activities, the presence of others while doing such activities, and the place where activities are taking place (including, for instance, home, workplace, or means of transport, among others). Furthermore, activities are coded according to Eurostat's HETUS harmonized activities, and ten aggregated time uses are pre-defined (personal care, paid work, study, housework and care of relatives, voluntary work and meetings, social life, sports and out-of-home leisure, social media and Internet, communications, and trips).

The sample used throughout the analysis is restricted to employees between 16 and 65 years of age who filled in diaries on working days, defined as those days in which workers spend more than 60 minutes working (excluding commuting), consistent with the main text. The final sample consists of 4,496 employed individuals, of which 2,439 (54.2%) are men, and 2,058 (45.8%) are women. Employees in the sample are classified in two groups, i.e., (heavily) supervised and non- (or slightly) supervised workers, in terms of their occupation. For instance, the STUS includes ten categories of occupations. We follow Levenson and Zoghi (2006) and Ross and Zenou (2008), and define Office and administrative support; Farming, fishing, and forestry; Construction and extraction; Installation, maintenance, and repair; Production; and Transportation as (heavily) supervised occupations. That leaves Business administration; Technicians and scientific professionals; Support technicians and professionals; and Sales as non- (slightly) supervised occupations. In our sample, 38.7% of females work in supervised occupations, against 54.5% of their male counterparts. That leaves 61.3% of the females and 45.5% of the males working in non-supervised occupations.

The information included in the STUS allows us to define the time uses required to empirically analyze the assumptions and predictions of the theoretical model, including shirking at work, leisure, and commuting. The time devoted to shirking at work is defined following the definition in the main text. Specifically, shirking time is defined as the time spent at the workplace that is not reported as paid work, which includes time devoted at work to leisure, Internet shopping, or the use of social media, among others. The time devoted to leisure is defined as in Aguiar and Hurst (2007), including social life, sports, out-of-home leisure, and home leisure. The time spent commuting to/from work is defined in terms of the STUS code "910" (activity "*Trayectos de ida o vuelta al trabajo*").[19] Table 1.B1 shows the average times of shirking, leisure and commuting, differentiating between (heavily) supervised and non- (slightly) supervised workers, and including sample weights provided by the STUS. Supervised workers spend 172.4 minutes per day in leisure activities, against the 173.3 minutes spent by non-supervised workers, with this difference not being significant at standard levels. Regarding the time spent shirking at work, workers in supervised occupations spend 10.0 minutes shirking, vs 15.8 minutes spent by workers in non-supervised occupations, with this difference being highly significant ($p < 0.001$). Finally, supervised and non-supervised workers spend 59.8 and 53.3 minutes per day commuting to/from work, with this difference again being significant at the 99% level ($p = 0.003$).

Besides these main time-use variables, the STUS includes a range of information on sociodemographic and economic factors. The following variables are defined: gender, age, education level (two dummies are defined: secondary education, and University education, in terms of the ISCED), being Spanish, living in couple, having children, and the number of individuals in the household. Summary statistics of these variables are shown in Table 1.B1. The STUS also includes information on monthly labor earnings, and hourly wages are defined in terms of middle points, divided by monthly hours of work.[20] Table 1.B1 shows that the average hourly wage of supervised workers is 6.4 Euros/hour, while the analogous wage for their non-supervised counterparts is 8.3 Euros/hour. This difference (which is significant at standard levels, $p < 0.001$) could

[19] We must acknowledge that commuting times defined in terms of this activity coded "910" could lead to measurement errors, as time spent doing ancillary activities while commuting are coded as different activities. For example, a trip from home to a child's school, and from the school to the workplace, is classified as two categories: the first one (home-child's school) refers to trips related to childcare, while the second one (child's school-workplace) is defined as commuting.

[20] Income is defined in terms of the following groups: less than 600 Euros, 600-1200 Euros, 1200-1600 Euros, 1600-2000 Euros, 2000-2500 Euros, 2500-3000 Euros, more than 3000 Euros.

be driven by the fact that non- or slightly supervised occupations are characterized by a higher level of specialization than supervised occupations.

## Empirical results

Four aspects of the Ross and Zenou (2008) model are to be tested: 1) A negative correlation between leisure and shirking. 2) A negative correlation between leisure and commuting. 3) A positive correlation between shirking and commuting. 4) A positive correlation between wages and commuting. The STUS does not include the required information to replicate the employment analysis, as housing stock variables, or other variables required to instrument commutes in a reliable way are not included. Control variables in the equations to be estimated include: being male, age, age squared, secondary education, university education, being Spanish, living in couple, having children, family size, region (NUTS-2) fixed effects, and occupation fixed effects. Estimates include sample weights provided by the STUS, and robust standard errors are clustered at the regional and occupation level. All time uses are included in the equations in logarithms, so estimated coefficients can be interpreted as the estimated elasticities between these magnitudes, as in the main text.

### Shirking at work and leisure

Results of estimating the relationship between shirking at work and leisure time are shown in Table 1.B2. Column (1) shows estimates for supervised employees, while Column (2) shows analogous estimates for their non-supervised counterparts. The elasticity between shirking and leisure is found to be negative and highly significant, regardless of the supervision status of workers. For instance, a 10% increase in the time spent in leisure is associated with a 1.31% and 1.54% decrease in the time spent shirking at work among supervised and non-supervised workers, respectively. These coefficients do not differ at standard levels, according to a t-type test ($p = 0.392$).

Results are consistent with the urban efficiency wage theory in general terms, and confirm the benchmark hypothesis of the Ross and Zenou (2008) model regarding the substitution relationship between leisure and shirking at work. For the remaining explanatory variables, results indicate that male workers tend to shirk more than their female counterparts. However, none of the remaining explanatory variables are found to be significantly correlated to the time spent shirking at work.

**Leisure, shirking at work, and commuting time**

Results of estimating the relationship between leisure and commuting time are shown in Columns (1) and (2) of Table 1.B3, for supervised and non-supervised employees, respectively. The elasticity between commuting and leisure is negative, but only significant for unsupervised workers. Specifically, a 10% increase in commuting time is associated with a 0.95% decrease in the time available for leisure for non-supervised workers. For supervised workers, results show an elasticity of -0.067, not different from 0 at standard levels. These results suggest that commuting time is a shock to time endowments, as expected, which has a small impact on the time available for leisure. However, this impact is significant only for employees working in non-supervised occupations.

Regarding the rest of the explanatory variables, males spend more time in leisure activities than females, but only in supervised occupations. On the contrary, age shows a U-shaped relationship with leisure time, but only among non-supervised workers. Spanish workers in supervised occupations also enjoy more leisure than their non-Spanish counterparts, while workers with children enjoy less leisure than workers without children, both among supervised and non-supervised occupations. Finally, family sizes are negatively related to leisure times, with this relationship being significant only for non-supervised employees.

Columns (3) and (4) of Table 1.B3 show estimates of the relationship between shirking at work and commuting time for supervised and non-supervised employees, respectively. The conditional correlation between commuting and shirking is found to be positive and significant for both supervised and non-supervised workers. For instance, a 10% increase in commuting time is associated with an increase of 1.8% and 5.17% in the time spent shirking at work for supervised and non-supervised workers, respectively. The difference between supervised and non-supervised workers is highly significant ($p = 0.009$).

Interestingly, the impact of commuting on shirking is larger than both the impact of commuting on leisure and the impact of leisure on shirking. Thus, although the main conclusion that can be read from Tables 1.B2 and 1.B3 is that assumptions and predictions of the Ross and Zenou (2008) model in terms of time endowments are supported by the data, results indicate that commuting time has an additional impact on shirking behaviors, beyond that of leisure time, especially among unsupervised workers.

For the rest of explanatory variables in Columns (3) and (4) of Table 1.B3, male workers tend to shirk more than their female counterparts (robust to the estimates in Table 1.B2). In addition, for non-supervised employees, workers with a University education level, or who live in couple, report lower levels of shirking at work, while the presence of children in the household is associated with more shirking at work, as expected, given the increased pressure from childcare at home and the absence of supervision mechanisms.

#### Wages and commuting time

Results of estimating the relationship between wages and commuting time are shown in Columns (1) and (2) of Table 1.B4, for supervised and non-supervised employees, respectively. Given that wages are defined in terms of bracketed labor income, and then are subject to potential measurement error, estimates are replicated including reported labor income, in brackets, in Columns (3) and (4), where ordered logit models are estimated, controlling for the weekly working hours of individuals.

Results in Columns (1) and (2) show a positive and non-significant elasticity between commuting and wages for both supervised and non-supervised workers. However, ordered logit estimates in Columns (3) and (4) show a positive correlation between log-commuting times and labor income, which is significant at the 99% level for supervised and non-supervised workers, but stronger for the former ($p < 0.001$). As a consequence, estimates suggest the existence of measurement errors in the estimation of the commuting-wages elasticity, as ordered logit models show results highly compatible with the Ross and Zenou (2008) urban efficiency wage model, and in line with prior research reporting a positive correlation between income and commuting.

Finally, regarding the rest of the explanatory variables, and focusing on estimates in Columns (3) and (4), results show that males report higher income than females, and age is related to income following an inverted-U shape. Education is positively correlated with income, while Spanish workers, and workers who live in couple or who have children also report higher income than their counterparts. Finally, family size is negatively associated with income, while working hours show a positive conditional correlation.

## Results for Aragón

Finally, the same analyses are replicated for the case of Aragón. It has to be noted that cross-region equations could be estimated but, unfortunately, sample sizes would be too small for proposing a rigorous analysis. (A table of conditional correlations for all the Spanish regions is available upon request.) Consequently, an alternative approach is proposed, where I interact a dummy variable that takes value 1 for those individuals who reside in Aragón (0 otherwise) with the main explanatory variables. That way, such interaction represents any additional (and regional-specific) effect than that captured by the main variable.

Results are shown in Table 1.B5. Estimates indicate that, in any of the four models estimated, Aragón shows different trends than those observed in Spain in general terms. Consequently, results indicate that the urban labor market of Aragón shows the same characteristics than that at the national level, where time uses are consistent with the model, and earnings point to the payment of efficiency wages according to the sign of the elasticity between wages and commuting.

## Conclusions

This Appendix tests urban efficiency wages using Spanish time use data from years 2009-2010, under the Ross and Zenou (2008) theoretical framework. The empirical results are consistent with model assumptions and is the first empirical analysis to report a substitution relationship between leisure time and shirking at work in Spain. Furthermore, results are also in line with the implications of the Ross and Zenou (2008) model in terms of time endowments, as results show a negative impact of commuting on leisure time, and a positive impact on the time spent shirking at work, which is stronger for workers in non-supervised occupations. In fact, results suggest that commuting has an additional impact on shirking behaviors through the substitution relationship between shirking and leisure. Finally, results show a positive correlation between commuting and labor income, consistent with the theoretical framework and with a number of prior analyses studying these relationships in other countries.

Setting aside potential measurement errors and different definitions of activities between the STUS and the American Time Use Survey, results show significant differences compared to the US. For instance, workers report more leisure, less shirking, and longer commutes in Spain than in the US. Furthermore, the relationship between leisure and shirking is estimated to be stronger in the US than in Spain for supervised workers, while the opposite is found for unsupervised workers. On the other hand, commuting seems to have a larger impact on leisure time in the US than in Spain, but the elasticity between commuting and shirking is greater in Spain, especially for workers in non-supervised occupations.

The empirical analysis has certain implications for employers and firms, as it may allow us to distinguish which types of workers are more prone to participate in shirking behaviors while at work, thus decreasing their performance at work and their productivity. Furthermore, both leisure and commuting are found to be significantly related to shirking, although these correlations are stronger among non-supervised employees. This indicates that supervision mechanisms influence the ability of workers to shirk, although they cannot completely eliminate shirking. In that way, increasing wages for workers with longer commutes may act as an incentive to workers to reduce their shirking behaviors.

The empirical analysis has certain limitations. First, estimates cannot be interpreted as causal results, and there may be endogeneity issues between commuting, wages, and other time uses. However, as the model is a general equilibrium model, conditional correlations are sufficient. Second, income is defined in brackets in the STUS, so wages potentially suffer from measurement error. Third, some of the estimated correlations are significant at standard levels but quantitatively small, suggesting that the processes analyzed may not be quantitatively relevant.

Table 1.B1: Summary statistics

| VARIABLES | Supervised | | Non-supervised | | Difference | |
|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Diff. | $p$-value |
| Leisure time | 172.411 | 111.448 | 173.261 | 111.389 | -0.850 | (0.502) |
| Shirking time | 9.986 | 40.433 | 15.796 | 48.843 | -5.810 | (<0.001) |
| Commuting time | 59.834 | 46.775 | 53.302 | 39.264 | 6.533 | (0.003) |
| Hourly earnings | 6.437 | 3.069 | 8.253 | 4.397 | -1.816 | (<0.001) |
| Being male | 0.628 | 0.483 | 0.498 | 0.500 | 0.130 | (<0.001) |
| Years working | 24.798 | 12.333 | 22.630 | 11.857 | 2.169 | (<0.001) |
| Years working squared | 7.670 | 6.851 | 6.526 | 6.123 | 1.144 | (<0.001) |
| Primary education | 0.279 | 0.449 | 0.125 | 0.330 | 0.155 | (<0.001) |
| Secondary education | 0.638 | 0.481 | 0.520 | 0.500 | 0.118 | (<0.001) |
| University education | 0.083 | 0.276 | 0.356 | 0.479 | -0.273 | (<0.001) |
| Being Spanish | 0.795 | 0.404 | 0.899 | 0.301 | -0.105 | (<0.001) |
| Living in couple | 0.753 | 0.431 | 0.707 | 0.455 | 0.046 | (0.091) |
| Have children | 0.088 | 0.284 | 0.139 | 0.346 | -0.050 | (<0.001) |
| Family size | 3.340 | 1.222 | 3.241 | 1.207 | 0.099 | (0.115) |
| Observations | 2,126 | | 2,371 | | | |

Note: The sample (STUS 2009-2010) is restricted to employees who work the diary-day. Commuting, leisure and shirking times are measured in daily minutes. Hourly earnings are measured in Euros. Gender takes the value 1 for men and 0 for women. Years working squared is defined as the square of years working, divided into 10. Differences are defined as the mean value of the correspondent variable for supervised employees, minus the corresponding value for non-supervised employees. $T$-test $p$-values for the mean differences in parentheses.

Table 1.B2: Shirking-leisure relationship

| | Log-shirking | |
|---|---|---|
| | Supervised | Non-supervised |
| VARIABLES | (1) | (2) |
| Log-leisure | -0.131*** | -0.154*** |
| | (0.016) | (0.021) |
| Being male | 0.240*** | 0.127** |
| | (0.048) | (0.050) |
| Years working | 0.002 | -0.001 |
| | (0.006) | (0.010) |
| Years working sq. | -0.016 | 0.002 |
| | (0.012) | (0.016) |
| Secondary ed. | -0.122 | -0.029 |
| | (0.075) | (0.065) |
| University ed. | -0.151 | -0.163 |
| | (0.125) | (0.104) |
| Being Spanish | 0.067 | -0.062 |
| | (0.063) | (0.066) |
| Living in couple | -0.032 | -0.063 |
| | (0.054) | (0.058) |
| Have children | -0.003 | 0.004 |
| | (0.058) | (0.129) |
| Family size | 0.005 | -0.010 |
| | (0.015) | (0.022) |
| Constant | 6.508*** | 6.254*** |
| | (0.199) | (0.192) |
| Region FE | Yes | Yes |
| Occupation FE | Yes | Yes |
| Observations | 2,126 | 2,370 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-Region level. The sample (STUS 2009-2010) is restricted to employees in supervised occupations (Column 1) and non-supervised occupations (Column 2). The dependent variable is the logarithms of daily minutes devoted to shirking. * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

Table 1.B3: Leisure- and shirking-commuting relationships

| | Log-leisure | | Log-shirking | |
|---|---|---|---|---|
| | Supervised | Non-sup. | Supervised | Non-sup. |
| VARIABLES | (1) | (2) | (3) | (4) |
| Log-commuting | -0.067 | -0.095*** | 0.180*** | 0.517*** |
| | (0.045) | (0.026) | (0.044) | (0.117) |
| Being male | 0.209** | 0.106 | 0.167*** | 0.097* |
| | (0.100) | (0.091) | (0.048) | (0.052) |
| Years working | -0.019 | -0.023** | 0.004 | 0.011 |
| | (0.013) | (0.010) | (0.005) | (0.008) |
| Years working sq. | 0.034 | 0.051*** | -0.016 | -0.014 |
| | (0.023) | (0.019) | (0.012) | (0.013) |
| Secondary ed. | 0.112 | 0.095 | -0.099 | -0.038 |
| | (0.098) | (0.176) | (0.068) | (0.054) |
| University ed. | 0.173 | 0.294 | -0.156 | -0.215** |
| | (0.151) | (0.193) | (0.111) | (0.088) |
| Being Spanish | 0.361* | 0.248 | 0.023 | -0.023 |
| | (0.183) | (0.222) | (0.053) | (0.068) |
| Living in couple | 0.052 | -0.004 | -0.054 | -0.101* |
| | (0.075) | (0.073) | (0.048) | (0.057) |
| Have children | -0.223* | -0.297* | 0.054 | 0.157* |
| | (0.123) | (0.155) | (0.050) | (0.082) |
| Family size | -0.040 | -0.070** | 0.012 | 0.013 |
| | (0.037) | (0.032) | (0.015) | (0.019) |
| Constant | 5.236*** | 5.327*** | 5.163*** | 3.495*** |
| | (0.319) | (0.276) | (0.218) | (0.435) |
| Region FE | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes |
| Observations | 2,126 | 2,370 | 2,126 | 2,370 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-Regional level. The sample (STUS 2009-2010) is restricted toemployees in supervised occupations (Columns 1, 3), and non-supervised occupations (Columns 2, 4). The dependent variable is the logarithms of the daily minutes devoted to leisure (Columns 1 and 2) and to shirking (Columns 3 and 4). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

Table 1.B4: Wages-commuting relationship

| | Log-wage | | Ordered logit | |
|---|---|---|---|---|
| VARIABLES | Supervised (1) | Non-sup. (2) | Supervised (3) | Non-sup. (4) |
| Log-commuting | 0.006 | 0.002 | 0.119*** | 0.050*** |
| | (0.005) | (0.005) | (0.000) | (0.000) |
| Being male | 0.033*** | 0.048*** | 1.208*** | 0.895*** |
| | (0.009) | (0.013) | (0.000) | (0.000) |
| Age | 0.006*** | 0.011*** | 0.106*** | 0.140*** |
| | (0.001) | (0.002) | (0.000) | (0.000) |
| Age squared | -0.009*** | -0.015*** | -0.176*** | -0.198*** |
| | (0.003) | (0.003) | (0.000) | (0.000) |
| Secondary education | 0.032** | 0.107*** | 0.412*** | 1.277*** |
| | (0.015) | (0.033) | (0.000) | (0.000) |
| University education | 0.057** | 0.224*** | 0.922*** | 2.651*** |
| | (0.025) | (0.037) | (0.000) | (0.000) |
| Being Spanish | 0.044*** | 0.013 | 0.684*** | 0.440*** |
| | (0.017) | (0.036) | (0.000) | (0.000) |
| Living in couple | 0.030** | -0.002 | 0.353*** | 0.056*** |
| | (0.014) | (0.022) | (0.000) | (0.000) |
| Have children | 0.023** | 0.039* | 0.421*** | 0.443*** |
| | (0.012) | (0.020) | (0.000) | (0.000) |
| Family size | -0.007** | -0.008 | -0.126*** | -0.110*** |
| | (0.003) | (0.005) | (0.000) | (0.000) |
| Weekly working hours | - | - | 0.006*** | 0.005*** |
| | | | (0.000) | (0.000) |
| Constant | 0.217*** | 0.392*** | - | - |
| | (0.038) | (0.055) | | |
| Region FE | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes |
| Observations | 2,126 | 2,370 | 2,126 | 2,370 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-Regional level. The sample (STUS 2009-2010) is restricted toemployees in supervised occupations (Columns 1, 3), and non-supervised occupations (Columns 2, 4). The dependent variable is the logarithm of hourly wages in Euros (Columns 1, 2), and the bracketed labor income (Columns 3, 4). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

Table 1.B5: Main estimates for Aragón

| | Log-shirking | | Log-leisure | | Log-shirking | | Log-wage | |
|---|---|---|---|---|---|---|---|---|
| | Supervised | Non-sup. | Supervised | Non-sup. | Supervised | Non-sup. | Supervised | Non-sup. |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log-leisure | -0.131*** | -0.154*** | - | - | - | - | - | - |
| | (0.016) | (0.022) | | | | | | |
| *Aragón | -0.004 | 0.014 | - | - | - | - | - | - |
| | (0.016) | (0.051) | - | - | - | - | - | - |
| Log-commuting | - | - | -0.067 | -0.096*** | 0.181*** | 0.522*** | 0.006 | 0.002 |
| | | | (0.045) | (0.027) | (0.044) | (0.121) | (0.005) | (0.005) |
| *Aragón | - | - | 0.020 | 0.032 | -0.019 | -0.118 | 0.012 | -0.021 |
| | | | (0.038) | (0.047) | (0.020) | (0.260) | (0.008) | (0.017) |
| Observations | 2,126 | 2,370 | 2,126 | 2,370 | 2,126 | 2,370 | 2,126 | 2,370 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-Regional level. The sample (STUS 2009-2010) is restricted to employees in supervised occupations (Columns 1, 3, 5, 7), and non-supervised occupations (Columns 2, 4, 6, 8). The dependent variable is the logarithms of the daily minutes devoted to leisure (Columns 1 to 4), to shirking (Columns 5 and 6), or the logarithm of hourly wages in Euros (Columns 7 and 8). All models control for individual and family attributes, and region and Occupation fixed effects. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

# Appendix 1.C: The case of the self-employed

According to the efficiency wages models, employed workers may receive a higher wage than that of the labor market equilibrium in order to discourage shirking. However, efficiency wages focus on wage earners or firms, and self-employed workers have been largely overlooked, as they are not paid a wage but receive income from their own business, and thus are not compensated for longer commuting times. Self-employment earnings are determined by a production function, and productivity (i.e., effort at work) might affect such function. Within this framework, self-employed workers who devote more time to commuting may have comparatively less time for leisure activities, and thus may decrease their effort at work, which reduces their productivity and ultimately their earnings. Therefore, the main hypothesis of urban efficiency wage models regarding time endowments could analogously operate on self-employed workers.

Against this background, we develop in this Appendix 1.C an analytical model based on Ross and Zenou (2008)'s model with a spatial pattern that incorporates self-employed workers, aimed at explaining the differential behavior of self-employed workers in comparison to employees. According to the theoretical setting, commuting and effort at work are endogenously determined, leisure time is negatively related to commuting and positively to effort, and thus we hypothesize that workers who devote comparatively less time to leisure will not be as productive as they could otherwise be. Furthermore, the efficiency wage mechanism cannot be extended to self-employment, and thus the self-employed tend to live nearer to urban cores than do employees. As a consequence, commuting time is positively related to the probability of unemployment (in contrast to employment and self-employment), and the probability of self-employment is lower in comparison to the probability of employment, in the relationship with commuting.

We empirically check the predictions of the model using the American Time Use Survey (ATUS) for the years 2003-2014. Results show that the probability of being employed or self-employed is negatively related to expected commuting times, i.e., those who are employed or self-employed tend to live closer to the business districts than do the unemployed. When we compare the probability of being employed or self-employed, we find that longer commuting is related to a lower probability of self-employment in favor of the probability of being employed. Additionally, we empirically study the main hypothesis of the model, and find a relationship of substitutability (complementarity) between leisure and shirking (effort at work) among self-employed workers.

This Appendix contributes then to the literature by analyzing the spatial distribution of employment and self-employment, developing an urban model where productivity, commuting, and leisure are of major importance, in an urban efficiency wage setting. To the best of our knowledge, prior research has not included self-employed workers in such models.

## The model

Consider a linear, monocentric and closed city where the Central District, $CD$, is located at one end ($x = 0$), and the city fringe, $x_f$, at the other ($x = 1$). The city is fully centralized, i.e., all jobs and places of business are located at the Business District, $BD$, which is located in the $CD$, $BD = CD$.

There are two types of individuals, workers and landlords. Landlords own all the available land and play no role in the development of the model. Workers are risk-neutral, do not have inter-temporal preferences, and can be unemployed, employees, or self-employed. We assume that workers can endogenously decide their residential location, $x$, such that $BD < x < x_f$, and their effort at work, $e$. There are infinite moving costs, i.e., once workers choose their residential location, it remains invariable over time. We consider a population of workers normalized to 1, implying that unemployment, employment, and self-employment levels coincide with the respective rates.[21]

The process behind the transitions between the three conditions of worker, employed, self-employed, or unemployed, is governed by a Markovian time process. We assume a rate $\theta \in (0, 1)$ of abandoning unemployment. Then, individuals go to a fictitious intermediate state that immediately leave to become self-employed, with a probability $p_1 > 0$, or finding an employer, with probability $p_2 > 0$, such that $p_1 + p_2 = 1$. The self-employed decide to give up their business and become unemployed at a rate $\delta_1 \in (0, 1)$, and employees are fired at a rate $\delta_2 \in (0, 1)$. We maintain that there are no direct transitions from self-employment to employment, and the reverse, allowing frictional unemployment.

Under these hypotheses, the expected time that an individual will be unemployed

[21] It must be noted that the key point is not the location of the $BD$, but the distance between residential locations and the $BD$. All these assumptions are general in urban models. Although new models have generalized the concept of the monocentric city to multi-centric employment, results are often invariable to the type of city modeled (Ross and Zenou, 2008).

until he/she becomes employed or self-employed is $1/\theta$, and the expected time workers will be self-employed or employees until they become unemployed are $1/\delta_1$ and $1/\delta_2$, respectively. Then, we can obtain the percentage of life that workers will be unemployed ($u$), self-employed ($se$), and employed ($we$):

$$u = \frac{1/\theta}{\frac{1}{\theta} + \frac{1}{\delta_1} + \frac{1}{\delta_2}} = \frac{\delta_1 \delta_2}{\alpha},$$

$$se = \frac{1/\delta_1}{\frac{1}{\theta} + \frac{1}{\delta_1} + \frac{1}{\delta_2}} = \frac{\theta \delta_2}{\alpha},$$

$$we = \frac{1/\delta_2}{\frac{1}{\theta} + \frac{1}{\delta_1} + \frac{1}{\delta_2}} = \frac{\theta \delta_1}{\alpha},$$

with $\alpha = \delta_1 \delta_2 + \theta \delta_1 + \theta \delta_2$.

Note that $u$, $se$ and $we$ coincide with the levels, and rates, of unemployment, self-employment, and employment, respectively, and with the respective probabilities in the steady state. Now, we define, for each type of worker, the instant utility and the indirect utility that will allow us to develop the equilibrium.

Following Ross and Zenou (2008), we define an instant utility $z + V(l, e)$, where $z$ is the consumption of goods (at unitary prices), and $V(.)$ is the instant utility from leisure and effort at work, $l$ and $e$, respectively. We assume that $l = l(x)$, i.e., the availability of leisure depends on the commute from home to work or, in our setting, on the residential location. For instance, $l'(x) < 0$ and, then, the more commuting, the less time available for leisure (Ross and Zenou, 2008). Further, we maintain that the extent to which individuals benefit from shirking, and not putting effort into work, arises from the availability of leisure time.

$V(l, e)$ has the following properties: it increases with leisure, $\partial V(l, e)/\partial l > 0$, and it decreases with effort at work, $\partial V(l, e)/\partial e < 0$. In both cases, there are decreasing returns to scale, and $\partial^2 V(l, e)/\partial l \partial e > 0$, and less time devoted to leisure has as a consequence an increase in the benefits derived from leisure at work (i.e., from shirking).

We assume fixed and exogenous wages, $w$, and working times, $T$. We normalize the total available time to 1, and we then have the following budgetary and time constraints:

$$wT = z + R(x) + \tau x,$$

$$1 - T = l + tx,$$

where $R(x)$ represents the living costs in $x$, and $\tau$ and $t$ represent the relationship between commuting costs and distance, and commuting time and distance, respectively. With these constraints, we can define the indirect utility of the employed workers:

$$I_{we}(x, e) = wT + V(1 - T - tx, e) - R(x) - \tau x,$$

which measures income, plus utility from leisure and effort, minus living costs and commuting costs.

The instant utility of the unemployed also depends on the unitary consumption of goods, although it cannot depend on leisure and effort at work because unemployed workers cannot make effort at work, nor do they commute, and thus $l = 1$.[22] We can assume that their instant utility can be expressed as a constant, $z_0 + V_0$, with $z_0 < z$. As $l = 1$, the unemployed do not have a temporal constraint, but only a budgetary one. If we assume that the unemployed receive a benefit $b$ from unemployment, normalized to 0, the instant utility of the unemployed can be written as follows:

$$I_u(x) = V_0 - R(x).$$

The self-employed receive no wage from an employer, but income from an individual production function. Then, there is no theoretical background supporting the existence of efficiency wages, or any similar mechanism, for these workers. Despite that, the main idea of substitutability between leisure and shirking (or complementarity between leisure and effort at work) is invariable to the type of work. Hence, we maintain that the self-employed can be added to the model. Their instant utility and time constraint are the same as for employees. However, their income is given by a production function $F(T, k, e)$, where $T$ is the time input, $k$ the capital input, and $e$ the personal effort at work. In the current setting, we assume that $T$ is fixed (as for the employees), and $k$ is exogenous.[23] Thus, $F = F(e)$, and self-employment outcomes directly depend on

[22] Alternatively, we could assume that unemployed workers employ some resources in finding a job, which requires time and effort. We assume that this time (and effort/cost) cannot be considered equivalent to the time and cost of commuting for employees and self-employed workers (e.g., dealing with daily trips to/from work, whose frequency, and effect on time allocations, may be meaningfully different than that of going to job interviews), especially in a framework where the unemployed are characterized by shirking behaviors. We then omit commuting costs for the unemployed, since today, the search for a job (and even job interviews) is undertaken on the Internet, and thus entails no commuting costs. Nevertheless, an extension considering commuting costs for the unemployed is available upon request, and results derived from that extension do not significantly vary from the general conclusions derived from the model.

[23] In the case of employees, as work times may depend on scheduled work arrangements, to assume a fixed work time $T$ may not be a strong hypothesis. However, the self-employed may have the option to adapt work times. The current development of the model does not allow for non-fixed work times

personal effort at work. We assume that $F'(e) > 0$ and $F''(e) < 0$. The budgetary constraint is then $F(e) = z + R(x) + \tau x$, and the indirect utility of the self-employed can be expressed as follows:

$$I_{se} = F(e) + V(1 - T - tx, e) - R(x) - \tau x.$$

By weighting these indirect utility by the corresponding probability (in the steady state), we can obtain the expected life-cycle utility of workers:

$$I = I(x, e) = \frac{\theta\delta_1}{\alpha} wT + \frac{\theta\delta_2}{\alpha} F(e) + \frac{\theta(\delta_1 + \delta_2)}{\alpha} V(1 - T - tx, e) + \frac{\delta_1\delta_2}{\alpha} I_u - \frac{\theta(\delta_1\delta_2)}{\alpha} \tau x - R(x).$$

**Equilibrium**

We define the equilibrium of the model as the point where all workers have the same expected life-cycle utility, in terms of their effort at work and their residential location. To that end, we propose two levels of effort at work, in terms of the idiosyncrasy of workers regarding their level of effort: effort at work, $e_1$, and shirking at work, $e_0$, with $e_1 > e_0$ (Ross and Zenou, 2008).

As in Ross and Zenou (2008), shirking operates in employment through a monitoring technology $m > 0$. For the self-employed, there is no mechanism of monitoring. However, here $F$ plays a major role, and $F(e_1) > F(e_0)$, since $F' > 0$. Then, we can suppose that the productive self-employed will have a greater probability of not giving up their business, in contrast to shirkers, which can be expressed by $m$. Then:

$$u_0 = \frac{(\delta_1 + m)(\delta_2 + m)}{\beta},$$

$$we_0 = \frac{\theta(\delta_1 + m)}{\beta},$$

$$se_0 = \frac{\theta(\delta_2 + m)}{\beta},$$

with $\beta = (\delta_1 + m)(\delta_2 + m) + \theta(\delta_2 + m) + \theta(\delta_1 + m) > \alpha$.

When we compare these rates with the corresponding rates of the non-shirkers, we find that non-shirker workers tend to spend less time unemployed during their life-cycle. The demonstration is straightforward, as $u_0 > u_1 \Leftrightarrow \frac{(\delta_2 + m)(\delta_1 + m)}{\beta} > \frac{\delta_1\delta_2}{\alpha} \Leftrightarrow \frac{\theta}{\delta_2 + m} + \frac{\theta}{\delta_1 + m} < \frac{\theta}{\delta_1} + \frac{\theta}{\delta_2}$, which is true by definition.

As a consequence, non-shirker workers spend more time, during their expected life-cycle, employed and self-employed than their shirker counterparts, as $u + we + se = 1$. That is to say, among non-shirkers, employees and the self-employed will predominate in comparison with shirkers.

In the steady state, all workers will have the same life-cycle utility, $I_{eq}$. For the non-shirkers, $I_1 = I_{eq}$, which has already been defined. For shirkers, however:

$$I_0 = \frac{\theta(\delta_1 + m)}{\beta} wT + \frac{\theta(\delta_1 + m)}{\beta} F(e_0) + \frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} V(1 - T - tx, e_0) +$$

$$\frac{(\delta_1 + m)(\delta_2 + m)}{\beta} I_u - \frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} \tau x - R(x).$$

These equations allow to clear $R(x)$ and, then, obtain an expression of the bid rent functions of workers, in terms of $x$ and $I$. Bid rents represent workers' demand for land, i.e., the amount that they are willing to pay, in the equilibrium, for a unit of land located in $x$:

$$\psi_1(x, I_{eq}) = \frac{\theta\delta_1}{\alpha} wT + \frac{\theta\delta_2}{\alpha} F(e_1) + \frac{\theta(\delta_1 + \delta_2)}{\alpha} V(1 - T - tx, e_1) + \frac{\delta_1\delta_2}{\alpha} I_u - \frac{\theta(\delta_1 + \delta_2)}{\alpha} \tau x - I_{eq},$$

$$\psi_2(x, I_{eq}) = \frac{\theta(\delta_1 + m)}{\beta} wT + \frac{\theta(\delta_2 + m)}{\beta} F(e_0) + \frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} V(1 - T - tx, e_0) +$$

$$\frac{(\delta_1 + m)(\delta_2 + m)}{\beta} I_u - \frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} \tau x - I_{eq}.$$

Note that $\partial\psi_i/\partial x < 0$ for $i = 0, 1$, as $\partial V/\partial l > 0$, $\partial l/\partial x < 0$, and $\tau > 0$. That is to say, both groups prefer to live as near as possible to the $BD$. However, only the group with the greater demand for land nearer the $BD$ will live there, and the other group will be relegated to the outskirts and the city fringe. Further, as bid rents are monotonously decreasing and continuous, there must be a point, $\tilde{x}$, that separates the areas where both groups choose to locate their residences. Then, the group with the steepest slope bid rent will choose to reside in $BD < x < \tilde{x}$, and the group with the lesser steep slope will reside in the outskirts, $\tilde{x} < x < x_f$.

By evaluating bid rents, we find that non-shirker workers will reside between the $BD$ and $\tilde{x}$. To demonstrate this result, it is necessary to study whether $\partial\psi_1/\partial x < \partial\psi_0/\partial x$. Note that:

$$-\frac{\partial\psi_1}{\partial x} = -\frac{\theta(\delta_1 + \delta_2)}{\alpha} \frac{\partial V(l, e_1)}{\partial l} \frac{\partial l(x)}{\partial x} + \frac{\theta(\delta_1 + \delta_2)}{\alpha} \tau,$$

$$-\frac{\partial \psi_2}{\partial x} = -\frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} \frac{\partial V(l, e_0)}{\partial l} \frac{\partial l(x)}{\partial x} + \frac{\theta(\delta_1 + \delta_2 + 2m)}{\beta} \tau.$$

As $\partial V(l, e)/\partial l \partial e < 0$, $\partial l(x)/\partial x < 0$, and $1 - u_1 > 1 - u_0$, the result follows.

Note that this result indicates that shirker workers will reside in the outskirts, far from the BD, and individuals who make effort at work will live near the BD. Under the same conditions of agreed working hours, non-shirkers will devote less time to commuting and will have more time for leisure. Then, even when they personally tend not to shirk, their endogenously-chosen residential locations encourage effort at work, under the key assumption of substitution between leisure and shirking. On the other hand, the residential location of shirkers additionally promotes shirking, since they have longer commutes and thus less leisure time. These patterns promote the formation of clusters in urban areas, with productive workers living in the surroundings of business districts. This would mean that, if firms can detect shirking and observe workers' residential location, centralized cities would concentrate the employed population near the city center, while decentralized and polycentric ones would concentrate the employed in the surroundings of the corresponding employment cores, favoring the polarization of urban areas.

**Self-employed versus employees' residential location**

The existing literature suggests that the self-employed belong to a different labor-search market than employees, since they in fact look for places where they can establish a business, leading them to less-imperfect information and shorter commutes. We try to find differences in a scenario where such variations are not considered, and the only difference is that income is exogenous for the employees, but endogenous for the self-employed. We limit our analysis to those individuals who do not shirk, although it would be analogous for shirkers.

Increases in $w$ would discourage shirking and increase $e$ among employees, under the efficiency wages theory. Then, when wages increase, the percentage of shirker employees in the city would decrease, and $\tilde{x}$ would consequently increase (Ross and Zenou, 2008). When we analyze the corresponding relationship among the self-employed, we cannot develop an analogous argument. If there is an increase in $F$ due to a general increase of $e$ among all workers, the causal relationship between income and effort at work would be opposite to that for employees: income increases because individuals devote, in general, more effort at work, but there is no reason to consider an increase of $e$ due to increases in self-employment outcomes.

Let us suppose that there is an increase in $F$ that is due to an external shock, and it is independent of $e$. Then, what would be the effect on $e$? Conceptually, it can be that:

a) Workers reduce their effort, keeping $F$ and $x$ invariable.

b) Workers maintain their levels of effort and adjust their commuting behavior.

c) Workers increase their level of effort, analogous to the efficiency wage mechanism.

To shed light on these potential effects, we analyze the relationship between $F$ and $\tilde{x}$, and compare it with the relationship between $w$ and $\tilde{x}$.

Assume that $F$ increses. It must be that $\psi_1(I_{eq}, \tilde{x}) = \psi_0(I_{eq}, \tilde{x})$. Then, $(1-u_0)V_S - (1-u_1)V_{NS} = (we_1 - we_0)wT + (se_1F(e_1) - se_0F(e_0)) - \tau\tilde{x}(u_0 - u_1) + I_u(u_1 - u_0)$. Differentiating respect $\tilde{x}$, and given that $\partial^2 V/\partial l \partial e < 0$:

$$\frac{\partial w}{\partial \tilde{x}} > \frac{\partial w}{\partial \tilde{x}} T(we_1 - we_0) = \left(t\frac{\partial V}{\partial l} + \tau\right)(u_0 - u_1) + \frac{\partial F}{\partial \tilde{x}}(se_0 - se_1) > 0.$$

Finally, using the reverse triangle inequality:

$$\frac{\partial w}{\partial \tilde{x}} > |\frac{\partial F}{\partial \tilde{x}}|.$$

As a consequence, there is no clear mechanism analogous to efficiency wages for self-employed workers, according to the developed framework. Furthermore, if such mechanism existed, it would be smaller than that for efficiency wages. Therefore, the self-employed would live nearer the $BD$ than their employed counterparts.

## Data and variables

We use data from the ATUS for the years 2003-2014 to analyze the relationship between employment, self-employment and unemployment in urban areas. We apply analogous restrictions to the sample than in the main analysis. However, now the self-employed are not restricted. This leaves with 5,623 self-employed workers, in addition to the main sample. As commuting is not observed for the unemployed, it is predicted using the same strategy than in the main analysis, but now the self-employed are included in the commuting model.[24] Table 1.B1 shows summary statistics for the self-employed.

[24] Estimates are available upon request.

## Empirical results and conclusions

We first estimate Equations 1.1 and 1.2 for the self-employed, to analyze the relationships between leisure and shirking, commuting and shirking, and commuting and leisure for these workers and, then, study the main hypothesis and time-use predictions of the model. Estimates are shown in Table 1.C2.

In column (1), we observe an estimated elasticity between leisure and shirking of -0.171, indicating that a one percent increase in self-employed workers' time of shirking is correlated with a decrease of around 0.17% in their leisure time. The estimates provide evidence in favor of the substitutability between leisure and shirking among the US self-employed workers, and give empirical support to the main hypothesis of the theoretical framework. Hence, we can conclude that the idea of substitution between leisure and shirking is not solely applicable to employees, and that urban models of self-employment should take that into account.

In Columns (2) and (3), we estimate the elasticity between leisure and commuting, and shirking and commuting, respectively. Results indicate that a one percent increase in self-employed workers' time of commuting is correlated with a decrease of around 0.09% in their leisure, and with an increase of 0.24% in their shirking time. These estimates provide, again, evidence in favor of the model for the self-employed workers, as the behavioral relationships between commuting, leisure and shirking are the expected, and consistent with the behaviors of the employed workers. Therefore, results reinforce the idea that urban models could be applied to the self-employed, asd the hypotheses and results of Ross and Zenou (2008) could be extended to the self-employed, at least regarding time endowments.

Then, we estimate the following equation (i.e., a linear probability model):

$$Y_{is} = \alpha_0 + \alpha_1 C_{is} + \alpha_2 X_i s + \alpha_3 W_{is} + \alpha_s + \varepsilon_{is},$$

where $Y_{is}$ represents a dummy variable for employment status of a given individual $i$ living in MSA $s$ (1 if $i$ is employed/self-employed, 0 if $i$ is unemployed). The rest of variables are analogous to Equation 1.4. Given that we are using generated regressors, we bootstrap the standard errors of the regressions (500 replications) (Pagan, 1984; Murphy and Topel, 1985). Results are shown in Column (1) of Table 1.C3. We find that one more minute of commuting is significantly associated, on average, with increases in the probability of being unemployed of 4.6%. These results provide empirical support to the model, as unemployed workers appear to live further from job places than their employed and self-employed counterparts.

We next analyze the probability of being self-employed in comparison to being employed, dropping the unemployed from the analysis. The theoretical model establishes that the higher the commuting time, the higher the probability of being employed (vs. self-employed). Given that this relationship is obtained in the market equilibrium, we do not attempt to estimate causal effects, and the estimation of a conditional correlation using OLS estimates is sufficient, as in the main analysis. We then re-estimate the model in Column (2) of Table Tab1.C3, but now $Y_{is}$ is now the dummy variable being self-employed (value 1 if individual $i$ is self-employed, 0 if employed), and $C_{is}$ is now the reported (log) commuting time. Results show that, according to reported commutes, one additional minute of expected commuting is associated with a decrease of 4.2% in the probability of being self-employed (vs. being employed). This result indicates that there exists a negative relationship between commuting and the probability of being self-employed, in comparison with being employed, consistent with the theory. The main conclusion of Table 1.C3 is, then, that the self-employed live closer to their respective workplaces, in comparison to the employed. Furthermore, both self-employed workers and employees live nearer workplaces than the unemployed.

The study shown in this Appendix, as well as the main analyses, has certain limitations. First, the analysis is restricted to the supply side of the labor market, and we omit the behaviors of firms and employers, such as the hiring of non-shirkers only (assuming that employers can always monitor employees), the actions of labor unions, establishment sizes, or government regulation, all of which play a significant role in efficiency wages. Second, by using cross sectional data, unobserved heterogeneity has a strong impact on our empirical modeling. The relationships are obtained in the market equilibrium, and the estimation of conditional correlations using OLS models is sufficient to test the model. Nonetheless, empirical results must be interpreted as conditional correlations, and not as causal effects. Finally, and more importantly, we do not have data on self-employment earnings, and we cannot analyze the relationship with commuting times. More research on this topic is needed.

Table 1.C1: Summary statistics

| | Self-employed | |
|---|---|---|
| VARIABLES | Mean | S.D. |
| Leisure time | 105.807 | 98.753 |
| Shirking time | 11.040 | 20.148 |
| Commuting time | 29.203 | 44.134 |
| Being male | 0.637 | 0.481 |
| Years working | 24.640 | 10.532 |
| Years working squared | 71.802 | 52.137 |
| Primary education | 0.054 | 0.226 |
| Secondary education | 0.237 | 0.426 |
| University education | 0.709 | 0.454 |
| Being white | 0.886 | 0.318 |
| Being American | 0.854 | 0.353 |
| Being Asian | 0.032 | 0.176 |
| Being Pacific/Islander | 0.002 | 0.050 |
| Living in couple | 0.702 | 0.457 |
| Partner's labor force status | 0.533 | 0.499 |
| Have children | 0.533 | 0.499 |
| Family size | 2.972 | 1.519 |
| Observations | 5,623 | |

Note: The sample (ATUS 2013-2014) is restricted to self-employed workers who work the diary-day.

Table 1.C2: Shirking, leisure and commuting

| VARIABLES | Log-shirking (1) | Log-leisure (2) | Log-shirking (3) |
|---|---|---|---|
| Log-leisure | -0.171*** | - | - |
| | (0.023) | | |
| Log-commuting | - | -0.093*** | 0.240*** |
| | | (0.012) | (0.014) |
| Being male | 0.310*** | 0.014 | 0.173*** |
| | (0.058) | (0.044) | (0.057) |
| Years working | 0.002 | -0.015* | 0.003 |
| | (0.011) | (0.009) | (0.011) |
| Years working sq. | -0.002 | 0.003* | -0.002 |
| | (0.002) | (0.002) | (0.002) |
| Secondary ed. | -0.113 | -0.048 | -0.105 |
| | (0.157) | (0.131) | (0.155) |
| University ed. | -0.328** | 0.180 | -0.317** |
| | (0.154) | (0.130) | (0.150) |
| Being American | -0.399*** | -0.006 | -0.265*** |
| | (0.097) | (0.066) | (0.099) |
| Being Asian | 0.221 | 0.014 | 0.265 |
| | (0.241) | (0.238) | (0.220) |
| Being Pacific Isl. | 0.781 | 0.450* | 0.583 |
| | (0.633) | (0.252) | (0.623) |
| Being white | 0.020 | 0.215** | -0.013 |
| | (0.108) | (0.098) | (0.105) |
| Living in couple | 0.184* | 0.143* | 0.103 |
| | (0.100) | (0.082) | (0.098) |
| Couple's labor status | -0.128* | -0.065 | -0.078 |
| | (0.077) | (0.063) | (0.077) |
| Have children | 0.036 | -0.161** | 0.065 |
| | (0.093) | (0.066) | (0.089) |
| Family size | -0.004 | 0.053** | -0.008 |
| | (0.032) | (0.023) | (0.031) |
| Constant | 2.110*** | 4.249*** | 0.833** |
| | (0.376) | (0.240) | (0.341) |
| MSA FE | Yes | Yes | Yes |
| Ind. and Occ. FE | Yes | Yes | Yes |
| Housing FE | Yes | Yes | Yes |
| Observations | 5,623 | 5,623 | 5,623 |

Note: Robust standard errors in parentheses. All standard errors are clustered at the Occupation-MSA level. The sample (ATUS 2013-2014) is restricted to self-employed workers. The dependent variable is the logarithm of the daily minutes devoted to shirking (Columns 1 and 3), or to leisure (Column 2). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

Table 1.C3: Commuting and self-employment

| VARIABLES | Employed/self-employed vs unemployed (1) | Self-employed vs employees (2) |
|---|---|---|
| Pred. log-commuting | -0.046** | - |
| | (0.020) | |
| Log-commuting | - | -0.042*** |
| | | (0.002) |
| Being male | 0.032*** | 0.055*** |
| | (0.003) | (0.004) |
| Years working | 0.005*** | 0.005*** |
| | (0.001) | (0.001) |
| Years working sq. | -0.001*** | -0.000 |
| | (0.000) | (0.000) |
| Secondary ed. | 0.091*** | 0.002 |
| | (0.007) | (0.009) |
| University ed. | 0.128*** | 0.042*** |
| | (0.007) | (0.009) |
| Being American | -0.026*** | -0.003 |
| | (0.005) | (0.006) |
| Being Asian | 0.075*** | 0.009 |
| | (0.009) | (0.013) |
| Being Pacific Isl. | 0.034 | 0.045 |
| | (0.039) | (0.041) |
| Being white | 0.089*** | 0.028*** |
| | (0.006) | (0.006) |
| Living in couple | 0.054*** | 0.017*** |
| | (0.005) | (0.007) |
| Couple's labor status | 0.001 | 0.010 |
| | (0.004) | (0.006) |
| Have children | -0.001 | 0.012** |
| | (0.005) | (0.006) |
| Family size | -0.017*** | -0.002 |
| | (0.002) | (0.002) |
| Constant | 0.798*** | 0.046** |
| | (0.070) | (0.021) |
| MSA FE | Yes | Yes |
| Housing FE | Yes | Yes |
| Observations | 43,928 | 38,983 |

Note: Bootstrapped ($n = 500$) standard errors in Column (1). Robust standard errors clustered at the Occupation-MSA level in parentheses in Column (2). The sample (ATUS 2003-2014) is restricted to employee, unemployed, and self-employed workers in Column (1), and to employee and self-employed workers in Column (2). The dependent variable is the dummy being employed or self-employed (Column 1), or the dummy being self-employed (Column 2). * Significant at the 90% level, ** significant at the 95% level, *** significant at the 99% level.

# Chapter 2

# Intertemporal labor supply and intrahousehold commitment

This Chapter adopts an intertemporal labor supply perspective to study intrahousehold non-commitment, limited commitment, and full commitment. It investigates whether, after controlling for current and future (expected) wages, past wage shocks have a lasting and significant impact on present labor supply. Using data from the US Panel Study of Income Dynamics and the European Union Statistics of Income and Living Conditions, the Chapter shows positive evidence in favor of the limited commitment model, rejecting full commitment and non-commitment. Specially, unexpected past wage shocks affect household labor supply in the way predicted by theory, as spouses' past wage deviations have a negative impact on their labor supply.
Keywords: collective model; intertemporal commitment; labor supply; PSID; EU-SILC

## 2.1 Introduction

This Chapter explores intertemporal aspects of household labor supply and intrahousehold commitment in the US and Europe, from the perspective of collective models (Chiappori, 1988, 1992). Traditionally, household studies have followed the so-called unitary model, which takes the family as a single decision unit whose preferences can be represented by a single, well-behaved utility function. However, this unitary approach has come under heavy criticism over the last decades. The assumption of a unique family utility for a household, regardless of the family composition, is an ad-hoc construct, with little or no theoretical justification. For instance, it disregards issues regarding the allocation of power within the household, and tends to generate biased estimations of intrahousehold inequality. Last but not least, its empirical predictions, in particularly the well known "income pooling" property (whereby only total household income matters for household behavior, irrespective of spouses' contributions), are typically rejected (e.g., Thomas, 1990; Lundberg et al., 1997; Duflo, 2003; Ward-Batts, 2008).

Several models of household behavior, which appeared in the literature in the 1980s, have tried to diverge from the unitary assumption by explicitly recognizing that individual preferences may differ, and trying to model the decision process through which these preferences interact. See, for instance, Manser and Brown (1980); Ashworth and Ulph (1981); McElroy and Horney (1981); Apps (1981, 1982); Bourguignon (1984); Apps and Jones (1986); Ulph (1988); or Woolley (1988). Chiappori (1988, 1992) then proposed a general framework for analyzing intrahousehold behavior, the collective model, in which individuals are only assumed to reach Pareto efficient outcomes. Since then, some authors have proposed various extensions of the collective model. For instance, Bourguignon et al. (1993) developed a model with caring preferences, Chiappori (1997) introduced household production, Browning and Chiappori (1998) provided general identification results introducing the concept of "distribution factors", Blundell et al. (2005) developed a model of labor supply with public consumption, and Chiappori and Ekeland (2006, 2009) and Bourguignon et al. (2009) provided general results for identification and characterization.[1] Since then, several studies have pointed to the empirical validity of the collective model (e.g., Browning et al., 1994; Haddad and Hoddinott, 1994; Lundberg et al., 1997; Browning and Chiappori, 1998; Chiappori et al., 2002; Rapoport et al., 2011; Attanasio and Lechene, 2014; Lyssiotou, 2017; Armand et al., 2016). See Donni and Chiappori (2011) and Donni and Molina (2019) for extensive reviews of the literature.

## Intertemporal issues in the collective framework

The collective models developed in the 1990s and the 2000s were mostly static, which leads to strong limitations. For instance, they cannot be used to evaluate policies entailing any intertemporal aspect, as they essentially ignore the dynamics of intrahousehold processes (Mazzocco, 2007; Lise and Yamada, 2018). Conversely, most of the recent theoretical and empirical literature on household intertemporal decisions has remained in the unitary field (e.g., Scholz et al., 2006; Krueger and Perri, 2006; Heathcote et al., 2010). A basic reason for this limitation is the sheer complexity of the issues raised by

[1] Distribution factors are variables affecting the bargaining position of spouses, but not preferences or the budget constraint.

intertemporal behaviors in a collective model.

Commitment is a particularly important example of these difficulties. While it is straightforward and easy to implement in static versions of the collective model (i.e., efficiency is equivalent to equilibrium), any collective model involving a dynamic decision process must rely on some specific assumptions regarding agents' ability to commit on their future behavior. Therefore, behavioral predictions in a dynamic or intertemporal setting will crucially depend on the assumption made regarding intertemporal commitment. As a result, the relevance of any policy recommendation derived from such predictions will presumably vary with the assumptions made (Chiappori and Mazzocco, 2017). To take but one example, an analysis of the long-term impact of specific legislations governing divorce or cash transfers cannot ignore the limitations (if any) introduced by the spouse's ability to commit.

In the collective setting, three models of intertemporal household behavior have emerged to fill this gap:

1. the full intertemporal commitment (FIC) model,
2. the non-commitment (NC) model,
3. the limited (or partial) intertemporal commitment (LIC) model.

According to the NC model, spouses renegotiate Pareto weights every period, regardless of previous exogenous variables, bargaining powers and household decisions. Thus, setting aside assets, NC models consist of a series of non-related static models, and only assume static Pareto efficiency at each period (ex post efficiency). However, the main limitation of NC models is their dynamic ex ante inefficiency. In a NC context, agents' decisions at each period only depend on current (and future) values of the relevant variables. Such a constraint severely hampers the agents' ability to share risk, and generally to efficiently allocate resources across periods and states of the world (Basu, 2006).

The opposite scenario is that of FIC models, according to which household members are able, at the beginning of the relationship, to fully commit on all future (possibly state-contingent) allocations (ex ante efficiency). In practice, ex ante efficiency imposes that Pareto weights must be fully determined at the beginning of the relationship, and cannot be affected by any future non-anticipated shock. Despite FIC models generate ex ante efficient allocations, such a constraint supposes a strong limitation in term of realism (e.g., divorces). In particular, FIC models ignore individual rationality (IR) constraints: it might be the case that an agent remains married despite the fact that their welfare would be higher if divorced.

The LIC framework, proposed by Mazzocco (2004, 2007), provides an elegant solution to these problems. LIC models recognize that spouses always have an "outside option", usually associated with divorce and household dissolution, which they cannot commit not to use. As a result, IR constraints must always be satisfied. If, following exogenous changes in the economic environment, a continuation of the previous intrahousehold agreement would imply the IR constraint of a spouse to be violated, then a renegotiation takes place, with two possible outcomes. If no reallocation of intrahousehold power is compatible with both IR constraints simultaneously, then separation results. Otherwise, Pareto weights are modified (i.e., renegotiated) in such a way that the IR constraint that was initially violated becomes exactly binding. The property of the LIC model is, therefore, that intrahousehold allocations are (ex ante) second best optimal. That is to say, spouses implement an allocation that is ex ante efficient under the IR constraints.

In that context, however, few empirical tests have been proposed in the literature to evaluate intertemporal commitment. For instance, so far these tests have exclusively rejected the FIC model against their partial or non-commitment counterparts, without distinguishing between them. Mazzocco (2007) first proposed a test based on Euler consumption equations to reject the unitary and FIC models. Then, Lise and Yamada (2018) proposed a functional form of Pareto weights and, using Japanese data, rejected again the FIC model. In principle, testing for full commitment is straightforward following the strategy of Mazzocco (2007). However, studying limited commitment requires additional insights. Specifically, testing for limited versus non-commitment requires to analyze the way in which Pareto weights, *which are not observable*, change.

This Chapter follows then a "reduced form" approach, based on a collective model of labor supply, to study intertemporal commitment in terms of how spouses' labor supply respond to unexpected wage shocks. The intuition, inspired by Lise and Yamada (2018), is as follows. Assume that spouses' wages vary in terms of expectations plus unexpected shocks. Under FIC, unexpected shocks cannot have any type of effect on Pareto weights or household behaviors. Under NC, current unexpected shocks must affect only current behavior, but are forgotten immediately in future renegotiations. Finally, under LIC, unexpected shocks affect Pareto weights and household behaviors through IR constraints. Then, a(n) (accumulation of) shock(s) may change Pareto weights and, then, household behaviors in a semi-permanent way.

We test this prediction using two sources of data: 1) The PSID of the United States for years 2015 and earlier.[2] 2) The EU-SILC of Austria, Belgium, France, Greece, Italy, Luxembourg, Spain and Sweden for years 2003-2016. For the US, estimates reject the FIC and NC models, and provide evidence in favor of the LIC model. Moreover, these effects appear to be specific to couples, as singles' labor supply exhibits totally different patterns, which strongly support the LIC version of the collective model. Results for Europe also reject the NC and FIC models for all the countries studied, and are in line with the dynamics generated under limited commitment.

The main contribution of the Chapter is, then, the empirical study of intertemporal commitment patterns in Europe and the US, a topic that has been barely studied (Mazzocco, 2007; Lise and Yamada, 2018). In particular, this is the first empirical analysis of intertemporal commitment in Europe.

The rest of the Chapter is organized as follows. Section 2.2 describes the intertemporal collective model and shows its empirical implementation. Section 2.3 describes the PSID data and variables, and Section 2.4 shows the empirical analysis for the US. Sections 2.5 and 2.6 introduce the EU-SILC data and show results for Europe, respectively. Section 2.7 presents the main conclusions. The Appendix 2.A introduces the classical (i.e., static) collective model, Appendices 2.B and 2.C show additional results for the US and Europe, respectively. Finally, the Appendix 2.D estimates the main analysis for the case of Aragón and other Spanish regions.

## 2.2 The limited commitment model

Assume that a household consists of two spouses, $j = A, B$, where $A$ represents the wife and $B$ the husband, and face a face a $T$-period intertemporal maximization process, $T > 1$. In the most general case, assume that each spouse enjoys utility from public consumption within the household, $Q_t$, private consumption, $q_{jt}$, and (private) leisure, $1-h_{jt}$, with $h_{jt}$ being spouse $j$ labor supply, and $t$ the time index. Prices are normalized to 1, and home production and household and individual assets are not considered in

[2] The 2015 wave of the PSID was the most recent wave when this Chapter was written.

the model. The household then solves the following program:

$$\begin{aligned}
&\max_{\{Q_t,q_{jt},h_{jt}\}_j^t} && E_0 \sum_{t=0}^{T} \beta^t \left\{\mu_{A(t)} u_A \left(Q_t, q_{At}, 1-h_{At}\right) + \mu_{B(t)} u_B \left(Q_t, q_{Bt}, 1-h_{Bt}\right)\right\} \\
&\text{s.t.:} && \sum_{t=0}^{T} \left(Q_t + q_{At} + q_{Bt}\right) = \sum_{t=0}^{T} \left(w_{At}h_{At} + w_{Bt}h_{Bt} + y_t\right)
\end{aligned} \tag{P$_0$}$$

where $\beta$ represents the common discount factor, $u_j$ is spouse $j$ period utility, $w_{jt}$ represents spouses' wages (which are considered exogenous), and $y_t$ is household non-labor income, net of savings.[3] Thus, the restriction of the program represents the budget constraint of the household.

In this scenario, the parameters $\mu_{j(t)}$ represent spouse $j$'s bargaining power within the household in period $t$, and are often called *Pareto weights*. In a static scenario, these Pareto weights completely characterize intrahousehold allocations, assuming that household members cooperate and therefore reach Pareto efficient outcomes, which is the benchmark hypothesis of collective models (see, for instance, Chiappori et al., 2002). However, such a scenario would be incomplete in an intertemporal framework, and a series of individual rationality (IR) constraints, or participation constraints, *may* be required for all $t \geq 0$ (Mazzocco, 2004, 2007). Otherwise, the model would be exclusively a full commitment model, behaviors would be ex ante efficient, and no reallocations and renegotiations would be possible:

$$\begin{aligned}
&\max_{\{Q_t,q_{jt},h_{jt}\}_j^t} && E_0 \sum_{t=0}^{T} \beta^t \left\{\mu_{A(t)} u_A \left(Q_t, q_{At}, 1-h_{At}\right) + \mu_{B(t)} u_B \left(Q_t, q_{Bt}, 1-h_{Bt}\right)\right\} \\
&\text{s.t.:} && \sum_{t=0}^{T} \left(Q_t + q_{At} + q_{Bt}\right) = \sum_{t=0}^{T} \left(w_{At}h_{At} + w_{Bt}h_{Bt} + y_t\right) \\
& && \lambda_{At}: \quad E_t \sum_{\tau=t}^{T} \beta^{\tau-t} u_A \geq V_{At}^*(d_{At}), \;\; t \geq 0 \\
& && \lambda_{Bt}: \quad E_t \sum_{\tau=t}^{T} \beta^{\tau-t} u_B \geq V_{Bt}^*(d_{Bt}), \;\; t \geq 0
\end{aligned} \tag{P$_1$}$$

where $E_t \sum_{\tau=t}^{T} \beta^{\tau-t} u_j$ represents the individual utility continuation withing the household of spouse $j$ in period $t$, under the initial situation, which depends on distribution factors known at $t = 0$, $d$, determining spouses' initial bargaining powers. On the other

[3] See Chiappori et al. (2002) for a static version of the collective model of labor supply that inspired this theoretical specification.

hand, $V_{jt}^*$ represents the value of spouse $j$ outside option, and $d_{jt}$ are exogenous variables that affect spouse $j$'s outside options. The intuition behind IR constraints is as follows. For each spouse $j$ and time $\tau \geq 1$, the utility generated in the marriage under $\tau$'s intrahousehold contract must be greater or equal than the reserve utility associated with the outside option.

### Intertemporal commitment and intrahousehold bargaining power

Some issues regarding the evolution of Pareto weights must be remarked once the household program is specified as Program $P_1$. First of all, if the model was a full commitment model, IR constrains never bind or do not exist, as spouses could completely anticipate any future change. That is to say, spouses commit to any future allocation of resources. As a consequence, Programs $P_0$ and $P_1$ would be analogous, variables $d_{jt}$ could be excluded, and Pareto weights would be fixed values, depending only on initial or time invariant distribution factors $d$, that can be expressed as:

$$\mu_{j(t)} = \mu_j(d), \ \ j = A, B, \ \ t \geq 0.$$

Full commitment describes, then, a scenario of first-best allocations, which is clearly not realistic.[4]

On the other hand, under limited commitment, spouses commit to any future allocation as long as IR constraints are satisfied. That is to say, the *initial* Pareto weights are identified as in the FIC model, and remain fixed as long as the IR constraints do not bind. However, violation of IR constraints *may* occur because of variables $d_{jt}$, $j = A, B$, $t \geq 1$, that can improve spouses' utilities associated to their respective outside option. That is to say, if under the current intrahousehold contract spouses obtain a higher utility cooperating with their counterpart, they remain in the marriage under such contract. However, if at any period $\tau \geq 1$ there is a shock that causes one of the IR constraints to bind, then some alternatives emerge. First, if both spouses' IR constraints bind simultaneously, then no reallocations of bargaining powers are possible, and the household comes to an end. Similarly, if only one spouses' constraint binds, but there are not reallocations compatible, the marriage also finishes. (These two scenarios are, however, not considered in this Chapter, and are left for future research). On the other hand, if there exists a reallocation satisfying both constraints to remain true, spouses have the obligation of renegotiate to keep efficiency. Assume without

[4] Full commitment is nested within limited commitment, as shown by (Mazzocco, 2007).

loss of generality that $A$'s constraint binds at $t = \tau$. In particular, the Pareto weight of $A$ increases in such a way that the constraint becomes exactly true, that is to say, increases just by $\lambda_{A\tau}$ (Ligon et al., 2002).

Under limited commitment, we can express Pareto weights as:

$$\mu_{jt} = \mu_{jt-1} + \frac{\lambda_{jt}}{\beta^t}, \;\; j = A, B, \;\; t \geq 1,$$

where $\lambda_{j\tau}$ is positive if $j$'s IR constraint binds at $t = \tau$, 0 otherwise. Under this formulation, the intuition behind the dynamics of Pareto weights can be characterized by variables $d_{j\tau}$, which represent contemporaneous information observable at $t = \tau$, which was not observable at $t < \tau$. Contemporaneous information is relevant if and only if an IR constraint binds, which is not expected to happen *always*. Assume that $A$'s IR constraint binds at $t = \tau$. Then, $A$'s bargaining power increases by $\lambda_{A\tau}$, which in particular depends on $d_{A\tau}$. Assume that no IR constraint binds at $\tau + 1$. Then, past history in $t = \tau + 1$, captured by $d_{A\tau}$ and $\mu_{j\tau-1}$, is relevant in determining $\tau + 1$'s bargaining positions of spouses.[5] This is to say, as long as IR constraints do not bind, initial Pareto weights lead to efficient outcomes. However, Pareto weights may change in accordance with an iterative process governed by IR constraints. When one of the IR constraints binds at time $\tau$, then $\lambda_{i\tau} \neq 0$ and spouses' bargaining positions change in a semi-permanent way, i.e., until an IR constraints binds again.

Under limited commitment, Program $P_1$ can be rewritten as:

$$\begin{aligned} \max_{\{Q_t, q_{jt}, h_{jt}\}_j^t} \quad & E_0 \sum_{t=0}^{T} \beta^t \sum_{j=1}^{2} \left( \mu_{jt} u_j - \lambda_{jt} V_{jt}^* \right) \\ \text{s.t.:} \quad & \sum_{t=0}^{T} (Q_t + q_{At} + q_{Bt}) = \sum_{t=0}^{T} (w_{At} h_{At} + w_{Bt} h_{Bt} + y_t) \end{aligned} \tag{P$_2$}$$

where the underlying dynamics generated by the IR constraints that determine spouses bargaining positions are reflected in Pareto weights, which can be expressed as:

$$\mu_{jt} = \mu_{jt}(d, d_{jt}, \mu_{jt-1}), \;\; j = A, B, \;\; t \geq 1.$$

Note that $\mu_{jt}$ depends on $\mu_{jt-1}$ and, as a consequence, it also depends on past information. This dependence reflects binding past information constraints, and is the key

[5]In particular, $\mu_{j\tau-1}$, $j = A, B$ summarizes all past history. That is to say, *if observable*, Pareto weights behave as a first order Markov chain. The shortcoming is, in practice, that Pareto weights cannot be observed.

mechanism that characterizes limited intertemporal commitment, against the full commitment (which does not depend on contemporaneous information, no on past history), and against the non-commitment model (which does not depend on past history, as described below).

Finally, let us consider the non-commitment case. Without commitment, spouses do not commit to any future allocation of resources. Any new information $d_{jt}$ revealed at time $t$ shifts spouses bargaining positions as in a static collective model, and therefore Pareto weights can be expressed as:

$$\mu_{jt} = \mu_j(d, d_{jt}), \;\; j = A, B, \;\; t \geq 0,$$

just as in the model proposed by Lise and Yamada (2018). In particular, the household problem is a series of repeated static models where past history is always irrelevant by definition. It is important to remark that non-commitment is not limited commitment with IR constraints binding each period. If this was the case, then Pareto weights should be expressed as a recursive function. As happened in the full commitment scenario, assuming non-commitment is not realistic, as it assumes that spouses cannot commit to any future allocation of resources.

### 2.2.1 Implementation of the model

The classical analysis of dynamic labor supply models, based on Euler equations at the household level, is specific to unitary models and does not consider intrahousehold aspects. Therefore, it is not suitable for collective models. In this context, few empirical tests have been proposed in the literature to evaluate intertemporal collective models. In fact, so far these contributions exclusively test the FIC model against partial or non-commitment (Mazzocco, 2007; Voena, 2015; Blau and Goodstein, 2016; Lise and Yamada, 2018)

In principle, testing for full commitment (against non- or limited commitment) is straightforward, following Mazzocco (2007)'s outline. One only need to check whether actual behaviors are compatible with constant Pareto weights. Although Pareto weights cannot be observed, such a task is facilitated by the fact that Pareto weights can be identified throughout labor supply or consumption behavior (see Browning et al., 2014). On the other hand, testing for limited versus non-commitment is more difficult. In both cases, Pareto weights may vary in response to shocks, and the difference between the two versions relates to the specific manner that variations may take place.

Given that Pareto weights cannot be directly observed, but only identified, direct tests of limited versus non-commitment cannot be proposed in general terms. A possible alternative approach would exploit the Markovian nature of changes in Pareto weights under the LIC assumptions, as in Lise and Yamada (2018). However, precisely because of the non-observability of Pareto weights, this strategy requires an explicit, structural model of household behavior, implying that any test would be a joint test of the particular specification used for that purpose.

In that context, this Chapter proposes a different approach to tackle limited commitment versus non-commitment and full commitment, on the basis of a collective model of labor supply, from a "reduced form" perspective. A semi-log parametrization of labor supply equations is adopted, which provides an empirical test for intrahousehold intertemporal commitment. The approach adopted relies on the following intuition.[6] Consider a couple that, after marriage, is hit by some random productivity shocks. Under FIC, these shocks, whether past or current, cannot possibly have an impact on spouses' Pareto weights and, ultimately, observed behaviors. Under NC, current shocks systematically affect current behavior. However, past shocks are bygones and should be forgotten (at least to the extend that they cannot affect future wages).

LIC models, however, generate more complex dynamics. These productivity shocks typically affect an agent's outside options, and may thus make their IR constraint more difficult to satisfy. A large, unexpected shock or, equivalently, an accumulation of smaller shocks, may result in a violation of an IR constraint and, therefore, in a change in Pareto weights. These changes, however, are semi-permanent in the LIC version of the collective model: the new Pareto weights will remain unchanged until some IR constraint is again violated.

Specifically, we investigate whether, once current and future (expected) wages are controlled for, unexpected past shocks have a long term impact on labor supply behavior, measured by hours of work. The link between individual bargaining powers (as summarized by the Pareto weights) and labor supply has been repeatedly established in the literature (e.g., Chiappori et al., 2002; Voena, 2015; Lyssiotou, 2017). In a LIC context, past shocks affecting wages should have a similar impact. That is, if one spouse experiences particularly large, positive wage shocks, the resulting shift in bargaining positions should result in that spouse attracting a larger fraction of household resources, which should increase that spouse's demand for leisure. As a consequence,

[6] The intuition is directly related to Ligon et al. (2002), and Dubois et al. (2008).

this spouse's labor supply is expected to decline. Similarly, a negative shock would have the opposite impact.

Some issues must be considered when performing estimations of intertemporal labor supply. First of all, wage realizations at any given period can affect Pareto weights only if they were not anticipated. Indeed, expected future wage increases would typically have been taken into account at the beginning of the relationship, and thus integrated into the initial Pareto weights negotiation. To address this issue, we first estimate a model of wage dynamics based on Altonji et al. (2013). Then, at any period, we can distinguish between expected and unexpected wage variations, and we concentrate on the labor supply impact of the latter type. Second, selection effects should be considered, particularly since matching on the marriage market is typically assortative on wages and human capital. We therefore systematically control for initial wages (i.e., individual wages at the beginning of either the marital relationship or the data record). Alternatively, we also exploit the panel structure of the PSID and EU-SILC data to introduce household fixed effects in the econometric models -although this probably leads to underestimating the effects at stake, since the lasting impacts of early shocks are typically hard to distinguish from a household fixed effect. Given that estimates include generated regressors, we follow Pagan (1984) and Murphy and Topel (1985) and bootstrap estimates (reproducing 500 iterations).

Finally, we consider some of robustness tests[7]:

*i*) First, changes in Pareto weights should, in principle, affect all aspects of household behavior and not only labor supply.[8] We therefore analyze the effects of past wage shocks on the household's demand for a public good in the US -in the case of PSID data, housing.[9] Unlike labor supply, the direction of the impact is not a priori clear, since it depends on the spouses' respective preferences: increasing a spouse's bargaining position boosts household demand for a public good if and only if that spouse's marginal willingness to pay for the public good

[7]See the Appendices 2.B and 2.C.

[8]The impact of distribution factors on household demand have been empirically considered in several contributions (Thomas, 1990; Lundberg et al., 1997; Mazzocco, 2007; Cherchye et al., 2012; Attanasio and Lechene, 2014). In the current intertemporal framework, past shocks play exactly the role of distribution factors. Previous research has used sex ratios as a distribution factor (Chiappori et al., 2002; Rapoport et al., 2011; Campaña et al., 2018). However, we do not follow this approach, as data shows no significant changes in the sex ratio over the period under consideration. See Figure 2.B1 in the Appendix 2.B and Table 2.C1 in the Appendix 2.C.

[9]The PSID also provides information on children expenditures. However, an exhaustive analysis of children as public goods would also involve an investigation of parental time and production functions of children human capital. The EU-SILC data does not provide information for this task.

is more income-sensitive than that of the partner (Blundell et al., 2005). Still, a significant impact of past wage shocks on current demand for public goods, when wealth, total expenditures and current and future wages are controlled for, would be hard to explain in an unitary, FIC or NC framework.

*ii*) Second, the effects under consideration are specific to the bargaining mechanism implicit in a collective framework. As such, they should not be present in single-person households. Therefore, similar estimates are studied in the case of singles, in order to check that the results are indeed specific to couples.

*iii*) Third, we study the extensive margin of the labor market. That is to say, whether individuals work or not (wages and wage deviations are defined as zero for the periods at which individuals report not to be working, following Altonji et al., 2013).

*iv*) Finally, we repeat estimates including a wider range of controls that might affect intrahousehold bargaining processes. These controls include the immigrant status of households, legal and first marriages, State/region fixed effects, or the role of the recent economic crisis in the prediction of spouses' wages.

### 2.2.2 Parametrization

Assume that $i$ represents the household, $T$ (0) the last (first) year available for household $i$, and $j = A, B$ represents the wife and the husband, without loss of generality.[10] We then estimate the following system of SUR labor supply equations, using the PSID and the EU-SILC data:

$$\begin{aligned} h_{iAT} = f_0 \quad & + f_1^0 \log w_{iA0} + f_2^0 \log w_{iB0} + f_3^0 y_{i0} \\ & + f_1 \log w_{iAT} + f_2 \log w_{iBT} + f_3 y_{iT} \\ & + f_4 \log E_T w_{iA(T+1)} + f_5 \log E_T w_{iB(T+1)} \\ & + f_6 d_{iAT} + f_7 d_{iAT^-} + f_8 d_{iBT} + f_9 d_{iBT^-} + f_{10} z_{iAT} + \alpha_T + \varepsilon_{iAT} \end{aligned} \tag{2.1}$$

[10]For the PSID data, $T = 2015$, as it was the most recent year available when this Chapter was written.

and

$$\begin{aligned} h_{iBT} = m_0 \quad & + m_1^0 \log w_{iA0} + m_2^0 \log w_{iB0} + m_3^0 y_{i0} \\ & + m_1 \log w_{iAT} + m_2 \log w_{iBT} + m_3 y_{iT} \\ & + m_4 \log E_T w_{iA(T+1)} + m_5 \log E_T w_{iB(T+1)} \\ & + m_6 d_{iAT} + m_7 d_{iAT^-} + m_8 d_{iBT} + m_9 d_{iBT^-} + m_{10} z_{iBT} + \alpha_T + \varepsilon_{iBT} \end{aligned} \tag{2.2}$$

where, omitting the household index $i$, $h_{jT}$ represents working hours at date $T$ of spouse $j = A, B$; $w_{j0}$ and $w_{jT}$ represent the wages of spouse $j$ at dates 0 and $T$; $y_0$ and $y_T$ represent household non-labor income at 0 and $T$; $E_T w_{j(T+1)}$ represents the expected wage of spouse $j$ at $T+1$; $d_{jT}$ represents the wage deviation of spouse $j$ at $T$; $d_{jT^-}$ represents the cumulative wage deviation of spouse $j$ at dates $0, ..., T-1$; $z_{jT}$ is a vector of sociodemographics of spouse $j$ at date $T$; $\alpha_T$ represents region fixed effects; and $\varepsilon_{jT}$ is the error term.

Note, first, that the index $T$ is, in Equations 2.1 and 2.2, fixed for each household. Secondly, the inclusion of future wages is required for the model not to be misspecified. If future expected wages were not included, estimates would potentially suffer from omitted variable bias, and results could not be consistent. We precisely want to test whether, controlling for current and future expected wages, previous wage deviations still have an effect on spouses' labor supply. Lastly, standard errors are estimated by bootstrapping ($n = 500$), to take into account the fact that some regressors were estimated in first-stage regressions.

On the other hand, Equations 2.1 and 2.2 are re-estimated exploiting the longitudinal information provided by the PSID and the EU-SILC. That is to say, initial observables $(w_{A0}, w_{B0}, y_0)$ are omitted and, instead, equations are estimated including household fixed effects. The Equations are as follows. Assume now that $t = 0, ..., T$ is the time index (which is no longer constant for each household), and $\alpha_i$ represents household $i$ fixed effects (which may lead to underestimating the effects at stake, as they are assumed to come from intrahousehold processes). For each $t \geq 1$, we estimate the following equations:

$$\begin{aligned} h_{iAt} = \alpha_i \quad & + f_1 \log w_{iAt} + f_2 \log w_{iBt} + f_3 y_{it} \\ & + f_4 \log E_t w_{iA(t+1)} + f_5 \log E_t w_{iB(t+1)} \\ & + f_6 d_{iAt} + f_7 d_{iAt^-} + f_8 d_{iBt} + f_9 d_{iBt^-} + f_{10} z_{iAt} + \alpha_t + \varepsilon_{iAt} \end{aligned} \tag{2.3}$$

and

$$h_{iBt} = \alpha_i \quad +m_1 \log w_{iAt} + m_2 \log w_{iBt} + m_3 y_{it}$$
$$+m_4 \log E_t w_{iA(t+1)} + m_5 \log E_t w_{iB(t+1)} \tag{2.4}$$
$$+m_6 d_{iAt} + m_7 d_{iAt^-} + m_8 d_{iBt} + m_9 d_{iBt^-} + m_{10} z_{iBt} + \alpha_t + \varepsilon_{iBt}$$

where the variables are defined analogously to Equations 2.1 and 2.2. Standard errors are also estimated by bootstrapping ($n = 500$).

## 2.3 PSID Data

We first use data from the Panel Study of Income Dynamics (PSID) of the US. The PSID is "the longest running longitudinal household survey in the world".[11] It is conducted every two years by the University of Michigan and contains data on a range of factors, including employment, income, wealth, and marriage, among others, and covers information at the family and individual level, for all individuals in each of the interviewed households.

We use data from the PSID interviews from year 2015, with interviews referring to the previous year. For households interviewed in 2015, we also use data from all the previous waves of the PSID in which they appear, back to 2001.[12] We restrict the sample to two-member households formed by a husband and a wife, or cohabiting unmarried partners, between 18 and 65 years old. We concentrate on households whose composition has remained stable over the analyzed period. Therefore, we eliminate those families in which there has been a divorce, and/or a wife or husband has engaged in a new marriage or cohabitation. The study of the interaction between household formation and/or dissolution and collective labor supply is an intriguing topic beyond the scope of this Chapter, which is left for future research. We also eliminate families with missing information in the variables used throughout the analysis. Finally, we retain households with information in uninterrupted periods only. These restrictions leave us with a sample of 2,106 households. Each household appears on average in 7.25 waves, with 70.3% of the sample (1,480 households) being followed back to 2001.

The PSID allows to directly define the labor supply of wives and husbands as the

[11] More information at https://psidonline.isr.umich.edu/.

[12] Previous waves did not include the required information to define consistently non-labor income; however, additional information about past wages is also taken from the 1997 and 1999 waves of the PSID.

total annual hours of market work on all jobs. For wages, the PSID provides information on the total annual labor income (in dollars) of individuals, on all jobs. We define wage rates of wives and husbands as the rate of total labor income over total hours of work. The PSID provides information for demographics at the individual level, including age (measured in years) and the number of completed years of education (measured in years). The PSID also provides information at the family level, i.e., information that refers to households as units. For instance, we have information about the total annual income (in dollars) of every interviewed family (including taxable income, transfer income, and Social Security income of the household). However, we define non-labor annual income, net of savings, as the household total expenses, minus the sum of labor income of family members. This definition excludes savings and avoids an important source of endogeneity and bias that would emerge if using total income in the definition of non-labor income. (Despite of that, estimates using total income are similar.)

The PSID also provides data on the region in which the household resides, and we define four dummies, classifying households in four regions: Northeast, North, West, and South. Information about States instead of regions is additionally used as a robustness check. Furthermore, the PSID contains information about all the family members, and we consider the age of those members, and in particular the number of children in each household. Given that the age of the children may condition the behavior of mothers and fathers (Miller and Mulvey, 2000; Silvers, 2000; Campaña et al., 2016), we define two variables at family level: the number of children aged 6 or younger in the household, and the number of children between ages 7 and 17 (inclusive). Finally, the PSID allows to define the household's housing expenditure, in dollars per year.[13]

Table 2.1 shows summary statistics of variables, differentiating between wives and husbands in the case of variables defined at the individual level. These descriptives are computed using the specific weights provided by the PSID: 69.8% of wives and 89.6% of husbands report being employed, with 1,305 households where both the wife and the husband work. The average hours of work per year is 1,714 for working wives, and 2,203 for working husbands. The average hourly wages are 23.8 and 30.3 dollars per hour for wives and husbands. The average age of wives is 47.5 years, while that of husbands is 48.9 years. Women in the sample are slightly more educated than men, with 13.947 years of complete education on average, vs 13.678 of men. Finally, 77.4% (82.7%) of wives (husbands) are white, and 4.7% (7.5%) are black. The remainder of the

[13]The PSID only provides data on expenditures at the household level, which prevents from a more detailed analysis of sharing rules and bargaining power using individual consumptions and/or exclusive goods.

Table 2.1: Summary statistics

| | Wives | | Husbands | | Difference |
|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | $p$-value |
| Individual variables | | | | | |
| Labor participation | 0.698 | 0.459 | 0.896 | 0.305 | (<0.001) |
| Hours of work | 1.714 | 0.692 | 2.203 | 0.671 | (<0.001) |
| Wage | 23.838 | 16.495 | 30.300 | 24.299 | (<0.001) |
| Log-wage | 2.922 | 0.843 | 3.081 | 1.071 | (<0.001) |
| Predicted log-wage | 2.986 | 0.461 | 3.212 | 0.563 | (<0.001) |
| Age | 47.463 | 10.593 | 48.945 | 10.677 | (<0.001) |
| Years of education | 13.947 | 2.765 | 13.678 | 2.822 | (<0.001) |
| White | 0.774 | 0.419 | 0.827 | 0.378 | (<0.001) |
| Black | 0.047 | 0.212 | 0.075 | 0.263 | (<0.001) |
| Family variables | | | | | |
| Non-labor income | 2.029 | 6.242 | - | - | |
| Expenditure in housing | 24.606 | 15.634 | - | - | |
| N. children $\leq$ 6 years | 0.244 | 0.614 | - | - | |
| N. children 7-17 years | 1.063 | 1.142 | - | - | |
| N. Families | 2,106 | | | | |

Note: The sample (PSID 2015) is restricted to stable households. Labor force participation takes value 1 if individuals report positive hours of work, zero otherwise. Hours of work is measured in hours worked per year, divided by 1,000 (only for working individuals). Wages are measured in dollars per hour of work (only for working individuals). Log-wages are defined as the logarithm of 1 plus wages (only for working individuals). Non-labor income, and household expenditures are measured in dollars per year, divided by 1,000. Differences are defined as the mean value of the correspondent variable for wives, minus the corresponding value for husbands. $T$-test $p$-values for the mean differences in parentheses.

sample are non-whites and non-blacks, including Asians, Latin-Americans, and others. All these differences between women and men are statistically significant at standard levels. Regarding household attributes, the average non-labor income of households is $2,029 per year, net of savings. The average number of children under 6 years is 0.244, while the average number of children between 7 and 17 years is 1.063.

### Wage dynamics

We estimate wages using a model based on Altonji et al. (2013), who analyzed wages, earnings, employment and work hours, and study several aspects of these dynamics, including the effects of various shocks, such as human capital, job changes, and unemployment. As wages are modeled in terms of factors that can be observed by individuals, this represents an adequate model for expected wages. Since we are interested only in the predicted outcome of the wage model, i.e., in expected wages, we only need to estimate the main log-wage model.

We regress log-wages over race (a dummy that takes value 1 if individuals are black, 0 otherwise), years of education, a polynomial on experience and employer tenure, a dummy measuring job changes (taking value 1 if the individual has changed job in the previous year, 0 otherwise), and two lags of log-wages.[14] We also include year and region fixed effects. In order to control for selection into employment, we estimate a Heckman (1979) model, in which the selection equation is identified from the exclusion in the main equation of the marital indicator and the presence of children. Estimates are shown in Table 2.B2 in the Appendix 2.B.[15] The inverse Mills ratio is significant and negative for women, indicating the presence of sample selection bias. For men, the inverse Mills ratio is non-significant.

Lastly, these estimates allow us to decompose, for any period $t$, the observed wage into the sum of an expected (predicted) component and an "unexpected deviation". The main purpose is to study the impact of these past deviations on current behavior, controlling for current and future expected wages. In particular, the prediction of future wages at the end of the observation period requires some assumptions, as we do not have information of individuals for subsequent years. The value of several variables, as experience, education or gender, can be unequivocally predicted. Moreover, we assume that individuals will not change their region of residence. We also assume that individuals base their wage expectation on their current job, that is to say, that these expectations do not involve a job change in the next period. Different assumptions would require additional and more complex predictions of future job changes, which is left for future research.

## 2.4 Results in the US

Estimates of Equations 2.1 and 2.2 are shown in Columns (1) and (2) of Table 2.2, restricted to households where spouses report positive hours of work. The initial wages

[14] See Figure 2.A2 in the Appendix 2.B for the theoretical system of equations that determine log wages in Altonji et al. (2013). Variables are defined and computed from the PSID following Altonji et al. (2013).

[15] For the first two years of a household in the sample, we cannot include two lags of log wages. To reduce potential omitted variable bias, information of lagged wages for the years 2003 and 2001 is taken from the 1999 and 1997 waves of the PSID. 63.5% of the sample can be followed back to 1997. Additional results are available upon request.

of both the husband and the wife significantly affect husband's labor supply, suggesting unobserved heterogeneity and assortative matching in the marriage; however, wife's labor supply is not significantly impacted by initial wages. The wage of each spouse is found to increase that spouse's labor supply and decrease the partner's, as expected from a standard income effect. However, the impact is smaller for the husband (in particular, his labor supply appears inelastic to both the expected and unexpected component of his wage). The same pattern is observed for the non expected deviation of current wages, with essentially the same magnitudes. Lastly, future (expected) wages are not significant.

The main conclusion of this Table is the impact of past, unexpected wage variations. The signs are exactly as predicted by the theoretical arguments sketched above: when a spouse did better than expected in terms of past wage realizations, that spouse works less and their partner works more, although cross effects are not significant. Interestingly, the wife's past wage deviations appear to have a quantitatively much larger own-impact that the husband's, suggesting that respective bargaining positions are more sensitive to her past wages than to his.

Regarding the rest of the explanatory variables, we find that age is negatively correlated with the hours of work of wives and husbands. Race is not significant, and education is only significant, and negative, for wives. The number of children is negatively correlated with the hours of work of wives, but positively correlated with hours of work of husbands, especially for children under 6 years old. These results are in line with other theories, such as the household responsibilities hypothesis (Giménez-Nadal and Molina, 2016), or Becker (1991)'s model of division of labor within households.

Table 2.3 presents the results of estimating Equations 2.3 and 2.4, i.e., introducing household fixed effects in the regressions. Concentrating on the impact of past variations, we find that the signs remain unchanged, but the coefficients of the wife's previous shocks are no longer significant. On the other hand, the husband's past shocks are found to significantly increase her labor supply, again comforting the LIC version of the collective model.

### Results for singles

Table 2.4 provides a robustness check by presenting analogous regressions on a sample of singles. The observed patterns are quite interesting. Regarding women, the impact of past wage shocks is not significant (and quantitatively much smaller than for couples) in both regressions. For men, past wages shocks are only significant in the baseline regression, but their impact is now positive. This clearly shows that, at least regarding this aspect, the dynamics of labor supply are quite different for couples than for singles, and that the specific patterns observed in the previous regressions are specific to household decision processes. In fact, while the impact of past shocks on current labor supply may, at least in a small part and only for male labor supply, result from an imperfect estimation of the wage dynamics, the estimates on single men indicate that this bias would if anything go against us, suggesting an even stronger impact of past shocks on current bargaining positions. Lastly, all these effects totally disappear in the fixed effect version of the singles regression.

### Public expenditure of the household

In order to provide a complementary analysis of collective behavior, we estimate the impact of wage deviations on housing expenditures. We thus estimate the following equation using the fixed effects estimator:

$$\begin{aligned} C_{it} = \alpha_i \quad & + c_1 \log w_{iAt} + c_2 \log w_{iBt} + c_3 y_{it} \\ & + c_4 \log E_t w_{iA(t+1)} + c_5 \log E_t w_{iB(t+1)} + c_X X_{it} \\ & + c_6 d_{iAt} + c_7 d_{iAt^-} + c_8 d_{iBt} + c_9 d_{iBt^-} + c_{10} z_{it} + \alpha_t + \varepsilon_{it} \end{aligned} \tag{2.5}$$

where, omitting the household index $i$, $C_t$ represents the households *share* of expenditures on housing (including mortgages and loans, rent, property tax, insurance, utilities, TV, telephone, Internet, repairs, and furnishings); $z_t$ represents the union of $z_{At}$ and $z_{Bt}$; and $X_t$ is total expenditures, included in order to capture wealth effects. The remaining variables are defined analogously to Equations 2.3 and 2.4, and standard errors are also estimated by bootstrapping ($n = 500$).

Table 2.5 shows estimates of Equation 2.5 in the fixed effect model. The main conclusion is that the wife's past wage deviations have a significant, negative effect on housing expenditures. When she did better than expected in the past, in terms of wage realizations, this tends to decrease the amount spent on housing. Note that this pattern is unlikely to reflect any omitted wealth effect, since it is hard to see how better than expected past wage realizations (for the wife) could possibly reduce either current or future (expected) wealth. Again, the LIC framework provides a natural explanation: the shocks resulted in changes in Pareto weights, and wives show a smaller preference for public consumption in terms of housing expenditure than husbands.

Table 2.2: Labor supply estimates

| VARIABLES | Wives (1) | Husbands (2) |
|---|---|---|
| Initial observables | | |
| Log-wage (wife) | -0.010 | -0.190*** |
| | (0.051) | (0.056) |
| Log-wage (husband) | -0.020 | -0.150*** |
| | (0.049) | (0.048) |
| Non-labor income | -0.004 | -0.021*** |
| | (0.006) | (0.006) |
| Present observables | | |
| Log-wage (wife) | 0.420*** | -0.023 |
| | (0.075) | (0.065) |
| Log-wage (husband) | -0.185*** | 0.090 |
| | (0.052) | (0.059) |
| Non-labor income | -0.011 | 0.002 |
| | (0.008) | (0.008) |
| Expected wages $(t+1)$ | | |
| Log-wage (wife) | 0.157 | -0.037 |
| | (0.113) | (0.107) |
| Log-wage (husband) | -0.172 | 0.116 |
| | (0.112) | (0.125) |
| Wage deviations | | |
| Present (wife) | 0.416*** | -0.051 |
| | (0.075) | (0.063) |
| Previous (wife) | -0.566*** | 0.032 |
| | (0.090) | (0.085) |
| Present (husband) | -0.160*** | 0.094 |
| | (0.050) | (0.059) |
| Previous (husband) | 0.119 | -0.167* |
| | (0.083) | (0.091) |
| Constant | 1.755*** | 2.245*** |
| | (0.289) | (0.335) |
| Sociodemographics | Yes | Yes |
| Region F.E. | Yes | Yes |
| Observations | 1,305 | 1,305 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (PSID 2015) is restricted to stable households. The dependent variable is the annual hours of work of wives and husbands, divided by 1,000. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.3: Labor supply fixed effects estimates

| VARIABLES | Wives (1) | Husbands (2) |
|---|---|---|
| Present observables | | |
| Log-wage (wife) | 0.336*** | 0.008 |
| | (0.015) | (0.015) |
| Log-wage (husband) | -0.029** | 0.307*** |
| | (0.015) | (0.021) |
| Non-labor income | -0.016*** | -0.022*** |
| | (0.003) | (0.004) |
| Expected wages $(t+1)$ | | |
| Log-wage (wife) | 0.073* | -0.268*** |
| | (0.042) | (0.047) |
| Log-wage (husband) | -0.187*** | -0.055 |
| | (0.033) | (0.041) |
| Wage deviations | | |
| Present (wife) | -0.255*** | -0.040 |
| | (0.028) | (0.025) |
| Previous (wife) | -0.005 | 0.000 |
| | (0.008) | (0.009) |
| Present (husband) | -0.027 | -0.338*** |
| | (0.021) | (0.032) |
| Previous (husband) | 0.022*** | -0.010 |
| | (0.007) | (0.008) |
| Constant | 1.363*** | 2.600*** |
| | (0.209) | (0.230) |
| Sociodemographics | Yes | Yes |
| Region F.E. | Yes | Yes |
| Observations | 7,455 | 7,455 |
| Households | 1,305 | 1,305 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (PSID 2001-2015) is restricted to stable households. The dependent variable is the annual hours of work of wives and husbands, divided by 1,000. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.4: Labor supply estimates for singles

| | Baseline | | Fixed effects | |
|---|---|---|---|---|
| | Women | Men | Women | Men |
| VARIABLES | (1) | (2) | (3) | (4) |
| Initial observables | | | | |
| Log-wage | -0.023 | -0.056 | - | - |
| | (0.030) | (0.038) | | |
| Non-labor income | -0.006* | -0.011*** | - | - |
| | (0.003) | (0.004) | | |
| Present observables | | | | |
| Log-wage | 0.448*** | 0.523*** | 0.156*** | 0.125* |
| | (0.079) | (0.099) | (0.058) | (0.069) |
| Non-labor income | -0.036*** | -0.040*** | -0.034*** | -0.034*** |
| | (0.003) | (0.005) | (0.002) | (0.004) |
| Expected wages $(t+1)$ | | | | |
| Log-wage | -0.151* | -0.430*** | -0.290*** | -0.237*** |
| | (0.081) | (0.094) | (0.059) | (0.081) |
| Wage deviations | | | | |
| Present | -0.298*** | -0.104 | -0.363*** | -0.346*** |
| | (0.060) | (0.072) | (0.042) | (0.050) |
| Previous | -0.003 | 0.045* | -0.022 | -0.002 |
| | (0.016) | (0.024) | (0.015) | (0.020) |
| Constant | 1.727*** | 1.397*** | 2.342*** | 1.439*** |
| | (0.238) | (0.251) | (0.263) | (0.454) |
| Sociodemographics | Yes | Yes | Yes | Yes |
| Region F.E. | Yes | Yes | Yes | Yes |
| Observations | 1,212 | 952 | 4,219 | 2,905 |
| Individuals | - | - | 1,212 | 952 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (PSID 2001-2015) is restricted to single workers. The dependent variable is the annual hours of work of women and men, divided by 1,000. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.5: Public expenditure on housing

| VARIABLES | Fixed effects (1) | IV fixed effects (2) |
|---|---|---|
| Present observables | | |
| Log-wage (wife) | -0.141 | -0.205 |
| | (0.248) | (0.254) |
| Log-wage (husband) | 0.300 | 0.256 |
| | (0.224) | (0.239) |
| Non-labor income | 0.136*** | 0.126*** |
| | (0.038) | (0.039) |
| Total expenditure | -0.062*** | 0.001 |
| | (0.015) | (0.054) |
| Expected wages $(t+1)$ | | |
| Log-wage (wife) | 0.866 | 0.733 |
| | (0.664) | (0.676) |
| Log-wage (husband) | 1.394** | 1.160** |
| | (0.547) | (0.588) |
| Wage deviations | | |
| Present (wife) | 0.435 | 0.398 |
| | (0.417) | (0.414) |
| Previous (wife) | -0.244** | -0.241** |
| | (0.119) | (0.112) |
| Present (husband) | 0.274 | 0.150 |
| | (0.403) | (0.430) |
| Previous (husband) | -0.010 | -0.001 |
| | (0.108) | (0.113) |
| Constant | 33.275*** | 34.828*** |
| | (4.225) | (4.178) |
| Sociodemographics | Yes | Yes |
| Region F.E. | Yes | Yes |
| Observations | 11,969 | 11,969 |
| N. households | 2,106 | 2,106 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (PSID 2001-2015) is restricted to stable households. The dependent variable is the share of annual expenditure of the household in housing, in percentage. Total expenditure is instrumented by total household income in Column (2). Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

## 2.5 EU-SILC data

We also use data from the European Union Statistics on Income and Living Conditions (EU-SILC) to reproduce the analysis in the case of Europe.[16] The EU-SILC is a comparable, longitudinal, and multidimensional microdata, and is part of the European Statistical System (more information at http://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions). It is conducted every year by Eurostat (since 2003). The EU-SILC provides information at the family and individual level for interviewed households. It covers a range of factors, including income, labor characteristics, poverty, and living conditions, among others (European Commission, 2017). One difference between the PSID and the EU-SILC databases is that, in the latter, households are only interviewed up to four consecutive years, in such a way that the EU-SILC constitutes an overlapping panel and therefore provides a lower range of longitudinal variation than the PSID.

We use data from the EU-SILC interviews from years 2003 to 2016. The sample used throughout the analysis is restricted to two-member households formed by married or unmarried but cohabiting partners, between 18 and 65 years old. Furthermore, we retain those households that have completed at least three of the four-year interviews, and eliminate those households in which, during the interview period, a divorce or new marriage has occurred, in order to concentrate on households whose composition has remained stable (Chiappori et al., 2002; Mazzocco, 2007). As standard practice, we also eliminate families with missing information in the variables used throughout the analysis. The potential selection bias that may arise from these restrictions is omitted, as is usual when studying collective behaviors.

The EU-SILC data allows us to directly define the labor supply of wives and husbands as the hours of (market) work per week, and wages are provided by the gross and net individual labor income of interviewees.[17] We define then wage rates of wives and husbands as the rate of labor income per annual hours of work.[18] The EU-SILC also provides information for demographics at the individual level, including age (measured in years) and the maximum education level achieved by spouses, defined in terms of the International Standard Classification of Education (ISCED). Two dummies are

[16] Access to data has been granted by the Contract RPP 119/2018.

[17] Defined in terms of net cash plus non-cash individual income from labor, plus net self-employment benefits in the case of self-employed workers. Variables regarding income and labor supply are defined in "income reference periods", which are defined as 12-month periods that may be fixed or moving, for comparability purposes, according to the EU-SILC methodology (European Commission, 2017).

[18] Annual hours of work are defined as 7/365 times weekly hours of work.

defined: University education, which takes value 1 if individuals have reached University (0 otherwise); and secondary education, that takes value 1 if individuals have reached secondary, non-compulsory education (0 otherwise). Thus, the reference group for education would correspond to low educated individuals who have not reached non-compulsory education.

The EU-SILC provides information at the family level, including total annual income, and the level of income that makes ends meet (in Euros) of every interviewed family (including taxable income, transfer income, and Social Security income of the household). We define non-labor annual income, net of savings, as the household total income that makes ends meet, minus the sum of labor income of family members, to exclude savings. Finally, for each country, the EU-SILC provides data on the region in which the household resides (NUTS-3), and on the number of children, allowing us to distinguish between the number of children under 4 years old, the number of children between 5 and 15 years, and the number of children over 16 years.[19]

From the original sample of the EU-SILC data, which contained information for 31 European countries, these restrictions leave us with information for Austria, Belgium, France, Greece, Italy, Luxembourg, Portugal, Spain, Sweden, Bulgaria, Estonia, Latvia, Poland and Slovenia.[20] Portugal is dropped from the sample due to its small sample size (less than 500 observations), and countries of Eastern Europe are also omitted, to focus only on Western Europe. The analysis of intertemporal commitment in Eastern Europe is left for future research. Thus, the final sample includes households from Austria (3,762 observations), Belgium (3,157), France (2,087), Greece (3,521), Italy (11,018), Luxembourg (2,097), Spain (8,051), and Sweden (3,094). Table 2.6 shows summary statistics of the main variables, computed using the specific weights provided by the EU-SILC, for each of the eight countries considered.

[19]The EU-SILC does not provide information on the expenditure in goods publicly consumed within the household.

[20]The initial EU-SILC sample consists of 164,750 households and 310,150 individuals from Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, UK, Iceland, Norway and Serbia.

Table 2.6: Summary statistics

| | Austria | Belgium | France | Greece | Italy | Luxembourg | Spain | Sweden |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | Mean | Mean | Mean | Mean | Mean | Mean | Mean | Mean |
| Labor participation (wives) | 0.751 | 0.846 | 0.808 | 0.642 | 0.622 | 0.72 | 0.64 | 0.97 |
| Labor participation (husbands) | 0.898 | 0.926 | 0.887 | 0.864 | 0.89 | 0.94 | 0.838 | 0.983 |
| Hours worked per week (wives) | 24.275 | 28.089 | 28.12 | 23.715 | 21.116 | 24.117 | 22.694 | 34.993 |
| Hours worked per week (husbands) | 38.938 | 38.619 | 37.278 | 37.134 | 37.43 | 40.54 | 35.706 | 39.398 |
| Log-wage (wives) | 1.843 | 2.149 | 1.97 | 1.177 | 1.534 | 1.96 | 1.42 | 2.535 |
| Log-wage (husbands) | 2.341 | 2.438 | 2.305 | 1.686 | 2.137 | 2.845 | 1.936 | 2.697 |
| Non-labor income | 3.041 | 3.637 | 5.952 | 9.761 | 4.557 | 5.422 | 5.731 | 0.566 |
| Age (wives) | 43.554 | 42.757 | 41.827 | 43.311 | 45.453 | 41.858 | 44.661 | 44.017 |
| Age (husbands) | 46.397 | 45.074 | 43.96 | 47.452 | 48.336 | 44.341 | 46.871 | 46.064 |
| Secondary ed. (wives) | 0.666 | 0.336 | 0.446 | 0.416 | 0.483 | 0.355 | 0.224 | 0.416 |
| Secondary ed. (husbands) | 0.642 | 0.382 | 0.498 | 0.409 | 0.474 | 0.387 | 0.239 | 0.538 |
| University ed. (wives) | 0.19 | 0.542 | 0.421 | 0.342 | 0.193 | 0.326 | 0.409 | 0.53 |
| University ed. (husbands) | 0.284 | 0.472 | 0.349 | 0.314 | 0.163 | 0.325 | 0.359 | 0.38 |
| N. of children under 4 | 0.192 | 0.335 | 0.303 | 0.233 | 0.188 | 0.346 | 0.237 | 0.328 |
| N. of children | 0.642 | 0.697 | 0.748 | 0.698 | 0.603 | 0.759 | 0.624 | 0.694 |
| Observations | 3,762 | 3,157 | 2,087 | 3,521 | 11,018 | 2,097 | 8,051 | 3,094 |

Note: The sample (EUSILC 2003-2016 data) is restricted to stable households of countries. Variables are defined analogously to Table 2.1.

**Wage dynamics**

In the case of the EU-SILC, we follow a similar approach for wage deviations to that followed using the PSID data. That is to say, we propose a wage model based on Altonji et al. (2013). However, we cannot completely replicate that model, as we cannot include information regarding race, nor regarding employment tenure, given that those variables are not provided by this database. Therefore, it may be that wage models estimated for European countries suffer from an omitted variable bias, at least compared to wage models using the PSID data for the US. Estimates are shown in Tables 2.C2 to 2.C7 in Appendix 2.C.

Once expected wages are predicted, we decompose, for any period $t$, the observed wage into the sum of the expected and the unexpected components. Therefore, as in the study of the US, we can estimate the impact of these past unexpected deviations on current behavior, controlling for current and future wages. Predicted future wages at the last period for which information is available are defined, making assumptions analogous to those made for the case of the US.

## 2.6 Results in Europe

Tables 2.7 and 2.8 show estimates of Equations 2.1 and 2.2. First, estimates clearly reject the income pooling property in all the studied cases, as one additional Euro does not have the same correlation with spouses' labor supply, regardless of the recipient. Therefore, estimates reject the unitary framework. Second, according to the estimates, past wages or non-labor income are significant at some extent for all the countries, in terms of present labor supply. That automatically rejects the NC model. The FIC model is analogously rejected, since present deviations are, in general terms, highly significant.

In particular, it is important to point out that estimates indicate the existence of heterogeneity between countries in terms of income and substitution effects. For male workers, the correlation between labor supply and (own) wages is positive and significant in Austria, France, Italy, Spain and Sweden, while it is negative and significant in Belgium, and non-significant in the rest of the countries. Furthermore, Spain is the only country in which a significant and negative cross-effect is estimated in terms of husbands' labor supply and wives' wages. Cross-coefficients are non-significant in the rest of countries. The analogous coefficients between wives' labor supply and wages are positive and significant in Austria, France, Italy and Spain, and non-significant in the rest of the cases; husbands' wages show negative correlations with wives hours of work in all the countries except Greece and Sweden. Finally, expected future wages show different (cross and own) coefficients in the countries analyzed.

Regarding the LIC framework, controlling for current wages, present wage deviations, and the distribution of (future) wage expectations, we would expect that previous wage deviations had a negative (positive) effect on own (spouse's) present hours worked, and therefore such effect should happen via Pareto weights. Estimates show that these trends are precisely the figures suggested by labor supply equations in all the countries studied, under the same specification. In Austria, France, Greece, Italy, Spain and Sweden, we find that wives' and husbands' previous wage deviations are negatively correlated with their own labor supply. Results are analogous (i.e., negative coefficients) for Belgium and Luxembourg, but the correlation between husbands' hours of work and own past deviations are not significant at standard levels. Furthermore, in Austria, Belgium, France, Greece, Italy and Spain, we find a positive effect of husbands' previous deviations on wives' labor supply, although these coefficients are only significant for Austria and Belgium. These results strengthen the conclusions about the validity of the LIC model. On the other hand, the correlation between husbands' past deviations and wives' hours of work is negative and non-significant in Luxembourg and Sweden. Finally, the effect of wives' past deviations on husbands' labor supply is non-significant in all the analyzed countries. The main conclusion of Tables 2.7 and 2.8 is, consequently, that predictions of the LIC model are consistent with labor supply estimates, while the FIC and NC models, and also the unitary model, are clearly rejected. Thus, results show the importance of considering collective behaviors in an intertemporal context, where ex ante efficiency is clearly rejected (Mazzocco, 2007; Lise and Yamada, 2018), as is non-commitment.

Table 2.7: Labor supply estimates (I)

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Initial observables | | | | | | | | |
| Log-wage (wife) | 0.615** | 0.240 | 1.488*** | 0.034 | 0.526* | -0.898** | 0.816 | -1.166** |
| | (0.269) | (0.241) | (0.316) | (0.308) | (0.308) | (0.354) | (0.511) | (0.555) |
| Log-wage (husband) | -0.910** | -0.322 | -0.696** | -0.389 | 0.593* | 0.128 | 0.121 | 0.644 |
| | (0.356) | (0.322) | (0.348) | (0.341) | (0.318) | (0.368) | (0.524) | (0.569) |
| Non-labor income | -0.017 | -0.057* | 0.026 | 0.012 | 0.045** | -0.026 | -0.058* | -0.053 |
| | (0.034) | (0.031) | (0.024) | (0.024) | (0.018) | (0.021) | (0.034) | (0.037) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 21.187*** | 1.372 | -2.761 | -1.363 | 5.785** | -1.063 | 0.572 | 0.382 |
| | (2.213) | (1.811) | (2.005) | (1.898) | (2.607) | (2.840) | (2.827) | (2.861) |
| Log-wage (husband) | -12.773*** | 10.525*** | -7.218*** | -6.817*** | -5.953*** | 9.060*** | -2.637 | 1.225 |
| | (2.457) | (2.324) | (2.001) | (2.033) | (2.308) | (2.756) | (2.647) | (3.032) |
| Non-labor income | -0.085*** | -0.141*** | -0.142*** | -0.078*** | -0.127*** | -0.038 | -0.194*** | -0.184*** |
| | (0.030) | (0.027) | (0.023) | (0.023) | (0.028) | (0.033) | (0.035) | (0.038) |
| Expected wages ($t+1$) | | | | | | | | |
| Log-wage (wife) | -31.263*** | -2.616 | 6.313** | 5.870*** | 1.821 | 3.279 | -6.226* | 0.389 |
| | (2.857) | (2.069) | (3.026) | (2.159) | (3.267) | (3.267) | (3.244) | (3.019) |
| Log-wage (husband) | 11.220*** | -16.155*** | 7.354*** | -3.835 | 4.488* | -14.456*** | 1.743 | -6.721** |
| | (2.606) | (2.565) | (2.238) | (3.061) | (2.490) | (3.142) | (2.644) | (3.296) |
| Wage deviations | | | | | | | | |
| Present (wife) | -17.847*** | -1.225 | -5.203*** | 0.405 | -9.935*** | 0.386 | -6.694*** | -1.756 |
| | (1.714) | (1.446) | (1.749) | (1.674) | (2.260) | (2.482) | (1.309) | (1.406) |
| Previous (wife) | -1.349*** | -0.300 | -0.938*** | -0.034 | -1.036*** | 0.329 | -2.783*** | 0.177 |
| | (0.229) | (0.203) | (0.230) | (0.220) | (0.215) | (0.245) | (0.463) | (0.492) |
| Present (husband) | 9.761*** | -7.930*** | 4.938*** | 0.395 | 4.023** | -9.140*** | 0.043 | -3.199*** |
| | (1.942) | (1.816) | (1.676) | (1.619) | (1.882) | (2.226) | (1.033) | (1.132) |
| Previous (husband) | 1.383*** | -0.945*** | 0.737*** | -0.338 | 0.138 | -1.213*** | 0.568 | -2.618*** |
| | (0.290) | (0.266) | (0.222) | (0.215) | (0.250) | (0.292) | (0.512) | (0.572) |
| Constant | 39.844*** | 41.109*** | 50.170*** | 60.338*** | 31.669*** | 35.897*** | 53.709*** | 58.980*** |
| | (2.515) | (2.295) | (2.276) | (2.295) | (2.980) | (3.406) | (2.515) | (2.719) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,745 | 2,745 | 2,608 | 2,608 | 1,605 | 1,605 | 1,888 | 1,888 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.8: Labor supply estimates (II)

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Initial observables | | | | | | | | |
| Log-wage (wife) | 0.732*** | 0.022 | 0.575 | 0.288 | 1.191*** | 0.077 | 0.532** | -0.108 |
| | (0.174) | (0.163) | (0.367) | (0.293) | (0.204) | (0.170) | (0.222) | (0.187) |
| Log-wage (husband) | 0.065 | 0.941*** | -0.729 | 0.553 | 0.205 | 0.685*** | 0.011 | 0.583*** |
| | (0.203) | (0.190) | (0.527) | (0.421) | (0.203) | (0.169) | (0.267) | (0.225) |
| Non-labor income | 0.008 | 0.018 | 0.011 | 0.062** | 0.001 | 0.030*** | 0.008 | 0.009 |
| | (0.015) | (0.014) | (0.038) | (0.031) | (0.012) | (0.010) | (0.029) | (0.024) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 5.235*** | 0.391 | -4.218 | -2.590 | 7.770*** | -4.056*** | -0.585 | 0.338 |
| | (1.153) | (0.961) | (2.967) | (2.184) | (1.342) | (1.075) | (1.257) | (1.049) |
| Log-wage (husband) | -4.221*** | 4.945*** | -5.696** | -2.338 | -8.118*** | 4.182*** | 2.308 | 3.014* |
| | (0.966) | (0.977) | (2.753) | (2.544) | (1.309) | (1.152) | (1.858) | (1.593) |
| Non-labor income | -0.120*** | -0.138*** | -0.154*** | -0.092*** | -0.167*** | -0.138*** | -0.298*** | -0.240*** |
| | (0.022) | (0.021) | (0.041) | (0.033) | (0.027) | (0.022) | (0.058) | (0.049) |
| Expected wages ($t+1$) | | | | | | | | |
| Log-wage (wife) | -10.438*** | -1.426 | 6.166 | 2.523 | -10.688*** | 4.294*** | 2.738* | 1.232 |
| | (1.525) | (1.084) | (3.824) | (2.530) | (1.780) | (1.240) | (1.571) | (1.226) |
| Log-wage (husband) | 3.595*** | -9.998*** | 5.128* | -5.121* | 8.160*** | -13.750*** | 0.975 | -2.155 |
| | (1.051) | (1.256) | (2.772) | (2.796) | (1.518) | (1.643) | (1.859) | (1.635) |
| Wage deviations | | | | | | | | |
| Present (wife) | -7.352*** | -0.347 | -2.768 | 1.388 | -11.469*** | 2.425** | -4.904*** | -0.621 |
| | (0.752) | (0.672) | (2.031) | (1.559) | (1.158) | (0.947) | (1.001) | (0.842) |
| Previous (wife) | -0.600*** | -0.121 | -1.303*** | 0.439 | -0.937*** | 0.131 | -0.273** | 0.075 |
| | (0.169) | (0.157) | (0.377) | (0.300) | (0.173) | (0.143) | (0.110) | (0.094) |
| Present (husband) | 1.589** | -7.545*** | 1.893 | -0.230 | 5.518*** | -6.728*** | -3.382** | -7.216*** |
| | (0.657) | (0.621) | (1.786) | (1.568) | (1.099) | (0.933) | (1.612) | (1.386) |
| Previous (husband) | 0.034 | -0.840*** | -0.190 | -0.418 | 0.244 | -0.984*** | -0.250 | -0.979*** |
| | (0.186) | (0.176) | (0.435) | (0.373) | (0.168) | (0.142) | (0.228) | (0.199) |
| Constant | 43.008*** | 47.907*** | 51.969*** | 57.412*** | 36.367*** | 50.353*** | 29.921*** | 32.207*** |
| | (1.138) | (1.132) | (3.487) | (2.738) | (1.542) | (1.301) | (3.999) | (3.333) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,006 | 7,006 | 1,383 | 1,383 | 4,545 | 4,545 | 2,829 | 2,829 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.9: Labor supply fixed effect estimates (I)

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 0.592 | 2.002 | -1.715* | 0.021 | -4.605** | 0.604 | -8.823** | -3.426 |
| | (1.695) | (1.280) | (0.887) | (0.995) | (2.221) | (1.643) | (3.907) | (2.610) |
| Log-wage (husband) | 1.481 | 0.249 | -0.369 | -2.245** | -0.977 | -2.892 | -3.090 | -5.589** |
| | (1.217) | (0.960) | (1.331) | (1.087) | (1.916) | (1.930) | (4.643) | (2.350) |
| Non-labor income | -0.044* | -0.123*** | -0.045 | -0.063 | -0.082** | -0.123*** | -0.121*** | -0.119*** |
| | (0.023) | (0.030) | (0.039) | (0.055) | (0.034) | (0.034) | (0.031) | (0.040) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -4.271* | -1.222 | -1.768 | 2.145 | 7.481 | -0.470 | -2.613 | 3.134 |
| | (2.480) | (1.517) | (2.802) | (2.423) | (4.733) | (2.504) | (5.589) | (3.076) |
| Log-wage (husband) | -0.575 | -0.755 | -1.562 | 2.396 | -1.521 | 1.921 | 3.136 | -2.398 |
| | (1.892) | (1.217) | (3.798) | (2.051) | (3.150) | (2.373) | (5.743) | (2.452) |
| Wage deviations | | | | | | | | |
| Present (wife) | -2.291* | -1.796 | -0.886 | 0.004 | 1.246 | -1.166 | -0.888 | 1.142 |
| | (1.372) | (1.128) | (0.806) | (0.840) | (1.687) | (1.400) | (1.619) | (1.435) |
| Previous (wife) | -0.585 | -0.025 | -1.363*** | 0.211 | -0.341 | 0.161 | -1.004 | 0.476 |
| | (0.480) | (0.347) | (0.358) | (0.378) | (0.551) | (0.395) | (0.919) | (1.017) |
| Present (husband) | -1.030 | -2.074** | 0.801 | -0.190 | 0.886 | 0.282 | 0.208 | -0.633 |
| | (0.958) | (0.833) | (0.754) | (0.803) | (1.402) | (1.556) | (1.567) | (1.183) |
| Previous (husband) | 0.086 | -0.600 | 1.154*** | -0.358 | 0.147 | 0.092 | 0.178 | -0.554 |
| | (0.351) | (0.372) | (0.321) | (0.404) | (0.440) | (0.604) | (1.136) | (1.013) |
| Constant | 32.480*** | 46.481*** | 30.717*** | 45.356*** | 59.608 | 41.857*** | 49.769*** | 62.810*** |
| | (8.974) | (5.577) | (8.504) | (6.187) | (48.585) | (8.200) | (10.896) | (10.473) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,677 | 4,677 | 3,936 | 3,936 | 1,962 | 1,962 | 2,421 | 2,421 |
| N. Households | 1,559 | 1,559 | 1,312 | 1,312 | 654 | 654 | 807 | 807 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.10: Labor supply fixed effect estimates (II)

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | -5.756*** | -0.249 | -0.188 | 1.533 | -2.116 | 1.496 | -3.174** | 4.329*** |
| | (1.634) | (1.177) | (2.347) | (1.111) | (1.708) | (1.246) | (1.544) | (0.982) |
| Log-wage (husband) | 1.462 | -1.828** | -1.984 | -3.863*** | -0.176 | -2.577** | -0.685 | -9.574*** |
| | (1.028) | (0.914) | (3.449) | (1.256) | (1.211) | (1.195) | (1.268) | (1.051) |
| Non-labor income | -0.120*** | -0.116*** | -0.155*** | -0.127*** | -0.109*** | -0.136*** | -0.198*** | -0.260*** |
| | (0.021) | (0.024) | (0.053) | (0.047) | (0.021) | (0.023) | (0.042) | (0.046) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | 2.216 | 0.812 | -3.670 | -3.638** | -1.042 | -0.694 | 2.330 | -15.134*** |
| | (2.294) | (1.626) | (4.127) | (1.666) | (3.625) | (2.532) | (3.648) | (1.705) |
| Log-wage (husband) | -3.516** | -0.679 | 2.396 | 2.302** | -3.083 | 1.664 | 1.360 | 18.370*** |
| | (1.642) | (1.325) | (5.123) | (1.009) | (2.647) | (2.555) | (2.682) | (1.874) |
| Wage deviations | | | | | | | | |
| Present (wife) | -0.141 | -0.233 | -2.563* | -1.348 | -1.568 | -1.698* | -1.200 | -0.802 |
| | (0.983) | (0.785) | (1.496) | (0.934) | (1.304) | (0.959) | (0.845) | (0.668) |
| Previous (wife) | -1.333*** | -0.264 | -0.553 | -0.288 | -1.309*** | 0.096 | -0.546 | 1.265*** |
| | (0.364) | (0.335) | (0.667) | (0.384) | (0.341) | (0.283) | (0.443) | (0.312) |
| Present (husband) | -0.173 | -1.895*** | 0.571 | -0.178 | 0.175 | -0.568 | -0.491 | 1.764** |
| | (0.631) | (0.618) | (1.783) | (1.020) | (0.867) | (0.810) | (0.925) | (0.798) |
| Previous (husband) | 0.178 | -1.236*** | -0.025 | -0.552 | 0.331 | -0.497 | 0.012 | -2.090*** |
| | (0.334) | (0.362) | (0.803) | (0.629) | (0.312) | (0.320) | (0.396) | (0.441) |
| Constant | 41.242*** | 43.697*** | 24.863* | 58.693*** | 34.350*** | 42.164*** | 44.699*** | 35.168*** |
| | (5.026) | (3.769) | (13.610) | (5.902) | (5.544) | (3.936) | (7.233) | (5.661) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,278 | 10,278 | 2,112 | 2,112 | 5,541 | 5,541 | 4,020 | 4,020 |
| N. Households | 3,426 | 3,426 | 704 | 704 | 1,847 | 1,847 | 1,340 | 1,340 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Tables 2.9 and 2.10 show estimates of Equations 2.3 and 2.4 (i.e., including household fixed effects, exploiting the longitudinal information collected by the EU-SILC). In general terms, estimates reject the unitary model. Further, the FIC model is, again, clearly rejected, as labor supply is not compatible with time-invariant Pareto weights, identified from past wage deviations as distribution factors (Mazzocco, 2007; Lise and Yamada, 2018). Similarly, the NC scenario is automatically rejected, as estimates show that the relationship between past wage deviations and labor supply behaviors is significant. Thus, constant renegotiation of intrahousehold contracts is not supported by estimates.

For instance, focusing on the estimates of coefficients associated with own and cross past wage deviations, results are consistent with predictions of the limited commitment model. Specifically, estimates for Belgium, Greece, Spain, and Sweden are fully compatible with the LIC model, as results show a negative impact of own past wage deviations on present hours of work, but a negative effect of spouses' deviations. These trends are found for both husbands and wives. However, the statistical significance of coefficients differs across countries. In Belgium, past deviations are only significant for wives' labor supply, but not for husbands'. Sweden shows exactly the opposite result, as coefficients are only significant for males. In Spain, only the impact of wives' past wage deviations on their own labor supply is significant. However, no significant coefficients are estimated in Belgium. Results for Italy also support the LIC version of the collective model, as past wage deviations have a significant and positive impact on own labor supply for both males and females. However, wives' deviations show a negative but not significant correlation with husbands' hours of work. Similar results are found in Austria, France and Luxembourg, where own-effects are as predicted by the LIC model, but coefficients are not significant.[21] Future research should, again, dive deeper in particular countries, following different parametric forms or wage predictions to study these divergences.

[21] A potential reason for the non-significance of coefficients in the fixed effect estimates of Equations 2.1 and 2.2 might arise from underestimating the effect of past wage deviations, as also happened in the case of the US. Furthermore, as we are focusing on stable households, these estimates might represent a lower bound of the estimated process for the general population including non-stable couples (Mazzocco, 2007).

Table 2.11: Labor supply estimates for singles (I)

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Women | Men | Women | Men | Women | Men | Women | Men |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Initial observables | | | | | | | | |
| Log-wage | 0.117 | -0.318 | 1.962*** | 3.420*** | 1.897** | -0.961 | 5.274*** | 2.933** |
| | (0.609) | (0.792) | (0.644) | (0.786) | (0.833) | (0.954) | (1.175) | (1.246) |
| Non-labor income | -0.039 | -0.029 | 0.104 | 0.354*** | 0.126* | 0.036 | 0.073 | 0.052 |
| | (0.067) | (0.117) | (0.075) | (0.065) | (0.075) | (0.040) | (0.072) | (0.087) |
| Present observables | | | | | | | | |
| Log-wage | -2.517 | -0.038 | -10.285*** | -13.158*** | 0.497 | 2.922 | -4.445 | -1.198 |
| | (2.497) | (2.561) | (2.074) | (2.099) | (3.426) | (4.070) | (5.286) | (6.897) |
| Non-labor income | -0.178 | -0.047 | -0.530*** | -0.594*** | -0.548*** | -0.083 | -0.356*** | -0.275** |
| | (0.109) | (0.100) | (0.157) | (0.154) | (0.098) | (0.133) | (0.077) | (0.131) |
| Expected wages ($t+1$) | | | | | | | | |
| Log-wage | 3.857 | -4.469 | 19.675*** | 15.303*** | 6.798 | -3.786 | 3.257 | -10.913 |
| | (2.878) | (3.054) | (3.324) | (3.944) | (4.741) | (4.274) | (6.836) | (8.689) |
| Wage deviations | | | | | | | | |
| Present | -2.146 | -2.749 | -0.194 | 1.868* | -7.438** | -6.132 | -7.507 | -4.937 |
| | (2.456) | (2.676) | (1.055) | (0.957) | (3.249) | (4.045) | (4.841) | (6.468) |
| Previous | 0.174 | 0.084 | -0.066 | -0.624* | -0.609 | 0.503 | -1.653* | -0.871 |
| | (0.330) | (0.358) | (0.273) | (0.324) | (0.438) | (0.510) | (0.989) | (0.913) |
| Constant | 38.574*** | 36.098*** | 44.928*** | 54.167*** | 30.123*** | 35.267*** | 46.051*** | 52.102*** |
| | (4.749) | (4.860) | (4.754) | (5.237) | (4.510) | (6.455) | (5.637) | (6.538) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,200 | 921 | 829 | 639 | 654 | 413 | 507 | 481 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to single workers of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.12: Labor supply estimates for singles (II)

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Women | Men | Women | Men | Women | Men | Women | Men |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Initial observables | | | | | | | | |
| Log-wage | 0.640 | 1.635*** | 0.986 | 0.196 | 1.875*** | 0.602 | 0.681 | 0.296 |
| | (0.399) | (0.408) | (0.967) | (1.057) | (0.572) | (0.714) | (0.693) | (0.865) |
| Non-labor income | -0.010 | 0.092*** | 0.043 | 0.141 | 0.042 | 0.090 | 0.136* | -0.034 |
| | (0.031) | (0.031) | (0.080) | (0.108) | (0.047) | (0.068) | (0.073) | (0.106) |
| Present observables | | | | | | | | |
| Log-wage | 7.150*** | 2.714 | 5.423 | 11.833** | -3.722 | -4.811* | -7.489** | 0.610 |
| | (2.004) | (2.201) | (4.224) | (4.792) | (2.319) | (2.533) | (3.670) | (3.070) |
| Non-labor income | -0.219*** | -0.156*** | -0.286*** | -0.056 | -0.440*** | -0.363*** | -1.191*** | -0.154** |
| | (0.037) | (0.043) | (0.073) | (0.082) | (0.065) | (0.101) | (0.140) | (0.060) |
| Expected wages ($t+1$) | | | | | | | | |
| Log-wage | -8.593*** | -6.412** | -7.346 | -17.650*** | 2.788 | -6.390** | 12.723*** | -2.729 |
| | (2.278) | (2.573) | (4.515) | (6.009) | (2.909) | (3.120) | (4.335) | (4.469) |
| Wage deviations | | | | | | | | |
| Present | -13.713*** | -8.914*** | -11.457*** | -17.435*** | -2.625 | -1.084 | -1.670 | -5.826* |
| | (1.991) | (2.218) | (4.284) | (4.917) | (2.352) | (2.969) | (3.289) | (3.299) |
| Previous | 0.273 | 0.040 | -0.607 | 0.216 | -1.332*** | -0.517 | 0.145 | 0.217 |
| | (0.264) | (0.297) | (0.548) | (0.443) | (0.395) | (0.429) | (0.361) | (0.389) |
| Constant | 34.663*** | 42.205*** | 36.286*** | 29.900*** | 43.584*** | 56.910*** | 54.404*** | 40.176*** |
| | (2.469) | (2.627) | (7.758) | (8.104) | (3.103) | (3.664) | (8.748) | (7.548) |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,628 | 2,267 | 473 | 363 | 1,247 | 746 | 536 | 557 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to single workers of countries. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

**Estimates for singles**

Equations 2.1 and 2.2 are re-estimated on an analogous sample of single workers, to determine whether different relationships are characteristic of spouses or are consistent with singles' labor supply in Europe. Estimates are shown in Tables 2.11 and 2.12. Results indicate that, first, there exists some degree of heterogeneity in the countries analyzed in terms of the signs of coefficients associated with past wage deviations. Specifically, coefficients are positive and non-significant for males and females in Austria, Italy and Sweden. In France and Luxembourg, on the other hand, past deviations are positive and not significant for single men, while negative and non-significant for single women. Finally, the only significant coefficients associated with past deviations are estimated for male singles in Belgium, and female singles in Greece and Spain.

As a consequence, estimates suggest that the negative (positive) effect of past deviations on own (cross) labor supply is found to operate mainly for spouses and, thus, to be characteristic of intrahousehold negotiation processes. However, results for singles in Belgium, Greece, and Spain indicate that deeper analyses should investigate labor supply and wage dynamics in these countries, to disentangle the different trends found for singles, including, for instance, different wage models or different parametrizations. This is left for future research. The main implication from Tables 2.11 and 2.12 is, however, that results for singles are not consistent with the limited commitment version of the collective model in general terms. Therefore, estimates provide empirical support to results for couples in relation to the LIC model.

## 2.7 Conclusions

This Chapter explores intertemporal aspects of household labor supply and intrahousehold commitment from the perspective of collective models. To that end, a collective model of labor supply is proposed, with an empirical specification that focuses on the ability of spouses to commit in the mid- and long-term. Based on this model, a test for intrahousehold commitment is proposed to distinguish between limited or partial commitment, non-commitment, and full commitment.

The analysis has certain limitations. First of all, as Pareto weights can only be identified but not observed, results derived from the labor supply equations should be interpreted cautiously and as suggestive evidence about intertemporal commitment. Second, the specification involves a model for wage dynamics that aims to capture the expected part of wages. As a consequence, there might be the case that estimated wages cannot fully capture the dynamics of wage expectations. Third, the sample selection focuses on stable households and, as a consequence, results must be understood as representative for this population. Further research should focus on non-stable households and couples who divorce. Finally, although using longitudinal data and specific panel data models, measurement errors prevent me from strictly talking about effects, and results may be more accurately representing conditional correlations. Nevertheless, a few conclusions emerge from this analysis.

Even controlling for present and future wages, as well as for selection, it appears that unexpected shocks on wages have a lasting effect on labor supply. Moreover, the resulting patterns fit the predictions of the LIC version of the collective model. When a spouse did better than expected, (s)he works less, suggesting that (s)he attracts a larger fraction of household resources. Furthermore, the impact of past shocks is not limited to labor supply; it also affects household demand (in the case of the US), in a manner that can again be explained only by a shift in the spouses' respective bargaining positions through the LIC model.

On the basis of these results, conclusions indicate that, at least tentatively, the empirical study of the intertemporal aspects of household labor supply and consumption, using the PSID and EU-SILC data, provides evidence in favor of the collective model, and particularly of its limited commitment formulation, against both the unitary framework and the non-commitment and full commitment models. The strongest result might arise from the fact that the estimated dynamics of labor supply, and more generally of decision processes, are quite different for couples than for singles. That indicates how evolving bargaining positions seem to play an important role in couples' dynamics, in a way that is much more complex than either full or non-commitment models would suggest.

Understanding intrahousehold allocations is crucial to understanding the effects of public policies, which often have intertemporal or dynamic aspects. Also, intrahousehold processes, such as household formation, divorce, income, and wealth transfers are important for policy issues, and have a dynamic dimension. But most collective models that were taken to data were based on a static formulation, which prevents a full understanding of intrahousehold processes, and the effects of household policies may then be inaccurately predicted. Within this context, the development of a dynamic framework for collective models is needed, to improve our knowledge of the dynamics of intrahousehold bargaining, household formation and dissolution, wealth transfers, and policy interventions. This Chapter strongly suggests that LIC models constitute an excellent candidate for the further development of dynamic models.

# Appendix 2.A: Static collective models

The traditional collective model, in its static version, consists of a household model in which spouses have distinct preferences and utility functions. Assume that $X = (X_k) \in \mathbb{R}^N$ and $x = (x_k) \in \mathbb{R}^n$ represent two vector of public and private goods consumed, with prices $P \in \mathbb{R}^N$ and $p \in \mathbb{R}^n$, $N, n \in \mathbb{N}$. If the household is formed by two spouses $A$ and $B$ with (egoistic) utility functions,

$$U^i = U^i(X, x), \;\; i = A, B,$$

wages are represented by $w_i$, household total income is $Y$, and labor supply (hours of work) of spouses are represented by $h_i$, the collective model can be formulated, for $i = A$ or $B$ without loss of generality, as follows:

$$\begin{aligned} &\max_{\{X,x\}} \;\; U^i(X, x) \\ &\text{s.t.:} \;\; P'X + p'x = Y \\ &\qquad \mu_j^* : \;\; U^j \geq \hat{U}^j, \;\; j \neq i \end{aligned} \tag{CM}$$

where $U^j \geq \hat{U}^j$ represents the individual rationality of the spouse, which guarantees efficiency.

By simplicity, the problem can be reformulated as follows:

$$\begin{aligned} &\max_{\{X,x\}} \;\; \mu U^A(X, x) + (1 - \mu) U^B(X, x) \\ &\text{s.t.:} \;\; P'X + p'x = Y. \end{aligned} \tag{CM$_2$}$$

Under this formulation, $0 \leq \mu \leq 1$ characterizes the bargaining powers of spouses, and is often called Pareto weight. Is important to note that Pareto weights are in general non-observable, and in this setting they depend on prices, wages, income, and factors that do not affect preferences or the budget constraint. This factors ($d$) are commonly known as distribution factors (Browning and Chiappori, 1998). Therefore, Pareto weights can be formally defined as:

$$\mu = \mu(P, p, Y, d),$$

where $\mu(.)$ is differentiable and homogeneous (Chiappori, 1988). In that context, distribution factors' relevance is twofold. First, they provide an exogenous (and observable) source of variation of Pareto weights and, second, they provide a robust identification of the collective model, from a theoretical point of view.

The identification of the collective model in its most general form is complex. However, let us assume that the utility function of spouses is defined as $U^i = U^i(1 - c_i, h^i)$, for $i = A, B$, where $c = c_A + c_B$ represents the consumption of private goods with normalized prices. Then, if $y$ represents household non-labor income, the program can be reformulated as follows:

$$\begin{aligned} \max_{\{h^A, h^B, c_A, c_B\}} \quad & \mu U^A(c_A, 1 - h^A) + (1 - \mu) U^B(c_B, 1 - h^B) \\ \text{s.t.:} \quad & c = w_A h^A + w_B h^B, \end{aligned} \tag{CM$_3$}$$

where $\mu = \mu(w_A, w_B, y, d)$.

The (benchmark) hypothesis of Pareto efficiency allows to (almost straightforwardly) apply the second fundamental welfare theorem (Chiappori et al., 2002). Therefore, it allows to decentralize the program in a two-stage process whereby, first, spouses negotiate a sharing rule of non-labor income:

$$\varphi_A = \varphi(\mu), \;\; \varphi_B = y - \varphi(\mu).$$

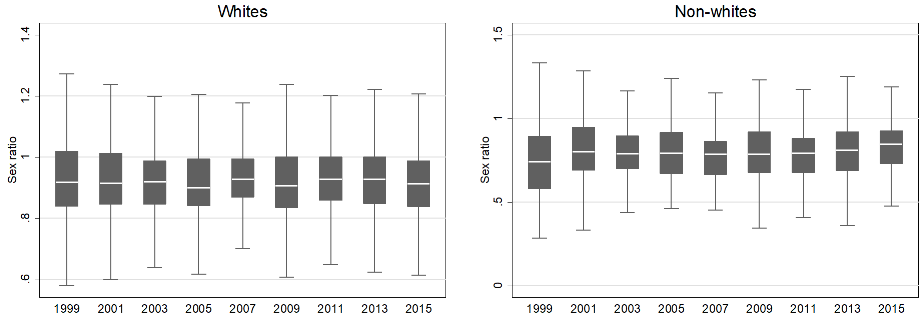
Then, they maximize an individual program subject to such sharing rule. This decentralization allows to recover a relationship between two expressions of the labor supply of spouses:

$$h^i(w_A, w_B, y, d) = H^i(w_i, \varphi_i(w_A, w_B, y, d)), \;\; i = A, B.$$

According to these expressions, it is possible to find a series of over-identification restrictions that the (observed) labor supply functions must fulfill. If they are satisfied, then the problem is identified. Furthermore, they also allow to recover a functional form of the sharing rule equation, in terms of the partial derivatives of the labor supply functions. This process is often called "identification and testable restrictions". A detailed explanation, along with a concrete parametrization and an empirical application, can be seen in Chiappori et al. (2002).

# Appendix 2.B: Additional results for the US

Figure 2.B1: Evolution of sex ratios in the US




Source: United States Current Population Survey. Sex ratios computed as the number of males per each female, by age groups and state of residence.

Figure 2.B2: Altonji et al. (2013)'s wage model

$$wage_{it} = E_{it} wage_{it}^{lat}, \quad (1)$$

$$wage_{it}^{lat} = \left[X_{it}\gamma_X^w + \gamma_{t^3}^w t^3\right] + P(TEN_{it})\gamma_{TEN}^w + \delta_\mu^w \mu_i + \omega_{it} + \nu_{ij(t)}, \quad (2)$$

$$\omega_{it} = \rho_w \omega_{i,t-1} + \gamma_{1-E_t}^\omega (1 - E_{it}) + \gamma_{1-E_{t-1}}^\omega (1 - E_{t-1}) + \varepsilon_{it}^\omega, \quad (3)$$

$$\nu_{ij(t)} = (1 - S_{it})\nu_{ij(t-1)} + S_{it}\nu'_{ij'(t)}, \quad (4)$$

$$\nu'_{ij'(t)} = \rho_\nu \nu_{ij(t-1)} + \varepsilon_{ij(t)}^\nu. \quad (5)$$

Source: Altonji et al. (2013) pp. 1401. $Wage_{it}$ represents log-wage rates. $E_{it}$ represents employment ($E_{it} = 1$ for employed individuals, 0 otherwise). $Wage^{lat}$ represents latent wages. $X_{it}$ represents race, years of education, experience, and experience squared. $t^3$ represents the cube of experience. $P(TEN_{it})$ represents a polynomial on employer tenure. $\mu_i$ represents unobserved ability. $\omega_{it}$ represents a stochastic component that reflects persistence of skills and past wages. $\nu_{ij(t)}$ is the job-match-specific term, where $j(t)$ represents job offers at $t$.

Table 2.B1: Summary statistics - Wage model

| | Wives | | Husbands | | Difference |
|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | $p$-value |
| Log-wage | 2.875 | 0.660 | 3.170 | 0.714 | (<0.001) |
| Black | 0.046 | 0.210 | 0.076 | 0.265 | (<0.001) |
| Years of education | 13.679 | 2.547 | 13.569 | 2.703 | (<0.001) |
| Experience | 2.595 | 1.063 | 2.718 | 1.069 | (<0.001) |
| Tenure | 0.728 | 0.827 | 0.851 | 0.957 | (<0.001) |
| Job change | 0.478 | 0.499 | 0.660 | 0.474 | (<0.001) |
| Married | 0.866 | 0.341 | 0.866 | 0.341 | - |
| N. children $\leq 6$ | 0.271 | 0.627 | 0.271 | 0.627 | - |
| N. children 6-17 | 0.894 | 1.085 | 0.894 | 1.085 | - |
| N. Observations | 24,888 | | 24,888 | | |

Note: The sample (PSID 2001-2015) is restricted to stable households and single workers. Children of interviewed households are not included in the sample. Log wages are defined as log of dollars per hour (only for working individuals). Experience and tenure are measured in years. Differences are defined as the mean value of the correspondent variable for wives, minus the corresponding value for husbands. T-test p-values for the mean differences in parentheses.

Table 2.B2: Heckman wage model

| | Main equation | | Selection equation | |
|---|---|---|---|---|
| | Women | Men | Women | Men |
| VARIABLES | (1) | (2) | (3) | (4) |
| Black | -0.036*** | -0.120*** | -0.091* | -0.231*** |
| | (0.011) | (0.009) | (0.049) | (0.048) |
| Years of education | 0.056*** | 0.058*** | -0.003 | 0.004 |
| | (0.002) | (0.002) | (0.007) | (0.008) |
| Experience | 0.286*** | 0.416*** | -0.765*** | 0.119 |
| | (0.041) | (0.041) | (0.179) | (0.239) |
| Experience sq. | -0.113*** | -0.134*** | 0.207*** | -0.060 |
| | (0.019) | (0.017) | (0.078) | (0.096) |
| Experience cub. | 0.013*** | 0.014*** | -0.024** | -0.000 |
| | (0.003) | (0.002) | (0.010) | (0.012) |
| Tenure | 0.136*** | 0.115*** | 159.66 | 526.70 |
| | (0.027) | (0.022) | (0.000) | (0.000) |
| Tenure sq. | -0.025 | -0.029* | -64.386 | -36.816 |
| | (0.022) | (0.017) | (0.000) | (0.000) |
| Tenure cub. | 0.001 | 0.004 | 17.689 | 17.604 |
| | (0.005) | (0.003) | (0.000) | (0.000) |
| Log wage ($t$ - 1) | 0.411*** | 0.438*** | -0.233*** | -0.306*** |
| | (0.007) | (0.006) | (0.018) | (0.017) |
| Log wage ($t$ - 2) | 0.078*** | 0.081*** | 0.171*** | 0.181*** |
| | (0.004) | (0.004) | (0.014) | (0.014) |
| Job change | -1.045*** | -1.206*** | 141.27 | 751.53 |
| | (0.022) | (0.023) | (0.000) | (0.000) |
| Married | - | - | 1.604*** | -0.124** |
| | | | (0.073) | (0.052) |
| N. children $\leq 6$ | - | - | -0.140*** | 0.071** |
| | | | (0.027) | (0.034) |
| N. children 7-17 | - | - | 0.020 | -0.027 |
| | | | (0.017) | (0.019) |
| Inverse Mill's ratio | -0.068*** | 0.001 | - | - |
| | (0.013) | (0.016) | | |
| Constant | 1.561*** | 1.581*** | -1.674*** | -0.626*** |
| | (0.044) | (0.044) | (0.183) | (0.233) |
| Year F.E. | Yes | Yes | Yes | Yes |
| Region F.E. | Yes | Yes | Yes | Yes |
| Observations | 24,888 | 24,888 | 24,888 | 24,888 |

Note: Standard errors in parentheses.The sample (PSID 2001-2015) is restricted to stable households and single workers. The dependent variable is the log hourly wage. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.B3: Robustness checks (I)

| | Economic crisis | | Marriages and immigrants | |
|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) |
| Initial observables | | | | |
| Log-wage (wife) | 0.036 | -0.191*** | 0.036 | -0.191*** |
| | (0.045) | (0.045) | (0.045) | (0.045) |
| Log-wage (husband) | 0.010 | -0.170*** | 0.010 | -0.170*** |
| | (0.041) | (0.040) | (0.041) | (0.040) |
| Non-labor income (t = 0) | 0.002 | -0.018*** | 0.002 | -0.018*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Present observables | | | | |
| Log-wage (wife) | 0.359*** | -0.115* | 0.362*** | -0.115* |
| | (0.064) | (0.063) | (0.065) | (0.063) |
| Log-wage (husband) | -0.147*** | 0.032 | -0.147*** | 0.032 |
| | (0.049) | (0.050) | (0.049) | (0.050) |
| Non-labor income | -0.013** | -0.001 | -0.013** | -0.001 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Cross log-wage | 0.047*** | 0.008 | 0.047*** | 0.008 |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| Immigrant household | -0.113* | 0.010 | -0.112* | 0.010 |
| | (0.062) | (0.061) | (0.062) | (0.061) |
| First marriage | 0.011 | 0.111** | 0.011 | 0.111** |
| | (0.045) | (0.045) | (0.045) | (0.045) |
| Expected wages ($t+1$) | | | | |
| Log-wage (wife) | 0.144 | -0.091 | -0.351*** | 0.032 |
| | (0.098) | (0.092) | (0.088) | (0.093) |
| Log-wage (husband) | -0.351*** | 0.033 | 0.145 | -0.092 |
| | (0.088) | (0.093) | (0.099) | (0.092) |
| Wage deviations | | | | |
| Present (wife) | 0.359*** | -0.142** | 0.362*** | -0.143** |
| | (0.064) | (0.063) | (0.064) | (0.063) |
| Previous (wife) | -0.585*** | 0.130* | -0.588*** | 0.130* |
| | (0.075) | (0.074) | (0.075) | (0.074) |
| Present (husband) | -0.123** | 0.036 | -0.122** | 0.036 |
| | (0.048) | (0.049) | (0.048) | (0.049) |
| Previous (husband) | 0.016 | -0.136* | 0.016 | -0.136* |
| | (0.071) | (0.073) | (0.071) | (0.072) |
| Constant | 1.961*** | 2.731*** | 1.956*** | 2.732*** |
| | (0.255) | (0.258) | (0.255) | (0.258) |
| Sociodemographics | Yes | Yes | Yes | Yes |
| Observations | 1,305 | 1,305 | 1,305 | 1,305 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (PSID 2001-2015) is restricted to stable households. Wage deviations for Columns (1) and (2) are based on predictions from a model controlling for the per capita GDP growth, by year and State. Results are available upon request. Additional estimates are available upon request. Per capita GDP growth taken from the US Bureau of Labor Statistics. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.B3: Robustness checks (II)

| | State F.E. | | Extensive margin | |
|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) |
| Initial observables | | | | |
| Log-wage (wife) | 0.038 | -0.192*** | 0.006 | 0.005 |
| | (0.045) | (0.045) | (0.006) | (0.007) |
| Log-wage (husband) | 0.016 | -0.166*** | 0.014*** | -0.016** |
| | (0.040) | (0.040) | (0.005) | (0.006) |
| Non-labor income | 0.001 | -0.017*** | 0.001* | -0.000 |
| | (0.007) | (0.007) | (0.001) | (0.001) |
| Present observables | | | | |
| Log-wage (wife) | 0.368*** | -0.112* | 0.336*** | 0.001 |
| | (0.064) | (0.063) | (0.009) | (0.005) |
| Log-wage (husband) | -0.146*** | 0.023 | -0.006* | 0.260*** |
| | (0.049) | (0.050) | (0.004) | (0.006) |
| Non-labor income | -0.013** | 0.003 | -0.002*** | -0.004*** |
| | (0.007) | (0.006) | (0.001) | (0.001) |
| Expected wages $(t+1)$ | | | | |
| Log-wage (wife) | 0.105 | -0.055 | -0.039** | -0.028** |
| | (0.098) | (0.092) | (0.017) | (0.012) |
| Log-wage (husband) | -0.340*** | 0.064 | -0.020** | 0.014 |
| | (0.088) | (0.092) | (0.009) | (0.013) |
| Wage deviations | | | | |
| Present (wife) | 0.371*** | -0.137** | 0.328*** | 0.002 |
| | (0.064) | (0.062) | (0.009) | (0.005) |
| Previous (wife) | -0.570*** | 0.127* | -0.349*** | -0.010 |
| | (0.075) | (0.073) | (0.008) | (0.008) |
| Present (husband) | -0.123** | 0.029 | -0.005 | 0.252*** |
| | (0.049) | (0.050) | (0.004) | (0.006) |
| Previous (husband) | 0.011 | -0.124* | 0.007 | -0.295*** |
| | (0.072) | (0.073) | (0.005) | (0.007) |
| Constant | 2.564*** | 2.710*** | 0.387*** | 0.715*** |
| | (0.426) | (0.425) | (0.027) | (0.031) |
| Sociodemographics | Yes | Yes | Yes | Yes |
| Region F.E. | No | No | Yes | Yes |
| State F.E. | Yes | Yes | No | No |
| Observations | 1,305 | 1,305 | 2,106 | 2,106 |

Note: Bootstrapped ($n$ = 500) standard errors in parentheses. The sample (PSID 2001-2015) is restricted to stable households. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

# Appendix 2.C: Additional results for Europe

Table 2.C1: Evolution of sex ratios

| | Sex ratio | | |
|---|---|---|---|
| Year | 2005 | 2010 | 2015 |
| Austria | 1.06 | 1.06 | 1.06 |
| Belgium | 1.05 | 1.05 | 1.05 |
| France | 1.05 | 1.05 | 1.05 |
| Greece | 1.07 | 1.07 | 1.06 |
| Italy | 1.06 | 1.06 | 1.06 |
| Luxembourg | 1.05 | 1.05 | 1.05 |
| Spain | 1.06 | 1.06 | 1.06 |
| Sweden | 1.06 | 1.06 | 1.06 |

Note: Sex ratios are defined as sex ratio at birth (male to female births), and taken from the Human Development Reports.

Table 2.C2: Heckman log-wage model estimates (I)

| | AUSTRIA | | | | BELGIUM | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| VARIABLES | Main eq. (1) | Selection eq. (2) | Main eq. (3) | Selection eq. (4) | Main eq. (5) | Selection eq. (6) | Main eq. (7) | Selection eq. (8) |
| Log-wage ($t$ - 1) | 0.214*** | 0.539*** | 0.234*** | 0.590*** | 0.137*** | 0.678*** | 0.184*** | 0.492*** |
| | (0.016) | (0.023) | (0.013) | (0.024) | (0.011) | (0.033) | (0.012) | (0.031) |
| Log-wage ($t$ - 2) | 0.079*** | 0.141*** | 0.058*** | 0.036 | 0.031*** | 0.184*** | 0.042*** | 0.194*** |
| | (0.009) | (0.022) | (0.008) | (0.022) | (0.007) | (0.034) | (0.008) | (0.032) |
| Secondary ed. | 0.116*** | 0.078 | 0.128*** | 0.324*** | 0.072*** | 0.334*** | 0.093*** | 0.160** |
| | (0.023) | (0.058) | (0.031) | (0.088) | (0.022) | (0.082) | (0.022) | (0.078) |
| University ed. | 0.280*** | 0.242*** | 0.205*** | 0.484*** | 0.230*** | 0.480*** | 0.222*** | 0.315*** |
| | (0.030) | (0.073) | (0.034) | (0.095) | (0.024) | (0.083) | (0.024) | (0.084) |
| Years working | 0.299*** | 0.737*** | 0.285*** | 0.250 | 0.194*** | 1.249*** | 0.248*** | 0.819*** |
| | (0.086) | (0.180) | (0.098) | (0.244) | (0.058) | (0.199) | (0.073) | (0.273) |
| Years working2 | -0.083* | -0.103 | -0.080* | 0.072 | -0.017 | -0.361*** | -0.069** | -0.297** |
| | (0.043) | (0.099) | (0.041) | (0.106) | (0.031) | (0.117) | (0.035) | (0.133) |
| Years working3 | 0.006 | -0.017 | 0.006 | -0.032** | -0.004 | 0.017 | 0.005 | 0.018 |
| | (0.007) | (0.016) | (0.005) | (0.014) | (0.005) | (0.019) | (0.005) | (0.019) |
| Job change | -0.189*** | | -0.168*** | | -0.113*** | | -0.103*** | |
| | (0.029) | | (0.031) | | (0.027) | | (0.028) | |
| Married couple | | -0.200*** | | -0.219*** | | -0.308*** | | 0.069 |
| | | (0.063) | | (0.071) | | (0.086) | | (0.081) |
| N. children under 4 | | -0.304*** | | 0.054 | | 0.079 | | 0.100* |
| | | (0.050) | | (0.055) | | (0.052) | | (0.060) |
| N. children 4-15 | | 0.065** | | 0.118*** | | -0.038 | | -0.030 |
| | | (0.026) | | (0.029) | | (0.033) | | (0.037) |
| N. children older | | 0.077*** | | 0.101*** | | 0.001 | | 0.082* |
| | | (0.028) | | (0.030) | | (0.039) | | (0.042) |
| Lambda | 0.282*** | | 0.513*** | | 0.129*** | | 0.475*** | |
| | (0.058) | | (0.045) | | (0.046) | | (0.065) | |
| Constant | 0.814*** | -2.825*** | 0.790*** | -2.251*** | 1.725*** | -1.099*** | 1.587*** | -0.342* |
| | (0.155) | (0.141) | (0.119) | (0.203) | (0.060) | (0.147) | (0.072) | (0.201) |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,355 | 7,355 | 7,355 | 7,355 | 5,239 | 5,239 | 5,239 | 5,239 |

Note: Standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households and single workers of countries. The dependent variable is the log hourly wage. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C3: Heckman log-wage model estimates (II)

| | FRANCE | | | | GREECE | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log-wage ($t$ - 1) | 0.130*** | 0.393*** | 0.200*** | 0.297*** | 0.520*** | 0.969*** | 0.721*** | 0.910*** |
| | (0.014) | (0.025) | (0.021) | (0.024) | (0.032) | (0.040) | (0.061) | (0.040) |
| Log-wage ($t$ - 2) | 0.064*** | 0.117*** | 0.055*** | 0.094*** | 0.075*** | 0.215*** | 0.021 | 0.016 |
| | (0.009) | (0.027) | (0.013) | (0.025) | (0.019) | (0.039) | (0.031) | (0.038) |
| Secondary ed. | 0.080*** | 0.074 | 0.027 | 0.062 | 0.040 | -0.096 | 0.079 | 0.041 |
| | (0.028) | (0.068) | (0.040) | (0.068) | (0.033) | (0.060) | (0.049) | (0.057) |
| University ed. | 0.191*** | 0.271*** | 0.223*** | 0.152** | 0.125*** | 0.023 | 0.187*** | 0.078 |
| | (0.034) | (0.073) | (0.048) | (0.077) | (0.041) | (0.073) | (0.067) | (0.075) |
| Years working | 0.296*** | 1.354*** | 0.417*** | 0.797*** | 0.620*** | 2.028*** | 0.415* | 0.958*** |
| | (0.092) | (0.189) | (0.141) | (0.231) | (0.131) | (0.171) | (0.242) | (0.295) |
| Years working2 | -0.055 | -0.494*** | -0.104 | -0.280** | -0.234*** | -0.892*** | -0.162 | -0.420*** |
| | (0.046) | (0.111) | (0.065) | (0.113) | (0.069) | (0.106) | (0.099) | (0.123) |
| Years working3 | 0.002 | 0.061*** | 0.009 | 0.031* | 0.027** | 0.123*** | 0.019 | 0.054*** |
| | (0.007) | (0.018) | (0.009) | (0.016) | (0.011) | (0.018) | (0.012) | (0.016) |
| Job change | -0.113** | | -0.086 | | -0.051 | | -0.073 | |
| | (0.047) | | (0.066) | | (0.051) | | (0.079) | |
| Married couple | | -0.309*** | | -0.026 | | -0.301* | | -0.080 |
| | | (0.056) | | (0.058) | | (0.179) | | (0.184) |
| N. children under 4 | | -0.124*** | | 0.028 | | 0.066 | | 0.233*** |
| | | (0.045) | | (0.048) | | (0.053) | | (0.061) |
| N. children 4-15 | | -0.042 | | -0.057** | | 0.034 | | 0.092*** |
| | | (0.026) | | (0.028) | | (0.031) | | (0.032) |
| N. children older | | -0.032 | | -0.041 | | 0.013 | | -0.038 |
| | | (0.034) | | (0.036) | | (0.032) | | (0.031) |
| Lambda | 0.112 | | 0.848*** | | 0.691*** | | 1.349*** | |
| | (0.079) | | (0.169) | | (0.061) | | (0.168) | |
| Constant | 1.507*** | -0.268 | 1.322*** | 0.093 | 0.004 | -1.294*** | -0.098 | -0.688* |
| | (0.191) | (0.465) | (0.294) | (0.491) | (0.158) | (0.372) | (0.317) | (0.390) |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,856 | 4,856 | 4,856 | 4,856 | 5,959 | 5,959 | 5,959 | 5,959 |

Note: Standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households and single workers of countries. The dependent variable is the log hourly wage. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C4: Heckman log-wage model estimates (III)

| | ITALY | | | | LUXEMBOURG | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log-wage ($t$ - 1) | 0.316*** | 0.770*** | 0.379*** | 0.678*** | 0.275*** | 0.607*** | 0.396*** | 0.438*** |
| | (0.010) | (0.018) | (0.019) | (0.019) | (0.017) | (0.028) | (0.060) | (0.034) |
| Log-wage ($t$ - 2) | 0.061*** | 0.221*** | 0.049*** | 0.099*** | 0.059*** | 0.201*** | 0.117*** | 0.185*** |
| | (0.006) | (0.018) | (0.010) | (0.019) | (0.011) | (0.028) | (0.035) | (0.033) |
| Secondary ed. | 0.139*** | 0.226*** | 0.156*** | 0.309*** | 0.069*** | -0.017 | 0.181** | 0.219*** |
| | (0.011) | (0.030) | (0.019) | (0.033) | (0.026) | (0.064) | (0.073) | (0.081) |
| University ed. | 0.304*** | 0.487*** | 0.293*** | 0.300*** | 0.233*** | 0.145** | 0.319*** | 0.172* |
| | (0.015) | (0.044) | (0.029) | (0.055) | (0.032) | (0.073) | (0.100) | (0.093) |
| Years working | 0.406*** | 1.601*** | 0.466*** | 1.820*** | 0.285*** | 0.524** | 0.046 | 0.298 |
| | (0.052) | (0.107) | (0.116) | (0.177) | (0.090) | (0.209) | (0.283) | (0.295) |
| Years working2 | -0.113*** | -0.523*** | -0.155*** | -0.743*** | -0.051 | -0.053 | 0.046 | -0.085 |
| | (0.026) | (0.061) | (0.050) | (0.079) | (0.049) | (0.131) | (0.136) | (0.148) |
| Years working3 | 0.010** | 0.046*** | 0.015** | 0.084*** | 0.004 | -0.004 | -0.011 | 0.003 |
| | (0.004) | (0.010) | (0.007) | (0.011) | (0.008) | (0.023) | (0.020) | (0.022) |
| Job change | -0.049*** | | -0.083** | | -0.162*** | | -0.163* | |
| | (0.015) | | (0.033) | | (0.035) | | (0.099) | |
| Married couple | | -0.137*** | | 0.131** | | -0.498*** | | -0.221** |
| | | (0.050) | | (0.056) | | (0.085) | | (0.097) |
| N. children under 4 | | 0.104*** | | 0.242*** | | -0.034 | | -0.044 |
| | | (0.031) | | (0.042) | | (0.046) | | (0.060) |
| N. children 4-15 | | 0.026 | | 0.044** | | -0.009 | | -0.077** |
| | | (0.019) | | (0.022) | | (0.030) | | (0.039) |
| N. children older | | -0.032* | | 0.002 | | -0.080** | | 0.081 |
| | | (0.018) | | (0.020) | | (0.036) | | (0.051) |
| Lambda | 0.503*** | | 1.057*** | | 0.372*** | | 1.762*** | |
| | (0.026) | | (0.077) | | (0.059) | | (0.376) | |
| Constant | 0.682*** | -1.906*** | 0.645*** | -1.265*** | 1.204*** | -0.795*** | 0.810*** | 0.038 |
| | (0.053) | (0.081) | (0.109) | (0.138) | (0.092) | (0.145) | (0.308) | (0.215) |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,469 | 19,469 | 19,469 | 19,469 | 4,216 | 4,216 | 4,216 | 4,216 |

Note: Standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households and single workers of countries. The dependent variable is the log hourly wage. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C5: Heckman log-wage model estimates (IV)

| | SPAIN | | | | SWEDEN | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. | Main eq. | Selection eq. |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log-wage ($t$ - 1) | 0.159*** | 0.528*** | 0.193*** | 0.434*** | 0.254*** | 0.389*** | 0.201*** | 0.314*** |
| | (0.008) | (0.019) | (0.007) | (0.017) | (0.022) | (0.022) | (0.018) | (0.021) |
| Log-wage ($t$ - 2) | 0.049*** | 0.160*** | 0.061*** | 0.081*** | 0.059*** | 0.099*** | 0.066*** | 0.113*** |
| | (0.005) | (0.019) | (0.005) | (0.017) | (0.013) | (0.022) | (0.012) | (0.022) |
| Secondary ed. | 0.111*** | 0.128*** | 0.145*** | 0.169*** | 0.104** | 0.255*** | 0.037 | 0.051 |
| | (0.013) | (0.038) | (0.012) | (0.038) | (0.050) | (0.074) | (0.033) | (0.064) |
| University ed. | 0.229*** | 0.327*** | 0.264*** | 0.301*** | 0.143*** | 0.378*** | 0.114*** | 0.090 |
| | (0.015) | (0.037) | (0.013) | (0.038) | (0.055) | (0.076) | (0.039) | (0.072) |
| Years working | 0.261*** | 3.436*** | 0.318*** | 3.239*** | -0.111* | 0.201* | -0.019 | 0.170 |
| | (0.064) | (0.092) | (0.074) | (0.098) | (0.060) | (0.110) | (0.058) | (0.131) |
| Years working2 | -0.056** | -1.375*** | -0.082*** | -1.121*** | 0.108*** | -0.046 | 0.035 | -0.046 |
| | (0.029) | (0.053) | (0.028) | (0.048) | (0.037) | (0.066) | (0.036) | (0.079) |
| Years working3 | 0.004 | 0.166*** | 0.007** | 0.117*** | -0.019*** | -0.002 | -0.008 | -0.001 |
| | (0.004) | (0.009) | (0.003) | (0.007) | (0.006) | (0.010) | (0.006) | (0.012) |
| Job change | -0.272*** | | -0.240*** | | -0.015 | | -0.035 | |
| | (0.017) | | (0.017) | | (0.043) | | (0.040) | |
| Married couple | | -0.061 | | 0.093* | | 0.117** | | -0.042 |
| | | (0.053) | | (0.053) | | (0.047) | | (0.049) |
| N. children under 4 | | 0.041 | | 0.047 | | 0.092** | | 0.120*** |
| | | (0.032) | | (0.034) | | (0.042) | | (0.046) |
| N. children 4-15 | | -0.007 | | -0.050** | | 0.003 | | 0.047* |
| | | (0.020) | | (0.020) | | (0.025) | | (0.026) |
| N. children older | | 0.013 | | -0.087*** | | -0.003 | | 0.028 |
| | | (0.020) | | (0.020) | | (0.031) | | (0.031) |
| Lambda | 0.079** | | 0.224*** | | 1.095*** | | 0.956*** | |
| | (0.031) | | (0.042) | | (0.177) | | (0.166) | |
| Constant | 1.121*** | -2.816*** | 1.056*** | -2.797*** | 1.567*** | 0.326*** | 1.942*** | 0.829*** |
| | (0.070) | (0.106) | (0.086) | (0.113) | (0.109) | (0.117) | (0.089) | (0.119) |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 15,238 | 15,238 | 15,238 | 15,238 | 9,573 | 9,573 | 9,573 | 9,573 |

Note: Standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to stable households and single workers of countries. The dependent variable is the log hourly wage. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C6: Robustness checks (I) - Crisis

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 19.828*** | 1.258 | 13.399*** | 0.795 | 5.543* | -1.694 | 0.799 | 0.369 |
| | (2.320) | (1.795) | (4.242) | (3.423) | (2.893) | (2.778) | (3.199) | (2.942) |
| Log-wage (husband) | -13.281*** | 10.419*** | 2.665 | 4.655 | -6.010*** | 8.698*** | -2.962 | 1.189 |
| | (2.447) | (2.851) | (3.481) | (5.373) | (2.326) | (2.930) | (2.764) | (3.841) |
| Non-labor income | -0.086** | -0.141*** | -0.124 | -0.059 | -0.127*** | -0.039 | -0.194*** | -0.184*** |
| | (0.035) | (0.040) | (0.128) | (0.073) | (0.036) | (0.065) | (0.038) | (0.043) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -29.250*** | -2.440 | -12.487** | 3.194 | 2.252 | 4.113 | -6.506* | 0.402 |
| | (3.216) | (2.076) | (5.323) | (3.610) | (3.504) | (3.270) | (3.644) | (3.111) |
| Log-wage (husband) | 11.556*** | -16.076*** | -2.098 | -15.837** | 4.574* | -13.966*** | 2.112 | -6.696* |
| | (2.548) | (3.120) | (3.855) | (7.066) | (2.468) | (3.561) | (2.820) | (4.002) |
| Wage deviations | | | | | | | | |
| Present (wife) | -16.921*** | -1.154 | -19.098*** | -1.339 | -9.757*** | 0.892 | -6.758*** | -1.749 |
| | (1.770) | (1.444) | (3.685) | (3.173) | (2.513) | (2.429) | (1.487) | (1.509) |
| Previous (wife) | -1.309*** | -0.297 | -2.276*** | -0.320 | -1.023*** | 0.347 | -2.813*** | 0.180 |
| | (0.241) | (0.205) | (0.380) | (0.328) | (0.236) | (0.243) | (0.517) | (0.496) |
| Present (husband) | 10.186*** | -7.845*** | -3.188 | -8.522** | 4.053** | -8.878*** | 0.085 | -3.175** |
| | (1.947) | (2.208) | (2.884) | (4.156) | (1.924) | (2.318) | (0.946) | (1.315) |
| Previous (husband) | 1.449*** | -0.929*** | -0.374 | -1.624*** | 0.146 | -1.195*** | 0.585 | -2.610*** |
| | (0.287) | (0.358) | (0.396) | (0.499) | (0.247) | (0.277) | (0.533) | (0.702) |
| Constant | 39.386*** | 41.028*** | 15.395** | 41.079*** | 31.739*** | 36.790*** | 53.772*** | 58.974*** |
| | (2.911) | (2.528) | (7.781) | (8.463) | (3.504) | (3.437) | (2.581) | (2.914) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,745 | 2,745 | 2,126 | 2,126 | 1,605 | 1,605 | 1,888 | 1,888 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Wage deviationsare are based on predictions from a model controlling for the per capita GDP growth, by year, region and country. Results are available upon request. Additional estimates are available upon request. Per capita GDP growth taken from the OCDE in the case of France, and the Eurostat in the remaining countries. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C7: Robustness checks (II) - Crisis

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 5.226*** | 0.416 | -4.265 | -2.590 | 7.845*** | -4.060*** | -0.589 | 0.338 |
| | (1.263) | (1.038) | (3.158) | (2.223) | (1.495) | (1.149) | (1.464) | (0.996) |
| Log-wage (husband) | -4.224*** | 4.923*** | -5.725** | -2.385 | -8.191*** | 4.102*** | 2.341 | 2.999 |
| | (1.048) | (1.128) | (2.816) | (3.617) | (1.376) | (1.385) | (1.840) | (1.965) |
| Non-labor income | -0.120*** | -0.138*** | -0.154*** | -0.092** | -0.167*** | -0.138*** | -0.297*** | -0.240*** |
| | (0.023) | (0.025) | (0.050) | (0.042) | (0.028) | (0.028) | (0.092) | (0.066) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -10.429*** | -1.455 | 6.188 | 2.528 | -10.779*** | 4.289*** | 2.745 | 1.229 |
| | (1.747) | (1.151) | (3.866) | (2.548) | (1.915) | (1.318) | (2.163) | (1.245) |
| Log-wage (husband) | 3.597*** | -9.965*** | 5.156* | -5.064 | 8.244*** | -13.632*** | 0.935 | -2.140 |
| | (1.109) | (1.461) | (2.900) | (3.944) | (1.592) | (1.812) | (1.868) | (2.086) |
| Wage deviations | | | | | | | | |
| Present (wife) | -7.346*** | -0.363 | -2.727 | 1.385 | -11.536*** | 2.434** | -4.902*** | -0.621 |
| | (0.829) | (0.717) | (2.257) | (1.579) | (1.355) | (1.022) | (1.055) | (0.798) |
| Previous (wife) | -0.600*** | -0.123 | -1.300*** | 0.438 | -0.940*** | 0.131 | -0.273** | 0.075 |
| | (0.191) | (0.176) | (0.433) | (0.309) | (0.194) | (0.147) | (0.116) | (0.095) |
| Present (husband) | 1.590** | -7.539*** | 1.911 | -0.205 | 5.582*** | -6.667*** | -3.406** | -7.203*** |
| | (0.746) | (0.755) | (1.863) | (2.118) | (1.155) | (1.065) | (1.562) | (1.744) |
| Previous (husband) | 0.035 | -0.837*** | -0.182 | -0.422 | 0.244 | -0.983*** | -0.252 | -0.976*** |
| | (0.217) | (0.205) | (0.441) | (0.518) | (0.176) | (0.179) | (0.219) | (0.255) |
| Constant | 42.977*** | 47.936*** | 51.847*** | 57.366*** | 36.636*** | 50.013*** | 29.850*** | 32.186*** |
| | (1.236) | (1.345) | (3.643) | (3.028) | (1.558) | (1.327) | (4.231) | (4.037) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,006 | 7,006 | 1,383 | 1,383 | 4,545 | 4,545 | 2,829 | 2,829 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Wage deviationsare are based on predictions from a model controlling for the per capita GDP growth, by year, region and country. Results are available upon request. Additional estimates are available upon request. Per capita GDP growth taken from the OCDE in the case of France, and the Eurostat in the remaining countries. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C8: Robustness checks (III) - Legal marriages

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 21.065*** | 1.380 | -2.767 | -1.406 | 5.782** | -1.278 | 0.723 | 0.412 |
| | (2.324) | (1.798) | (2.456) | (2.199) | (2.821) | (2.841) | (3.419) | (2.968) |
| Log-wage (husband) | -12.330*** | 10.516*** | -7.191*** | -6.778*** | -6.031** | 8.713*** | -2.524 | 1.244 |
| | (2.456) | (2.853) | (2.511) | (2.475) | (2.391) | (3.014) | (2.857) | (3.869) |
| Non-labor income | -0.085** | -0.141*** | -0.144 | -0.077 | -0.128*** | -0.041 | -0.194*** | -0.184*** |
| | (0.035) | (0.040) | (0.116) | (0.081) | (0.039) | (0.062) | (0.040) | (0.045) |
| Married couple | -1.452** | 0.160 | -0.730 | 0.711 | 0.260 | 2.162*** | -2.244 | -0.416 |
| | (0.567) | (0.517) | (0.457) | (0.521) | (0.464) | (0.584) | (1.962) | (2.039) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -31.206*** | -2.615 | 6.146* | 5.948** | 1.835 | 3.608 | -6.394 | 0.358 |
| | (3.212) | (2.093) | (3.416) | (2.397) | (3.497) | (3.260) | (3.892) | (3.081) |
| Log-wage (husband) | 10.697*** | -16.141*** | 7.344*** | -3.883 | 4.556* | -14.110*** | 1.650 | -6.735* |
| | (2.559) | (3.124) | (2.560) | (4.146) | (2.549) | (3.538) | (2.816) | (4.086) |
| Wage deviations | | | | | | | | |
| Present (wife) | -17.763*** | -1.231 | -5.182** | 0.444 | -9.934*** | 0.573 | -6.721*** | -1.763 |
| | (1.768) | (1.443) | (2.111) | (1.978) | (2.470) | (2.525) | (1.498) | (1.475) |
| Previous (wife) | -1.321*** | -0.303 | -0.939*** | -0.027 | -1.036*** | 0.334 | -2.782*** | 0.176 |
| | (0.241) | (0.205) | (0.279) | (0.257) | (0.228) | (0.243) | (0.525) | (0.505) |
| Present (husband) | 9.446*** | -7.924*** | 4.915** | 0.361 | 4.082** | -8.912*** | 0.009 | -3.206** |
| | (1.952) | (2.205) | (2.067) | (1.867) | (1.963) | (2.422) | (1.023) | (1.395) |
| Previous (husband) | 1.337*** | -0.943*** | 0.741*** | -0.348 | 0.144 | -1.199*** | 0.566 | -2.619*** |
| | (0.286) | (0.359) | (0.265) | (0.259) | (0.242) | (0.281) | (0.555) | (0.755) |
| Constant | 39.924*** | 41.110*** | 50.563*** | 59.943*** | 31.792*** | 36.951*** | 55.661*** | 59.353*** |
| | (2.890) | (2.524) | (3.416) | (3.268) | (3.304) | (3.747) | (3.032) | (3.391) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,745 | 2,745 | 2,608 | 2,608 | 1,605 | 1,605 | 1,888 | 1,888 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C9: Robustness checks (IV) - Legal marriages

| VARIABLES | ITALY Wives (1) | ITALY Husbands (2) | LUXEMBOURG Wives (3) | LUXEMBOURG Husbands (4) | SPAIN Wives (5) | SPAIN Husbands (6) | SWEDEN Wives (7) | SWEDEN Husbands (8) |
|---|---|---|---|---|---|---|---|---|
| Present observables | | | | | | | | |
| Log-wage (wife) | 5.212*** | 0.398 | -4.413 | -2.473 | 7.737*** | -4.027*** | -0.583 | 0.309 |
| | (1.248) | (1.069) | (3.353) | (2.309) | (1.513) | (1.134) | (1.467) | (1.021) |
| Log-wage (husband) | -4.220*** | 4.947*** | -5.130* | -2.589 | -8.033*** | 4.111*** | 2.319 | 2.934 |
| | (1.030) | (1.072) | (2.716) | (3.602) | (1.321) | (1.320) | (1.842) | (1.975) |
| Non-labor income | -0.120*** | -0.138*** | -0.148*** | -0.095** | -0.166*** | -0.139*** | -0.297*** | -0.242*** |
| | (0.023) | (0.025) | (0.052) | (0.043) | (0.031) | (0.026) | (0.093) | (0.063) |
| Married couple | -0.139 | 0.058 | -2.072** | 0.935 | -0.919 | 0.906** | -0.030 | 0.253 |
| | (0.381) | (0.378) | (0.819) | (0.588) | (0.566) | (0.439) | (0.337) | (0.271) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -10.409*** | -1.434 | 6.212 | 2.444 | -10.668*** | 4.247*** | 2.737 | 1.241 |
| | (1.640) | (1.200) | (3.954) | (2.648) | (1.963) | (1.288) | (2.253) | (1.378) |
| Log-wage (husband) | 3.595*** | -10.002*** | 4.666 | -4.892 | 8.061*** | -13.648*** | 0.968 | -2.105 |
| | (1.104) | (1.384) | (2.838) | (4.014) | (1.535) | (1.782) | (1.904) | (2.065) |
| Wage deviations | | | | | | | | |
| Present (wife) | -7.339*** | -0.351 | -2.633 | 1.315 | -11.444*** | 2.409** | -4.906*** | -0.599 |
| | (0.835) | (0.749) | (2.359) | (1.675) | (1.318) | (0.997) | (1.060) | (0.837) |
| Previous (wife) | -0.599*** | -0.122 | -1.216*** | 0.401 | -0.936*** | 0.132 | -0.273** | 0.076 |
| | (0.187) | (0.167) | (0.417) | (0.307) | (0.195) | (0.149) | (0.120) | (0.094) |
| Present (husband) | 1.590** | -7.547*** | 1.559 | -0.092 | 5.465*** | -6.689*** | -3.390** | -7.159*** |
| | (0.729) | (0.697) | (1.674) | (2.107) | (1.131) | (1.062) | (1.592) | (1.756) |
| Previous (husband) | 0.035 | -0.841*** | -0.206 | -0.417 | 0.236 | -0.978*** | -0.251 | -0.974*** |
| | (0.207) | (0.207) | (0.452) | (0.478) | (0.177) | (0.182) | (0.221) | (0.240) |
| Constant | 43.091*** | 47.876*** | 53.263*** | 56.794*** | 36.827*** | 49.898*** | 29.888*** | 32.467*** |
| | (1.198) | (1.340) | (3.898) | (3.142) | (1.545) | (1.337) | (3.997) | (4.179) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,006 | 7,006 | 1,383 | 1,383 | 4,545 | 4,545 | 2,829 | 2,829 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C10: Robustness checks (V) - Extensive margin

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 0.637*** | -0.004 | 0.368*** | -0.034*** | 0.561*** | 0.005 | 1.105*** | 0.056*** |
| | (0.006) | (0.003) | (0.009) | (0.006) | (0.004) | (0.003) | (0.031) | (0.021) |
| Log-wage (husband) | -0.014*** | 0.558*** | -0.037*** | 0.378*** | -0.004 | 0.541*** | -0.027 | 0.877*** |
| | (0.005) | (0.005) | (0.008) | (0.011) | (0.004) | (0.005) | (0.025) | (0.038) |
| Non-labor income | 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) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -0.645*** | 0.006 | -0.058 | 0.080*** | -0.580*** | -0.018** | -0.864*** | -0.105*** |
| | (0.016) | (0.007) | (0.037) | (0.020) | (0.012) | (0.009) | (0.045) | (0.030) |
| Log-wage (husband) | 0.026** | -0.538*** | 0.040** | -0.193*** | 0.003 | -0.557*** | 0.014 | -0.526*** |
| | (0.011) | (0.009) | (0.019) | (0.032) | (0.007) | (0.009) | (0.030) | (0.048) |
| Wage deviations | | | | | | | | |
| Present (wife) | -0.560*** | -0.001 | -0.194*** | 0.074*** | -0.487*** | -0.003 | -0.447*** | -0.018 |
| | (0.006) | (0.003) | (0.012) | (0.008) | (0.004) | (0.004) | (0.022) | (0.013) |
| Previous (wife) | -0.035*** | 0.003*** | -0.014*** | 0.007*** | -0.016*** | 0.002 | -0.088*** | 0.010* |
| | (0.002) | (0.001) | (0.003) | (0.002) | (0.001) | (0.001) | (0.007) | (0.006) |
| Present (husband) | 0.011** | -0.455*** | 0.072*** | -0.204*** | 0.001 | -0.432*** | -0.011 | -0.298*** |
| | (0.004) | (0.006) | (0.010) | (0.012) | (0.003) | (0.005) | (0.010) | (0.016) |
| Previous (husband) | 0.005*** | -0.042*** | 0.007*** | -0.016*** | 0.001 | -0.034*** | -0.006 | -0.169*** |
| | (0.002) | (0.001) | (0.003) | (0.002) | (0.001) | (0.002) | (0.006) | (0.006) |
| Constant | 0.515*** | 0.695*** | 0.310*** | 0.360*** | 0.418*** | 0.497*** | 0.778*** | 0.679*** |
| | (0.019) | (0.015) | (0.025) | (0.026) | (0.012) | (0.013) | (0.031) | (0.033) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,762 | 3,762 | 3,157 | 3,157 | 2,087 | 2,087 | 3,521 | 3,521 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The dependent variable is the labor participation. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C11: Robustness checks (VI) - Extensive margin

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 0.753*** | 0.001 | 0.625*** | -0.002 | 0.690*** | -0.008*** | 0.443*** | -0.004 |
| | (0.006) | (0.004) | (0.009) | (0.007) | (0.003) | (0.002) | (0.011) | (0.004) |
| Log-wage (husband) | -0.010** | 0.668*** | -0.013 | 0.579*** | -0.008*** | 0.645*** | 0.025*** | 0.442*** |
| | (0.005) | (0.006) | (0.009) | (0.014) | (0.003) | (0.004) | (0.006) | (0.006) |
| Non-labor income | 0.000 | -0.000 | 0.001*** | -0.001* | 0.000*** | 0.000 | -0.001 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -0.683*** | -0.025*** | -0.623*** | 0.012 | -0.745*** | 0.005 | -0.334*** | 0.006 |
| | (0.012) | (0.007) | (0.017) | (0.014) | (0.008) | (0.006) | (0.023) | (0.007) |
| Log-wage (husband) | 0.009 | -0.549*** | 0.018 | -0.475*** | 0.009 | -0.676*** | -0.076*** | -0.352*** |
| | (0.007) | (0.011) | (0.012) | (0.021) | (0.006) | (0.010) | (0.010) | (0.011) |
| Wage deviations | | | | | | | | |
| Present (wife) | -0.496*** | 0.006* | -0.433*** | -0.001 | -0.588*** | 0.005* | -0.360*** | 0.002 |
| | (0.005) | (0.003) | (0.006) | (0.009) | (0.003) | (0.003) | (0.008) | (0.004) |
| Previous (wife) | -0.068*** | 0.005*** | -0.042*** | 0.001 | -0.026*** | 0.005*** | -0.013*** | 0.007*** |
| | (0.002) | (0.001) | (0.002) | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) |
| Present (husband) | 0.005 | -0.426*** | 0.005 | -0.368*** | 0.004* | -0.528*** | -0.020*** | -0.378*** |
| | (0.003) | (0.005) | (0.007) | (0.009) | (0.003) | (0.003) | (0.006) | (0.006) |
| Previous (husband) | 0.002 | -0.072*** | 0.003 | -0.065*** | 0.005*** | -0.034*** | 0.005*** | -0.035*** |
| | (0.001) | (0.002) | (0.002) | (0.004) | (0.001) | (0.001) | (0.002) | (0.001) |
| Constant | 0.523*** | 0.619*** | 0.381*** | 0.682*** | 0.419*** | 0.503*** | 0.289*** | 0.167*** |
| | (0.010) | (0.012) | (0.013) | (0.020) | (0.008) | (0.009) | (0.022) | (0.016) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,018 | 11,018 | 2,097 | 2,097 | 8,051 | 8,051 | 3,094 | 3,094 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The dependent variable is the labor participation. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C12: Robustness checks (VII) - Region F.E.

| | AUSTRIA | | BELGIUM | | FRANCE | | GREECE | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 21.372*** | 1.378 | 8.509** | -0.198 | 9.397** | 0.712 | 0.340 | 0.540 |
| | (2.315) | (1.799) | (4.022) | (3.128) | (3.692) | (3.749) | (3.205) | (2.816) |
| Log-wage (husband) | -9.201*** | 10.740*** | -6.379** | -3.317 | -4.370* | 14.284*** | -2.116 | 1.784 |
| | (2.489) | (2.913) | (3.076) | (4.827) | (2.572) | (3.398) | (2.792) | (3.850) |
| Non-labor income | -0.081** | -0.141*** | -0.139 | -0.065 | -0.121*** | -0.038 | -0.213*** | -0.202*** |
| | (0.034) | (0.040) | (0.138) | (0.075) | (0.038) | (0.061) | (0.042) | (0.045) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -31.709*** | -2.649 | -7.515 | 4.818 | -2.041 | 1.404 | -6.289* | 0.045 |
| | (3.187) | (2.097) | (5.176) | (3.621) | (4.372) | (4.097) | (3.601) | (2.968) |
| Log-wage (husband) | 7.715*** | -16.368*** | 7.363** | -9.350 | 3.295 | -19.846*** | 0.798 | -7.657* |
| | (2.548) | (3.171) | (3.206) | (6.576) | (2.755) | (4.056) | (2.781) | (3.967) |
| Wage deviations | | | | | | | | |
| Present (wife) | -17.860*** | -1.220 | -15.333*** | -0.819 | -13.049*** | -1.181 | -6.535*** | -1.766 |
| | (1.751) | (1.446) | (3.477) | (2.801) | (3.254) | (3.197) | (1.465) | (1.374) |
| Previous (wife) | -1.314*** | -0.297 | -1.468*** | 0.026 | -1.145*** | 0.280 | -2.626*** | 0.208 |
| | (0.241) | (0.206) | (0.294) | (0.303) | (0.247) | (0.260) | (0.521) | (0.497) |
| Present (husband) | 6.964*** | -8.096*** | 3.772 | -1.905 | 2.715 | -13.445*** | 0.140 | -3.181** |
| | (1.991) | (2.247) | (2.632) | (3.815) | (2.118) | (2.704) | (1.005) | (1.458) |
| Previous (husband) | 1.025*** | -0.967*** | 0.834*** | -0.479 | 0.055 | -1.527*** | 0.531 | -2.599*** |
| | (0.292) | (0.364) | (0.290) | (0.334) | (0.259) | (0.308) | (0.554) | (0.702) |
| Constant | 35.952*** | 40.839*** | 35.343*** | 54.115*** | 30.077*** | 26.431*** | 55.849*** | 55.455*** |
| | (2.944) | (2.574) | (6.172) | (6.312) | (5.008) | (6.481) | (3.121) | (3.662) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,745 | 2,745 | 2,341 | 2,341 | 1,605 | 1,605 | 1,888 | 1,888 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.C13: Robustness checks (VIII) - Region F.E.

| | ITALY | | LUXEMBOURG | | SPAIN | | SWEDEN | |
|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Present observables | | | | | | | | |
| Log-wage (wife) | 7.327*** | -0.557 | -4.218 | -2.590 | 11.752*** | -2.192* | -1.046 | 0.056 |
| | (1.347) | (1.149) | (3.464) | (2.211) | (1.753) | (1.249) | (1.490) | (1.023) |
| Log-wage (husband) | -2.653** | 3.240** | -5.696** | -2.338 | -5.621*** | 7.545*** | 0.341 | 2.224 |
| | (1.222) | (1.396) | (2.748) | (3.441) | (1.644) | (1.829) | (1.975) | (2.138) |
| Non-labor income | -0.128*** | -0.133*** | -0.154*** | -0.092** | -0.171*** | -0.136*** | -0.299*** | -0.242*** |
| | (0.023) | (0.023) | (0.055) | (0.040) | (0.030) | (0.027) | (0.092) | (0.064) |
| Expected wages $(t+1)$ | | | | | | | | |
| Log-wage (wife) | -12.711*** | -0.373 | 6.166 | 2.523 | -15.474*** | 2.385* | 3.034 | 1.486 |
| | (1.820) | (1.293) | (4.157) | (2.562) | (2.166) | (1.435) | (2.274) | (1.295) |
| Log-wage (husband) | 2.113* | -8.342*** | 5.128* | -5.121 | 5.539*** | -17.440*** | 2.453 | -1.533 |
| | (1.265) | (1.708) | (2.811) | (3.883) | (1.786) | (2.304) | (1.980) | (2.082) |
| Wage deviations | | | | | | | | |
| Present (wife) | -8.695*** | 0.235 | -2.768 | 1.388 | -14.767*** | 0.883 | -4.500*** | -0.403 |
| | (0.882) | (0.794) | (2.455) | (1.571) | (1.522) | (1.095) | (1.083) | (0.842) |
| Previous (wife) | -0.798*** | -0.032 | -1.303*** | 0.439 | -1.112*** | 0.052 | -0.292** | 0.072 |
| | (0.195) | (0.174) | (0.442) | (0.300) | (0.200) | (0.149) | (0.120) | (0.098) |
| Present (husband) | 0.555 | -6.456*** | 1.893 | -0.230 | 3.460** | -9.392*** | -1.640 | -6.530*** |
| | (0.872) | (0.877) | (1.810) | (1.984) | (1.345) | (1.457) | (1.684) | (1.907) |
| Previous (husband) | -0.172 | -0.623*** | -0.190 | -0.418 | 0.056 | -1.198*** | -0.076 | -0.914*** |
| | (0.215) | (0.218) | (0.454) | (0.494) | (0.190) | (0.195) | (0.239) | (0.274) |
| Constant | 41.886*** | 48.199*** | 51.969*** | 57.412*** | 33.621*** | 46.929*** | 34.264*** | 33.374*** |
| | (1.255) | (1.332) | (3.717) | (2.957) | (2.100) | (1.845) | (4.299) | (4.651) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,006 | 7,006 | 1,383 | 1,383 | 4,545 | 4,545 | 2,829 | 2,829 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

# Appendix 2.D: The case of Spanish regions

In this Appendix, we replicate the main analysis for Aragón and other Spanish regions, using information from the EU-SILC data for the period 2003-2016. Estimates of the main analysis are shown in Table 2.D1, distinguishing the following regions according to NUTS-1 codes:[22]

- North-West (code "ES1"): Galicia, Asturias and Cantabria.
- Noth-East (code "ES2"): Basque country, Navarra, La Rioja and Aragón.
- Center (codes "ES3"-"ES4"): Madrid, Castilla y León, Castilla-La Mancha and Extremadura.
- East (code "ES5"): Catalonia, Valencia and Balearic Islands.
- South (code "ES6"): Andalucía, Murcia, Ceuta and Melilla.

In the North-West and East of Spain, estimates suggest that individuals' labor supply is determined by the impact of their own observables. Furthermore, the signs of own wage deviations are highly compatible with the LIC model. In addition, the sign and significance of spouses' past deviations is also compatible with the LIC model in the East of Spain. Results for husbands' labor supply are mostly analogous. In the North-West, only own past wage deviations have a significant impact on males' hours of work. In the East, wives' past deviations also have the predicted effect on husbands' labor supply. On the other hand, in the North-East, Center, and South of Spain, results reject the NC and FIC models, but these regions show different trends. Specifically, spouses' labor supply is also determined significantly by spouses' attributes. Focusing on the coefficients of interest, estimates show a negative and significant impact of wives' past deviations on their own labor supply in the North-East and Center of Spain, while the coefficient is not significant in the South. However, in the South, wives' past deviations have a positive and significant impact on husbands' hours of work, as suggested by the limited commitment model. Finally, husbands' past deviations show a negative effect on their own labor supply, although it is only significant in the regions of the Center and South of Spain, being non-significant in the North-East.

[22] 136 Spanish individuals living in the Canary Islands (NUTS-1 code "ES7") are omitted from the analysis. Sample sizes do not allow for a more disaggregated (e.g., NUTS-2) analysis at the regional level.

The case of Aragón is studied in a separate analysis in Table 2.D2. As in the general cases, results reject the full commitment and non-commitment versions of the collective model, given that present and past observables have an impact on spouses' labor supply. However, spouses' labor supply functions seem to be not very sensitive to own and cross wages. For wives, the only significant coefficients are those associated with past wages and present non-labor income, whereas present income, expected income, and present and past wage deviations (both own and cross) are non-significant. On the other hand, males' labor supply shows different results, as it is mainly determined by their own expected income, but also by their present and past wage deviations, with signs being compatible with the LIC model. Specifically, when husbands perform or have performed worse than expected in the past, they tend to work more hours per week in the present, as predicted by the limited commitment model.[23]

[23]Due to the limited sample size, and as long as it is unknown whether samples at the regional level are representative for the whole population, these results should be interpreted cautiously.

Table 2.D1: Labor supply estimates for Spanish regions

| | North-West | | North-East | | Center | | East | | South | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands | Wives | Husbands |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Present observables | | | | | | | | | | |
| Log-wage (wife) | 14.228*** | 1.719 | 0.314 | -3.023 | 11.936*** | -3.251 | 10.561*** | -2.952 | 13.673*** | -8.288*** |
| | (4.618) | (3.729) | (3.087) | (2.424) | (2.570) | (2.119) | (2.614) | (2.229) | (3.814) | (2.790) |
| Log-wage (husband) | -5.405 | 1.155 | -11.989*** | 0.385 | -8.276*** | 7.272*** | -3.511 | 6.953*** | -7.286** | 6.974** |
| | (4.896) | (4.490) | (3.339) | (2.853) | (2.490) | (2.271) | (2.540) | (2.404) | (3.463) | (2.793) |
| Non-labor income | -0.050 | -0.225*** | -0.352*** | -0.222*** | -0.200*** | -0.076* | -0.134*** | -0.131*** | -0.213*** | -0.148*** |
| | (0.085) | (0.072) | (0.079) | (0.064) | (0.049) | (0.042) | (0.045) | (0.040) | (0.073) | (0.056) |
| Expected wages $(t+1)$ | | | | | | | | | | |
| Log-wage (wife) | -19.769*** | -0.846 | -3.616 | 3.633 | -14.979*** | 4.251* | -14.424*** | 2.883 | -15.176*** | 7.223** |
| | (6.028) | (4.315) | (4.002) | (2.795) | (3.369) | (2.380) | (3.394) | (2.528) | (5.320) | (3.292) |
| Log-wage (husband) | 6.775 | -9.294 | 12.035*** | -10.397*** | 7.986*** | -18.812*** | 3.113 | -15.229*** | 7.266* | -17.057*** |
| | (5.563) | (6.094) | (3.743) | (3.778) | (2.878) | (3.264) | (2.935) | (3.445) | (4.124) | (4.105) |
| Wage deviations | | | | | | | | | | |
| Present (wife) | -16.983*** | -4.896 | -6.113** | 2.144 | -14.685*** | 2.400 | -13.055*** | 0.660 | -18.245*** | 7.475*** |
| | (3.854) | (3.167) | (2.642) | (2.113) | (2.225) | (1.877) | (2.285) | (1.985) | (3.262) | (2.456) |
| Previous (wife) | -1.921*** | 0.053 | -0.856** | -0.134 | -1.055*** | -0.325 | -0.701** | 0.546* | -0.833 | 0.711* |
| | (0.510) | (0.428) | (0.375) | (0.302) | (0.334) | (0.288) | (0.327) | (0.288) | (0.546) | (0.411) |
| Present (husband) | 2.138 | -4.221 | 7.464*** | -3.738 | 6.861*** | -8.577*** | 1.483 | -9.174*** | 4.208 | -9.057*** |
| | (4.015) | (3.555) | (2.737) | (2.274) | (2.132) | (1.868) | (2.137) | (1.946) | (2.910) | (2.259) |
| Previous (husband) | -0.446 | -1.914*** | 0.428 | -0.508 | -0.171 | -0.816*** | 0.638** | -1.150*** | 0.301 | -1.169*** |
| | (0.541) | (0.466) | (0.383) | (0.316) | (0.320) | (0.279) | (0.322) | (0.290) | (0.490) | (0.379) |
| Constant | 27.285*** | 46.012*** | 44.981*** | 51.622*** | 30.723*** | 49.452*** | 34.471*** | 47.770*** | 26.895*** | 53.572*** |
| | (5.697) | (4.666) | (4.091) | (3.348) | (2.927) | (2.573) | (3.097) | (2.763) | (4.049) | (3.103) |
| Initial observables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | | |
| Sociodemographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 518 | 518 | 919 | 919 | 1,163 | 1,163 | 1,157 | 1,157 | 652 | 652 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to Spain. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

Table 2.D2: Labor supply estimates for Aragón

| VARIABLES | Wives (1) | Husbands (2) |
|---|---|---|
| Initial observables | | |
| Log-wage (wife) | 2.490*** | -0.140 |
| | (0.851) | (0.679) |
| Log-wage (husband) | 0.259 | 0.827 |
| | (0.826) | (0.662) |
| Non-labor income | 0.006 | 0.065 |
| | (0.096) | (0.076) |
| Present observables | | |
| Log-wage (wife) | -1.305 | 2.868 |
| | (7.770) | (5.749) |
| Log-wage (husband) | 1.790 | 9.762 |
| | (6.878) | (5.943) |
| Non-labor income | -0.275* | 0.008 |
| | (0.146) | (0.116) |
| Expected wages $(t+1)$ | | |
| Log-wage (wife) | -3.029 | -3.320 |
| | (9.344) | (6.186) |
| Log-wage (husband) | 0.013 | -18.851** |
| | (7.558) | (7.742) |
| Wage deviations | | |
| Present (wife) | -5.549 | -2.320 |
| | (6.751) | (5.095) |
| Previous (wife) | -0.718 | -0.880 |
| | (0.712) | (0.550) |
| Present (husband) | -2.331 | -13.226*** |
| | (5.838) | (4.848) |
| Previous (husband) | -1.058 | -1.431** |
| | (0.774) | (0.612) |
| Constant | 33.398*** | 33.665*** |
| | (8.770) | (7.025) |
| Sociodemographics | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 275 | 275 |

Note: Bootstrapped ($n = 500$) standard errors in parentheses. The sample (EUSILC 2003-2016 data) is restricted to Aragón. The dependent variable is the hours of work per week. Additional estimates are available upon request. *** significant at the 1%, ** significant at the 5%, * significant at the 10%.

# Chapter 3

# Short- vs long-term intergenerational correlation of employment and self-employment in Europe

This Chapter analyzes the existence of short- and long-term intergenerational correlation of employment and self-employment in European countries, using data from the European Union Statistics on Income and Living Conditions. Using longitudinal data for the period 2003-2016, fixed effect estimates show a significant short-term correlation between the current employment status of parents and that of their children. However, short-term correlation of self-employment seems to be driven only by father-son correlations. Conversely, using the special module on Intergenerational Transmissions for the year 2011, estimates show a strong and significant correlation between respondents' self-employment status, and that of their parents when respondents were 14 years old. This suggests that self-employment decisions are not related to short-term family labor supply decisions, but to long-term intergenerational transmission.
Keywords: Intergenerational transmission, employment, self-employment; EU-SILC data

## 3.1 Introduction

The study of intergenerational transmission is especially important in several fields, including Economics, Industrial Relations, and Demography, as it investigates how and to what extent certain factors can be transmitted from parents to children. Those factors include income and poverty, education and skills, human development, occupational choices, and self-employment, among others. Attributes such as education and human, financial, and social capital have been found to be associated with employment and self-employment (Dunn and Holtz-Eakin, 2000; Fairlie and Robb, 2007). Prior research has shown that these values can be transmitted both horizontally (i.e., weak ties) and vertically (i.e., intergenerational transmission, or strong ties).

Furthermore, prior research has also identified the existence of intergenerational transmission of employment and self-employment, although the literature on employment is scarce and relatively novel (Galassi et al., 2019). Such transmissions are a particular case of intergenerational socio-economic mobility, whereby the status of individuals within households is assumed to be transmitted from one generation to the next. Transmission of employment and unemployment also suppose a particular case of intergenerational transmission of poverty, which has received significant attention in recent years. Unemployment is considered, indeed, one of the main labor-related issues of young workers in Europe (Mäder et al., 2015), especially since the recent economic crisis in the Mediterranean countries (with youth unemployment rates well above 20%). Given the importance of family background and parents' investments in the future socio-economic development of children (Del Boca et al., 2016; Chiappori et al., 2017), it is important to study the intergenerational correlations of employment. The literature has demonstrated a positive correlation between young workers' employment and unemployment status, and that of their parents, in various countries (O'Neill and Sweetman, 1998; Corak et al., 2004; Bratberg et al., 2008; Ekhaugen, 2009; Macmillan, 2010; Gregg et al., 2012). Nevertheless, there is no consensus as to the channels, or the extent, of these transmissions, with results that differ significantly among countries and methods.

Entrepreneurship and self-employment are labor alternatives for those workers who cannot - or do not want to - find an employer; but they are also a complex phenomenon, and a model of life (Coduras et al., 2016). Further, they have traditionally been associated with development, innovation, and economic growth (e.g., Grimm and Paffhausen, 2015). Thus, several measures aimed at stimulating self-employment and entrepreneurial activity have been developed at both national and international levels, with the ultimate objective of overcoming some of the negative effects of the recent economic crisis (Minniti and Naudé, 2010). In this sense, self-employment can be seen as an alternative for those workers who do not want to be employed or cannot find an employer, and it is a complex (social and academic) phenomenon (Coduras et al., 2016). Prior research has identified self-employment as a significant tool through which to balance work and family conflicts and responsibilities (e.g., Presser, 1989; Connelly, 1992; Lombard, 2001; Giménez-Nadal et al., 2012).

Within this framework, this Chapter explores the short- and long-term intergenerational transmission of employment and self-employment in 12 European countries, empirically estimating the relationship between the labor status of children and that of their parents. Europe is a particularly important region in which to study these transmissions, given the large impact of the recent economic crisis on unemployment in European countries, and the moderating role of family background on that impact (Mascherini, 2019). In doing so, we use the EU-SILC data from two different sources. First, we investigate short-term correlations of employment and self-employment using the EU-SILC longitudinal data for the years 2003-2016, for Austria, Belgium, Denmark, Greece, Spain, Finland, France, Italy, Luxembourg, the Netherlands, Sweden, and the UK. Using fixed effects models, we estimate a positive and significant correlation between respondents' current employment status, and the current employment status of their parents. However, the self-employed status of parents appears to be correlated only with that of male workers. These results may, however, reveal family labor supply decisions, suggesting that parents' employment is a strong predictor of the children's short-term decision.

We then analyze long-term intergenerational transmissions, using the 2011 special module on Intergenerational Transmissions of Disadvantages of the cross-sectional EU-SILC data. This special module, which is not available for the longitudinal data, allows us to estimate the current employment and self-employment status of respondents in terms of the labor status of their parents when respondents were 14 years old. Estimates show that the (employment) self-employment status of workers is strongly correlated with their parents being (employed) self-employed in the past. This suggests that there exists a significant channel of self-employment arising from intergenerational correlations that is not driven by short-term family labor supply decisions, but instead from long-term transmission.

The contributions of the Chapter are twofold. First, we document the existence of a significant short- and long-term correlation of employment from parents to children, which may reveal both family labor supply decisions and intergenerational transmissions. It is worth noting that most of the empirical research on intergenerational transmissions has focused on single countries, and international and cross-country analyses are quite limited. Second, results suggest that self-employment intergenerational correlation is especially significant in the long-term, but not in the short-term. Furthermore, the intergenerational correlation of self-employment is estimated to be somewhat smaller than in prior research. To the best of our knowledge, this Chapter represents the first empirical comparison of short- and long-term intergenerational correlation of employment and self-employment. Future research should focus on investigating the specific channels that drive these long-term transmissions.

The remainder of the Chapter is organized as follows. Section 2 includes a literature review, and Section 3 shows the data used throughout the analysis. Section 4 sets out the empirical strategy and the main results for the analysis of the short-term intergenerational correlation. Section 5 does the same for the long-term transmissions. Finally, Section 6 discusses the different results, Section 7 concludes, and Appendices 3.A and 3.B show additional estimates and results for single-parent individuals.

## 3.2 Literature review

Intergenerational transmissions have been widely studied in the literature, focusing on how socio-economic conditions and attitudes are transmitted from parents to children, beyond pure selection theories (Black et al., 2005). For instance, one of the factors that has been found to be transmitted from parents to children is human capital and education, as parents with higher education level have, in general terms, more formally-educated children than parents with lower education (Black et al., 2005). Other socio-economic factors found to be transmitted from parents to children are human development (Francesconi and Heckman, 2016), financial capital and poverty (Becker and Tomes, 1979), and occupational practices and economic outcome (e.g., Fernández et al., 2004; Doepke and Zilibotti, 2017). Dohmen et al. (2011) studied intergenerational transmission of risk attitudes, and Binder (2018) and Olivetti et al. (2018) studied transmissions of gender roles. In turn, employment outcomes may be determined by all these factors (e.g., Lazear, 2005). However, the most studied intergenerational employment outcome is (potential) earnings (see Black and Devereux, 2011), along with the intensive margin of labor supply, i.e., work hours (Altonji and Dunn, 2000).

Understanding intergenerational transmission is of key relevance for planners and policy makers, as it may help in understanding the characteristics transmitted from generation to generation. For instance, policies aiming to reduce poverty and inequality of opportunity could be more efficiently implemented if the factors that determine such sources were known to be transmitted from parents to children. Hence, intergenerational transmissions are of special relevance for children, given that they may determine future socio-economic behaviors (Stith et al., 2000). In this context, transmission of employment and self-employment are of special importance in Europe, given that during the recent economic crisis the levels of unemployment have reached high thresholds. Furthermore, the largest impact has been on youth, with percentages of unemployment above 40% in Greece and Spain, and between 40% and 20% in Italy, France, Belgium and Finland, according to the Eurostat.

Some authors have analyzed the intergenerational transmission of employment and unemployment in different countries, trying to find both conditional correlations and causal links between the employment status of parents and children. However, despite the fact that prior studies have found a significant correlation, the evidence so far at the family level is scarce, inconclusive, and most of the existing research is limited to single-country cross-sectional studies (Mäder et al., 2015; Galassi et al., 2019).

In Europe, O'Neill and Sweetman (1998); Macmillan (2010); Gregg et al. (2012), and Zwysen (2016) studied intergenerational transmission of unemployment in the UK. O'Neill and Sweetman (1998) estimated a positive correlation between the unemployment histories of fathers and sons, where sons of unemployed fathers were found to be twice as likely to experience unemployment; and Zwysen (2016) found that non-working fathers had sons with less negative attitudes towards unemployment. However, Macmillan (2010) found no significant findings on intergenerational causality, in terms of "worklessness", and Gregg et al. (2012) established that fathers' job loss has a negative impact on children's educational attainment and is positively correlated to youth unemployment. On the other hand, Bratberg et al. (2008); Ekhaugen (2009), and Corak et al. (2004) have addressed transmission of unemployment in Scandinavian countries. Bratberg et al. (2008) found that worker displacement is negatively correlated to unemployment, but has no impact on children's labor outcomes, in Norway. Conversely, Ekhaugen (2009) found a positive intergenerational correlation of unemployment in Norway, but no evidence of causal links; and Corak et al. (2004) found that parental unemployment is not correlated with unemployment insurance in Sweden. Mäder et al. (2015) analyzed conditional correlations for the case of Germany, using an IV approach, to find that not only is father's unemployment an important determinant of children's employment, but father's age and education play an important role in the relationship. Hérault and Kalb (2016) found father-son and mother-daughter correlations in labor market outcomes, but not cross-transmission, and Galassi et al. (2019) studied the case of the US, finding that transmission of employment are stronger from mothers to daughters than to sons. Morales (2019) analyzed, for the case of Spain, the correlation between mothers' unemployment and children's unemployment and self-employment, finding that family support is a significant predictor of self-employment.

Transmissions of self-employment and entrepreneurship have been studied in the literature. Specifically, prior research has focused on horizontal transmission (i.e., through peer effects, or weak ties), and vertical transmission (i.e., intergenerational transmissions, or strong ties), providing mixed results (Brüderl and Preisendörfer, 1998; McPherson et al., 2001; Zhang et al., 2009; De Jong and Marsili, 2015). In that context, "first generation" self-employed and entrepreneurs, who have not been influenced by self-employed parents, may value different factors than do "second generation" self-employed workers. That is to say, the latter may be influenced by different paternity-driven factors that cannot affect the first generation self-employed, such as experience, social and work values, and concrete managerial skills (Gauly, 2017).

The question of whether individuals become entrepreneurs or are born that way has been directly addressed by prior studies, with mixed results. For instance, Nicolaou et al. (2008) and Nicolaou and Shane (2010) study the influence of genetic factors on self-employment intentions, documenting a stronger relevance of heritability and genetics, rather than that of the environment. Conversely, Lindquist et al. (2015) study the intergenerational association of entrepreneurship and self-employment in Sweden, with a focus on pre- and post-birth factors, and find that this association is mainly driven by post-birth factors and role models, and not by genetic factors. Gauly (2017) also studies the intergenerational correlation of attitudes between parents and children, with results pointing to the importance of attitudes, environmental factors, and assortative mating, as transmissions do not seem to be purely genetic. Matthews et al. (2011) report that self-employment seems to depend on opportunity, personality, and skills, while there is no clear answer as to whether the self-employed are born or made.

Despite prior research suggesting the existence of intergenerational transmission of self-employment, results vary significantly across countries and methods, and the reasons behind these transmissions remain unclear (Colombier and Masclet, 2008). For instance, Dunn and Holtz-Eakin (2000) find that parents' financial and human capital are relevant in the transition into self-employment. Schmitt-Rodermund (2004) finds that authoritarian parenting is related to entrepreneurship in Germany. Wang and

Wong (2004) find that family experience with business is crucial in determining entrepreneurial interests in Singapore. Similarly, Fairlie and Robb (2007) find that being a business owner is correlated with having a self-employed family member. Sørensen (2007) reports that parental roles are an important source of the transmission of self-employment in Denmark. Colombier and Masclet (2008) find that managerial skills transmitted by parents are important for the second-generation self-employed in France. Andersson and Hammarstedt (2010) and Andersson and Hammarstedt (2011) indicate that the father is the strongest role model among self-employed immigrants. Laspita et al. (2012) indicate that transmissions of self-employment may vary across cultures. Levie and Autio (2013) find that parental aspirations may have a negative impact on entrepreneurship in the UK. Fritsch et al. (2015) highlight the importance of considering the self-employment status of parents when studying self-employment. Blumberg and Pfann (2016), using Dutch data, find different determinants of self-employment between first- and second-generation self-employed workers. Finally, Ferrando-Latorre et al. (2019) find a non-gender- or time-driven intergenerational correlation of self-employment in Spain.

## 3.3 Data and variables

We first use data from the longitudinal European Union Statistics on Income and Living Conditions (EU-SILC), for the years 2003-2016, and the following countries: Austria, Belgium, Denmark, Greece, Spain, Finland, France, Italy, Luxembourg, the Netherlands, Sweden, and the United Kingdom.[1] The EU-SILC data is conducted every year by Eurostat, and combines data at the household and individual levels, for all working-age individuals of the interviewed households. The longitudinal EU-SILC is overlapped panel data, and households interviewed are followed for up to four years.

The sample is restricted to individuals between 16 and 65 years old for whom there is information for both of their parents. Individuals for whom there is information only for the father or the mother are studied separately. Furthermore, those individuals for whom information about either of their parents does not include labor characteristics (i.e., retired, early retired, and disabled or other inactive parents) are omitted from the

[1] Access to the data has been granted by the Contract RPP 119/2018 for the period 01/01/2018-30/06/2023. The sample is restricted to countries with information on the variables of interest. Since developing economies have lower rates of female labor participation, different self-employment behaviors, more inequality in self-employment, and different gender and identity roles, we have left the study of Eastern Europe for future research (Mondragón-Vélez and Peña, 2010; Terjesen and Amorós, 2010).

analysis.[2] The main units of analysis are, then, working age respondents of interviewed households who cohabit with both of their (working) parents.[3] Consequently, sample sizes and the number of individuals and observations will refer to working-age children as the main unit.

The employment status of individuals and their mothers and fathers appears in terms of the (self-defined) current economic status of interviewees in the EU-SILC questionnaire. All household members (aged 16 and over) are asked what is their "labour information/basic labour information on current activity and on current job". The possible categories identified are: 1) Employee (full-time). 2) Employee (part-time). 3) Self-employed worker (full-time, including family workers). 4) Self-employed worker (part-time, including family workers). 5) Unemployed. 6) Pupil, student, training or in unpaid work experience. 7) In retirement, early retirement or given up business. 8) Permanently disabled or unfit to work. 9) In compulsory military service or community service. 10) Fulfilling domestic tasks and care responsibilities. 11) Other inactive person. With these classifications, we define employees from categories (1) and (2), and self-employed workers from categories (3) and (4). This identification of employees and self-employed workers holds for both mothers and fathers. Students, pupils, individuals in training or in unpaid work experience, individuals in retirement, early retirement or having given up business, disabled or unfit to work individuals, and individuals in compulsory military and community service are omitted from the sample. This leaves unemployed workers, individuals fulfilling domestic and care tasks, and other inactive persons as "non-working" individuals.

Restrictions leave a total sample of 36,119 observations, corresponding to 9,235 individuals, for whom there is information for the mother and the father simultaneously. Among these observations, 7,490 are for non-working individuals, 11,393 are for self-employed workers, and 17,236 are for employees. See Table 3.1 for a summary of sample sizes, by country, showing both the number of observations and the number of individuals. In addition, 3,997 individuals report living with only one of their parents.

The EU-SILC data allows us to define the following control variables. The gender of individuals, measured with a dummy variable ("being male") that takes value 1 for

[2] The longitudinal EU-SILC data does not include information about the previous labor status of individuals. Therefore, it could be that individuals whose parents were self-employed in the past are omitted from the longitudinal sample, or not considered as self-employed parents. Hence, a source of bias (sample selection bias and measurement error) must be acknowledged.

[3] For simplicity, these main units of analysis will be denoted as "children". One limitation of the study is that the data does not allow identification of which individuals are foster children, which limits the analysis, as there may be genetic factors explaining employment and self-employment decisions.

Table 3.1: Sample sizes, by country

| | EU-SILC 2013-2016 | | EU-SILC 2011 |
|---|---|---|---|
| COUNTRY | Observations | Individuals | Individuals |
| Austria | 1,867 | 478 | 5,012 |
| Belgium | 1,389 | 361 | 4,599 |
| Denmark | 1,105 | 278 | - |
| Finland | 1,119 | 285 | - |
| France | 557 | 160 | 12,758 |
| Greece | 4,171 | 1,056 | 2,876 |
| Italy | 14,516 | 3,699 | - |
| Luxembourg | 799 | 209 | 17,897 |
| Netherlands | 2,289 | 573 | 5,392 |
| Spain | 6,531 | 1,685 | 4,597 |
| Sweden | 1,080 | 276 | 1,572 |
| UK | 696 | 175 | 4,639 |
| Total | 36,119 | 9,235 | 59,342 |

Note: The longitudinal EU-SILC 2013-2016 is restricted to working-age children of interviewed two-parent households who are not students, retired, or disabled. The cross-sectional EU-SILC 2011 is restricted to working-age individuals who filled-in the Special Module on Intergenerational Transmissions, of interviewed two-parent households who are not students, retired, or disabled.

males, 0 for females. The age of respondents, measured in years (and age squared, defined as $\text{age}^2/10$). The marital status of individuals, measured with a dummy that identifies those individuals who have never been married over their life cycle (value 1, 0 otherwise). The maximum level of education achieved by individuals is measured using the International Standard Classification of Education. Form this information, we define two educational dummy variables: "secondary education", which takes value 1 for those individuals who have achieved a secondary but non-compulsory level of formal education (0 otherwise); and "University education", which takes value 1 if individuals have achieved University education. We define some variables at the household level, including the total household disposable income (measured in Euros per year), the type of dwelling (including two dummies for those who live in a house, or in an apartment or flat), and the presence of a car in the household, in order to control for wealth effects. We also compute the number of children present in the household to control for household structure, which may be an important determinant of self-employment. To avoid computing the analyzed individual as household child, we identify the number of children under 4 years (inclusive), and the number of children between 5 and 15 years (inclusive). See Table 3.2 for descriptive statistics of variables.

Table 3.2: Summary statistics, EU-SILC 2003-2016

| | Non-working | | Self-employed | | Employees | |
|---|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| Individual | | | | | | |
| Being male | 0.591 | 0.492 | 0.536 | 0.499 | 0.665 | 0.472 |
| Age | 25.076 | 4.518 | 21.898 | 4.246 | 25.412 | 4.432 |
| Never married | 0.971 | 0.168 | 0.991 | 0.094 | 0.983 | 0.131 |
| Secondary ed. | 0.496 | 0.5 | 0.56 | 0.496 | 0.547 | 0.498 |
| University ed. | 0.169 | 0.375 | 0.131 | 0.337 | 0.215 | 0.411 |
| Household | | | | | | |
| Disposable income | 38235 | 31393 | 41492 | 25779 | 50525 | 25358 |
| Dwelling: house | 0.545 | 0.498 | 0.581 | 0.493 | 0.654 | 0.476 |
| Dwelling: apartment/flat | 0.438 | 0.496 | 0.397 | 0.489 | 0.334 | 0.472 |
| N. children under 4 | 0.061 | 0.306 | 0.031 | 0.206 | 0.028 | 0.194 |
| N. children 5-15 | 0.197 | 0.47 | 0.303 | 0.574 | 0.153 | 0.412 |
| Mothers | | | | | | |
| Age | 51.183 | 5.635 | 49.133 | 5.729 | 51.635 | 5.584 |
| Secondary ed. | 0.309 | 0.462 | 0.368 | 0.482 | 0.353 | 0.478 |
| University ed. | 0.075 | 0.263 | 0.18 | 0.384 | 0.087 | 0.281 |
| Self-employed | 0.059 | 0.236 | 0.072 | 0.258 | 0.057 | 0.232 |
| Employee | 0.232 | 0.422 | 0.502 | 0.5 | 0.436 | 0.496 |
| Fathers | | | | | | |
| Age | 54.424 | 5.493 | 52.19 | 5.771 | 54.611 | 5.551 |
| Secondary ed. | 0.277 | 0.447 | 0.357 | 0.479 | 0.364 | 0.481 |
| University ed. | 0.112 | 0.315 | 0.215 | 0.411 | 0.103 | 0.304 |
| Self-employed | 0.119 | 0.324 | 0.094 | 0.292 | 0.102 | 0.302 |
| Employee | 0.371 | 0.483 | 0.739 | 0.439 | 0.626 | 0.484 |
| Observations | 7,490 | | 11,393 | | 17,236 | |

Note: The sample (EU-SILC 2013-2016) is restricted to working-age children of interviewed households who are not students, retired, or disabled. Summary statistics include sample weights.

Additionally, we use data from the Intergenerational Transmissions of Disadvantages special module, a cross-sectional dataset for the year 2011 that includes the following countries: Austria, Belgium, France, Greece, Luxembourg, the Netherlands, Spain, Sweden, and the UK. Information for Denmark, Finland, and Italy is not available in the special module, so these countries are omitted from the cross-sectional sample. Unfortunately, despite the fact that longitudinal and cross-sectional samples of the EU-SILC include analogous variables, the longitudinal and cross-section samples are not linkable at the micro level, as the surveyed individuals are different. Therefore, information from the 2011 special module on transmissions cannot be matched with the 2003-2016 longitudinal sample.

This special module includes information for all the individuals of the interviewed

Table 3.3: Summary statistics, EU-SILC 2011 special module

| | Non-working | | Self-employed | | Employees | |
|---|---|---|---|---|---|---|
| VARIABLES | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| Individual | | | | | | |
| Being male | 0.230 | 0.421 | 0.647 | 0.478 | 0.487 | 0.500 |
| Age | 41.087 | 10.638 | 43.833 | 8.878 | 41.937 | 9.380 |
| Never married | 0.319 | 0.466 | 0.251 | 0.434 | 0.297 | 0.457 |
| Secondary ed. | 0.335 | 0.472 | 0.399 | 0.490 | 0.408 | 0.491 |
| University ed. | 0.159 | 0.366 | 0.311 | 0.463 | 0.350 | 0.477 |
| Household | | | | | | |
| Disposable income | 29066 | 24768 | 40044 | 43906 | 41229 | 29921 |
| Dwelling: house | 0.505 | 0.500 | 0.611 | 0.487 | 0.582 | 0.493 |
| Dwelling: apartment/flat | 0.489 | 0.500 | 0.381 | 0.486 | 0.413 | 0.492 |
| N. children at 14 years old | 2.620 | 1.612 | 2.410 | 1.457 | 2.491 | 1.449 |
| Mothers | | | | | | |
| Age | 41.979 | 6.025 | 42.116 | 5.598 | 41.990 | 5.652 |
| Secondary ed. | 0.120 | 0.325 | 0.157 | 0.364 | 0.159 | 0.366 |
| University ed. | 0.054 | 0.227 | 0.078 | 0.269 | 0.088 | 0.283 |
| Self-employed | 0.084 | 0.277 | 0.143 | 0.350 | 0.068 | 0.251 |
| Employee | 0.201 | 0.401 | 0.276 | 0.447 | 0.375 | 0.484 |
| Fathers | | | | | | |
| Age | 45.566 | 6.153 | 45.427 | 5.959 | 45.038 | 5.936 |
| Secondary ed. | 0.125 | 0.331 | 0.198 | 0.399 | 0.212 | 0.409 |
| University ed. | 0.090 | 0.286 | 0.131 | 0.337 | 0.127 | 0.333 |
| Self-employed | 0.263 | 0.441 | 0.365 | 0.481 | 0.188 | 0.391 |
| Employee | 0.668 | 0.471 | 0.605 | 0.489 | 0.780 | 0.414 |
| Observations | 3,575 | | 9,006 | | 46,761 | |

Note: The sample (EU-SILC 2011) is restricted to working-age individuals who filled the Special Module on Intergenerational Transmissions, of interviewed two-parent households who are not students, retired, or disabled. Summary statistics include specific sample weights of the 2011 special module on Intergenerational Transmissions.

households aged between 24 and 60 years old (i.e., born between 1951 and 1985, inclusive). The main purpose of the special module was to collect information about household and parents' characteristics when respondents were 14 years old. Fathers (mothers) refer to the person that the respondent considered their father (mother), which in general referred to the biological father (mother). However, if respondents considered someone else to be the father (mother), answers should refer to that person. Unfortunately, as happened in the longitudinal sample, there is no information about whether or not information refers to the biological father (mother).[4]

[4] An additional advantage of the 2011 special module, compared to the 2003-2016 longitudinal sample, is that we do not need to restrict the sample to children of households who cohabit with the parents, thus avoiding a source of potential sample selection bias.

The 2011 sample is restricted to individuals who completed the special module (between 25 and 59 years old), for whom there is information for both of their parents through the special module, i.e., information about the parents when the respondent was 14 years old. Individuals for whom there is information only for the father or the mother in the special module are studied in Appendix 3.B. We eliminate from the sample respondents who report being, at the date of the 2011 interview, students, pupils, individuals in training or in unpaid work experience, individuals in retirement, early retirement or having given up business, disabled or unfit to work individuals, and individuals in compulsory military and community service. The classification of individuals according to their economic status is, then, analogous to the classification followed for the longitudinal sample. The sociodemographic information and employment status of respondents is also defined in an equivalent way, identifying employees, self-employed workers, and non-working individuals analogously. Restrictions leave a total sample of 59,342 individuals, for whom there is information for the mother and the father. Among these observations, 9,006 correspond to self-employed workers, and 46,761 to employees. See Table 3.1 for a summary of sample sizes, by country.

The information available in the special module about parents, including their age, education level, and employment status, refers to the year in which the respondent was 14 years old. The number of children in the household is also taken from the special module. The maximum level of education of parents is defined in a four-scale rank, including: 0) "Father could neither read nor write in any language"; 1) "Low level (pre-primary, primary education or lower secondary education)"; 2) "Medium level (upper secondary education and post-secondary non-tertiary education)"; and 3) "High level (first and second stage of tertiary education)". We then define three dummies for the father, and three dummies for the mother: basic education (categories 0 and 1); secondary education (category 2); and University education (category 3). This results in aclassification for education level analogous to that of the longitudinal survey. Finally, the employment status of the parents when the respondent was 14 years old includes the following categories: 1) "Employed", 2) "Self-employed (including family worker)", 3) "Unemployed", 4) " In retirement or in early retirement or had given up business", 5) "Fulfilling domestic tasks and care responsibilities", and 6) "Other inactive person". Thus, we can straightforwardly identify those respondents whose parent was an employee (category 1) or a self-employed worker (category 2). The remaining control variables defined from the 2011 cross-section EU-SILC data are analogous to those defined in the longitudinal data. See Table 3.3 for descriptive statistics of variables.

### 3.3.1 Descriptive results

Figure 3.1 (Panel A) shows preliminary results for intergenerational transmission of employment, by country, of the longitudinal sample, showing the percentage of employed workers who have an employed mother ($Y$-axis) or father ($X$-axis). The size of the bubbles indicates the relative sample size of each country. This figure suggests a strong intergenerational correlation of employment, which appears stronger among fathers than among mothers. The largest percentage of employed workers with an employed mother (father) is found in Denmark, where 92.08% (95.17%) of the employed workers have an employed mother (father). Conversely, the lowest percentages are found in Greece, Italy, and Spain, in terms of mothers' employment status, and in Greece, Italy, Luxembourg, and Spain, in terms of the fathers'. Furthermore, the figure shows an increasing linear trend, suggesting that the magnitudes represented on both axes are positively correlated. Figure 3.1 (Panel B) shows an analogous picture for self-employment, using the longitudinal sample. These percentages are well below the analogous percentages for the general employment status, but the linear trend suggests, again, a positive correlation between the magnitudes represented on the axis. Almost all the percentages are below 10% for both mothers and fathers. The only exceptions are Greece (12.02% of the self-employed have a self-employed mother, and 12.96 have a self-employed father), and the UK (12.00% and 20.80%, respectively). This descriptive evidence suggests the existence of cross-country differences, with two main clusters: Denmark, the Netherlands, Belgium, Austria, France and Sweden show the lowest percentages of transmission, followed by Italy, Spain, Finland, and Luxembourg. Greece and the UK appear to be outliers, reporting the largest percentages of self-employed individuals with self-employed parents.

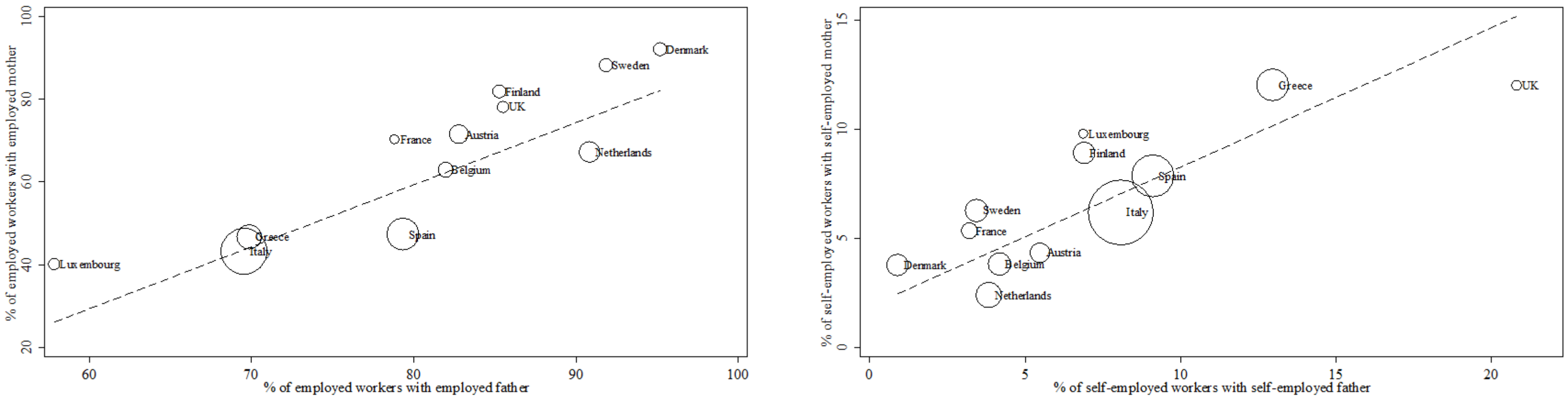
Figure 3.2 shows similar results, for the case of the 2011 sample from the special module. Panel A shows, by country, the percentage of employed workers who had an employed mother ($Y$-axis) or father ($X$-axis) when they were 14 years old. Analogously, Panel B shows the percentage of self-employed worker with self-employed parents when they were 14 years old. We can observe that the trends are quite different in Panel A, suggesting that labor attributes of parents at the date of the interview and labor attributes of parents when respondents were young may be different. Specifically, between 95.6% and 98.8% of the employed respondents had an employed parent when they were 14 years old, while the percentage of employed mothers lies between 25.1% found in France and 91.1% in Greece. However, no clear trends can be found in this figure. On the other hand, Panel B shows a positive relationship between the probability of self-employed respondents having a self-employed mother and father when they were young, as was also found in Figure 3.1. The UK, Spain, and Sweden report the lowest percentages of self-employed who had a self-employed mother (about 10%) and father (between 25% and 30%). Luxembourg and France also show low percentages of self-employed workers with a self-employed mother (about 15%), while about 40% of these respondents had a self-employed father. The third cluster that can be found is formed by Austria, Belgium, and the Netherlands, where about 40% (30%) of the respondents had a self-employed father (mother). Finally, Greece seems to be the only country in which there is a larger proportion of self-employed respondents with a mother who was self-employed (45%), than a father (38%).

Given that this descriptive analysis does not allow us to control for other factors that may be affecting these intergenerational transmissions of employment and self-employment, Figures 3.1 and 3.2 present only a first descriptive picture. In the following sections, we study these intergenerational transmissions, net of other observable factors.

Figure 3.1: Parents' and children's employment, by country – longitudinal sample

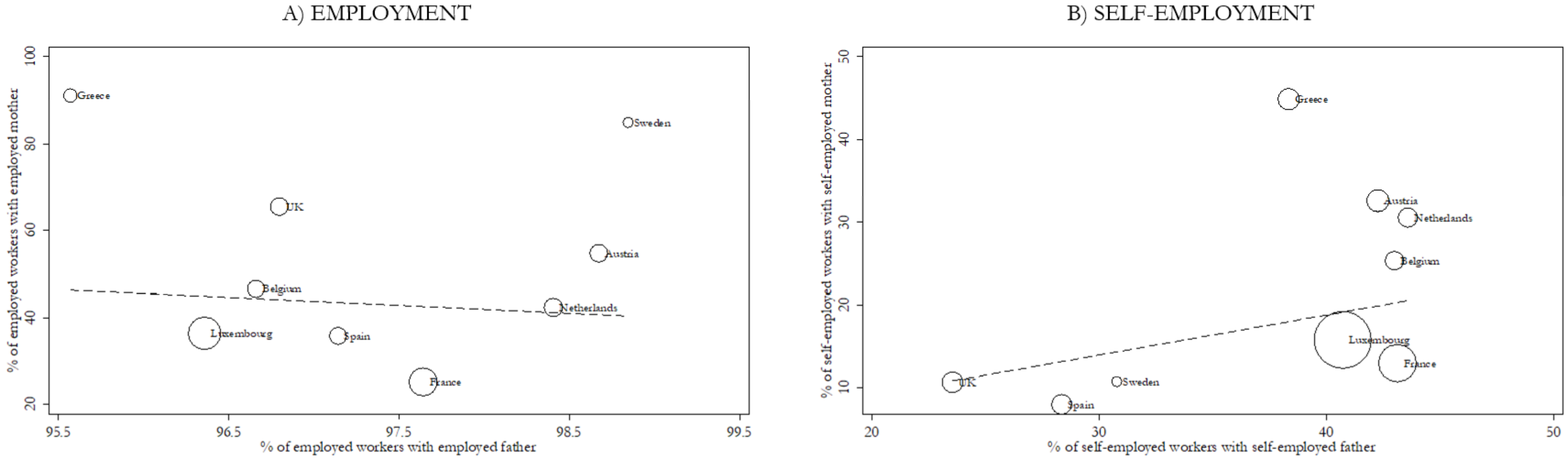
A) EMPLOYMENT

B) SELF-EMPLOYMENT




Note: The sample (longitudinal EU-SILC 2013-2016) is restricted to working-age children of interviewed households who are employed or self-employed.

Figure 3.2: Parents' and children's employment, by country – 2011 special module




Note: The sample (cross-sectional EU-SILC 2011) is restricted to working-age children of interviewed households who are employed or self-employed.

## 3.4 Short-term correlations

### 3.4.1 Empirical strategy

The first objective of the empirical analysis is to analyze whether or not the current employment status of individuals is significantly influenced by their parents' current employment status.[5] The econometric strategy relies on fixed effects models, which assume that differences across individuals can be captured by differences in the constant term, which is time-invariant and individual-specific. Thus, this constant term represents time-invariant individual heterogeneity not captured by the included regressors.

The econometric model is as follows. Assume that $i$ represents the reference individual of household $j$, and that $M$ and $F$ refer to the mother and the father of individuals, respectively. Given the existence of assortative mating mechanisms in the marriage market (Chiappori and Mazzocco, 2017), it is important to control for both parents' characteristics, and not only for mothers' or fathers', as is the usual practice (Galassi et al., 2019). The pair $ij$ characterizes individuals in the sample, whereas $kj$ characterizes mothers ($k = M$) and fathers ($k = F$). If $t$ represents the time index, the following equation will be estimated using the fixed effects panel data estimator:

$$\begin{aligned} Y_{ijt} = \;& \alpha_{ij} + \beta_{1M} SE_{Mjt} + \beta_{2M} E_{Mjt} + \beta_{1F} SE_{Fjt} + \beta_{2F} E_{Fjt} \\ & + \beta_c X_{ijt} + \beta_H X_{jt} + \beta_M X_{Mjt} + \beta_F X_{Fjt} + \alpha_t + u_{ijt} \end{aligned} \tag{3.1}$$

where $Y_{ijt}$ is a dummy variable indicating whether individuals are employed (value 1; 0 otherwise) at time $t$.[6] $E_{kjt}$ and $SE_{kjt}$ are dummy variables indicating whether parents are employees or self-employed, respectively (value 1; 0 otherwise), at time $t$, for $k = M, F$. $X_{ijt}$, $X_{jt}$, and $X_{kjt}$ represent sociodemographics of household $j$, the individual $ij$, or the parent $kj$, for $k = M, F$, at time $t$.[7] Finally, $u_{ijt}$ represents the error term, and $\alpha_{ij}$ represents individual fixed effects. Equation 3.1 will be estimated separately for men and women; all estimates include year as a linear trend, and time-invariant sample weights at the individual level. Standard errors are clustered at the country level, to partially deal with the degree of heterogeneity among European countries.

[5] The objective of the analysis is not to follow the epidemiological approach (Fernández, 2007, 2008), since the EU-SILC data does not include the required information.

[6] Additional models, available upon request, were estimated, including an interaction between parents' employment status, but those interactions were not significant.

[7] Individual controls include gender (being male), age, age squared, marital status, and education. Household controls include household income, dwelling type, and having a car. Parents' variables include age, age squared, and education.

Estimates also include two additional controls. The first is the average nest-leaving age of the analyzed countries, given that there may be cultural differences associated with nest-leaving behavior across countries (Giuliano, 2007), and such differences may condition results, as information for parents is available only if they live with the interviewed individuals in the same household. Thus, estimates including nest-leaving may partially amend selection biases arising from the sample of individuals living with their parents. We define the nest-leaving, by year and country, from the Eurostat databases, as the "share of young adults aged 18-34 living with their parents, by age and sex". The second control is the unemployment rate of the active population, by country and year, also taken from Eurostat, to control for the current macroeconomic context and partially deal with cross-country heterogeneity arising from the difficulty of finding a job in the analyzed countries. (Estimates excluding these controls are robust, and available upon request.)

The second objective of the Chapter is to analyze the existence of intergenerational correlations of self-employment vs paid employment, that is to say, whether the self-employment status of individuals is significantly correlated with the parents' self-employment status. To do so, we run a similar empirical approach, where non-working individuals are omitted, and the following equation is estimated, by gender, using the fixed effects estimator:

$$\begin{aligned} Y_{ijt} = \ & \alpha_{ij} + \beta_{1M} SE_{Mjt} + \beta_{1F} SE_{Fjt} \\ & + \beta_c X_{ijt} + \beta_H X_{jt} + \beta_M X_{Mjt} + \beta_F X_{Fjt} + \alpha_t + u_{ijt} \end{aligned} \tag{3.2}$$

where $Y_{ijt}$ is now a dummy variable indicating whether individuals are self-employed (value 1; 0 if employees) at time $t$, and the remainder is analogous and represents the same variables as in Equation 3.1. Estimates include year as a linear trend, sample weights at the individual level, and occupation fixed effects, given that the sample is now restricted to employed workers, for whom there is information about their current occupation.[8]

As we are including individual-specific intercept terms in Equations 3.1 and 3.2, the coefficients associated with the intergenerational correlations of employment and self-employment are identified from changes in parents' employment status at the date of the interviews. This is, in consequence, a short-term intergenerational correlation,

[8]The EU-SILC defines the occupation of workers in terms of the ISCO-08, including: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Services and sales workers; 6) Skilled agricultural, forestry and fishery workers; 7) Craft and related trades workers; 8) Plant and machine operators and assemblers; and 9) Elementary occupations.

which may reflect short-term household labor supply decisions.

### 3.4.2 Results

The main results of estimating Equation 3.1 are shown in Columns (1) and (2) of Table 3.4, for male and female individuals of the sample, respectively. Additional estimates are shown in Table 3.A1 in Appendix 3.A. Estimates show a positive correlation between mothers' and fathers' current self-employment and employee status, and the employment status of children. This suggests that employed parents tend to have employed children and, as a consequence, non-working parents tend to have non-working children, consistent with prior research. Furthermore, among male workers, the correlation with the father seems stronger than the correlation with the mother, both among self-employed parents ($p$-value of 0.002, according to a $t$-type test) and among employees ($p = 0.039$). However, these correlations do not differ between employees and self-employed, nor between fathers ($p = 0.814$) and mothers ($p = 0.294$).

Among female workers, general trends are similar, with the largest difference being found for the self-employed status of mothers, relative to that correlation for males, which is not significant at standard levels ($p = 0.240$). The remaining coefficients show no statistical differences with the corresponding coefficients of males, according to $t$-type tests. Besides that, the correlations with the father appear greater than the correlations with the mother between the self-employed and employees, but the difference is only significant at standard levels for the self-employed ($p = 0.026$, $p = 0.136$, respectively). Similarly, transmissions do not differ at standard levels, comparing employees and self-employed fathers ($p = 0.830$) and mothers ($p = 0.842$).

Columns (1) and (2) of Table 3.4 suggest that working parents tend to have working children, regardless of whether they are employees or self-employed workers. To disentangle these relationships, we estimate Equation 3.2 in Columns (3) and (4) of Table 3.4, to determine whether self-employed parents have self-employed children, or whether it is only the employment status (but not the employee/self-employed status) that is important in determining children's employment. Results indicate that the self-employment status of both the mother and the father shows a positive correlation with the self-employment status of male workers, relative to employees. Furthermore, the transmission appears to be stronger from fathers to sons, than from mothers to sons, according to $t$-type tests ($p = 0.059$). On the other hand, the self-employment status of mothers and fathers is positive and negatively correlated with that of daughters, but coefficients are not significant at standard levels. These results suggest that intergenerational correlation of self-employment is stronger among males than among females, mainly driven by fathers' impact on sons' self-employment status.

We have conducted certain robustness checks. First, we study whether the educational level of parents has any moderating effect on the transmission of employment and self-employment, as parents' education is a significant determinant of parents' investments in children's human capital (Heckman et al., 2006; Bono et al., 2016). Second, we split the sample into two groups: those individuals who are reported as children of the reference individuals of interviewed households, and reference individuals who cohabit with their parents. Thus, we can isolate those cultural values that cause adults to live with their parents. Results, shown in Tables 3.A2 and 3.A3 in the Appendix 3.A, are robust to the general case. Results for single-parent individuals are shown in Appendix 3.B.

## 3.5 Long-term correlations

### 3.5.1 Empirical strategy

Equations 3.1 and 3.2 include individual-specific intercept terms, so the estimated transmissions of employment and self-employment are identified from changes in parents' employment status at the date of the interviews, leading to short-term correlations that could reflect short-term household labor supply decisions. However, intergenerational transmissions are often identified from long-term correlations, or effects, from parents to children (Solon, 1992, 2002).

To overcome this issue, we use the cross-sectional information provided by the 2011 special module on Intergenerational Transmissions of the EU-SILC data, to study the current employment status of respondents, in terms of their parents' employment status when respondents were 14 years old. Assume that $i$ represents the reference individual of household $j$, and that $M$ and $F$ refer to the mother and the father. The following equation is estimated using OLS:

$$\begin{aligned} Y_{ij} = \quad & \beta_0 + \beta_{1M} SE_{Mj} + \beta_{2M} E_{Mj} + \beta_{1F} SE_{Fj} + \beta_{2F} E_{Fj} \\ & + \beta_c X_{ij} + \beta_H X_j + \beta_M X_{Mj} + \beta_F X_{Fj} + u_{ij} \end{aligned} \tag{3.3}$$

where $Y_{ij}$ is a dummy variable indicating whether individuals are employed (value 1; 0 otherwise) at the time of the interview (i.e., the year 2011). $E_{kj}^{sm}$ and $SE_{kj}^{sm}$ are

Table 3.4: Fixed effect estimates

| | Employed vs non-working | | Self-employed vs employee | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) |
| Self-employed: | | | | |
| Mother | 0.123*** | 0.156*** | 0.037** | 0.022 |
| | (0.018) | (0.021) | (0.016) | (0.015) |
| Father | 0.213*** | 0.216*** | 0.093*** | -0.017 |
| | (0.022) | (0.017) | (0.025) | (0.020) |
| Employee: | | | | |
| Mother | 0.157*** | 0.163*** | - | - |
| | (0.027) | (0.028) | | |
| Father | 0.219*** | 0.211*** | - | - |
| | (0.013) | (0.016) | | |
| Constant | 0.924 | 0.939 | 2.158*** | -0.982 |
| | (1.029) | (1.294) | (0.651) | (0.708) |
| Controls | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | Yes | Yes |
| Parents' occupation FE | No | No | Yes | Yes |
| Observations | 21,964 | 14,155 | 17,482 | 11,147 |
| Individuals | 5,614 | 3,632 | 5,266 | 3,364 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2013-2016) is restricted to working-age individuals of interviewed households who are not students, retired, or disabled and report living with their parents. Estimates include sample weights. Columns (3) and (4) are restricted to employed workers. The dependent variable is the dummy "employed" in Columns (1) and (2), and the dummy "self-employed" in Columns (3) and (4). Additional estimates shown in Table 3.A1 in the Appendix 3.A. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

dummy variables indicating whether parents were employees or self-employed in the past, for $k = M, F$. $X_{ij}$ and $X_j$ represent current sociodemographics of household $j$ and individual $ij$, while $X_{kj}^{sm}$ represents parents' past sociodemographics, for $k = M, F$. Finally, $\epsilon_{ij}$ represents the error term.

We next restrict the sample to employed workers, and study whether or not the current self-employment status of respondents is correlated with the past self-employment status of their parents. Following the same specification as in Equation 3.3, we estimate by OLS the following equation:

$$Y_{ij} = \beta_0 + \beta_{1M} SE_{Mj} + \beta_{1F} SE_{Fj} + \beta_c X_{ij} + \beta_H X_j + \beta_M X_{Mj} + \beta_F X_{Fj} + u_{ij} \quad (3.4)$$

where $Y_{ij}$ is now a dummy variable that indicates whether individuals are self-employed (value 1; 0 if employees) at the date of the interview. Equations 3.3 and 3.4 are estimated separately for men and women, and all estimates include country fixed effects, nest-leaving, and unemployment level controls, and specific sample weights at the individual level provided for the special module on Intergenerational Transmissions. Standard errors are clustered at the country level, to partially deal with the degree of heterogeneity among European countries. Equation 3.4 also includes occupation fixed effects.

### 3.5.2 Results

The main estimates of Equations 3.3 and 3.4 are shown in Table 3.5. Columns (1) and (2) show results of estimating Equation 3.3 for male and female respondents of the 2011 EU-SILC special module, respectively, where we analyze whether the employment status of fathers and mothers when respondents were 14 years old had any impact on their current labor participation. Additional estimates are shown in Table 3.A4 in Appendix 3.A, while results for single-parent individuals are shown in Appendix 3.B.

Estimates show a negative, small, and not significant correlation between mothers' past self-employment status and the current employment status of male workers. However, if the mother was an employee in the past, the probability of the male worker being employed (either self-employed or an employee) increases by about 1.1 percentage points, with that increase being significant at standard levels. On the other hand, if the father was self-employed when the male worker was 14 years old, the probability of him being employed at the date of the interview increases by 1.7 percentage points, and if the father was an employee in the past, that probability increases by 3.0 percentage points, with both magnitudes being statistically significant. This suggests that there exists an intergenerational transmission of employment status in the long-term for male workers, although such transmission is mainly driven by fathers. For instance, the employee status of the father seems to have a stronger impact than his self-employment status, but not at a statistically significant level ($p = 0.255$, according to a t-type test), while it is stronger than the impact of the employee status of the mother ($p = 0.039$).

Regarding female workers, estimates show that fathers' past employment status is not correlated with the current employment status of their daughters in a statistically significant way. However, the mother having been self-employed in the past increases the probability of the female worker being employed by about 2.8 percentage points, vs an increase of 3.8 percentage points if the mother was an employee when the female worker was 14 years old. The difference between these two coefficients is, nonetheless, not significant at standard levels ($p = 0.529$). This suggests that mothers appear to be more important for daughters in the long term, while fathers are more important for male workers, as happened in the case of the short-term correlations. Nevertheless, fathers were slightly important for female workers in the short term, while the long-term transmission appears not to be significant.

Columns (3) and (4) of Table 3.5 show analogous estimates of Equation 3.4 for male and female workers, respectively, with the sample restricted to employed workers only. That is to say, non-working individuals are omitted from the sample used to estimate Columns (3) and (4). Contrary to the case of the short-term correlations between the current self-employment status of parents and children, estimates show a strong and significant intergenerational transmission of self-employment in the long term. Specifically, focusing on male workers, if the mother was self-employed when the respondent was 14 years old, then the probability of he being self-employed at the current date increases by 7.3 percentage points, with this increase being significant at standard levels. Similarly, if the father was self-employed in the past, this probability increases by 15.0 percentage points, with this coefficient being highly significant, and larger than the mothers' at standard levels ($p = 0.010$). For female workers, estimates show that the self-employment status of both the father and the mother when respondents were 14 years old have a highly significant impact on their current self-employment status. For instance, if the mother was self-employed, the probability of the female worker being self-employed at the date of the interview increases by 7.5 percentage points. This impact is no different than that of mothers on sons, according to t-type tests ($p = 0.943$). Furthermore, if the father was self-employed, then the probability of the female respondent being self-employed at the current date increases by 3.7 percentage points. This coefficient, despite the fact of being lower than the correspondent coefficient for the male counterparts ($p < 0.001$), and also lower than the coefficient associated with the mother ($p = 0.012$), is still significant at standard levels.

Table 3.5: Estimates, Special Module

| | Employed vs non-working | | Self-employed vs employee | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) |
| Self-employed: | | | | |
| Mother | -0.007 | 0.028*** | 0.073** | 0.075*** |
| | (0.014) | (0.008) | (0.024) | (0.015) |
| Father | 0.017** | 0.043 | 0.150*** | 0.037*** |
| | (0.007) | (0.029) | (0.018) | (0.002) |
| Employee: | | | | |
| Mother | 0.011*** | 0.038** | - | - |
| | (0.002) | (0.014) | | |
| Father | 0.030*** | 0.052 | - | - |
| | (0.009) | (0.029) | | |
| Constant | 0.682*** | 0.035 | -0.341 | 0.168 |
| | (0.087) | (0.221) | (0.229) | (0.217) |
| Controls | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | Yes | Yes |
| Parents' occupation FE | No | No | Yes | Yes |
| Observations | 28,533 | 30,809 | 27,722 | 28,045 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2011) is restricted to working-age individuals who filled the Special Module on Intergenerational Transmissions, of interviewed two-parent households who are not students, retired, or disabled. Estimates include specific sample weights of the 2011 special module on Intergenerational Transmissions. Columns (3) and (4) are restricted to employed workers. The dependent variable is the dummy "employed" in Columns (1) and (2), and the dummy "self-employed" in Columns (3) and (4). Parents' variables represent parents' labor and sociodemographic attributes when the respondent was 14 years old. Additional estimates shown in Table 3.A4 in the Appendix 3.A. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## 3.6 Discussion of results

The analysis of the short-term correlation indicates that the children of parents who are employed at the current date have a higher probability of being currently employed. On the other hand, mothers' current self-employment status has an influence on their male and female children, which seems to be slightly larger for sons than for daughters, but not at standard levels. However, fathers strongly influence their sons, while the influence on their daughters is smaller and not significant at standard levels. Therefore, results suggest that there is a significant intergenerational correlation of the current employment status within families, despite the existence of gender differences. Nevertheless, as the intergenerational correlations estimated in Table 3.4 are identified from changes in the current employment status of parents, these estimates may be reflecting short-term household labor supply decisions.

Despite the fact that a direct comparison between the short- and long-term correlation analysis is not available, given the different samples and methods used, estimates show that short-term household labor supply decisions seem more relevant in general terms, when studying employment vs non-working, than long-term intergenerational transmissions. That could be due to different phenomena, such as household financial constraints. The results of the long-term intergenerational correlations reveal, however, a significant channel of self-employment arising from long-term intergenerational transmission. While short-term correlations seem to operate only for male workers, parents' self-employment status when female workers were young has a significant impact on the probability of their being self-employed when they grow. If anything, the analysis of long-term correlations indicates that past self-employment of parents has a highly significant impact on the current self-employment status of their children, relative to employees, regardless of the gender of children. These long-term correlations could be due to different intrahousehold or intergenerational processes, such as transmissions of culture towards work during workers childhood and adolescence (Vollebergh et al., 2001; Levine and Hoffner, 2006), but also transmissions of entrepreneurial spirit and role models (Sørensen, 2007; Kirkwood, 2007; Lindquist et al., 2015), or specific human capital and managerial abilities (Bae et al., 2014; Huber et al., 2014). Despite that, the estimated correlations are smaller than transmissions reported by prior research, where studies found that the self-employment status of parents increased the probability of children becoming self-employed, by between 30 and up to 300 percentage points (see Lindquist et al., 2015).

A potential explanation for the results found in this study is the investment in the children's human capital by parents (Chiappori et al., 2017). In that scenario, self-employed parents with certain managerial skills can have incentives to transfer such skills to their children during their childhood, hence increasing the probability of them becoming self-employed when entering the labor market. Conversely, while employee parents also invest in their children's education, they do not invest in the specifics of managerial human capital. Another (complementary) explanation for the results found in this study is the well-known intergenerational transmission of wealth and inequality (see Barbieri et al., 2019, for a recent contribution). According to this literature, there is a degree of intergenerational persistence in earnings, affecting financial constraints, which is a strong predictor of becoming self-employed (Fairlie and Krashinsky, 2012; Fairlie, 2013). However, the current self-employment status of parents should also influence household finances. Again, sample selection issues may condition these short-term results. A third explanation may be based on the transmission of the so-called "entrepreneurial spirit" (Blanchflower et al., 2001), which is related to certain social norms, culture, and labor attributes that are transmitted vertically. Becoming self-employed may be related to this unobservable and inherent phenomenon, where workers become entrepreneurs because they have a latent desire for running their own business. In this sense, children can develop a strong entrepreneurial spirit during their childhood if there is a parental role in their household that induces such feeling. However, given these examples, results should show similar trends in the short term. That is to say, if the parents were self-employed in the past, and transmitted certain skills to their children, why is parents' current self-employment status not correlated with the current self-employment status of children? A potential explanation for the absence of such short-term significant correlation arises from the strong constraints imposed on the sample, i.e., parents may have been self-employed in the past, but are not self-employed at the current date (e.g., they may have retired by the date of the interview). Unfortunately, given that we cannot compare both samples, we cannot provide a clear conclusion, which is left for future research.

## 3.7 Conclusions

This Chapter empirically studies intergenerational correlations of employment and self-employment in Europe, using harmonized and homogeneous data from the EU-SILC. We investigate the short-term correlations for the years 2003-2016, which may reflect household labor supply decisions. In doing so, we determine whether the current employment and self-employment status of mothers and fathers is significantly correlated with the employment and self-employment status of their children. We next analyze long-term intergenerational transmissions using data for the year 2011, which included a special module with information about parents' labor status when the respondent was 14 years old.

Results point to the existence of significant correlations between the employment status of parents and children in two-parent households. Furthermore, these transmissions appear stronger from fathers than from mothers, regardless of whether parents are employees or self-employed workers. However, only the current self-employment status of male workers seems to be determined by the current self-employment status of parents, while these correlations are not significant for female workers. Results also show that the self-employment status of workers is strongly correlated with their parents being self-employed in the past (when respondents were 14 years old). This result suggests that there exists a significant intergenerational transmission of self-employment, which is not driven by short-term family labor supply decisions. Overall, results support the existence of intergenerational socio-economic mobility, as the employment status of parents appears to be transmitted vertically to their children, while the impact of the self-employment status of parents on their children is also positive and significant, but quantitatively lower than that found by prior research.

The analysis has certain limitations. First, results do not allow us to talk about causal effects, given measurement errors and potential endogeneity. (Despite various IV checks, we could not find a proper instrumentation for the empirical analysis.) Second, the analysis may suffer from potential sample selection bias, as individuals who do not cohabit with their parents are systematically omitted from the longitudinal sample (since there is no information about the parents, regardless of whether they are self-employed or not); and from measurement error, as parents of studied individuals could have been self-employed in the past, but not at the date of the interview, or at the date of the special module. Finally, the data used throughout the analysis do not allow us to run an accurate analysis of cross-country or cross-occupation differences, given the limited sample size in some of the countries considered for analysis. Thus, cross-country differences in different dimensions, such as culture, institutions, or macroeconomic factors, might condition the results (e.g., Marcén, 2014).

The ultimate objective of this work is to record the significance of intergenerational transmission as a channel of employment and self-employment in European countries. The results may be important for planners and policy makers, as they may help to anticipate which workers may be employed and become self-employed in the future, in terms of their parents economic and sociodemographic characteristics. For instance, recent efforts have been made by institutions to promote self-employment and entrepreneurship, as a way of overcoming the devastating effects of the recent economic crisis. Results suggest that transmissions of employment are mainly driven by short-term family labor supply decisions, while intergenerational transmissions of self-employment may be determined by long-term transmissions when workers were young. Further research should focus on studying the different channels that drive these transmissions, such as culture, social norms, or the transmission of certain managerial skills, entrepreneurial spirit, and human capital related to self-employment.

# Appendix 3.A: Additional results

Table 3.A1. Fixed effect estimates – additional results

| | Employed vs non-working | | Self-employed vs employee | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) |
| Age | 0.042* | 0.016 | -0.009 | 0.011 |
| | (0.020) | (0.044) | (0.019) | (0.016) |
| Age squared | -0.005 | -0.004 | 0.007** | 0.003 |
| | (0.004) | (0.006) | (0.003) | (0.003) |
| Never married | -0.047 | 0.110* | 0.052 | -0.011 |
| | (0.039) | (0.055) | (0.096) | (0.049) |
| Secondary education | -0.016 | -0.057** | -0.022 | -0.030* |
| | (0.012) | (0.019) | (0.018) | (0.014) |
| University education | -0.012 | -0.070** | -0.094*** | -0.076*** |
| | (0.022) | (0.024) | (0.026) | (0.023) |
| Disposable income | 0.000*** | 0.000 | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dwelling: house | -0.017 | -0.147*** | -0.071 | 0.001 |
| | (0.044) | (0.029) | (0.059) | (0.015) |
| Dweling: appartament/flat | -0.024 | -0.085** | -0.043 | 0.008 |
| | (0.036) | (0.030) | (0.063) | (0.021) |
| Have a car | -0.010 | 0.022 | 0.001 | -0.003 |
| | (0.008) | (0.014) | (0.016) | (0.010) |
| N. children under 4 | 0.007 | -0.079* | 0.051 | 0.025* |
| | (0.023) | (0.039) | (0.033) | (0.014) |
| N. children 5-15 | 0.012 | -0.015 | 0.024 | 0.014** |
| | (0.007) | (0.014) | (0.039) | (0.006) |
| Mother Age | -0.106*** | -0.082 | -0.013 | 0.069 |
| | (0.030) | (0.049) | (0.027) | (0.041) |
| Age squared | 0.010** | 0.007 | 0.001 | -0.005 |
| | (0.003) | (0.005) | (0.003) | (0.004) |
| Secondary education | 0.031 | -0.017 | -0.000 | -0.000 |
| | (0.023) | (0.015) | (0.017) | (0.010) |
| University education | 0.030 | -0.024 | -0.021 | 0.039 |
| | (0.018) | (0.025) | (0.030) | (0.023) |
| Father: Age | 0.068 | 0.057*** | -0.048 | -0.035 |
| | (0.038) | (0.018) | (0.029) | (0.031) |
| Age squared | -0.007 | -0.006*** | 0.006* | 0.005* |
| | (0.004) | (0.002) | (0.003) | (0.002) |
| Secondary education | -0.004 | 0.027 | 0.033 | 0.008 |
| | (0.030) | (0.036) | (0.029) | (0.021) |
| University education | -0.067 | -0.073* | 0.126** | 0.028 |
| | (0.068) | (0.041) | (0.042) | (0.051) |

Note: Additional results to Table 3.4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.A2. Interaction estimates

| | Employed vs non-working | | Self-employed vs employee | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) |
| Self-employed: | | | | |
| Mother | 0.106*** | 0.132*** | 0.043 | 0.011 |
| | (0.021) | (0.018) | (0.024) | (0.016) |
| * Secondary ed. | 0.021 | 0.048 | -0.051 | 0.037 |
| | (0.037) | (0.061) | (0.064) | (0.027) |
| * University ed. | 0.153*** | 0.096 | 0.081 | 0.013 |
| | (0.046) | (0.112) | (0.059) | (0.041) |
| Father | 0.198*** | 0.243*** | 0.110*** | -0.024 |
| | (0.019) | (0.015) | (0.034) | (0.015) |
| * Secondary ed. | 0.010 | -0.049* | -0.100*** | 0.026 |
| | (0.029) | (0.025) | (0.016) | (0.054) |
| * University ed. | 0.107** | -0.112 | 0.143 | -0.018 |
| | (0.042) | (0.110) | (0.112) | (0.063) |
| Employee: | | | | |
| Mother | 0.119*** | 0.148*** | - | - |
| | (0.030) | (0.010) | | |
| * Secondary ed. | 0.059* | 0.021 | - | - |
| | (0.031) | (0.054) | | |
| * University ed. | 0.140*** | 0.070 | - | - |
| | (0.035) | (0.089) | | |
| Father | 0.208*** | 0.209*** | - | - |
| | (0.014) | (0.015) | | |
| * Secondary ed. | 0.010 | 0.007 | - | - |
| | (0.042) | (0.013) | | |
| * University ed. | 0.050 | -0.004 | - | - |
| | (0.034) | (0.083) | | |
| Constant | 1.047 | 0.993 | | |
| | (0.980) | (1.325) | | |
| Nest-leaving | Yes | Yes | Yes | Yes |
| Unemployment rate | Yes | Yes | Yes | Yes |
| Individual variables | Yes | Yes | Yes | Yes |
| Household variables | Yes | Yes | Yes | Yes |
| Parents variables | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | Yes | Yes |
| Parents occupation FE | No | No | Yes | Yes |
| Observations | 21,964 | 14,155 | 17,482 | 11,147 |
| Individuals | 5,614 | 3,632 | 5,266 | 3,364 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2013-2016) is restricted to working-age individuals of interviewed households who are not students, retired, or disabled and report living with their parents. Estimates include sample weights. Columns (3) and (4) are restricted to employed workers. The dependent variable is the dummy “employed” in Columns (1) and (2), and the dummy “self-employed” in Columns (3) and (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.A3. Working children and adults

| | Employed vs non-working | | | | Self-employed vs employee | | | |
|---|---|---|---|---|---|---|---|---|
| | Working children | | Adults | | Working children | | Adults | |
| | Males | Females | Males | Females | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Self-employed: | | | | | | | | |
| Mother | 0.146*** | 0.144*** | 0.078** | 0.194*** | 0.055*** | 0.039 | 0.006 | -0.050 |
| | (0.032) | (0.037) | (0.029) | (0.053) | (0.012) | (0.024) | (0.026) | (0.050) |
| Father | 0.207*** | 0.220*** | 0.175*** | 0.152*** | 0.108*** | -0.022 | 0.089* | -0.022 |
| | (0.029) | (0.024) | (0.035) | (0.025) | (0.019) | (0.027) | (0.047) | (0.027) |
| Employee: | | | | | | | | |
| Mother | 0.160*** | 0.162** | 0.141*** | 0.168*** | - | - | - | - |
| | (0.035) | (0.053) | (0.019) | (0.024) | | | | |
| Father | 0.228*** | 0.205*** | 0.148*** | 0.156*** | - | - | - | - |
| | (0.016) | (0.020) | (0.005) | (0.022) | | | | |
| Constant | 1.344 | 0.557 | 0.175 | 0.895 | 2.598** | -1.237* | 0.351 | -0.164 |
| | (1.699) | (1.731) | (0.636) | (1.051) | (0.967) | (0.607) | (0.850) | (0.976) |
| Nest-leaving | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Unemployment rate | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Parents variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Parents occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Observations | 11,981 | 7,813 | 7,061 | 4,940 | 9,499 | 6,186 | 5,455 | 3,748 |
| Individuals | 3,862 | 2,530 | 2,606 | 1,785 | 3,470 | 2,259 | 2,264 | 1,553 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2013-2016) is restricted to working-age individuals of interviewed households who are not students, retired, or disabled and report living with their parents. Estimates include sample weights. Columns (5)-(8) are restricted to employed workers. The dependent variable is the dummy "employed" in Columns (1)-(4), and the dummy "self-employed" in Columns (5)-(8). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.A4. Estimates, Special Module – additional results

| | Employed vs non-working | | Self-employed vs employee | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) |
| Individual variables | | | | |
| Age | 0.015*** | 0.022** | 0.014*** | 0.004 |
| | (0.002) | (0.009) | (0.001) | (0.004) |
| Age squared | -0.002*** | -0.002* | -0.001*** | -0.000 |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| Never married | -0.029** | 0.021* | 0.003 | -0.015*** |
| | (0.009) | (0.010) | (0.009) | (0.004) |
| Secondary education | 0.015* | 0.096*** | -0.003 | -0.002 |
| | (0.007) | (0.021) | (0.011) | (0.009) |
| University education | 0.014*** | 0.122*** | -0.026* | -0.006 |
| | (0.003) | (0.028) | (0.014) | (0.013) |
| Household variables | | | | |
| Disposable income | 0.000** | 0.000* | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dwelling: house | -0.014 | 0.021 | -0.052 | -0.073* |
| | (0.018) | (0.017) | (0.038) | (0.038) |
| Dweling: appartament/flat | -0.017 | 0.030* | -0.072 | -0.095** |
| | (0.016) | (0.014) | (0.042) | (0.037) |
| N. children at 14 years old | -0.001 | -0.007 | -0.006* | -0.004** |
| | (0.001) | (0.005) | (0.003) | (0.002) |
| Mother variables | | | | |
| Age | -0.000 | 0.018*** | 0.014* | 0.001 |
| | (0.003) | (0.003) | (0.007) | (0.010) |
| Age squared | 0.000 | -0.002*** | -0.002* | -0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Secondary education | -0.008 | -0.004 | 0.014 | 0.014 |
| | (0.005) | (0.005) | (0.010) | (0.011) |
| University education | 0.007 | -0.030*** | -0.003 | 0.018 |
| | (0.004) | (0.009) | (0.009) | (0.011) |
| Father variables | | | | |
| Age | -0.002 | -0.004 | -0.004 | -0.001 |
| | (0.004) | (0.004) | (0.009) | (0.005) |
| Age squared | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| Secondary education | 0.003 | 0.010 | 0.026** | 0.004 |
| | (0.003) | (0.007) | (0.009) | (0.007) |
| University education | -0.010** | -0.018** | 0.058*** | 0.020** |
| | (0.004) | (0.007) | (0.014) | (0.006) |
| Nest-leaving | -0.001*** | -0.001 | 0.002*** | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.002) |
| Unemployment rate | 0.000 | -0.001 | -0.002*** | -0.008 |
| | (0.000) | (0.001) | (0.000) | (0.005) |
| Observations | 28,533 | 30,809 | 27,722 | 28,045 |

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Appendix 3.B: Single-parent individuals

We estimate equations analogous to Equation 3.1 on a sample of single-mother and single-father male and female workers, in order to study whether, and to what extent, the intergenerational correlations estimated in Columns (1) and (2) of Table 3.4 are characteristic of two-member households (and, then, partially the potential outcome of intrahousehold decisions), or also hold for single-parent families. The main results are shown in Columns (1) to (4) of Table 3.B1. Additional estimates are available upon request. It is important to note the limited sample size associated with individuals cohabiting only with their father, which may be conditioning the estimates for single fathers. Estimates show a positive correlation between mothers' current self-employment and employee status, and the employment status of their children. Besides that, these correlations do not seem to be gender-dependent, according to t-type tests ($p = 0.327$ for the difference in the coefficient associated with self-employed mothers, $p = 0.595$ for employee mothers). On the other hand, for individuals in single father families, the self-employment status of the father is found to be significant at standard levels only for females, while the coefficient associated with the father's employee status is positive and significant for both males and females, but it is not gender-driven ($p = 0.479$).

Columns (5) to (8) of Table 3.B1 show estimates of Equitation 3.2 on the sample of single mother and single-father households. Results for single-father individuals are not significant, and limited to a reduced sample size. However, results do reveal a positive and significant correlation between single mothers' self-employment status, and that of their male and female children, which could be driven by the household responsibilities hypothesis, as self-employment has been found to be a way of balancing work and family, thereby allowing single mothers to reconcile their household and care responsibilities with their labor supply.

Table 3.B2 shows estimates of Equation 3.3 Columns (1) to (4), on a sample of single-parent respondents from the 2011 EU-SILC special module on Intergenerational Transmissions. Estimates do not show any significant correlation between the employment status of male and female workers and that of the parent for respondents who resided only with their mother. Similarly, the employment status of males who cohabited only with their father is again not significantly correlated with the employment status of fathers, while the employee and self-employment status of fathers seem to be positive and significantly correlated with the employment status of female respon-

dents. Furthermore, coefficients associated to the employee and self-employed status of fathers are not statistically different at standard levels ($p = 0.687$). On the other hand, Columns (1) to (4) of Table 3.B2 shows estimates of Equation 3.4. Estimates for male and female respondent cohabiting with a single mother when they were 14 years old show a significant correlation between the current self-employment status of respondents, the self-employment status of the mother in the past, in line with the main results. For instance, the coefficient for the male respondents is slightly larger than that of the female counterparts, but not at standard levels ($p = 0.105$), suggesting that transmissions are similar among males than among females. Finally, the analogous coefficients for respondents cohabiting only with their father when they were 14 years old are not significant at standard levels for both males and females.

Table 3.B1. Fixed effects estimates for single-parent households

| | Employed vs non-working | | | | Self-employed vs employee | | | |
|---|---|---|---|---|---|---|---|---|
| | Single mothers | | Single fathers | | Single mothers | | Single fathers | |
| | Males | Females | Males | Females | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Self-employed parent | 0.174*** | 0.127*** | 0.099 | 0.273*** | 0.081*** | 0.115*** | -0.065 | -0.066 |
| | (0.028) | (0.041) | (0.085) | (0.095) | (0.030) | (0.042) | (0.097) | (0.070) |
| Employee parent | 0.152*** | 0.178*** | 0.134** | 0.203*** | - | - | - | - |
| | (0.033) | (0.033) | (0.061) | (0.067) | | | | |
| Constant | 1.214 | -0.164 | 6.742 | 5.382 | 0.620 | -0.170 | 4.712 | 2.161 |
| | (1.328) | (1.640) | (4.106) | (4.709) | (0.926) | (1.518) | (3.786) | (5.756) |
| Nest-leaving | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Unemployment rate | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mother variables | Yes | Yes | No | No | Yes | Yes | No | No |
| Father variables | No | No | Yes | Yes | No | No | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Parents occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Observations | 7,750 | 5,020 | 1,531 | 791 | 5,973 | 3,815 | 1,216 | 605 |
| Individuals | 2,046 | 1,325 | 418 | 218 | 1,867 | 1,207 | 388 | 196 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2013-2016) is restricted to working-age individuals of interviewed households who are not students, retired, or disabled and report living with only one of their parents. Estimates include sample weights. Columns (5)-(8) are restricted to employed workers. The dependent variable is the dummy "employed" in Columns (1)-(4), and the dummy "self-employed" in Columns (5)-(8). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.B2. Fixed effects estimates for single-parent households, special module

| | Employed vs non-working | | | | Self-employed vs employee | | | |
|---|---|---|---|---|---|---|---|---|
| | Single mothers | | Single fathers | | Single mothers | | Single fathers | |
| | Males | Females | Males | Females | Males | Females | Males | Females |
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Self-employed parent | -0.010 | 0.003 | 0.075 | 0.071** | 0.144*** | 0.098*** | 0.072 | 0.044 |
| | (0.011) | (0.006) | (0.074) | (0.026) | (0.016) | (0.022) | (0.102) | (0.043) |
| Employee parent | 0.014 | 0.029 | 0.052 | 0.093* | - | - | - | - |
| | (0.010) | (0.029) | (0.074) | (0.048) | | | | |
| Constant | 0.325 | 1.250** | 0.786 | 1.334** | 0.532 | -0.529 | -0.034 | 0.139 |
| | (0.191) | (0.424) | (0.572) | (0.442) | (0.593) | (0.327) | (1.734) | (0.464) |
| Nest-leaving | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Unemployment rate | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mother variables | Yes | Yes | No | No | Yes | Yes | No | No |
| Father variables | No | No | Yes | Yes | No | No | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Parents occupation FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Observations | 2,531 | 3,109 | 516 | 512 | 1,462 | 1,810 | 439 | 410 |

Note: Robust standard errors clustered at the country level in parentheses. The sample (EU-SILC 2011) is restricted to working-age individuals who filled the Special Module on Intergenerational Transmissions, of interviewed single-parent households who are not students, retired, or disabled. Estimates include specific sample weights of the 2011 special module on Intergenerational Transmissions. Columns (5) to (8) are restricted to employed workers. The dependent variable is the dummy "employed" in Columns (1)-(4), and the dummy "self-employed" in Columns (5)-(8). Parents' variables represent parents' labor and sociodemographic attributes when the respondent was 14 years old. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Conclusions

This Thesis studies theoretically and empirically a range of population behaviors from the point of view of the supply side of the labor market, including urban efficiency wages in the US and Spain, household labor-supply decisions, intrahousehold intertemporal commitment in the US and Europe, and intergenerational correlation of employment and self-employment decisions in Europe.

Chapter 1 shows empirically how leisure time and shirking at work are negatively correlated, which is the main result of the analysis. This negative elasticity holds in the US and in Spain, indicating that individuals who enjoy more leisure at home might be more productive at work. Furthermore, and as long as commuting time is estimated to be negatively correlated to leisure time, but positively correlated to shirking at work, results suggest that the performance of workers who have longer commutes is comparatively lower than that of workers with shorter commuting times. Nevertheless, supervision mechanisms seem to play a moderating role on these relationships. Future research should focus on alternative measures of worker productivity and search for causal links of how commutes impact labor market outcomes. To the best of our knowledge, these topics have not been previously addressed. Furthermore, the demand side of the labor market, i.e., how firms hire their employees, and the role of workers' commuting and potential distance redlines in this decision, is also a novel field.

Chapter 2 represents, to the best of our knowledge, the first explorative analysis of intrahousehold intertemporal commitment in the literature, on the basis of a household collective model of labor supply. This Chapter explores the dynamics of intrahousehold bargaining powers, or Pareto weights, identified through spouses' labor supply decisions in two-member households, in terms of unanticipated wage shocks. These shocks play the role of distribution factors, as they determine the evolution of spouses' bargaining positions within the household. For instance, the work provides a test for intertemporal commitment, distinguishing among full commitment, non-commitment, and limited commitment, which is the main contribution of the Chapter. Results clearly reject the full and non-commitment model, as estimates fit the predictions of the limited commitment model.

Finally, Chapter 3 empirically studies the existence of intergenerational correlations of employment and self-employment in European countries, using a harmonized, cross-national and homogeneous source of information from the EU-SILC. We find a strong and significant correlation between the employment status of mothers and fathers and that of their male and female children, and fathers seem to be slightly more influential than mothers. Results also suggest that intergenerational decisions regarding self-employment are not related to short-term family labor supply decisions, but instead may depend on long-term transmissions. Future research should focus on investigating the specific channels that drive these long-term transmissions, and using different strategies, such as the epidemiological approach (whereby individual employment outcomes should be studied in terms of their ancestor culture). Such a focus, nonetheless, would require very specific data that is, unfortunately, not available in the databases used in this Thesis.

The results shown in this Thesis have several implications for firms, planners, and policy makers in the development of policies regarding the labor market, as we investigate worker and household behaviors. Processes such as worker time allocations, household formation, divorce, and wealth transfers are important in policy issues, and understanding well these processes through correctly grounded models is crucial to anticipate and evaluate the effects of public policies. Otherwise, conclusions may be inaccurate, leading to inefficient policies. For instance, the development of urban and communication infrastructures may improve worker mobility, thus improving productivity and discouraging shirking behaviors. On the other hand, social-welfare programs or cash transfers cannot be accurately evaluated without a deeper knowledge of their consequences: who should receive the cash? How do these programs impact the household? In terms of programs focusing on employment or encouraging self-employment, can these programs help unemployed workers to find a job, or to become self-employed workers? Might these programs have intergenerational effects? If so, when can we expect these effects?

The fact that we find that the relationship between leisure and shirking is stronger for workers in non-supervised occupations in the US and in Spain, with the difference being larger in the US, and that commuting time is found to be positively correlated with shirking for supervised workers in Spain, but not in the US, suggests that supervision mechanisms in Spain are not as effective as they are in the US, or that Spanish workers have a stronger preference for shirking that is not deterred by being supervised. This may be of special interest for employers and firms, as a way of boosting worker productivity in Spain. Second, we can conclude that, in the cases of Austria, Belgium, France, Greece, Italy, Luxembourg, Spain, Sweden, and the US, spouses behave similarly in terms of intrahousehold decisions, so they may be expected to respond to policies having an impact on the household in a similar way. Specifically, results suggest that concrete policies, such as wage increases of low-skilled workers, or programs dealing with inequality in opportunities, may shift intrahousehold bargaining positions in a semi-permanent way, therefore reducing intrahousehold inequality in the mid- and long-term. Furthermore, despite the results supporting the existence of intergenerational socio-economic mobility, as the employment status of parents seems to be transmitted vertically to their children, we could conclude that the estimated intergenerational correlation of self-employment is especially important in the long-term. This complements prior research studying the transmission of self-employment, and planners should take these results into consideration, in order to propose concrete policies aiming at overcoming inequality and poverty. For instance, the empirical analysis of intergenerational transmissions might help to anticipate which workers may be self-employed in the future in terms of the present situation of their parents, and intergenerational effects of policies promoting self-employment should be taken into account.

This Thesis presents some results which are of special importance in the field of Population Economics and, particularly, in Labor Economics and Family Economics. However, it is necessary to highlight two major limitations of the analyses presented. First, the empirical models estimated do not allow us to find causal results. In Chapter 1, the data is cross-sectional, and estimates might suffer from individual heterogeneity. Then, we cannot conclude if there are causal links among the different variables explored in that Chapter. In Chapter 2, the theoretical framework establishes that unexpected wage shocks must impact labor supply through changes in unobservable intrahousehold bargaining processes, therefore establishing a causal mechanism. However, the empirical analysis may suffer from measurement errors, as some regressors had to be predicted. Finally, the analysis presented in Chapter 3 is based on fixed effect models and linear models, but the results presented cannot be interpreted as causal links, as we could not find an adequate instrumentation to deal with spurious correlations between the labor status of parents and children.

The second main limitation of this Thesis is the potential role of sample selection bias. Chapter 1 is restricted to employees, although the self-employed are studied separately. However, the unemployed are not considered in the main analysis, and their commuting behaviors cannot be observed, which leads to sample selection bias. In Chapter 2, despite the fact that we partially control for selection as we estimate Heckman wage models, the main analysis is restricted to working spouses, which can lead to sample selection bias, as is usual when estimating collective models. Finally, Chapter 3 focuses first on individuals for whom there is information about their parents, but the data does not allow us to study the effect of the previous labor status of parents on the current labor status of children. To overcome this limitation, we then use the EU-SILC special module on Intergenerational Transmissions, which restricts the analysis to a cross-section sample, leading to unobserved heterogeneity and potential reverse causality.

# Conclusiones en español

Esta Tesis estudia, tanto teórica como empíricamente, una serie de comportamientos de la población desde el punto de vista de la oferta del mercado laboral. En concreto, se estudian los llamados salarios de eficiencia urbanos en España y en Estados Unidos, las decisiones y el compromiso intrafamiliar en un contexto intertemporal en Europa y en Estados Unidos, y la transmisión intergeneracional del empleo y el autoempleo en Europa.

En el Capítulo 1, se analiza empíricamente la relación entre tiempo de ocio y tiempo de elusión del trabajo, encontrando una correlación negativa entre ambas magnitudes. Dicha correlación prevalece tanto en Estados Unidos como en España, sugiriendo que los individuos que disfrutan de más tiempo de ocio en su hogar son más productivos en sus puestos de trabajo. Además, se estima una correlación negativa entre el tiempo de *commuting* y el tiempo de ocio de los trabajadores, y una correlación positiva entre el tiempo de *commuting* y el tiempo de elusión del trabajo, lo que puede indicar que la productividad de los trabajadores que deben desplazarse más para llegar a su puesto de trabajo es menor que la de los trabajadores que dedican menos tiempo a este tipo de desplazamientos. Los mecanismos de supervisión de trabajadores, a su vez, parecen jugar un papel moderador en las relaciones estimadas. En este contexto, se deja abierto para futuras líneas de trabajo el uso de diferentes instrumentos para medir la productividad de los trabajadores, la búsqueda de relaciones causales entre las diferentes magnitudes analizadas, o el análisis del lado de la demanda del mercado laboral, es decir, cómo las empresas contratan a sus trabajadores, y el posible papel que juega el tiempo que dedican éstos a desplazarse diariamente hasta sus puestos de trabajo.

El análisis presentado en el Capítulo 2 representa el primer análisis exploratorio de la capacidad de las familias formadas por dos cónyuges para llegar a acuerdos a lo largo del tiempo, es decir, el compromiso intertemporal intrafamiliar. El estudio parte del desarrollo de un modelo colectivo intertemporal de oferta laboral. En base a dicho modelo, se estudia primero la dinámica de los poderes de negociación dentro del hogar de cada uno de los cónyuges (también llamados pesos de Pareto en la literatura), que pese a no ser observables, quedan identificados a través de las decisiones familiares relativas a la oferta de trabajo. En particular, cómo esta oferta de trabajo responda a posibles variaciones salariales de cada uno de los cónyuges permitirá determinar la evolución de los pesos de Pareto. Los resultados del análisis empírico presentado coinciden con las predicciones del llamado modelo de compromiso limitado, y rechazan los modelos de compromiso total y de ausencia de compromiso. Estos resultados suponen la primera contribución empírica a la literatura distinguiendo entre los tres modelos simultáneamente, pues la literatura previa solamente había podido descartar el modelo de compromiso total, sin discernir totalmente entre los modelos de compromiso limitado y de ausencia de compromiso.

Finalmente, en el Capítulo 3 se estudia empíricamente la existencia de posibles correlaciones intergeneracionales del empleo y del autoempleo en Europa, utilizando los datos EU-SILC, una fuente de información armonizada y homogénea de la Unión Europea y el Eurostat. Los resultados muestran una correlación intergeneracional positiva y significativa entre la situación laboral de las madres y los padres, y la de sus hijas e hijos. Asimismo, los padres parecen ser ligeramente más influyentes que las madres, en relación a la actividad laboral de sus hijos. Pese a esto, los resultados muestran cómo el trabajo como autoempleado/a de los hijos e hijas no está relacionado de manera estadísticamente significativa con decisiones familiares a corto plazo, pero sí con la actividad como autoempleado/a de los padres y madres durante la adolescencia de los hijos, lo que sugiere la existencia de transmisiones intergeneracionales a largo plazo. En dicho contexto, se dejan como futuras líneas de trabajo el estudio de los diferentes canales que pueden conducir la transmisión intergeneracional del autoempleo, así como el uso de diversas técnicas que permitan establecer relaciones causales, como el llamado enfoque epidemiológico, que requiere datos muy específicos que, lamentablemente, no están disponibles en las bases de datos utilizadas en esta Tesis.

Los resultados que se muestran tienen varias implicaciones políticas, para las empresas, y para los propios trabajadores y familias. Los procesos como la distribución del tiempo disponible de los trabajadores, la formación y disolución de familias, o las transferencias de riqueza son relevantes desde un punto de vista político y económico, y comprender bien estos procesos a través de modelos correctamente fundamentados es crucial para anticipar y evaluar los efectos de las políticas públicas. De lo contrario, las conclusiones podrían ser inexactas y dar lugar a políticas ineficientes, pues las conclusiones de todo modelo dependerán de las hipótesis que ese modelo haga. Por ejemplo, el desarrollo de infraestructuras urbanas y comunicaciones puede mejorar la movilidad de los trabajadores, mejorando así tanto su productividad como el tiempo que pueden dedicar al ocio, desalentando los comportamientos relacionados con la elusión del trabajo. Por otro lado, los programas de asistencia social, o las transferencias de riqueza a familias poco favorecidas, no pueden evaluarse con precisión sin un conocimiento más profundo de sus consecuencias y, en concreto, de sus consecuencias dinámicas: ¿quién debe recibir la ayuda? ¿Cómo afectan estos programas al hogar a lo largo del tiempo? ¿Podemos esperar efectos permanentes, o solamente instantáneos? En cuanto a los programas que se centran en el empleo, o fomentan el autoempleo, ¿pueden estos programas ayudar a los trabajadores desempleados a encontrar un trabajo o convertirse en trabajadores por cuenta propia? ¿Podrían estos programas tener efectos intergeneracionales? Si es así, ¿cuándo podemos esperar estos efectos, en el corto plazo o en el largo plazo?

El hecho de que descubramos que la relación positiva estimada entre tiempo de ocio y tiempo de elusión del trabajo es mayor para los trabajadores en ocupaciones no supervisadas en Estados Unidos y en España sugiere que los mecanismos de supervisión de las empresas son efectivos. Sin embargo, las diferencias entre trabajadores en ocupaciones supervisadas y no supervisadas son mayores en Estados Unidos que en España. Dado que el tiempo de *commuting* se correlaciona positivamente con el tiempo de elusión del trabajo de los trabajadores supervisados en España, pero no en Estados Unidos, los resultados pueden sugerir que estos mecanismos de supervisión no son tan efectivos en España como en Estados Unidos, o que los trabajadores españoles tienen una preferencia más fuerte por eludir su trabajo que no se disuade mediante la supervisión. Este resultado puede ser de especial interés para las empresas, como medida para aumentar la productividad de sus trabajadores. En segundo lugar, podemos concluir que, en los casos de Austria, Bélgica, Francia, Grecia, Italia, Luxemburgo, España, Suecia y los Estados Unidos, los cónyuges se comportan de manera similar en términos de decisiones dentro del hogar, por lo que se espera que respondan a las políticas que tienen impacto en el hogar de manera similar. Específicamente, los resultados sugieren que las políticas que incrementen los ingresos de los trabajadores, como los aumentos salariales de los trabajadores poco cualificados, o los programas que abordan la desigualdad de oportunidades, pueden cambiar las posiciones de negociación dentro del hogar de forma semi-permanente, reduciendo así la desigualdad dentro del hogar en el medio y largo plazo. Además, a pesar de que los resultados respaldan la existencia de movilidad socioeconómica intergeneracional, ya que la situación laboral de los padres parece transmitirse verticalmente a sus hijos, podríamos concluir que la correlación intergeneracional del autoempleo es especialmente importante a largo plazo, y no a corto plazo. Estos resultados podrían ser útiles de cara a elaborar políticas públicas que busquen fomentar el autoempleo, con el fin último de incentivar el crecimiento económico y la innovación, o superar la desigualdad y la pobreza mediante el empleo por cuenta propia.

En esta Tesis se presentan resultados que pueden ser de especial importancia en el campo de la Economía de la Población y, en particular, de la Economía Laboral y la Economía de la Familia. Sin embargo, es necesario destacar dos limitaciones importantes de los análisis planteados. Primero, los modelos empleados no nos permiten, de forma general, encontrar resultados causales. En el Capítulo 1, los datos son transversales, lo que impide concluir si hay vínculos causales entre las diferentes variables exploradas. En el Capítulo 2, el marco teórico establece que las desviaciones salariales de los cónyuges deben afectar a su oferta de trabajo a través de cambios en los procesos de negociación intrafamiliar no observables, estableciendo teóricamente un mecanismo causal. Sin embargo, el análisis empírico puede pecar de errores de medición o de heterogeneidad no observada, por lo que los resultados han de interpretarse de forma cautelar. Finalmente, el análisis presentado en el Capítulo 3 se basa en modelos de efectos fijos y modelos de regresión lineal, pero las estimaciones no deben interpretarse como vínculos causales.

La segunda limitación principal de esta Tesis es la posible existencia de sesgos de selección muestral. El Capítulo 1 está restringido, en general, a los trabajadores empleados, no considerando a los trabajadores desempleados o a los trabajadores autoempleados en el análisis principal, lo que probablemente genere un sesgo de selección. En el Capítulo 2, a pesar de que se controla empíricamente la selección muestral mediante un modelo tipo Heckman, el análisis principal se limita a los cónyuges de las familias que trabajan y que no se separan durante el periodo analizado. Esta restricción también puede generar sesgos de selección, que son habituales en los trabajos empíricos sobre modelos colectivos. Finalmente, el Capítulo 3 analiza, primero, las familias para las que hay información sobre dos generaciones simultáneamente, lo que obliga a que los hijos e hijas de estas familias cohabiten con sus progenitores. Además, dado que se desconoce el estado laboral previo de los padres y las madres (es decir, pueden haber sido empleados, o autoempleados, en el pasado pero no en el momento de ser encuestados), el análisis mostrado puede presentar problemas de sesgos de selección, y sesgos por variable omitida. Para superar, al menos parcialmente, esta limitación, se usa un módulo especial de los datos EU-SILC sobre transmisiones intergeneracionales, que posiblemente resuelva el primero de los sesgos que se mencionan. No obstante, al ser un análisis transversal, no queda exento de limitaciones, como la heterogeneidad no observada o la causalidad inversa.

# Bibliography

Aguiar, M. and Hurst, E. (2007). Measuring trends in leisure: The allocation of time over five decades. *Quarterly Journal of Economics*, 122(3):969–1006.

Alonso, W. (1964). *Location and land use*. Harvard University Press.

Altonji, J. G. and Dunn, T. A. (2000). An intergenerational model of wages, hours, and earnings. *Journal of Human Resources*, 35(2):221–258.

Altonji, J. G., Smith Jr, A. A., and Vidangos, I. (2013). Modelling earnings' dynamics. *Econometrica*, 81(4):1395–1454.

Álvarez, B. and Miles-Touya, D. (2012). Exploring the relationship between parents' and children's housework time in Spain. *Review of Economics of the Household*, 10(2):299–318.

Andersson, L. and Hammarstedt, M. (2010). Intergenerational transmissions in immigrant self-employment: Evidence from three generations. *Small Business Economics*, 34(3):261–276.

Andersson, L. and Hammarstedt, M. (2011). Transmission of self-employment across immigrant generations: The importance of ethnic background and gender. *Review of Economics of the Household*, 9(4):555–577.

Apps, P. F. (1981). *A theory of inequality and taxation*. Cambridge University Press.

Apps, P. F. (1982). Institutional inequality and tax incidence. *Journal of Public Economics*, 18(2):217–242.

Apps, P. F. and Jones, G. (1986). Selective taxation of couples. *Journal of Economics*, 5:1–15.

Armand, A., Attanasio, O., Carneiro, P. M., and Lechene, V. (2016). The effect of gender-targeted conditional cash transfers on household expenditures: Evidence from a randomized experiment. *CEPR DP11465*.

Ashworth, J. S. and Ulph, D. T. (1981). Household models. In Brown, C. V., editor, *Taxation and labour supply*. Allend and Unwin.

Ateca-Amestoy, V. (2010). Cultural participation patterns: Evidence from the Spanish time use survey. In *ESA Research Network Sociology of Culture Midterm Conference: Culture and the Making of Worlds*.

Attanasio, O. P. and Lechene, V. (2014). Efficient responses to targeted cash transfers. *Journal of Political Economy*, 122(1):178–222.

Bae, T. J., Qian, S., Miao, C., and Fiet, J. O. (2014). The relationship between entrepreneurship education and entrepreneurial intentions: A meta–analytic review. *Entrepreneurship Theory and Practice*, 38(2):217–254.

Barbieri, T., Bloise, F., and Raitano, M. (2019). Intergenerational earnings inequality: New evidence from Italy. *Review of Income and Wealth*, forthcoming.

Basu, K. (2006). Gender and say: A model of household behaviour with endogenously determined balance of power. *Economic Journal*, 116(511):558–580.

Becker, G. S. (1973). A theory of marriage: Part I. *Journal of Political Economy*, 81(4):813–846.

Becker, G. S. (1974a). A theory of marriage: Part II. *Journal of Political Economy*, 82(2, Part 2):S11–S26.

Becker, G. S. (1974b). A theory of social interactions. *Journal of Political Economy*, 82(6):1063–1093.

Becker, G. S. (1985). Human capital, effort, and the sexual division of labor. *Journal of Labor Economics*, 3(1, Part 2):S33–S58.

Becker, G. S. (1991). *A treatise on the family*. Harvard university press.

Becker, G. S. and Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy*, 87(6):1153–1189.

Bianchi, S. M., Milkie, M. A., Sayer, L. C., and Robinson, J. P. (2000). Is anyone doing the housework? Trends in the gender division of household labor. *Social Forces*, 79(1):191–228.

Binder, A. (2018). Inter-generational transmission and the 21st century rise in skilled mothers' labor supply. *University of Michigan Technical Report*.

Black, S. and Devereux, P. (2011). Recent developments in intergenerational mobility. In *Handbook of Labor Economics, Vol. 4, Part B*, pages 1487–1541. Elsevier.

Black, S. E., Devereux, P. J., and Salvanes, K. G. (2005). Why the apple doesn't fall far: Understanding intergenerational transmission of human capital. *American Economic Review*, 95(1):437–449.

Blanchflower, D. G., Oswald, A., and Stutzer, A. (2001). Latent entrepreneurship across nations. *European Economic Review*, 45(4-6):680–691.

Blau, D. M. and Goodstein, R. M. (2016). Commitment in the household: Evidence from the effect of inheritances on the labor supply of older married couples. *Labour Economics*, 42:123–137.

Blumberg, B. F. and Pfann, G. A. (2016). Roads leading to self-employment: Comparing transgenerational entrepreneurs and self-made start-ups. *Entrepreneurship Theory and Practice*, 40(2):335–357.

Blundell, R., Chiappori, P.-A., and Meghir, C. (2005). Collective labor supply with children. *Journal of Political Economy*, 113(6):1277–1306.

Bonke, J. (2005). Paid work and unpaid work: Diary information versus questionnaire information. *Social Indicators Research*, 70(3):349–368.

Bono, E. D., Francesconi, M., Kelly, Y., and Sacker, A. (2016). Early maternal time investment and early child outcomes. *Economic Journal*, 126(596):F96–F135.

Bound, J., Jaeger, D. A., and Baker, R. M. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association*, 90(430):443–450.

Bourguignon, F. (1984). Rationalité individuelle ou rationalité stratégique: Le cas de l'offre familiale de travail. *Revue Économique*, 29:147–162.

Bourguignon, F., Browning, M., and Chiappori, P.-A. (2009). Efficient intra-household allocations and distribution factors: Implications and identification. *Review of Economic Studies*, 76(2):503–528.

Bourguignon, F., Browning, M., Chiappori, P.-A., and Lechene, V. (1993). Intra household allocation of consumption: A model and some evidence from French data. *Annales d'Economie et de Statistique*, 29:137–156.

Bratberg, E., Nilsen, Ø. A., and Vaage, K. (2008). Job losses and child outcomes. *Labour Economics*, 15(4):591–603.

Browning, M., Bourguignon, F., Chiappori, P.-A., and Lechene, V. (1994). Income and outcomes: A structural model of intrahousehold allocation. *Journal of Political Economy*, 102(6):1067–1096.

Browning, M. and Chiappori, P.-A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, 66(6):1241–1278.

Browning, M., Chiappori, P.-A., and Weiss, Y. (2014). *Economics of the Family*. Cambridge University Press.

Brüderl, J. and Preisendörfer, P. (1998). Network support and the success of newly founded business. *Small Business Economics*, 10(3):213–225.

Brueckner, J. K., Thisse, J.-F., and Zenou, Y. (1997). Why is central Paris rich and downtown Detroit poor? An amenity-based theory. *European Economic Review*, 43:91–107.

Brueckner, J. K. and Zenou, Y. (2003). Space and unemployment : The labor market effects of spatial mismatch. *Journal of Labor Economics*, 21(1):242–262.

Burda, M. C., Genadek, K. R., and Hamermesh, D. S. (2015). Not working at work: Loafing, unemployment and labor productivity. *IZA DP 9095*.

Campaña, J., Giménez-Nadal, J., and Molina, J. (2016). Diferencias entre auto-empleados y asalariados en los usos del tiempo: Aragón vs. Spain. *MPRA Paper 71463*.

Campaña, J. C., Gimenez, J. I., and Molina, J. A. (2018). Efficient labor supply for Latin families: Is the intra-household bargaining power relevant? *IZA DP 11695*.

Card, D. and Rothstein, J. (2007). Racial segregation and the black–white test score gap. *Journal of Public Economics*, 91(11-12):2158–2184.

Casado-Díaz, J. M. (2000). Local labour market areas in Spain: A case study. *Regional Studies*, 34(9):843–856.

Cherchye, L., De Rock, B., and Vermeulen, F. (2012). Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information. *American Economic Review*, 102(7):3377–3405.

Chiappori, P.-A. (1988). Rational household labor supply. *Econometrica*, 56(1):63–90.

Chiappori, P.-A. (1992). Collective labor supply and welfare. *Journal of Political Economy*, 100(3):437–467.

Chiappori, P.-A. (1997). Introducing household production in collective models of labor supply. *Journal of Political Economy*, 105(1):191–209.

Chiappori, P.-A. and Ekeland, I. (2006). The micro economics of group behavior: General characterization. *Journal of Economic Theory*, 130(1):1–26.

Chiappori, P.-A. and Ekeland, I. (2009). The micro economics of efficient group behavior: Identification. *Econometrica*, 77(3):763–799.

Chiappori, P.-A., Fortin, B., and Lacroix, G. (2002). Marriage market, divorce legislation, and household labor supply. *Journal of Political Economy*, 110(1):37–72.

Chiappori, P.-A. and Mazzocco, M. (2017). Static and intertemporal household decisions. *Journal of Economic Literature*, 55(3):985–1045.

Chiappori, P.-A., Salanié, B., and Weiss, Y. (2017). Partner choice, investment in children, and the marital college premium. *American Economic Review*, 107(8):2109–67.

Clark, W. and Withers, S. D. (1999). Changing jobs and changing houses: Mobility outcomes of employment transitions. *Journal of Regional Science*, 39(4):653–673.

Coduras, A., Clemente, J. A., and Ruiz, J. (2016). A novel application of fuzzy-set qualitative comparative analysis to gem data. *Journal of Business Research*, 69(4):1265–1270.

Colombier, N. and Masclet, D. (2008). Intergenerational correlation in self employment: Some further evidence from French ECHP data. *Small Business Economics*, 30(4):423–437.

Connelly, R. (1992). Self-employment and providing child care. *Demography*, 29(1):17–29.

Corak, M., Gustafsson, B., and Österberg, T. (2004). Intergenerational influences on the receipt of unemployment insurance in Canada and Sweden. In *Generational income mobility in North America and Europe*, pages 245–288. Cambridge University Press.

Cutler, D. M. and Glaeser, E. L. (1997). Are ghettos good or bad? *Quarterly Journal of Economics*, 112(3):827–872.

Dargay, J. and Van Ommeren, J. N. (2005). The effect of income on commuting time using panel data. *In 45th Conference of the European Regional Science Association at the Vrije Universiteit Amsterdam, Amsterdam.*

De Jong, J. P. and Marsili, O. (2015). Founding a business inspired by close entrepreneurial ties: Does it matter for survival? *Entrepreneurship Theory and Practice*, 39(5):1005–1025.

Del Boca, D., Flinn, C., and Wiswall, M. (2016). Transfers to households with children and child development. *Economic Journal*, 126(596):F136–F183.

Doepke, M. and Zilibotti, F. (2017). Parenting with style: Altruism and paternalism in intergenerational preference transmission. *Econometrica*, 85(5):1331–1371.

Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2011). The intergenerational transmission of risk and trust attitudes. *Review of Economic Studies*, 79(2):645–677.

Donni, O. and Chiappori, P.-A. (2011). Nonunitary models of household behavior: A survey of the literature. In Molina, J. A., editor, *Household economic behaviors*, pages 1–40. Springer New York.

Donni, O. and Molina, J. A. (2019). Household collective models: Three decades of theoretical contributions and empirical evidence. *IZA DP 11915.*

Dubois, P., Jullien, B., and Magnac, T. (2008). Formal and informal risk sharing in LDCs: Theory and empirical evidence. *Econometrica*, 76(4):679–725.

Duflo, E. (2003). Grandmothers and granddaughters: Old age pensions and intrahousehold allocation in South Africa. *World Bank Economic Review*, 17(1):1–25.

Dunn, T. and Holtz-Eakin, D. (2000). Financial capital, human capital, and the transition to self-employment: Evidence from intergenerational links. *Journal of Labor Economics*, 18(2):282–305.

Ekhaugen, T. (2009). Extracting the causal component from the intergenerational correlation in unemployment. *Journal of Population Economics*, 22(1):97–113.

European Commission (2017). Methodological guidelines and description of EU-SILC target variables, 2016 operation. *European Commission*, DocSILC065.

Evans, G. W., Wener, R. E., and Phillips, D. (2002). The morning rush hour: Predictability and commuter stress. *Environment and Behavior*, 34(4):521–530.

Evans, W. N., Oates, W. E., and Schwab, R. M. (1992). Measuring peer group effects: A study of teenage behavior. *Journal of Political Economy*, 100(5):966–991.

Fairlie, R. W. (2013). Entrepreneurship, economic conditions, and the great recession. *Journal of Economics & Management Strategy*, 22(2):207–231.

Fairlie, R. W. and Krashinsky, H. A. (2012). Liquidity constraints, household wealth, and entrepreneurship revisited. *Review of Income and Wealth*, 58(2):279–306.

Fairlie, R. W. and Robb, A. (2007). Families, human capital, and small business: Evidence from the characteristics of business owners survey. *ILR Review*, 60(2):225–245.

Fernández, R. (2007). Women, work, and culture. *Journal of the European Economic Association*, 5(2-3):305–332.

Fernández, R. (2008). Culture and economics. *The New Palgrave Dictionary of Economics: Volume 1–8*, pages 1229–1236.

Fernández, R., Fogli, A., and Olivetti, C. (2004). Preference formation and the rise of women's labor force participation: Evidence from WWII. Technical report, National Bureau of Economic Research w10589.

Ferrando-Latorre, S., Velilla, J., and Ortega, R. (2019). Intergenerational transmission of entrepreneurial activity in Spanish families. *Journal of Family and Economic Issues*, Forthcoming.

Francesconi, M. and Heckman, J. J. (2016). Child development and parental investment: Introduction. *Economic Journal*, 126(596):F1–F27.

Freund, F., Hawranek, F., Vom Berge, P., and Heuermann, D. (2015). The distributional effect of commuting subsidies-evidence from geo-referenced data and large-scale policy reform. *Paper presented at the Annual Conference 2015 (Muenster): Economic Development-Theory and Policy*, Session: Local Labor Markets 2 (No. F18-V2):Germany.

Fritsch, M., S. Kritikos, A., and Sorgner, A. (2015). Why did self-employment increase so strongly in germany? *Entrepreneurship & Regional Development*, 27(5-6):307–333.

Fu, S. and Ross, S. L. (2013). Wage premia in employment clusters: How important is worker heterogeneity? *Journal of Labor Economics*, 31(2):271–304.

Galassi, G., Koll, D., and Mayr, L. (2019). The intergenerational correlation of employment: Is there a role for work culture? *IZA DP 12595*.

García, J., Lera-López, F., and Suárez, M. J. (2011). Estimation of a structural model of the determinants of the time spent on physical activity and sport: Evidence for Spain. *Journal of Sports Economics*, 12(5):515–537.

Garreau, J. (1991). *Edge city: Life on the new frontier*. Doubleday, New York.

Gauly, B. (2017). The intergenerational transmission of attitudes: Analyzing time preferences and reciprocity. *Journal of Family and Economic Issues*, 38(2):293–312.

Giménez-Nadal, J. I., Molina, J. A., , and Zhu, Y. (2018a). Intergenerational mobility of housework time in the United Kingdom. *Review of Economics of the Household*, forthcoming.

Giménez-Nadal, J. I. and Molina, J. A. (2014). Regional unemployment, gender, and time allocation of the unemployed. *Review of Economics of the Household*, 12(1):105–127.

Giménez-Nadal, J. I. and Molina, J. A. (2016). Commuting time and household responsibilities: Evidence using propensity score matching. *Journal of Regional Science*, 56(2):332–359.

Giménez-Nadal, J. I., Molina, J. A., and Ortega, R. (2012). Self-employed mothers and the work-family conflict. *Applied Economics*, 44(17):2133–2147.

Giménez-Nadal, J. I., Molina, J. A., and Ortega, R. (2017). Like my parents at home? Gender differences in children's housework in Germany and Spain. *Empirical Economics*, 52(4):1143–1179.

Giménez-Nadal, J. I., Molina, J. A., and Velilla, J. (2018b). The commuting behavior of workers in the United States: Differences between the employed and the self-employed. *Journal of Transport Geography*, 66:19–29.

Giménez-Nadal, J. I., Molina, J. A., and Velilla, J. (2018c). Spatial distribution of US employment in an urban efficiency wage setting. *Journal of Regional Science*, 58(1):141–158.

Giménez-Nadal, J. I., Molina, J. A., and Velilla, J. (2019). Work time and well-being for workers at home: Evidence from the American Time Use Survey. *International Journal of Manpower*, forthcoming.

Giménez-Nadal, J. I. and Sevilla, A. (2012). Trends in time allocation: A cross-country analysis. *European Economic Review*, 56(6):1338–1359.

Giménez-Nadal, J. I. and Sevilla, A. (2014). Total work time in Spain: evidence from time diary data. *Applied Economics*, 46(16):1894–1909.

Giuliano, P. (2007). Living arrangements in Western Europe: Does cultural origin matter? *Journal of the European Economic Association*, 5(5):927–952.

Gobillon, L., Selod, H., and Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban Studies*, 44(12):2401–2427.

Gottholmseder, G., Nowotny, K., Pruckner, G. J., and Theurl, E. (2009). Stress perception and commuting. *Health Economics*, 18(5):559–576.

Gracia, P. (2014). Fathers' child care involvement and children's age in Spain: A time use study on differences by education and mothers' employment. *European Sociological Review*, 30(2):137–150.

Gracia, P. and Kalmijn, M. (2016). Parents' family time and work schedules: The split-shift schedule in Spain. *Journal of Marriage and Family*, 78(2):401–415.

Gregg, P., Macmillan, L., and Nasim, B. (2012). The impact of fathers' job loss during the recession of the 1980s on their children's educational attainment and labour market outcomes. *Fiscal Studies*, 33(2):237–264.

Grimm, M. and Paffhausen, A. L. (2015). Do interventions targeted at micro-entrepreneurs and small and medium-sized firms create jobs? A systematic review of the evidence for low and middle income countries. *Labour Economics*, 12(1):67–85.

Guryan, J., Hurst, E., and Kearney, M. (2008). Parental education and parental time with children. *Journal of Economic perspectives*, 22(3):23–46.

Gutiérrez-Domènech, M. (2010). Parental employment and time with children in spain. *Review of Economics of the Household*, 8(3):371–391.

Haddad, L. and Hoddinott, J. (1994). Women's income and boy-girl anthropometric status in the Côte d'Ivoire. *World Development*, 22(4):543–553.

Hamermesh, D. S. (1999). The timing of work over time. *Economic Journal*, 109(452):37–66.

Hamermesh, D. S. and Stancanelli, E. (2015). Long workweeks and strange hours. *ILR Review*, 68(5):1007–1018.

Hamilton, B. W. (1982). Wasteful commuting. *Journal of Political Economy*, 90(5):1035–1053.

Hämmig, O., Gutzwiller, F., and Bauer, G. (2009). Work-life conflict and associations with work-and nonwork-related factors and with physical and mental health outcomes: A nationally representative cross-sectional study in Switzerland. *BMC Public Health*, 9(1):435.

Hansson, E., Mattisson, K., Björk, J., Östergren, P.-O., and Jakobsson, K. (2011). Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. *BMC Public Health*, 11(1):834.

Harms, T., Berrigan, D., and Gershuny, J. (2019). Daily metabolic expenditures: estimates from US, UK and polish time-use data. *BMC Public Health*, 19(2):453.

Heathcote, J., Perri, F., and Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006. *Review of Economic Dynamics*, 13(1):15–51.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 78(4):1239–1283.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3):411–482.

Hérault, N. and Kalb, G. (2016). Intergenerational correlation of labor market outcomes. *Review of Economics of the Household*, 14(1):231–249.

Hoxby, C. M. (2000). Does competition among public schools benefit students and taxpayers? *American Economic Review*, 90(5):1209–1238.

Huber, L. R., Sloof, R., and Van Praag, M. (2014). The effect of early entrepreneurship education: Evidence from a field experiment. *European Economic Review*, 72(1):76–97.

Jansen, N. W., Kant, I., Kristensen, T. S., and Nijhuis, F. J. (2003). Antecedents and consequences of work–family conflict: A prospective cohort study. *Journal of Occupational and Environmental Medicine*, 45(5):479–491.

Jara-Díaz, S. and Rosales-Salas, J. (2015). Understanding time use: Daily or weekly data? *Transportation Research Part A: Policy and Practice*, 76:38–57.

Juster, F. T. and Stafford, F. (1985). Time, goods and well-being. *Michigan Institute for Social Research, University of Michigan.*

Kahneman, D. and Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *Journal of Economic Perspectives*, 20(1):3–24.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., and Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702):1776–1780.

Kain, J. F. (1968). Housing segregation, negro employment, and metropolitan decentralization. *Quarterly Journal of Economics*, 82(2):175–197.

Kirby, D. K. and LeSage, J. P. (2009). Changes in commuting to work times over the 1990 to 2000 period. *Regional Science and Urban Economics*, 39(4):460–471.

Kirkwood, J. (2007). Igniting the entrepreneurial spirit: Is the role parents play gendered? *International Journal of Entrepreneurial Behavior & Research*, 13(1):39–59.

Krueger, D. and Perri, F. (2006). Does income inequality lead to consumption inequality? Evidence and theory. *Review of Economic Studies*, 73(1):163–193.

Laspita, S., Breugst, N., Heblich, S., and Patzelt, H. (2012). Intergenerational transmission of entrepreneurial intentions. *Journal of Business Venturing*, 27(4):414–435.

Lazear, E. (2005). Entrepreneurship. *Journal of Labor Economics*, 23(4):649–680.

Leigh, J. P. (1986). Are compensating wages paid for time spent commuting? *Applied Economics*, 18(11):1203–1213.

Levenson, A. and Zoghi, C. (2006). The strength of occupation indicators as a proxy for skill. *CEO Public*, (G 06-17 (506)).

Levie, J. and Autio, E. (2013). Growth and growth intentions: A meta analysis of existing evidence. *ERC White Papers 1.*

Levine, K. J. and Hoffner, C. A. (2006). Adolescents' conceptions of work: What is learned from different sources during anticipatory socialization? *Journal of Adolescent Research*, 21(6):647–669.

Ligon, E., Thomas, J. P., and Worrall, T. (2002). Informal insurance arrangements with limited commitment: Theory and evidence from village economies. *Review of Economic Studies*, 69(1):209–244.

Lindquist, M. J., Sol, J., and Van Praag, M. (2015). Why do entrepreneurial parents have entrepreneurial children? *Journal of Labor Economics*, 33(2):269–296.

Lise, J. and Yamada, K. (2018). Household sharing and commitment: Evidence from panel data on individual expenditures and time use. *Review of Economic Studies*, forthcoming.

Lombard, K. V. (2001). Female self-employment and demand for flexible, nonstandard work schedules. *Economic Inquiry*, 39(2):214–237.

Lundberg, S. J., Pollak, R. A., and Wales, T. J. (1997). Do husbands and wives pool their resources? Evidence from the United Kingdom Child Benefit. *Journal of Human Resources*, 32(3):463.

Lyssiotou, P. (2017). The impact of targeting policy on spouses' demand for public goods, labor supplies and sharing rule. *Empirical Economics*, 53(2):853–878.

Macmillan, L. (2010). The intergenerational transmission of worklessness in the UK. *CMPO Working Paper 10/231, University of Bristol.*

Mäder, M., Riphahn, R. T., Schwientek, C., and Müller, S. (2015). Intergenerational transmission of unemployment: Evidence for German sons. *Jahrbücher für Nationalökonomie und Statistik*, 235(4-5):355–375.

Manser, M. and Brown, M. (1980). Marriage and household decision-making: A bargaining analysis. *International Economic Review*, 21(1):31.

Marcén, M. (2014). The role of culture on self-employment. *Economic Modelling*, 44(S1):S20–S32.

Mascherini, M. (2019). Origins and future of the concept of NEETs in the European policy agenda. In O'Reilly, J., Leschke, J., Ortlieb, R., Seeleib-Kaiser, M., and Villa, P., editors, *Youth Labor in Transition*. CIPE, University of Maryland.

Matthews, R. B., Stowe, C. R., and Jenkins, G. K. (2011). Entrepreneurs-born or made? In *Allied Academies International Conference. Academy of Entrepreneurship. Proceedings*. Jordan Whitney Enterprises, Inc.

Mazzocco, M. (2004). Saving, risk sharing, and preferences for risk. *American Economic Review*, 94(4):1169–1182.

Mazzocco, M. (2007). Household intertemporal behaviour: A collective characterization and a test of commitment. *Review of Economic Studies*, 74(3):857–895.

McElroy, M. B. and Horney, M. J. (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International Economic Review*, 22(2):333.

McKenzie, B. and Rapino, M. (2011). Commuting in the United States: 2009. *Washington, DC: U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau.*

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27(1):415–444.

Miller, P. and Mulvey, C. (2000). Women's time allocation to child care: Determinants and consequences. *Australian Economic Papers*, 39(1):1–24.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *American Economic Review*, 57(2):197–210.

Minniti, M. and Naudé, W. (2010). What do we know about the patterns and determinants of female entrepreneurship across countries? *European Journal of Development Research*, 22(3):277–293.

Mohíno, I., Solís, E., and Urena, J. M. (2017). Changing commuting patterns in rural metro-adjacent regions: The case of Castilla-La Mancha in the context of Madrid, Spain. *Regional Studies*, 51(7):1115–1130.

Mondragón-Vélez, C. and Peña, X. (2010). *Business ownership and self-employment in developing economies: The Colombian case*. University of Chicago Press.

Morales, M. (2019). Can family characteristics influence the future labor situation of children? Evidence for Spain. *International Journal of Social Economics*, Forthcoming.

Mulalic, I., Van Ommeren, J. N., and Pilegaard, N. (2014). Wages and commuting: Quasi-natural experiments' evidence from firms that relocate. *Economic Journal*, 124(579):1086–1105.

Muller, P. O. (1981). *Contemporary Suburban America*. Prentice Hall, NJ.

Murphy, K. M. and Topel, R. H. (1985). Estimation and inference in two-step econometric models. *Journal of Business & Economic Statistics*, 3(4):370–379.

Muth, R. F. (1969). *Cities and housing: The spatial pattern of urban residential land use*. University of Chicago Press.

Naudé, W. (2015). Is European entrepreneurship in crisis? *IZA DP 9817*.

Nicolaou, N. and Shane, S. (2010). Entrepreneurship and occupational choice: Genetic and environmental influences. *Journal of Economic Behavior & Organization*, 76(1):3–14.

Nicolaou, N., Shane, S., Cherkas, L., Hunkin, J., and Spector, T. D. (2008). Is the tendency to engage in entrepreneurship genetic? *Management Science*, 54(1):167–179.

Olivetti, C., Patacchini, E., and Zenou, Y. (2018). Mothers, peers, and gender-role identity. *Journal of the European Economic Association*, forthcoming.

O'Neill, D. and Sweetman, O. (1998). Intergenerational mobility in Britain: evidence from unemployment patterns. *Oxford Bulletin of Economics and statistics*, 60(4):431–447.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, 56(1):221–247.

Patacchini, E. and Zenou, Y. (2007). Spatial dependence in local unemployment rates. *Journal of Economic Geography*, 7(2):169–191.

Picard, P. M. and Zenou, Y. (2015). Urban spatial structure, employment and social ties: European versus American cities. *IZA DP 9166*.

Presser, H. B. (1989). Can we make time for children? The economy, work schedules, and child care. *Demography*, 26(4):523–543.

Rapoport, B., Sofer, C., and Solaz, A. (2011). Household production in a collective model: Some new results. *Journal of Population Economics*, 24(1):23–45.

Renkow, M. and Hoover, D. (2000). Commuting, migration, and rural-urban population dynamics. *Journal of Regional Science*, 40(2):261–287.

Roberts, J., Hodgson, R., and Dolan, P. (2011). "It's driving her mad": Gender differences in the effects of commuting on psychological health. *Journal of Health Economics*, 30(5):1064–1076.

Robinson, J. P. (1985). The validity and reliability of diaries versus alternative time use measures. In Juster, T. and Stafford, F., editors, *Time, goods, and well-being*, pages 33–62. Michigan Institute for Social Research, University of Michigan.

Rocha, F. and Aragon, J. (2012). La crisis económica y sus efectos sobre el empleo en España. *Gaceta Sindical*, 19:67–90.

Romani, J., Suriñach, J., and Artiís, M. (2003). Are commuting and residential mobility decisions simultaneous?: The case of Catalonia, Spain. *Regional Studies*, 37(8):813–826.

Ross, S. L. and Zenou, Y. (2008). Are shirking and leisure substitutable? An empirical test of efficiency wages based on Urban Economic Theory. *Regional Science and Urban Economics*, 38(5):498–517.

Rouwendal, J. and Meijer, E. (2001). Preferences for housing, jobs, and commuting: A mixed logit analysis. *Journal of Regional Science*, 41(3):475–505.

Rouwendal, J. and Nijkamp, P. (2004). Living in two worlds: A review of home-to-work decisions. *Growth and Change*, 35(3):11–41.

Royuela, V. and Vargas, M. A. (2009). Defining housing market areas using commuting and migration algorithms: Catalonia (Spain) as a case study. *Urban Studies*, 46(11):2381–2398.

Ruppert, P., Stancanelli, E., and Wasmer, E. (2016). Commuting, wages and bargaining power. *Annals of Economics and Statistics*, 95/96.

Schmitt-Rodermund, E. (2004). Pathways to successful entrepreneurship: Parenting, personality, early entrepreneurial competence, and interests. *Journal of Vocational Behavior*, 65(3):498–518.

Scholz, J. K., Seshadri, A., and Khitatrakun, S. (2006). Are Americans saving optimally for retirement? *Journal of Political Economy*, 114(4):607–1643.

Sebastian, R. (2018). Explaining job polarisation in Spain from a task perspective. *SERIEs*, 9(2):215–248.

Shapiro, C. and Stiglitz, J. E. (1984). Equilibrium unemployment as a worker discipline device. *American Economic Review*, 74(3):433–44.

Silvers, C. (2000). Being there: The time dual-earner couples spend with their children. *Canadian Social Trends*, 57(11-008):26–30.

Solon, G. (1992). Intergenerational income mobility in the united states. *American Economic Review*, 82(3):393–408.

Solon, G. (2002). Cross-country differences in intergenerational earnings mobility. *Journal of Economic Perspectives*, 16(3):59–66.

Sørensen, J. B. (2007). *Closure and exposure: Mechanisms in the intergenerational transmission of self-employment*. Emerald Group Publishing Limited.

Stith, S. M., Rosen, K. H., Middleton, K. A., Busch, A. L., Lundeberg, K., and Carlton, R. P. (2000). The intergenerational transmission of spouse abuse: A meta analysis. *Journal of Marriage and Family*, 62(3):640–654.

Stone, A. A. and Schneider, S. (2016). Commuting episodes in the United States: Their correlates with experiential wellbeing from the American Time Use Survey. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42:117–124.

Susilo, Y. O. and Maat, K. (2007). The influence of built environment to the trends in commuting journeys in the Netherlands. *Transportation*, 34(5):589–609.

Terjesen, S. and Amorós, J. E. (2010). Female entrepreneurship in Latin America and the Caribbean: Characteristics, drivers and relationship to economic development. *European Journal of Development Research*, 22(3):313–330.

Thomas, D. (1990). Intra-household resource allocation: An inferential approach. *Journal of Human Resources*, 25(4):635.

Ulph, D. T. (1988). A general non-cooperative nash model of household consumption behaviour. *Working paper Univ. Bristol.*

Van Ommeren, J. N. (1998). On-the-job search behavior: The importance of commuting time. *Land Economics*, pages 526–540.

Van Ommeren, J. N. and Gutiérrez-i-Puigarnau, E. (2011). Are workers with a long commute less productive? An empirical analysis of absenteeism. *Regional Science and Urban Economics*, 41(1):1–8.

Van Ommeren, J. N., Van den Berg, G. J., and Gorter, C. (2000). Estimating the marginal willingness to pay for commuting. *Journal of Regional Science*, 40(3):541–563.

Voena, A. (2015). Yours, mine, and ours: Do divorce laws affect the intertemporal behavior of married couples? *American Economic Review*, 105(8):2295–2332.

Vollebergh, W. A., Iedema, J., and Raaijmakers, Q. A. (2001). Intergenerational transmission and the formation of cultural orientations in adolescence and young adulthood. *Journal of Marriage and Family*, 63(4):1185–1198.

Wang, C. K. and Wong, P.-K. (2004). Entrepreneurial interest of university students in Singapore. *Technovation*, 24(2):163–172.

Ward-Batts, J. (2008). Out of the wallet and into the purse using micro data to test income pooling. *Journal of Human Resources*, 43(2):325–351.

Wener, R. E., Evans, G. W., Phillips, D., and Nadler, N. (2003). Running for the 7: 45: The effects of public transit improvements on commuter stress. *Transportation*, 30(2):203–220.

White, M. J. (1977). A model of residential choice and commuting by men and women workers. *Journal of Regional Science*, 17(1):41–52.

White, M. J. (1999). Urban areas with decentralized employment: Theory and empirical work. *Handbook of Regional and Urban Economics*, 3:1375–1412.

Woolley, F. (1988). A non-cooperative model of family decision making. *Working Paper no. 125. London School Econ.*

Yee-Kan, M. (2008). Measuring housework participation: The gap between "stylised" questionnaire estimates and diary-based estimates. *Social Indicators Research*, 86(3):381–400.

Zax, J. S. (1991). Compensation for commutes in labor and housing markets. *Journal of Urban Economics*, 30(2):192–207.

Zax, J. S. and Kain, J. F. (1991). Commutes, quits, and moves. *Journal of Urban Economics*, 29(2):153–165.

Zenou, Y. (2009). *Urban labor economics*. Cambridge University Press.

Zhang, Z., Zyphur, M. J., Narayanan, J., Arvey, R. D., Chaturvedi, S., Avolio, B. J., Lichtenstein, P., and Larsson, G. (2009). The genetic basis of entrepreneurship: Effects of gender and personality. *Organizational Behavior and Human Decision Processes*, 110(2):93–107.

Zivot, E., Startz, R., and Nelson, C. R. (1998). Valid confidence intervals and inference in the presence of weak instruments. *International Economic Review*, 39(4):1119–1144.

Zwysen, W. (2016). The effects of father's worklessness on young adults in the UK. *Journal of European Labor Studies*, 4(1):1–15.

# List of Figures

1.1 Relationship between commuting, leisure and shirking . . . . . . . . . . 24

1.2 Evolution of employment, commuting, and hourly earnings . . . . . . . 25

1.3 1.A1: K-density of commuting, leisure and shirking . . . . . . . . . . . 39

2.1 2.B1: Evolution of sex ratios in the US . . . . . . . . . . . . . . . . . . . 111

2.2 2.B2: Altonji et al. (2013)'s wage model . . . . . . . . . . . . . . . . . . 112

3.1 Parents' and children's employment, by country – longitudinal sample . 149

3.2 Parents' and children's employment, by country – 2011 special module 150

# List of Tables


1.1 Summary statistics . . . . . 22

1.2 Leisure and shirking by occupation . . . . . 23

1.3 Shirking-leisure relationship . . . . . 27

1.4 Leisure- and shirking-commuting relationships . . . . . 29

1.5 Wages- and employment-commuting relationships . . . . . 32

1.6 1.A1: Summary statistics - Commuting model . . . . . 40

1.7 1.A2: Commuting model . . . . . 41

1.8 1.A3: Alternative employment models . . . . . 42

1.9 1.B1: Summary statistics . . . . . 52

1.10 1.B2: Shirking-leisure relationship . . . . . 53

1.11 1.B3: Leisure- and shirking-commuting relationships . . . . . 54

1.12 1.B4: Wages-commuting relationship . . . . . 55

1.13 1.B5: main estimates for Aragón . . . . . 56

1.14 1.C1: Summary statistics . . . . . 67

1.15 1.C2: Shirking, leisure and commuting . . . . . 68

1.16 1.C3: Commuting and self-employment . . . . . 69

2.1 Summary statistics . . . . . 86

2.2 Labor supply estimates . . . . . 90

2.3 Labor supply fixed effects estimates . . . . . 91

2.4 Labor supply estimates for singles . . . . . . . . . . . . . . . . . . . . . . . 92

2.5 Public expenditure on housing . . . . . . . . . . . . . . . . . . . . . . . . 93

2.6 Summary statistics . . . . . . . . . . . . . . . . . . . . . . . . . . . . 96

2.7 Labor supply estimates (I) . . . . . . . . . . . . . . . . . . . . . . . . . 99

2.8 Labor supply estimates (II) . . . . . . . . . . . . . . . . . . . . . . . . 100

2.9 Labor supply fixed effect estimates (I) . . . . . . . . . . . . . . . . . . . 101

2.10 Labor supply fixed effect estimates (II) . . . . . . . . . . . . . . . . . . 102

2.11 Labor supply estimates for singles (I) . . . . . . . . . . . . . . . . . . . 104

2.12 Labor supply estimates for singles (II) . . . . . . . . . . . . . . . . . . 105

2.13 2.B1: Summary statistics - Wage model . . . . . . . . . . . . . . . . . . 113

2.14 2.B2: Heckman wage model . . . . . . . . . . . . . . . . . . . . . . . . 114

2.15 2.B3: Robustness checks (I) . . . . . . . . . . . . . . . . . . . . . . . . 115

2.16 2.B3: Robustness checks (II) . . . . . . . . . . . . . . . . . . . . . . . . 116

2.17 2.C1: Evolution of sex ratios . . . . . . . . . . . . . . . . . . . . . . . 117

2.18 2.C2: Heckman log-wage model estimates (I) . . . . . . . . . . . . . . . . 118

2.19 2.C3: Heckman log-wage model estimates (II) . . . . . . . . . . . . . . . 119

2.20 2.C4: Heckman log-wage model estimates (III) . . . . . . . . . . . . . . . 120

2.21 2.C5: Heckman log-wage model estimates (IV) . . . . . . . . . . . . . . . 121

2.22 2.C6: Robustness checks (I) - Crisis . . . . . . . . . . . . . . . . . . . . 122

2.23 2.C7: Robustness checks (II) - Crisis . . . . . . . . . . . . . . . . . . . 123

2.24 2.C8: Robustness checks (III) - Legal marriages . . . . . . . . . . . . . . 124

2.25 2.C9: Robustness checks (IV) - Legal marriages . . . . . . . . . . . . . . 125

2.26 2.C10: Robustness checks (V) - Extensive margin . . . . . . . . . . . . . 126

2.27 2.C11: Robustness checks (VI) - Extensive margin . . . . . . . . . . . . . 127

2.28 2.C12: Robustness checks (VII) - Region F.E. . . . . . . . . . . . . . . . 128

2.29 2.C13: Robustness checks (VIII) - Region F.E. . . . . . . . . . . . . . . 129

2.30 2.D1: Labor supply estimates for Spanish regions . . . . . . . . . . . . 133

2.31 2.D2: Labor supply estimates for Aragón . . . . . . . . . . . . . . . . . . 134

3.1 Sample sizes, by country . . . . . . . . . . . . . . . . . . . . . . . . . . 143

3.2 Summary statistics, EU-SILC 2003-2016 . . . . . . . . . . . . . . . . . . 144

3.3 Summary statistics, EU-SILC 2011 special module . . . . . . . . . . . . 145

3.4 Fixed effect estimates . . . . . . . . . . . . . . . . . . . . . . . . . . . 155

3.5 Estimates, Special Module . . . . . . . . . . . . . . . . . . . . . . . . . 158

3.6 3.A1. Fixed effect estimates – additional results . . . . . . . . . . . . . 163

3.7 3.A2. Interaction estimates . . . . . . . . . . . . . . . . . . . . . . . . . 164

3.8 Table 3.A3. Working children and adults . . . . . . . . . . . . . . . . . 165

3.9 Table 3.A4. Estimates, Special Module – additional results . . . . . . . 166

3.10 Table 3.B1. Fixed effects estimates for single-parent households . . . . 169

3.11 Table 3.B2. Fixed effects estimates for single-parent households, special module . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 170