Universitat Autònoma de Barcelona

Essays on Family, Health Inequalities and Labor Dynamics

Yuliya Kulikova

Universitat Autònoma de Barcelona

Facultat de Ciències Econòmiques

Departament d'Economia i d'Història Econòmica

Doctorat en Anàlisi Econòmica

Doctoral Thesis

Essays on Family, Health Inequalities and Labor Dynamics

Author:
Yuliya Kulikova

Supervisors:
Dr. Nezih Guner

Dr. Ana Rute Cardoso

April 2016

Acknowledgments

Every now and then in our life it is good to stop for a while and look backwards, evaluate what was has been achieved and build new plans for future. It looks like finishing this dissertation is one of such moments for me, a moment to make a brief pause, think about a several-years journey that is called "Graduate School" and especially thank all those people who made it possible, who were nearby during these very interesting, challenging but sometimes tough and stressful times.

First and foremost, I would like to thank my best advisor ever, Nezih Guner. Nezih, I am an extremely lucky and happy person to be your student, truly, you cannot dream for a better teacher. I admire you not only because you are the great researcher with great ideas, but also you as a personality, curious about everything around us, easily breaking the borders between different fields and acquiring new interests, so caring about everyone around you, so supportive, patient and encouraging. Every time when something was going wrong with my research, I was entering your office broken, lost and hopeless, and I was leaving it engaged, optimistic and ready to move mountains. I can not thank you enough for everything you have done for me.

Another person that affected me in so many positive ways and who helped me a lot throughout the PhD is Joan Llull, my coathor, who became a real friend. Joan, I've learned so much from you! You opened new fields for me and definitely shaped my scientific interests. It felt so good working until late, on weekends or in summer, knowing that the next door there was someone else, who is working hard, setting high standards for himself. Thank you for your every day smile, willingness to talk even under the time pressure and you excitement about the world.

There are many other professors in the IDEA and IAE that I would like to acknowledge. Ana Rute Cardoso – for your kindness and for giving a chance to finance my studies. Miguel Ángel Ballester – you spend an eternity explaining me the sequence spaces, thank you for believing in me and for your patience. Maite Cabeza, Michael Creel, Juan Enrique Martínez-Legaz – for a great teaching assistantship experience, I have learned a lot from you. Kiku Obiols – for your enormous optimism, constant jokes and support, your enthusiasm in discussions and a lot of feedback. Jordi Caballé, David Pérez-Castrillo, Inés Macho, Pedro Rey, Tomás Rodríguez-Barraquer, Johannes Gierlinger – your support and advice during the job market time was invaluable. Hannes Mueller and (again) Joan Llull – for beautiful passionate discussions in applied group. Javier Fernández Blanco, Sekyui Choi, Angela Fiedler, Joachim Jungherr – for profound discussions on the best macro papers and for understanding that even if you understand things there are a lot more things in them to understand. Special thanks to Evi Pappa – the fountain of creativity, in discussions with you I always felt energy and passion about research.

Àngels, Mercè, you were always there to help. Without you all the bureaucracy issues would become just a nightmare. Thank you for eagerness to help and for your smiles.

I would like to thank Gustavo Ventura for hosting me during my visiting period of

Arizona State University. My time there was crucial for maturing as an professional.

I acknowledge financial support from the Spanish Council for Scientific Research (CSIC) and from the Spanish Ministry of Economy and Competitiveness, through fellowship CSIC-JAE-PreDoc JAEPre002_2010_01226 and Grant ECO2013-49357-EXP.

A lot of thanks to my very best colleagues and amazing officemates: Francesco, Isabel, Benjamin, Dilan, Alberto, Javi, Alex, Edgardo, John, Tugce, Guillem (Vasya), Rodica; to my "academic brothers and sisters" – Andrii, Matt, Alessandro, Lesha, Alejandra, Ezgi, Chris, Efi. It was a great pleasure to share this part of my life with you. Arnau and Dima, you are my specials, you were always the first ones to discuss ideas, news and problems, thanks for making this journey together. I was missing you so much during my job market year!

My beloved friend Anechka, I am indebted to you, you put so much faith in me, that I always feel I cannot fail you, thanks for staying so close being so far. Gratitude to my dearest friends Tanechka, Katya, Natasha, Max, everyone else, who found time to come and visit – the time I spent with you walking around amazing Barcelona, balanced the pleasure of constant work with the pleasure of leisure activities. And a huge thank you goes to everyone in the Kondrashov's lab, my Barcelona family: Margo, Inna, Natalia, Dima, Petya, Anyuta, Dinara, Julia, Karen, Katya, Masha, Vika.

My dear family, Valentina, Alexander, and Anton, thank you for your unconditional support in every decision I make. You were always with me despite geographical distance and a big difference in time zones, at the times of downs when I mostly needed you, and in the times of ups just being happy for me. Habibik, my love, my inspiration, without you this journey would just not happen. Thank you for "the pleasure of finding things out", and thank you for your care and love.

A new chapter is opening.

Contents

List of Tables

List of Figures

Introduction

It's hard to overestimate the role of family in our lives. Starting from the initial endowments that we get from our parents through genes, continuing with parental investments into our education, health, personality, to the choices that we make ourselves for creation of our own families: giving birth to children, passing them our genes and participating in their life in so many ways. As an economist, I am extremely interested in the way families affect socioeconomic outcomes, such as health, education, labor supply, and income. This thesis consists of three chapters in which I consider family as a basic unit of the decision-making in the economy and I study the implications of these decisions for health inequalities and labor supply, very important socioeconomic outcomes. In the first chapter of this thesis I study the role of health, health policies, and parental investments into their children, for transmission of income over generations within the same family. In the second chapter I look at family dynamics itself and investigate what is the role of marital status for health inequalities in the society. In the last chapter, I study how decisions at the family level may affect labor market dynamics.

In the first chapter of this thesis, named *"Health Policies and Intergenerational Mobility"*, I study the role of health inequalities and health policies for income persistence over generations within family in the United States. According to recent estimates (Solon, 2002; Mazumder, 2005), the intergenerational correlation of income in the U.S. is high, around 0.4 to 0.6. This results in very different opportunities for children from rich and poor families. So, children of the families in the upper income quintile have 32% probability of staying in the upper income quintile, while only 9% of children from the families in bottom income quintile will reach the top income quintile during their lifetime. What is the importance of health and health policies for social mobility and inequality in the U.S.? While the role of education and education policies received a lot of attention in the literature on intergenerational mobility, we know very little about the role of health policies. This is rather surprising since, like education, health is persistent across generations, and affects an individual's lifetime income both directly (through limiting his capabilities) and indirectly (through its effect on human capital accumulation). This chapter is devoted to investigation of the importance of health and health policies for intergenerational income persistence and income inequality. I develop and estimate an overlapping generations model populated by heterogeneous households. I distinguish two forms of human capital: human capital, that is an innate ability enhanced by education, and health capital, which affects human capital accumulation during childhood and an individual's capabilities (how much he can exploit his human capital) as an adult. Hence, in the model households differ by health and human capital of parents and children. They also differ, however, by their family structure (single parents versus married couples) and fertility status (some households are childless while others have children in different points in their life-cycle). The model takes into account multidimensionality and dynamic and self-productive nature of human capital investments (as in Cunha, Heckman and Schennach (2010)). When deciding on investments into their children's health and education, parents take into account government policies on health and education. Government provides subsidies for early and late (college) education. It also runs a means-tested medical insurance program which is modeled to capture the key features of the Medicaid program in the U.S. Besides means-tested public insurance, the households also have access to private health insurance. I bring this structural model to the data and replicate important data moments for the U.S., related to insurance market, education, and health; and then I perform several counterfactual experiments with medical and educational policies. I find that both medical and education policies affect intergenerational mobility in the U.S. significantly, although the scale of the effect on average is moderate. There are important interactions between health and education policies. Changes in both policies have a larger effect than each one in isolation. Especially this interaction effect is important for children of the lowest income quintile. When Medicaid is eliminated, parents face a trade-off between spending their resources on education versus on health of their children. However, if we eliminate both educational policies together with the Medicaid policy, this trade-off becomes much more significant, especially for poorer households. As a result, we observe a huge increase in parental decisions gap regarding their investments in health and education of their children. If richer parents have resources to substitute for lost governmental investments into health and education of their children, poor households are constrained. They try hard to substitute for lost health policies but they give up on investments into education as health and ability are complements, and investments into education become inefficient for them. For rich parents the decisions look very different, they sacrifice slightly with their investments into health which results in slightly lower health levels for children, however they increase a lot investments into education to ensure high human capital for their children by the time of entering labor market. Thus, the gap in health between children from rich and poor households persists, the gap in ability between rich and poor children increases a lot, which results in higher income persistence and lower mobility in general.

In the second chapter of this thesis *"Marriage and Health: Selection, Protection, and Assortative Mating"* (joint with Nezih Guner and Joan Llull), we study how marital status affects health inequality. Married people are healthier than non-married people along the entire life cycle, with the difference of 3% in self-reported health for younger individuals and up to 12% at ages 50-60 years. There are two ways to interpret these results. First, marriage could have a protective effect, with marriage helping to ensure healthier food, more exercise or a reduction in risky behavior. Second, the difference could be attributed to selection into marriage whereby healthier people have higher probability to marry and stay married. We used panel data techniques, such as within-group estimation, grouped fixed effect estimation (like in Bonhomme and Manresa (2015)) and system generalized method of moments estimation (like in Arellano and Bover (1995)) to control for unobserved heterogeneity. We find that both selection and protective effects of marriage contribute to the difference at large, however, selection explains all of the effect for younger individuals, with a 6% protective effect of marriage for middle aged couples. We find that the benefits of marriage on health are cumulative, with 10 extra years of marriage increasing the probability of being healthy by about 3 percentage points remaining roughly constant after 35-39. We then explored possible mechanisms of marriage protection effects. Our results show that there are significant differences between married and single individuals for all categories of preventive care, access to health insurance, healthy behavior and medical expenditures. Thus, even though the selection effect into marriage is rather large, marital status appears one of the determinants of health inequality over the life cycle.

In the third chapter of this thesis, *"Household Labor Market Dynamics"*, coauthored with Nezih Guner and Arnau Valladares-Esteban, we study the role of labor supply decisions within family for the labor market dynamics. Why do we think it is important to look at households rather than individuals? On the one hand, family provides insurance from negative labor market shocks. As a result, an unemployed married person can rely on his partner's income while looking for a suitable job. On the other hand, having a partner may constrain job market options for dual career concerns (Guler, Guvenen and Violante, 2012; Browning, Chiappori and Weiss, 2014). Understanding the link between families and labor market outcomes, such as unemployment, may be important not only for explaining the evolution of unemployment, but also for labor market policies. In this chapter we study the joint labor market transitions of married couples between three labor market states: employment, unemployment, and out of the labor force. The results show that joint labor market transitions are important to understand both the secular rise in aggregate employment and the cyclical movements in unemployment. Following a decomposition exercise proposed by Shimer (2012), we assess the importance of different labor market transitions for married males and females. The results show that married men and women differ in their labor market dynamics. The transition between employment and unemployment is the key driver of cyclical movements in unemployment for married males. For married females, however, transitions in and out of the labor force play a key role. Hence modeling out of labor force as a distinct state is critical to understand joint labor market dynamics of married couples. The results also show that joint labor market transition of husbands and wives is affected by the coordination between labor market activities of household members. In particular, we concentrate on analysis of the "added worker effect", one of the ways spouses coordinate that results in an increase in married women's labor supply in response to their partner's unemployment spells. Previous literature, e.g. Lundberg (1985), Stephens (2002) and Juhn and Potter (2007) show that women's labor supply is quite responsive to their partner's entry into unemployment. We find that without the added worker effect, female labor participation and unemployment rates in 2000-2010 period would be about 2.5 and 0.3 percentage points higher, respectively. This 0.3 percentage points represents about 6.16% of the female unemployment rate. On the other hand, the added worker effect lowers the fraction of households with no employed members by about 0.4 percentage points in the same period, which is a significant (about 13.3%) of the fraction of households with no employed members.

Chapter 1

Health Policies and Intergenerational Mobility

1. Introduction

Parental characteristics, such as education, earnings, income, and health are strongly correlated with the same outcomes for children. Estimates of intergenerational elasticity of income, a common measure of intergenerational mobility, varies around 0.4-0.6 for the US – Solon (2002), Solon (2004), Zimmerman (1992), and Mazumder (2005).[1] These estimates imply that if a parent is 10% richer than the average person in the economy, his sun is likely to be 4-6% richer as well.[2] Intergenerational elasticity of life span of parents and children in the US is 0.28, and it is higher for father-son (0.356) and mother-daughter (0.32) pairs – Parman (2012). Furthermore, intergenerational mobility is closely related with inequality in a society. In societies with higher income inequality social mobility is lower, especially at the tails of the income distribution. This relation is called "Great Gatsby Curve", see Corak (2013), and it makes the "lottery" in which family a child is born in even more important – Chetty, Hendren, Kline and Saez (2014).

Recent literature shows that initial (pre-labor market conditions) are very important in determining later labor market outcomes of children. For example, Keane and Wolpin (1997) find that unobserved heterogeneity at age 16, explains about 90% of variation in lifetime utility. Huggett, Ventura and Yaron (2011) find that differences in initial conditions (human capital and wealth) at age 23 are more important than shocks received over the working lifetime for the variation in lifetime earnings, lifetime wealth, and lifetime utility. The key question is of course what determines initial conditions of children.

First, genes, or as it is labeled in the literature, nature matters: parents with better health/ability are more likely to give birth to more healthy/able children. Second, nurture, the environment in which children grow, plays an important role. Family background, such as education, parental abilities, health, and earnings determines the environment in which a child is growing up. If parents are educated, healthy and rich, the child most

[1] Corak (2013) and Guner (2015) review the recent literature on intergenerational mobility.

[2] Intergenerational income elasticity is calculated by regressing the log earnings of sons on log earnings of fathers, controlling for ages of both. However, there are other ways of estimating degree of intergenerational mobility. For example, Chetty et al. (2014) use correlation of parent's and child's income percentile ranks or calculate transition probability of moving from the bottom quintile to the upper one, while Güell, Mora and Telmer (2015) and Clark (2014) use joint distribution of surnames and economic outcomes to study intergenerational mobility.

probably will also be educated, healthy and rich. But what if parents are poor, not educated or not healthy? Their children are disadvantaged comparing to the children of healthy, educated and rich parents. The government policies then can play a role and try to equalize opportunities for all children, independently of their family background. Providing access to education and to health facilities, government may counteract the role of parental earnings and disadvantaged environment at home.

Education is known to be an excellent social lift (Restuccia and Urrutia (2004), Caucutt and Lochner (2012), Lee and Seshadri (2014)). On the other hand, we know almost nothing about how medical policies affect intergenerational mobility and inequality. To the best of my knowledge there are only few empirical papers devoted to this question. Mayer and Lopoo (2008) analyze association of total government spending and intergenerational mobility, using variation in the amount of government spending in different US states. They find that higher government spending reduce the importance of parental income for the economic success of children. Furthermore, Aizer (2014) analyzes empirically the relation between intergenerational mobility and different welfare policies, such as foster care, family planning, income transfer programs, residential mobility interventions, educational interventions and public health. Among all welfare policies she considers, increases in spending on health are most strongly associated with reductions in the importance of family background and declines in inequality in the production of child human capital (measured as PISA test scores among 15 year-olds). Case, Lubotsky and Paxton (2002) study health-income gradient, i.e. that children born to low-income parents tend to be in worse health status than children born to high-income parents. They find that neither health at birth, nor access to health insurance affects estimates of health-income gradient, and conclude that health affects intergenerational mobility through other channels, such as parental investments into health. Finally, O'Brien and Robertson (2015), study how Medicaid expansion of 1980s and 1990s affected intergenerational mobility using geographical variation in policy changes and find a positive, but not very large, effect of Medicaid on mobility. They find that increasing the proportion of women aged 15-44 eligible for Medicaid is associated with reduction in rank correlation of incomes of parents and children. They also find that children born to low-income parents after Medicaid expansions are more likely to move upwards. Brown, Kowalski and Lurie (2015) also show that Medicaid expansion affected child's income significantly positively, however they were not studying implications of this for intergenerational mobility. Cohodes, Kleiner, Lovenheim and Grossman (2014) explore the same Medicaid expansion of 1980s and 1990s and find that it had a substantial positive effect on child's schooling outcomes. Hence, while there is some evidence that suggests that health is important for intergenerational mobility, there has not been any attempts to understand the mechanisms through which health and health policies affect intergenerational mobility.

Meanwhile the U.S. government spends significant amount of resources on needs-based medical policies. In June 2013, over 28 million children were enrolled in Medicaid and another 5.7 million were enrolled in State Child Health Insurance Program (SCHIP).[3] Yet, according to 2012 National Health Interview Survey[4], 36% of families with children in the United States experienced financial burden of medical care, such as problem paying medical bills in the past 12 months, having currently medical bills that they are unable to pay, having currently medical bills that are being paid over time. Poorer families are

[3]Source: http://kff.org/health-reform/issue-brief/childrens-health-coverage-medicaid-chip-and-the-aca/

[4]Source: http://www.cdc.gov/nchs/data/databriefs/db142.htm

more likely to experience burden of medical care than the richer ones. In particular, families with income between 139% and 250% of Federal Poverty line (FPL) are affected the most, and this is exactly the group that is not always covered by Medicaid and SCHIP. On the other hand, government policies can also crowd out family investments (Cutler and Gruber 1996). How do then parents allocate their limited recourses between medical expenses and expenditures on other forms of human capital, such as education? Is poor health of children a barrier for upward mobility? How do a large-scale policy intervention, like Medicaid, affect intergenerational mobility and inequality? How do policies on health and education interact? These are the questions I try to answer in this thesis chapter.

I develop a human-capital based overlapping generations model of household decisions that take into account multidimensionality and dynamic nature of human capital investments. Following Grossman (1972), I model health as a human capital and hence distinguish two forms of human capital: health capital and human capital (ability). I assume that human capital eventually determines person's productivity while health capital determines physical capacity of acquiring and enjoying productivity. I follow Cunha, Heckman and Schennach (2010) and allow for dynamic complementarity and self-productivity of human capital.[5] These two factors produce a multiplier effect since one type of human capital enhances production of the other type of human capital.

Parents decide on consumption and investments into human and health capital of their children. These investment decisions, together with intrinsic health and ability that is correlated across generations, determine future health and productivity of children when they become adults. Health and human capital of adults define their physical ability to work and labor market productivity. I model explicitly governmental policies in education and health. Government provides educational spending on primary and secondary education, as well as income-based subsidies for college education. Furthermore, it provides income-based medical policy that closely mimics Medicaid in the U.S.

In this chapter I replicate important data moments for the US and then I perform several counterfactual experiments with medical policies. Results show that Medicaid as well as both education policies (early and late) affects intergenerational mobility in the US. There are important interactions between health and education policies. Changes in both policies have a larger effect than each one in isolation. Especially this interaction effect is important for children of the lowest income quintile. When Medicaid is eliminated, parents face a trade-off between spending their resources on education versus on health of their children. When both college subsidies and Medicaid are eliminated, this trade-off becomes much more significant, especially for poorer households. As a result, we observe that poor households do not invest into early education at all (and also they don't go to college in absence of college subsidies), while richer households substitute health investments (and as a result lower health level) by higher educational spending (and as a result higher ability).

The remainder of the chapter is organized as follows: in section 2 I provide a short literature review, section 3 is devoted to the model description, section 4 presents model estimation strategy and benchmark model, in section 5 on can find results for the counterfactual experiments, section 6 concludes.

[5] Self-productivity means that human capital produced at one stage make further human capital production more efficient. Dynamic complementarity means that levels of human capital investments at different ages are synergistic and fortify each other.

2. Related Literature

This work is naturally related to the large literature on intergenerational mobility and inequality. This literature dates back to Becker and Tomes (1979, 1986) and Loury (1981), who explore implications for intergenerational mobility of credit constraints and ability persistence over generations. Following their seminal contributions, a large body of literature is devoted to understand sources of intergenerational mobility and inequality as well as how different public policies affect them.

First, it is well known that inequality and social mobility are negatively correlated (Corak, 2013). However, policies that mitigate inequality do not necessarily work well to increase intergenerational mobility (Becker, Kominers, Murphy and Spenkuch, 2015).

Second, recent literature shows that parental investments into human capital (education) is a very important channel for intergenerational correlation of incomes. Becker et al. (2015) in their theory of intergenerational mobility find that even in a world of perfect capital markets with no differences in ability rich parents tend to invest more into their children's human capital than poor parents and as a result in the top of distribution earnings persistence is stronger than in the middle. There is a very large literature that shows that early childhood investments are very important in determining human capital of a child when he becomes adult (Cunha and Heckman, 2007; Cunha, Heckman and Schennach, 2010; Heckman, Yi and Zhang, 2013). Family environment along with family in vestments play a crucial role in this process (Carneiro and Heckman, 2003; Cunha, Heckman, Lochner and Masterov, 2006). Lefgren, Lindquist and Sims (2012) examine two transmission channels for intergenerational persistence of income: causal effect of parental income and causal effect of parental human capital. They find that both channels are active, around 37% is due to the causal impact of father's financial resources, the remainder is due to the transmission of father's human capital. Restuccia and Urrutia (2004) build an overlapping generations model with early and late investment in human capital. Their simulations show that around half of intergenerational correlation in earnings is attributed to parental investments into education (particularly, early education). Building a similar model, Caucutt and Lochner (2012) suggest that financial constraints might prevent parents from effective investments into their children. And as a result differences in initial conditions by the age of 20-25 explain up to 60% of variation in lifetime earnings, according to Huggett et al. (2011).

Third, government can intervene and affect both, intergenerational mobility and inequality. Lee and Seshadri (2014) also build an overlapping generations model with early and late investment in children human capital. They also allow on-the-job human capital investments for adults. They find that education subsidies and progressive taxation can significantly reduce the persistence in economic status across generations. However, it should be kept in mind that government investments can crowd out family investments, that's why it is important to keep in mind family responses to changes in government policies (Cutler and Gruber, 1996).

Finally, institutional differences matter. Herrington (2015) compares the US and Norway in mobility and inequality and finds that tax system and public education spendings are responsible for about one-third of difference in inequality and 14% difference in intergenerational earning persistence between Norway and the US. Mayer and Lopoo (2008) assess the relationship between government spending and intergenerational economic mobility using PSID data and find greater intergenerational mobility in high-spending states compared to low-spending states. They also find that the difference in mobility between advantaged and disadvantaged children is smaller in high-spending states and that expenditures aimed at low-income populations increase the future income of low-income children but not high-income children. Rauh (2015) looks at importance of political economy for distributional effects in education and it's implications for inequality and social mobility and finds that voter turnover can explain around one-fourth of cross-country differences in inequality and mobility.

All of the papers mentioned above as well as others in the literature abstract from health, and human capital is simply modeled as a function of parental and public investment on education. The only exception is Heckman et al. (2013) who also consider health as one of the dimensions of human capital. They show that early health shocks negatively affect all dimensions of child human capital: health, education, socioemotional skills and this effect is very important for policy implications.

On the other hand, the literature on health comes to a conclusion that health is very important in determining later life outcomes. Currie and Gruber (1996a,b) study the effects of the Medicaid expansion to pregnant women and low-income children and find big positive effect for children's health and negative effect for child mortality. Prados (2013) quantifies the health-income feedback and states that it accounts for 17% of earnings inequality. In seminal Grossman (1972)'s paper the notion of health capital is introduced and health is modeled as a result of investments into health and it's depreciation over time. This gave rise to macroeconomic models that incorporate health risks in a life-cycle framework. Attanasio, Kitao and Violante (2010), for example, study tax implications due to projected rise in medical spending financed through Medicare – governmentally provided partial insurance against negative health shocks for older people. Palumbo (1999) and De Nardi, French and Jones (2010a) study saving decisions of the elderly and the role of medical shocks in savings behaviour, Jung and Tran (2014) study medical expenditure behavior over the life cycle, separating pure age effects and cohort effects. Ozkan (2013) studies differences in the lifetime profile of health care usage between low- and high-income groups and finds that policies encouraging the use of health care (especially preventive) by the poor early in life have significant welfare gains, even when fully accounting for the increase in taxes required to pay for them. Kopecky and Koreshkova (2014) evaluate joint effect of social security and Medicaid on labor supply, savings, economic inequality and welfare due to idiosyncratic risks in labor earnings, health expenses and survival. Brown et al. (2015) study long-term impact of expansion of Medicaid and State Children's Health Insurance Program that occurred in 1980's and 1990's and find that the government will recoup 56 percent of spending on childhood Medicaid by the time these children reach 60. However, papers on health and health policies typically ignore human capital dimension.

The current work builds a bridge between literature on health and health policies on the one hand and human capital and human capital policies literature on the other and provides a more structural model to look at the relationship of health and health policies, their interaction with educational policies and intergenerational mobility.

3. The Model

Consider the following overlapping generations model. Time is discrete and the horizon is infinite. Each household consists of one child and parents. Parents can be single mothers or married couples (who act as a single decision making unit). Marital status of parents is denoted by $\theta = 0$ (single) and $\theta = 1$ (married). Each model period corresponds to 7 years. Each person lives for 8 periods: 3 as a child (0-7, 8-14, 15-21), denoted by j, 5 as adult (22-28, 29-35, 36-42, 43-49, 50-57), denoted by t.

Fertility is exogenous; when a person becomes an adult, after 3 periods of childhood, she can have no child or one child that is born in the 1st (22-28), 2nd (29-35) or 3rd (36-42) period of the adulthood. The childbearing status is denoted by $b = 0$ (childless), $b = 1$ (early childbearers), $b = 2$ (middle-age childbearers), and $b = 3$ (late childbearers).

Besides marital status and fertility, households differ by human capital of parents and children. I allow for multidimensionality of human capital. Each child has bidimensional human capital: health capital (h) and other types of human capital (a). The latter includes cognitive and socioemotional skills. Similarly, each parent has her health capital (H) and human capital A (whenever possible I use capital letters to indicate parental variables). Human capital determines earnings potential of an adult, while health determines how much labor he can supply.

If a family does not have children, it just consumes everything. If there is a child, households make two sets of decisions. First, they decide whether or not to buy medical insurance for their children. Then, they decide how much to spend on his education and health. There is also a government in the economy that provides health insurance for poor households. The government also gives education subsidies. While the education subsidies are universal for early education, they are income based for late (college) education.

Children are born with innate health (a^*) and innate ability (h^*), which are correlated across generations. Innate ability, together with investment by parents, government policies and luck, transforms into future ability of a child and eventually determines his productivity as an adult. Similarly, innate health, together with health spending by parents, government policies and luck, transforms into future health of a child and eventually into his health status as an adult.

Parents make decisions to maximize their lifetime utility and are altruistic, i.e. they care about their offspring's utility when they become adults. Thus, they care about leaving their children with high levels of health and human capital. I abstract from assets and physical capital in the model. There is no aggregate uncertainty as well.

3.1. Health, Ability and Human Capital

Human capital is bidimentional, it consists of health capital and human capital. I use the term human capital and ability interchangeably. Ability determines an adult agent's earnings potential. Health capital, on the other hand, determines the quantity of labor supplied by an adult individual on the labor market. For children, current ability and health are inputs for the production of future ability. After three periods with their parents, children become adults and their human capital and health capital determines their ability (productivity) and health as adults.

A central feature of the model is health and human capital production. Following Cunha, Heckman and Schennach (2010) I allow for dynamic complementarity and self-productivity of human capital. Children start their life with innate health h^* and innate ability, a^*, randomly drawn and correlated with their parent's innate health and ability. Let $\Gamma_{a^*|A^*}$ and $\Gamma_{h^*|H^*}$ represent the Markov processes for innate ability and health, where A^* and H^* are innate ability and health of parents.

Given $h_1 = h^*$, during the childhood, next period's health depends on previous period's health, medical spending by parents, denoted by m, and a health shock, denoted by υ. In particular, I assume that health status takes two values, good or bad, and the probability that next period health is equal to h_k, $k \in \{good, bad\}$, is given by the following logit relation

$$Pr(h' = h_k|h, m) = \Lambda(\alpha_0^h + \alpha_1^h h + \alpha_2^h m + \alpha_3^h h \cdot m), \tag{1.1}$$

where Λ is the logistic function. It is assumed that υ is independent and identically distributed with zero mean and variance σ_υ^2. I allow these production functions be different in the early childhood (period 1 and 2) and late childhood (period 3).

After 3 periods of childhood, children become adults and health in the first period of adulthood is given by

$$Pr(H_1 = H_k|h, m) = \Lambda(\alpha_{30}^h + \alpha_{31}^h h + \alpha_{32}^h m + \alpha_{33}^h h \cdot m). \tag{1.2}$$

Once H_1 is determined, future health as an adult is given by an exogenous process $Q_{H'|H}$, which captures life-cycle health transitions. Adult's health determines the number of hours an adult can work, denoted by $T_t(H)$. It is assumed that the effect of health on hours work depends on the age of the parent.

Every period parents and government invest into child's ability. These investments, together with the current health and ability, determines next period's ability. The process is, however, not deterministic and each period there is a shock for ability accumulation, denoted by ε. It is independent and identically distributed with zero mean and variance σ_ε^2.

In the 1st and 2nd periods, government provides each household with g units of resources to invest on their children. Given g, parents can complement them with private educational spending, denoted by $e \geq g$. Ability production function in the 1st and 2nd childhood periods take as inputs previous ability and health, amount of parental spending into education, as well as the random shock, ε_j. As health, human capital also can take two values, low and high, and the probability that next period's ability is equal to a_k, $k \in \{high, low\}$ is given by a logit function:

$$\begin{aligned} Pr(a' = a_k|a, h, e, A) = \Lambda(&\alpha_0^a + \alpha_1^a a + \alpha_2^a h + \alpha_3^a e + \\ &\alpha_4^a \cdot a \cdot e + \alpha_5^a \cdot h \cdot a + \alpha_6^a A + \alpha_7^a A \cdot e) \end{aligned} \tag{1.3}$$

In the 3rd period of childhood, parents make a decision whether or not to send their child into college. The college tuition is denoted by E. Depending on their income, parents qualify for subsidies to cover this tuition. If they don't send their children to college, children participate in the labor market during the last period of their childhood. Children then supply $t_3(h_3)$ hours in the market and contribute to household income.

After three periods of childhood, accumulated ability, health, along with decision on college education, determines the productivity of the child as an adult, A_1. The process is also subject to a shock ε_3, normally distributed with zero mean and variance σ_{inc}^2, which captures the fact that within a cohort, earnings vary and more than one-third of the variance is attributable to post-education factors (Huggett et al., 2011). A_1 is determined in the following way. First, for each child the following value Π is calculated:

$$\Pi = \alpha_{30}^a + \alpha_{31}^a a + \alpha_{32}^a h + \alpha_{33}^a col + \alpha_{34}^a \cdot a \cdot h + \alpha_{35}^a \cdot h \cdot col + \alpha_{36}^a \cdot a \cdot col + \varepsilon_3. \tag{1.4}$$

Then four threshold income levels x_1, x_2, x_3, and x_4 are selected such that about 20% of children are in the first, second, third, fourth and fifth quintiles of a normal distribution with zero mean and variance σ^2_{inc}, and each child is placed into the corresponding income quintile as an adult.

Starting from the first adult period, ability, A_1, is characterized by the productivity quintile of an adult and is subject to an exogenous stochastic process, $Q^{\theta}_{A'|A}$ that captures life-cycle behavior of productivity and is specific to the marital status θ.

3.2. Government

Government taxes income at a proportional tax τ and spends tax revenue on education and health. Governmental budget is balanced:

$$\tau Y = G + F + S,$$

where Y is the total income in the economy, G is the total spending on primary and secondary education, F is the total spending on college subsidies, and S is the total spending on Medicaid/SCHIP.

Education Policy In the US, primary and secondary education is obligatory and is guaranteed for all children of the age 5 to 18.[6] While young (2 to 5 years old) children can attend pre-kindergarten, these classroom based preschool program are run by private organizations and parents need to pay or them. There are, however, several government-funded programs (such as Head Start) that target mostly disadvantaged children.

In this chapter I assume that governmental educational spending for children in periods 1 (0-7) and 2 (8-15) are equally distributed among all children and parents can supplement governmental spending. At this stage I ignore any other programs, such as Head Start.

While they are in college, children can receive governmental federal grants for their studies. In the model government also provides income-based college subsidies. Functional form of the college subsidy is chosen to be rather general. For a household with income level $T_t(H)A$, it is given by

$$\kappa(T_t(H)A) = \max\{0, E - \kappa(AT_t(H))^{\phi}\},$$

where E is tuition cost, κ is the slope of the subsidy function and ϕ is a curvature parameter.

Medical Policy In the U.S., the government subsidizes children's health investments through Medicaid and State Children's Health Insurance Program (SCHIP) programs. Medicaid is a means-tested, needs-based social welfare and social protection program. Eligibility is categorical; some of these categories include low-income children below a certain age, pregnant women, parents of Medicaid-eligible children who meet certain income requirements, and low-income adults and seniors. A child may be eligible for Medicaid regardless of the eligibility status of his parents. In the 1997-2011 period all children from birth to age 5 with family incomes up to 133% of the Federal Poverty Line (FPL), that is about \$24,644 for a family of three in 2011, were eligible for Medicaid coverage. For children of age 6-18 the threshold was a little lower - 100% of FPL (\$18,530 for family of 3 in 2011).[7]

[6]Depending on the state with permission of parents child can drop out before he turns 18

[7]Source:http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Financing-and-Reimbursement/Downloads/Pov-Level-2011.pdf

SCHIP was designed to cover uninsured children in families with incomes that are modest but too high to qualify for Medicaid. States are given flexibility in designing their CHIP eligibility requirements and policies within broad federal guidelines. In general, in all states children from birth through age 19 who live in families with incomes above the Medicaid thresholds and up to around 241% of FPL on average are eligible for SCHIP (North Dakota currently has the lowest level at 160% of FPL. New York currently has the highest level at 400% of the FPL.)

The Affordable Care Act (ACA, known also as ObamaCare) was enacted in March 2010 and took effect in January 2014. It increases the level of eligibility for Medicaid for children of 6-18 years old from 100% of FPL to 133% of FPL (effectively to 138% of FPL due to a special deduction to income of 5% while determining Medicaid eligibility). It expands affordable Medicaid coverage for millions of low-income people that were not eligible for Medicaid before. Adults of the age 19-65 with the income lower than 133% of FPL (which is effectively 138%) now have a chance to get Medicaid in states that expanded Medicaid coverage according to ACA. However, there are some issues with implementation of Obamacare on the state level. States might reject implementation of Medicaid expansion. Now there are 29 states that expand Medicaid and 22 states that do not expand Medicaid. If a person lives in a state that does not expand Medicaid coverage, she still might be able to receive Medicaid if her income is less than 100% of FPL. For the purposes of this chapter I will consider that all adults of the age 19-21 are not different from children of age 6-18 in terms of Medicaid eligibility and have the same 100% FPL eligibility threshold.

Health Insurance in the Model Economy I model governmental policy with respect to health in a general way, but try to capture the main features of the current policy in the U.S. If parents have low income, their children are eligible for Medicaid/SCHIP. However, there are some short-cuts I have to make in my model. Actual Medicaid/SCHIP policies have higher threshold to be eligible for Medicaid (133% of FPL) for children between ages 0 to 5 than children of age 6-18 (100% of FPL); and children after age 18 are not eligible. In my model childhood periods are 0-7, 8-14 and 15-21. I assume that health policy does not change within model periods, i.e. those who were eligible until age 5 are still eligible until age 7. And those who were eligible until age 18 are eligible until age 21.[8]

Parents decide on buying private insurance for their child and on the amount of medical spending, taking into account insurance functions. Insurance mechanism is similar to Ozkan (2013). If parents buy private insurance for their child, they pay a tax-deductible insurance premium p_{ins}. Insurance premium is the same for all children of each cohort but might be different for different cohorts. I model insurance premium to be tax deductible as around 85% of private insurances are provided through employers.

If parental income in period j is lower than the threshold $\overline{I_j}$, the child is eligible for Medicaid and SCHIP and parent does not have to pay an insurance premium.[9] I will model insurance functions for private insurance (PRV) and Medicaid/SCHIP (MCD) in the same way. Both of them have a deductible $\eta^{MCD/PRV}$, up to which parents do not receive the reimbursement from insurance company/government, and for each dollar

[8] I abstract from eligibility of teenagers and young adults that got pregnant to Medicaid.

[9] In the data, being eligible for Medicaid and SCHIP does not mean that people enroll into it. Indeed, 8 million children remain uninsured, including 5 million who are eligible for Medicaid and SCHIP but not enrolled (Medicaid website). In this chapter I will abstract from this fact and assume that if child is Medicaid eligible, he is enrolled into the program, except for the case when parents purchased a private insurance for him.

above the threshold $\eta^{MCD/PRV}$, they receive a fraction $\mu^{MCD/PRV}$ as a copayment-rate. Hence, the amount they receive from the government as a subsidy for spending m is given by

$$\chi_j^{MCD/PRV}(m) = \begin{cases} 0 \text{ if } m \leq \eta_j^{MCD/PRV} \\ \mu^{MCD/PRV}(m - \eta_j^{MCD/PRV}) \text{ if } m > \eta_j^{MCD/PRV} \end{cases}.$$

Eligibility for Medicaid/SCHIP indicator is given by

$$\mathcal{I}_j^{MCD}(AT_t(H)) = \begin{cases} 0 \text{ if } AT_t(H) > \overline{I_j} \\ 1 \text{ if } AT_t(H) \leq \overline{I_j}. \end{cases},$$

where $\overline{I_j}$ corresponds to eligibility threshold set up by the Medicaid and SCHIP (which depends on the age of children), A is the productivity of a parent, and $T_t(H)$ is hours devoted by a parent of age t to the labor market (hence $AT_t(H)$ is their total income).

3.3. Household Problem

Households maximize their lifetime utility. The discount factor is $\beta < 1$. The per-period utility from consumption is assumed to take the following functional form

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}.$$

I start by describing the problem of parents who are childless, either because $b = 0$ (i.e. they never had children) or because their children already left the house or are not yet born.

Childless Parents

State space of the household without children is given by $\mathbf{x} = \{A, H, \theta, b\}$, where A is the current productivity, H is the health status, θ is marital status, and b is parental child-bearing status of parents. If a parent does not have any child at home, then she only consumes. Her value function is given by

$$V_{t,0}(\mathbf{x}) = \max \{u(c) + \beta E_{A',H'} V_{t+1,j}(\mathbf{x}')\},$$

subject to

$$c = (1-\tau)T_t(H)A,$$

and

$$j = \begin{cases} 0, \; b = 0, \text{ or } b = 1 \text{ and } t > 3, \text{ or } b = 2 \text{ and } t > 4, \\ 1, \text{ otherwise} \end{cases},$$

where τ is the tax rate, $T_t(H)$ is the time that parents devote to labor market as a function of their health. Hence, after-tax income of the household is given by $(1-\tau)T_t(H)A$, and absent any savings they consume their income in the current period. Note that the value functions of parents are indexed both by their age, t, and the age of their children, j. For a childless parent $j = 0$.

Next period, the household will have the same values of θ and b, but will have new draws for A and H, hence $\mathbf{x}' = \{A', H', \theta, b\}$. A household with no children today can still be without any child next period, if $b = 0$ or the children have already left the house. The household can also have a 1-year old child next period, if, for example, $t = 1$ and $b = 2$, i.e. the parents are one-year old and have their children in the second period. The last constraint summarizes how the number of children evolves for the households.

Parents with Children
Consider now the problem of parents with children. We will first start with the problem of a parent whose child is 3 years old and will become adult next period. We assume that each period parents with children decide whether to buy health insurance for the next period, except when their children is just born, i.e. $j = 1$, in which case they have to decide whether to buy health insurance for the current as well as the next (second period). As a result, a parent with a 3-year-old child arrives to the current period with heath insurance decision already made last period when the child was two years old. This decision was made before parents observe their own as well as their children heath and ability outcomes for the next period As a result, health insurance decision for the third period is not made conditional on children's current health. Given this insurance decision from last period, a parent with a 3-years old child decides how much to spend on his child's health. The parent also decides whether to send her child to college, given government college subsidy program. The problem for a parent with a 2-years-old child is quite similar. Given the insurance decision from last period, parents decide how much to spend on health and education of their children, given available government policies. When a parent has a 1-years old child, then he decides whether to buy health insurance for the current period, again before observing his child's current health and ability as well as makes a plan whether to buy insurance for the next period after first period health and ability are realized.

Third Period of Childhood ($j = 3$) Given an insurance decision from the last period, in the third period of the childhood parents take decisions on college education, medical spending, and consumption. The parent is altruistic and she cares about the expected utility of her adult child. As a result, parents are motivated to leave their children with highest possible productivity and health.

State space of a parent with a child in the third period of childhood in the beginning of a period is given by $\mathbf{x} = \{a^*, h^*, \theta, b, a, h, A, H\}$, where a^* and h^* are children's innate ability and health, a and h are child's current ability and health, and A and H are parents' current ability and health.

Given their insurance status (insured, i, or uninsured, u), parents' decision whether to send their children to college is given by the following value function

$$V^i_{t,3}(\mathbf{x}) = \max\{V^{c,i}_{t,3}(\mathbf{x}), V^{nc,i}_{t,3}(\mathbf{x})\},$$

and

$$V^u_{t,3}(\mathbf{x}) = \max\{V^{c,u}_{t,3}(\mathbf{x}), V^{nc,u}_{t,3}(\mathbf{x})\},$$

where superscript c corresponds to sending to college, and nc to not sending to college.

The value associated to each of these outcomes reflects optimal decisions by the parents. The value of sending the child to college and purchasing health insurance, for example, is given by

$$V^{c,i}_{t,3}(\mathbf{x}) = \max_{c,m} \left\{ u(c) + \beta EV_{t+1,0}(\mathbf{x}') + \psi E\hat{V}_{1,j}(\mathbf{x}'_{child,j}) \right\},$$

where $E\hat{V}_{1,j}$ is the expected value of the child when he becomes adult and child's state space when she becomes adult, $\mathbf{x}'_{child,j}$, is defined as her initial productivity level, which is the function $f(a_3, h_3, college, \upsilon_3)$, her initial health that is the function $g(h_3, m_3, \varepsilon_3)$, his marital and child-bearing shock, ψ is the degree of altruism of a parent, to which extent he enjoys utility of his child.

The budget constraint associated to this problem is given by:

$$c = (1-\tau)[T_t(H)A) - p_{ins}] - m + \chi^{PRV}(m) - (1-\kappa(T_t(H)A))E, \tag{1.5}$$

and

$$\kappa(T_t(H)A) = \max\{0, E - \kappa(AT_t(H))^{\phi}\},$$

where where c is consumption, τ is the tax rate, $T_t(H)$ is a function of health that determines parental labor supply, A is parent's productivity, p_{ins} is private insurance premium, m is medical spending, $\chi^{PRV}(m)$ is private insurance reimbursement of medical spending made by parents, E is the tuition fee for college, $\kappa(T_t(H)A)$ is governmental subsidy for college. Hence, the parent has $(1-\tau)[T_t(H)A - p_{ins}] + \chi^{PRV}(m)$ as her income after paying tax deductible insurance premium and receiving reimbursements from the private insurance company. She spends m on health care of her child and $(1-\kappa(T_t(H)A))E$ on college.

In the same spirit, the value function associated to not sending the child to college and not purchasing private insurance is given by

$$V_{t,3}^{nc,u}(\mathbf{x}) = \max_{c,m}\left\{u(c) + \beta EV_{t+1,0}(\mathbf{x}') + \psi E\hat{V}_{1,j}(\mathbf{x}_{child,j})\right\},$$

subject to:

$$c = (1-\tau)[T_t(H)A + t_3(h)a] - m + \chi^{MCD}(m)\mathcal{I}_3^{MCD}(T_t(H)A), \tag{1.6}$$

where $t_3(h)a$ is child's hours supplied to the labor market (child works if he does not attend college) and $\chi^{MCD}(m)\mathcal{I}_3^{MCD}(T_t(H)A)$ is reimbursement of medical spending by Medicaid in case child is Medicaid-eligible, i.e. if $\mathcal{I}_3^{MCD}(T_t(H)A) = 1$.

Second Period of Childhood ($j = 2$) As in the third period of childhood, parents arrive to the second period of childhood with an insurance decision from the last period. Then they decide on medical and educational spending and consumption as well as whether to buy insurance for the next period. State space of a parent with a child in the second period of childhood in the beginning of a period is given by $\mathbf{x} = \{a, h, a^*, h^*, A, H, \theta, b\}$. Then, the value function for an insured child is given by

$$V_{t,2}^{i}(\mathbf{x}) = \max_{c,e,m}\{u(c) + \beta\max\{E_{A',H',a',h'}V_{t+1,3}^{i}(\mathbf{x}'), E_{A',H',a',h'}V_{t+1,3}^{u}(\mathbf{x}')\}\},$$

subject to

$$c = (1-\tau)[AT_t(H) - p_{ins}] - m + \chi^{PRV}(m) - e,$$

$$a' = f(a, h, e, \upsilon), \text{ and } e \geq g$$

$$h' = g(h, m, \varepsilon)$$

and

$$Q_{H'|H}^{t}, \text{ and } \quad Q_{A'|A}^{t}.$$

where e is parental educational spending, g is governmental spending on secondary education, $Q_{H'|H}^{t}$ and $Q_{A'|A}^{t}$ are exogenous stochastic process that captures parental health and productivity life-cycle profiles. The terms $E_{A',H',a',h'}V^i_{t+1,3}(\mathbf{x}')$ and $E_{A',H',a',h'}V^u_{t+1,3}(\mathbf{x}')$ represent the expected value of being insured or uninsured in the third period of childhood, respectively.

The value function for an uninsured child is given by

$$V^u_{t,2}(\mathbf{x}) = E\max_{c,e,m}\left\{u(c) + \beta\max\{E_{A',H',a',h'}V^i_{t+1,3}(\mathbf{x}'), E_{A',H',a',h'}V^u_{t+1,3}(\mathbf{x}')\}\right\},$$

subject to

$$c = (1-\tau)[AT_t(H)] - m + \chi^{MCD}(m)\mathcal{I}_2^{MCD}(AT_t(H)) - e,$$

$$a' = f(a, h, e, \upsilon), \text{and } e \geq g,$$

$$h' = g(h, m, \varepsilon),$$

and

$$Q^t_{H'|H}, \text{ and } Q^t_{A'|A}.$$

where $\mathcal{I}_2^{MCD}(AT_t(H))$ is the indicator function for Medicaid eligibility in the period 2.

First Period of Childhood $(j = 1)$ Parents with a one-year-old child decide first whether to buy insurance for the current period. Then they decide how much to spend on education and health of their children as well as whether to buy insurance for the next period. At the start of the period, parents' state space is given by $\widetilde{\mathbf{x}} = \{\theta, b, A, H, A^*, H^*\}$. Hence they do not know yet a or h, and decide whether to buy insurance for the current period. Then a and h are realized and, given their health insurance decisions they decide on e, m and purchasing or not an insurance for the second period. The state space of the parent after the realization of a and h is denote by $\mathbf{x} = \{\theta, b, A, H, h, a\}$. Hence the health insurance decision of parents at the start of the period is characterized by the following value function

$$V_{t,1}(\widetilde{\mathbf{x}}) = \max\{E_{h,a}V^i_{t,1}((\mathbf{x}), E_{h,a}V^u_{t,1}(\mathbf{x})\},$$

where the expectations on a and h are conditional on A^* and H^* (recall that $a = a^*$ and $h = h^*$ in the first period of childhood and the innate health and ability are correlated across generations). Once h and a are realized the problem of parent with a one-year-old child looks very similar to the problem of parents with a two-years-old child. For parents with health insurance, it is given by

$$V^i_{t,1}(\mathbf{x}) = \max_{c,e,m}\left\{u(c) + \beta\max\{E_{A',H',a',h'}V^i_{t+1,2}(\mathbf{x}'), E_{A',H',a',h'}V^u_{t+1,2}(\mathbf{x}')\}\right\},$$

subject to

$$c = (1-\tau)[AT_t(H) - p_{ins}] - m + \chi^{PRV}(m) - e,$$

$$a' = f(a, h, e, g, \upsilon), \text{ and } e \geq g$$

$$h' = g(h, m, \varepsilon),$$

and

$$Q^t_{H'|H}, \text{ and } Q^t_{A'|A}.$$

For parents without health insurance, the problem reads as

$$V^u_{t,1}(\mathbf{x}) = E\max_{c,e,m}\left\{u(c) + \beta \max\{E_{A',H',a',h'}V^i_{t+1,2}(\mathbf{x}'), E_{A',H',a',h'}V^u_{t+1,2}(\mathbf{x}')\}\right\},$$

subject to

$$c = (1-\tau)[AT_t(H)] - m + \chi^{MCD}(m)\mathcal{I}_2^{MCD}(AT_t(H)) - e,$$

$$a' = f(a, h, e, g, \upsilon), \text{and } e \geq g,$$

$$h' = g(h, m, \varepsilon),$$

and

$$Q^t_{H'|H}, \text{and} \quad Q^t_{A'|A}.$$

4. Estimation

To estimate the model I adopt a two-step procedure similar to the one used by Gourinchas and Parker (2002), De Nardi, French and Jones (2010a), and Coşar, Guner and Tybout (2016). In the first step I select all parameters that could be assigned without simulating the model (either directly from the data or from previous literature). Most importantly, characteristics of public and private insurance schemes, and life cycle health profiles of adults are set in the first step. In the second step, I estimate the rest of the parameters with method of simulated moments, taking the first-step estimates as given. In this section I describe first step estimates, then I turn to the second step estimation.

4.1. First-step estimation

Few parameters can be determined based on available estimates in the literature or can be calculated directly from aggregate statistics.

Discount factor, β. I choose discount factor to be the standard value, 0.96 per year, from the literature.

Coefficient of relative risk-aversion, σ. Coefficient of relative risk-aversion is taken from De Nardi et al. (2010a) and is equal to 3.

Government spending for education, g. According to Digest of Education Statistics, total expenditures per pupil in public elementary and secondary schools in 2010-2011 is $12,908.[10]

Variance of health shocks, σ_υ, and variance of ability shocks in the first and second periods, σ_ε. As production functions are logits, variances are normalized to $\pi^2/3$.

Several other parameters are estimated directly using micro data.

[10]Source: `http://nces.ed.gov/programs/digest/d13/tables/dt13_236.55.asp`. Variable Expenditure per pupil in average daily attendance

Data

I use two datasets: Medical Expenditure Panel Survey (MEPS) for the period 1996-2009 to analyze insurance policies and medical spendings and Panel Study of Income Dynamics main survey (PSID, for years 1948-2011) and Child Development Supplement of PSID (CDS-PSID, for years 1997-2011) for the rest of the purposes.

Main source of the data is PSID and CDS-PSID. PSID is a yearly survey (biannual after year 1997) of a nationally representative sample of households in 1968. I am using main study of PSID for information on labor market outcomes, such as hours worked and income, marital status histories from Marital History Supplement, child-bearing information from Child and Adoption History Supplement. Although the Main Study contains information on all members of household, it is limited for the non-head and non-wife members.

CDS-PSID is a research component of PSID that gathers detailed information of children residing in main PSID households. The sample of CDS-PSID are children and their parents in PSID households of the age 0-12 in the year 1997. These families were recontacted and followed-up in 2002 and 2007. CDS-PSID gathered very extensive information on family demographic and economic data about the CDS target child's family as well as health, well-being, cognition, relationships, and early human capital formation. Moreover, children from CDS were followed in a substudy "CDS Youth's Transition into Adulthood" (TA) that was first conducted in 2005 and biannually since then. The TA was initiated to bridge a gap between CDS sample after they turn out 18 but before they form their own family and become head or wife of the household. The rich data structure of PSID, CDS-PSID, and TA allows for intergenerational links over generations of family members, that is the crucial for the purposes of this chapter.

Second source of the data is MEPS - a survey of a representative sample of individuals and households of all ages. It provides information about usage and cost of health care. It's a rotating panel survey, each household is interviewed 5 times over a two-year period. I use information on insurance usage and sources of medical expenditure (out-of-pocket, private insurance company, Medicaid) from this survey. PSID contain data on insurance, but it is more limited. The model design allows to combine different sources of the data, that's why I use MEPS data as a more reliable source. The reliability of MEPS comes from the fact that data on medical expenses and insurance is gathered twice: from the household and confirmed by the medical providers.

I describe now how different variables for the analysis are created (all monetary values are expressed in 2005 dollars):

Parental Health, H**.** Constructed from the self-rated health variable in PSID for mothers. Mothers rate their health as "excellent", "very good", "good", "fair" or "poor". As model period corresponds to 7 years, I take average of health over all available observations available during a 7-year period in the data. I create a health dummy where 1 (good health) corresponds to the first three grades, and 0 (bad health) to the other two.

I calculate Markov transition matrix for health evolution of parents, $Q^t_{H'|H}$, explicitly from the data. It's an exogenous stochastic process that depends on age of a parent. Numbers are presented in the Table 1.1. In general, good health status is very persistent. Bad health status is less persistent, however it becomes more persistent with age.

Table 1.1: Parental life cycle health profile.

From/To	Bad	Good
22-28 to 29-35		
Bad	0.506	0.494
Good	0.053	0.947
29-35 to 36-42		
Bad	0.595	0.405
Good	0.084	0.916
36-42 to 43-49		
Bad	0.711	0.289
Good	0.098	0.902
43-49 to 50-57		
Bad	0.749	0.251
Good	0.135	0.865

NOTE: Transitions are calculated from PSID 1968-2011.

Hours Worked, $T_t(H)$**,** $t_3(h_3)$. From PSID, I obtain values of total yearly hours worked by mothers and their spouses and total yearly hours worked by mothers in case of a two-parent and one-parent household, respectively. I average total hours worked over all observations corresponding to a 7-year model period for each level of health, that is also averaged for each of the model periods. Thus, there are two levels of working hours, for good and for bad health, for each model period. The same way I calculate hours worked for children who don't attend to college in their 3rd period of childhood, using PSID Transition to Adulthood. See Table 1.2 and Table 1.3 for numbers. People in good health on average have about 16% more of time available for work.

Table 1.2: Parental hours conditional on health.

Age/Health	Bad	Good
22-28	0.42	0.54
29-35	0.47	0.58
36-42	0.50	0.59
43-49	0.50	0.60
50-57	0.46	0.57

NOTE: Numbers are calculated from PSID 1968-2011.

Parental Productivity, A. This variable corresponds to productivity quintiles, calculated from the PSID data. Productivity levels are calculated as follows. First, I divide total taxable income of the household (mother and her spouse if two-parent household, mother's income if one-parent household) by total household hours worked. Then I assign to each household its potential yearly income as the product of hourly productivity times

Table 1.3: Children's hours conditional on health in period 3 if no college.

Age/Health	Bad	Good
15-21	0.18	0.24

NOTE: Numbers are calculated from CDS PSID 2005-2011.

$100 \cdot 52$ (I assume people have 100 available hours per week). The result of the calculations is split into quintiles, thus there are 5 levels of productivity for parents in each age group. Productivity profiles are different by marital status, θ. I present them in Table 1.4 for married parents and in Table 1.5 for single parents. Productivity of people from the last quintile is 5 to 12 times higher than the one of the people in the 1st quintile, increasing over age.

Table 1.4: Productivity life-cycle. Married

Average productivity	Q1	Q2	Q3	Q4	Q5
Age 22-28 (t=1)	40.12	73.02	95.16	120.77	187.49
Age 29-35 (t=2)	38.16	74.87	103.97	135.65	223.96
Age 36-42 (t=3)	36.06	79.38	111.62	153.35	262.76
Age 43-49 (t=4)	33.35	75.56	113.68	156.75	307.26
Age 50-57 (t=5)	26.38	69.60	109.87	161.59	339.79

NOTE: Average productivity is calculated for each income quintile from PSID 1968-2011.

Table 1.5: Productivity life-cycle. Singles

Average productivity	Q1	Q2	Q3	Q4	Q5
Age 22-28 (t=1)	10.27	34.35	53.27	75.98	130.92
Age 29-35 (t=2)	11.20	41.63	70.05	108.96	215.50
Age 36-42 (t=3)	11.80	42.07	71.57	115.65	254.21
Age 43-49 (t=4)	9.59	38.50	65.54	109.64	273.61
Age 50-57 (t=5)	3.38	28.55	54.49	89.92	241.86

NOTE: Average productivity is calculated for each income quintile from PSID 1968-2011.

I calculate Markov transition matrix for income quintile of parents, $Q^{\theta,t}_{A'|A}$, explicitly from the data. It's an exogenous stochastic process that depends on age and marital status of a parent. The processes are presented in Table 1.6 for married parents and in Table 1.7 for single. Productivity is persistent over time, becoming more persistent with age for higher productivity quintiles, especially for single parents.

Marital, θ, and child-bearing, b, shocks. Marital and child-bearing shocks are calculated from Children and Adoption History Supplement of PSID. A person is con-

Table 1.6: Parental life cycle ability profile. Married

From/To	Q1	Q2	Q3	Q4	Q5
22-28 to 29-35					
Q1	0.613	0.227	0.101	0.036	0.024
Q2	0.216	0.418	0.199	0.125	0.041
Q3	0.124	0.187	0.389	0.216	0.084
Q4	0.052	0.134	0.306	0.314	0.193
Q5	0.014	0.043	0.086	0.233	0.623
29-35 to 36-42					
Q1	0.689	0.227	0.046	0.031	0.007
Q2	0.231	0.399	0.270	0.074	0.026
Q3	0.095	0.277	0.336	0.238	0.053
Q4	0.023	0.113	0.207	0.446	0.211
Q5	0.023	0.037	0.080	0.182	0.678
36-42 to 43-49					
Q1	0.658	0.249	0.077	0.016	0.001
Q2	0.215	0.422	0.239	0.104	0.019
Q3	0.090	0.184	0.423	0.262	0.040
Q4	0.033	0.079	0.164	0.474	0.249
Q5	0.011	0.010	0.067	0.181	0.732
43-49 to 50-57					
Q1	0.667	0.244	0.062	0.027	0.000
Q2	0.156	0.494	0.257	0.061	0.032
Q3	0.105	0.154	0.413	0.255	0.073
Q4	0.015	0.082	0.160	0.511	0.232
Q5	0.008	0.015	0.067	0.159	0.751

NOTE: Transitions are calculated from PSID 1968-2011.

sidered married if she spends more than half of her adult life (ages 20-60) as married, non-married otherwise. In the model parents can have a child at the 1st, 2nd or 3rd period of adulthood (that correspond to 22-28, 29-35, 36-42 age periods). Using the same Supplement, I calculate the probability of first child born at a particular age frame conditional on giving birth to at least one child. In Table 1.8 I present these statistics. Around 65% of parents are married most of the time and with 85% probability they have at least one child. While single parents have a child with only 42% probability. The first child is most often born when his parents are 22-28 years old, twice less frequent when they are 29-35 age old and only around 3% when parents are 36-42 old.

Child's health, h. In the first two periods of child's life this variable correspond to a health of a child reported by a primary care giver (usually mother) in CDS PSID. "Excellent" and "very good" health corresponds to good health, "good", "fair" or "poor" corresponds to bad health. As you might have noticed, this division is a bit different from that of adult, this happens due to the fact that most of children in the data have rather

Table 1.7: Parental life cycle ability profile. Singles

From/To	Q1	Q2	Q3	Q4	Q5
22-28 to 29-35					
Q1	0.635	0.223	0.060	0.066	0.016
Q2	0.158	0.383	0.283	0.127	0.049
Q3	0.072	0.170	0.299	0.298	0.161
Q4	0.015	0.079	0.193	0.382	0.332
Q5	0.003	0.033	0.086	0.243	0.635
29-35 to 36-42					
Q1	0.694	0.212	0.073	0.011	0.010
Q2	0.126	0.468	0.263	0.100	0.044
Q3	0.074	0.108	0.359	0.290	0.169
Q4	0.031	0.062	0.135	0.543	0.229
Q5	0.008	0.015	0.042	0.167	0.769
36-42 to 43-49					
Q1	0.639	0.289	0.053	0.019	0.000
Q2	0.165	0.401	0.328	0.095	0.012
Q3	0.035	0.175	0.398	0.341	0.050
Q4	0.029	0.048	0.116	0.474	0.333
Q5	0.010	0.008	0.024	0.131	0.826
43-49 to 50-57					
Q1	0.641	0.282	0.048	0.018	0.011
Q2	0.135	0.347	0.414	0.104	0.001
Q3	0.066	0.173	0.379	0.362	0.021
Q4	0.026	0.050	0.074	0.393	0.457
Q5	0.000	0.019	0.036	0.093	0.852

NOTE: Transitions are calculated from PSID 1968-2011.

good health and very few children have "fair" or "poor" health. For the third childhood period health is taken from TA data, where children report their health themselves.

Table 1.8: Marital and child-bear shocks

Married				Non-married			
0.647				0.353			
No child	22-28	29-35	36-42	No child	22-28	29-35	36-42
0.153	0.581	0.235	0.031	0.577	0.276	0.111	0.036

NOTE: Numbers are calculated from Children and Adoption Supplement of PSID 1968-2011.

Child's Ability, a. Children of the age 3-17 were administered subtests of Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R)[11], in particular Letter-Word identification test (that assesses symbolic learning and reading skills), Passage Comprehension (assesses reading comprehension and vocabulary, and ability to use these two skills together in a sentence completion task) and the Applied Problems test (assesses knowledge of mathematical operations and ability to perform computations)[12]. Children of age 3-5 were administered only the Letter-Word Identification and Applied problems subtests, while from age 6 all 3 subtests were performed. That's why I use first two subtests to identify ability in the 1st model period and all 3 subtests in the 2nd and 3rd model periods. CDS-PSID along with raw scores provides age-standardized standard score and percentile scores and W score, that allows to analyze gains in achievement over time. I am using the standard scores (mean 100, standard deviation 15 for each age group), that facilitates comparisons of children of different age. If multiple test scores are available, I use the average of them. Then for each model period I perform a factor analysis of subtests scores. Ability distributions for each age group are presented on the Figure A.1 in the Appendix A.1. The resulting variable is split into 2 levels: less than median (that corresponds to low ability) and more than median (that corresponds to high ability). Thus, ability of a child is a binary variable: low or high.

Children productivity profiles, a_3**.** Children productivity profiles for those in $j = 3$ who do not attend college (and, consecutively, work) are calculated in the same way as for parents, using PSID TA data. As seen from the Table 1.9, productivity of the high ability children is 2.5 times higher than that of the low ability children.

Table 1.9: Children's productivity in period 3 if no college.

Age/Ability	Low	High
15-21	0.67	0.58

NOTE: Numbers are calculated from CDS PSID 2005-2011.

Insurance schemes. As explained in the section 3.2, the insurance schemes are described as:

$$\chi_j^{MCD/PRV}(m) = \begin{cases} 0 \text{ if } m \leq \eta_j^{MCD/PRV} \\ \mu^{MCD/PRV}(m - \eta_j^{MCD/PRV}) \text{ if } m > \eta_j^{MCD/PRV} \end{cases},$$

where $\eta^{MCD/PRV}$ is the deductible, up to which parents do not receive the reimbursement from insurance company/government, and for each dollar above the threshold $\eta^{MCD/PRV}$, they receive a fraction $\mu^{MCD/PRV}$ as a co-payment rate.

[11] User Guide on ability measurements is available from `https://psidonline.isr.umich.edu/Publications/Papers/tsp/2014-02_Achievement.pdf`. This test battery is widely used in child development literature, less in economic literature, for example, see Creel and Farell (2015), Araujo, Carneiro, Cruz-Aguayo and Schady (2014)

[12] In the CDS-I (1997) Calculations subtest was performed and combined with Applied Problems subtest Broad Math Score was calculated. I don't use Calculations subtest in defining ability as I prefer ability to be defined in a similar manner in all periods.

Table 1.10: Estimates for insurance function

Parameter	Period 1	Period 2	Period 3
η^{MCD}	0.000	0.000	0.000
μ^{MCD}	0.930	0.916	0.897
η^{PRV}	0.044	0.106	0.088
μ^{PRV}	0.818	0.795	0.767

NOTE: Coefficients are calculated from MEPS 1996-2009.

I use MEPS to estimate these functions for each model period. MEPS provides information on total medical spendings, insurance coverage and sources of payment, e.g. private insurance firm or Medicaid. To estimate this function for private insurance I pick a sample of children with private insurance coverage during the entire year and estimate deductible (as an average out-of-pocket expenditure of households with no other expenditures) and co-payment rate from the MEPS data (similar to Ozkan (2013)). For Medicaid it's difficult to estimate parameters due to a large number of people with zero out-of-pocket expenditure, especially for the low-income parents. Thus I assume zero deductible and estimate co-payment rate from the data. As we observe in Table 1.10, the co-payment rate slightly decreases with the age of the child.

4.2. Second-step estimation

After the first step of estimations I am left with 39 parameters to be determined. Let's denote the vector of parameters Ω. It contains 3 parameters for educational subsidy function $\{\kappa, \phi, E\}$, 4 parameters for insurance function $\{\overline{I}_1, \overline{I}_2, \overline{I}_3, p_{ins}\}$, 2 parameters on the main diagonal for intergenerational transmission of ability in the matrix $\Gamma_{a^*|A^*}$ and 2 parameters on the main diagonal for intergenerational transmission of health in the matrix $\Gamma_{h^*|H^*}$. Then, parameters for production functions: 8 parameters for health production function $\{\alpha_0^h, \alpha_1^h, \alpha_2^h\, \alpha_3^h\}$ and $\{\alpha_{30}^h, \alpha_{31}^h, \alpha_{32}^h, \alpha_{33}^h\}$, 7 parameters for ability production function in the first and second periods of childhood (α_0^a, α_1^a, α_2^a, α_3^a, α_4^a, α_5^a, α_6^a, α_7^a) and 10 parameters for ability production function in the third period of childhood $\{\alpha_{30}^a$, α_{31}^a, α_{32}^a, α_{33}^a, α_{34}^a, α_{35}^a,α_{36}^a,x_1, x_2, x_3, x_4, $\sigma_{inc}\}$. The last parameter is ψ, which characterizes the degree of parental altruism towards their children.

I use a total of 46 moments in the estimation. If the source of the data moments is not mentioned, it means they are calculated from PSID and/or CDS-PSID.

1. (2 moments) Intergenerational mobility variables. First, intergenerational elasticity of income. Calculated as γ_1 in the following regression:

$$logY_{ch} = \gamma_0 + \gamma_1 logY_p,$$

where Y_{ch} and Y_p are lifetime incomes of a child and parent, respectively. The target number is 0.4 (Solon, 2002; Mazumder, 2005). Second, probability of child moving from the bottom parental productivity quintile to the upper one. In the US this number corresponds to 9% (Chetty et al., 2014).

2. (2 moments) Correlations of child's and parent's health. As parental innate health is unobservable, I look at the correlations of parental health in the period when child is born with child's initial health. $Pr(h = good|H = bad) = 0.782$, $Pr(h = good|H = good) = 0.912$. This persistence difference is rather big, as at birth 86% of children are healthy.

3. (5 moments) Correlations of child's ability with parental productivity quintile in the period the child is born. The same way we don't observe innate parental health, we don't observe innate parental ability. For this reason we use correlations of initial ability of a child and parental productivity measure (productivity quintile) in the period the child is born. $Pr(a = high|Q_A = 1, 2, 3, 4, 5) = 0.368, 0.543, 0.618, 0.677, 0.737$.

4. (3 moments) Share of children in good health in each childhood period (86, 86, 81%).

5. (6 moments) Unconditional transition probabilities between health states (good/bad) over different periods. $Pr(h_2 = good|h_1 = bad/good) = 0.645/0.893$, $Pr(h_3 = good|h_2 = bad/good) = 0.653/0.836$, $Pr(H_1 = good|h_3 = bad/good) = 0.503/0.796$. We observe that health is persistent over periods, and in the earlier periods bad state is less persistent as in the last period.

6. (5 moments) Share of healthy people in the beginning of the adulthood, by income quintile (86.4, 93.9, 94.9, 96.7, 97.8%).

7. (8 moments) Expected probabilities of transition between ability levels (high/ low) conditional on previous ability, health and parental investments into education: $Pr(a' = high|a = high/low, h = good/bad, e = e_1/e_2)$ where as a measure of parental educational investments (e) in the data I use HOME score.[13] HOME score lower than the median HOME score is denoted e_1, e_2 corresponds to the HOME score that is higher than the median. These moments are very important to identify the parameters of the ability production function. I present these moments in the Table 1.11. One can notice that given the level of educational spending and the health level, high ability results in higher probability transiting to higher ability next period than low ability. Second important take-off from this table is having good health provides higher probability of transition to high ability for the given level of current ability. Finally, higher educational spending guarantee higher transition probabilities to high ability level.

8. (5 moments) The share of college educated people at the age 25-29, by productivity (wage) quintiles (18, 27, 34.9, 42, 65%).

9. (3 moments) Total share of college educated people in the economy (44%). Share of college students with federal grants (64%). Average amount of grant per student who received any Title IV aid from the government. In 2010-2011 is 9.630 thousand US\$. In 2005 price and per 1 year in a 7-year model period is \$4.777.[14].

[13]HOME is used by different authors as a measure of parental investments into education. See, for example, Cunha et al. (2010)

[14]Source:`https://nces.ed.gov/programs/digest/d13/tables/dt13_331.30.asp`

Table 1.11: Ability transitions conditional on health and educational spending

Low Educational Spending				
	Bad Health		Good Health	
Ability	Low	High	Low	High
Low	0.924	0.076	0.793	0.207
High	0.385	0.615	0.314	0.686
High Educational Spending				
Low	0.782	0.218	0.671	0.329
High	0.364	0.636	0.204	0.796

NOTE: Transition probabilities are calculated from CDS-PSID 1997-2011.

10. (3 moments) The fraction of children on Medicaid in each childhood period (30.4, 23.7, 15.6%).
11. (4 moments) In each income quintile there should be 20% of people.

The Estimator

Method of simulated moments picks the parameter vector Ω to minimize a weighted sum of square deviations between data moments $\widehat{\pi}$ and their model-based counterpart $\pi(\Omega)$. The estimator then is given by:

$$\widehat{\Omega} = argmin(\widehat{\pi} - \pi(\Omega))'\widehat{W}(\widehat{\pi} - \pi(\Omega)),$$

where $\widehat{W}$ is some positive semi-definite matrix. $\widehat{W}$ represents a weight of each moment relative to all moments, and for any $\widehat{W}$ the estimator $\widehat{\Omega}$ is consistent. Let's assume the same level of importance of each group of moments (that are described above) and give the same weight for each group, within each group the weight is distributed equally to all moments.

All parameters are identified jointly using all data moments and it is difficult to associate individual parameters of Ω to particular moments from $\widehat{\pi}$. Some of the moments, however, play crucial role in identification of particular parameters. For example, threshold levels for Medicaid eligibility $\{\overline{I}_1, \overline{I}_2, \overline{I}_3\}$ have a direct effect on amount of children receiving Medicaid while price of private insurance, p_{ins}, helps with identifying a share of children with private insurance.

Educational parameters $\{\kappa, \phi, E\}$ that enter governmental college subsidy function are mostly connected to such moments as shares of college educated people (total and by productivity quintiles) as well as a share of students with federal grant and average college subsidy. These parameters determine how many children receive college subsidy and how important is parental income in receiving college subsidy, or, in other words, who exactly gets a college subsidy. The same moments together with intergenerational income elasticity and probability of upward mobility for the lowest income quintile children affect estimates of ability production function in childhood period 3 (α^a_{30}, α^a_{31}, α^a_{32}, α^a_{33}, α^a_{34}, α^a_{35},α^a_{36} σ_{inc}), which determines the initial productivity quintile for children who become adults. Parameters for income thresholds (x_1, x_2, x_3, x_4) just help to mechanically allocate a proper number of individuals to each of the productivity quintiles.

Unconditional transition probabilities for health, shares of healthy children in each life period together with insurance moments help to identify parameters for health production function in periods 1 and 2 $\{\alpha_0^h, \alpha_1^h, \alpha_2^h, \alpha_3^h\}$ and in period 3 $\{\alpha_{30}^h, \alpha_{31}^h, \alpha_{32}^h, \alpha_{33}^h\}$. These parameters should be estimated within the model because their estimation from the data leads to an econometric bias due to unobservability of the health shocks. In particular parameter α_2^h that is related to medical spendings will have a negative sign if we run a logit in the data. We would interpret this as medical spendings are bad for health, however, in reality people who receive stronger health shocks spend more on medicine to compensate for the shocks. Not accounting for this bias will underestimate the role of medical expenditure in health investment. Moreover, I don't make a direct mapping between medical expenses in the data and medical expenses in the model. In the data only expenses for curative medicine could be observed. However in the model health is a form of capital, that also allows investments into it. Thus it's better to think of curative and preventive spending together while talking about medical spending in the model.

Conditional transition probabilities for health and ability will discipline ability production function in the first two periods of childhood, (α_0^a, α_1^a, α_2^a, α_3^a, α_4^a, α_5^a,α_7^a). These parameters determine relative roles of health, ability and parental and governmental investments for human capital production. It is important that health and ability moments are taken together as health enters ability production function as an input and so, production of health and human capital are very intertwined.

Estimates In the Table 1.12 I present all the parameter estimates of Ω.[15] According to the U.S. National Center for Education Statistics (NCES) in 2010-2011 average costs of one year of undergraduate full-time studies at a 4-year institution was 23,118 US\$. This would imply $23,118(4/7) = 13,210$ US\$ per year during a 7-year model period. The estimate of E implied by the model is \$24,500 which is larger. However the cost of college is not only tuition, but also materials, living arrangements etc., which according to College Board[16] is around \$13,203 per year. Taking this cost into account college spending is around \$20,500 per year in a 7-year period model, that is close to \$24,500 estimate we get in the model.

Insurance thresholds for 3 periods of childhood are estimated as \$25,000, \$42,000 and \$121,000, respectively. In the data for a family of three income thresholds are between \$29,648 and \$74,120 (depending on the state) with an average of \$44,657, which is also reasonably close to my estimate from the data for the first two periods. Third period threshold estimate is higher than the 1st and 2nd period thresholds. According to a recent report of Kaiser foundation employee's contribution to the average annual premiums for employer-sponsored health insurance is \$4,823, which is also close to the model's estimate of insurance premium $p_{ins} = \$4,000$.[17]

[15] Standard errors are under calculations.
[16] Source: http://trends.collegeboard.org/sites/default/files/College_Pricing_2011.pdf
[17] Source: http://files.kff.org/attachment/ehbs-2014-abstract-summary-of-findings

Table 1.12: Estimated Parameters

Parameter	Notation	Estimate
Income tax rate	τ	0.12412
Altruism parameter	ψ	0.29
Slope college subsidy wrt earnings	κ	0.5
Curvature parameter in subsidy funtions	ϕ	1.2
Tutition cost (in $1000)	E	24.5
Earnings threshold for eligibility for medical subsidy (in $1000)	I_1, I_2, I_3	25, 42, 121
Insurance premium (in $1000)	p_{ins}	4
	Intergenerational correlations	
Markov transition matrix for innate ability	Γ_a	[0.624 0.376; 0.3431 0.6569]
Markov transition matrix for innate health	Γ_h	[0.5975 0.4025; 0.3301 0.6699]
	Health production function	
Coefficients for health production function in $j = 1, 2$	α^h_0, α^h_1, α^h_2, α^h_3	0.49061, 1.5365, 0.1488, 0.3
Coefficients for health production function in $j = 3$	α^h_{30}, α^h_{31}, α^h_{32}, α^h_{33}	-1.6061, 1.535, 0.1088, 0.1
	Ability production function	
Coefficients for ability production function in $j = 1, 2$	α^a_0, α^a_1, α^a_2, α^a_3, α^a_4, α^a_5, α^a_6, α^a_7	-5.556, 0.559, 0.7015, 0.08, 0.0075, 0.03, 0, 0
Coefficients for ability production function in $j = 3$	α^a_{30}, α^a_{31}, α^a_{32}, α^a_{33}, α^a_{34}, α^a_{35},α^a_{36}	1.7319, 3, 0, 0.5, 0.51, 0.19, 2.1
Thresholds for productivity quintiles and variance	x_1, x_2, x_3, x_4, σ_{inc}	2.5075, 3.5075, 4.5063, 5.5875, 0.9094

To interpret estimates of the production functions I calculate marginal effects for an average person. In the Table 1.13 I present results for the health production function. In the first and second periods of childhood average medical spending are $5,490, in the third period somewhat higher – $9,220. In the first line of the Table 1.13 I present the baseline probabilities of transiting to good level of health conditional on the current level of health. The baseline probability of transition to good health conditional on current bad health is 66.8% in the 1st and in the 2nd periods and 35.4% in the 3rd period, while conditional on the good health is much higher: 88.9% and 87.6% correspondingly. What is the effect of an additional $1,000 of medical spending? The results are presented in the line 2 of Table 1.13. For the children in bad health the baseline probability of transitioning to good health increases by 2.2% (1-2 periods) and 2.5% (3rd period), for children in good health the marginal effect of additional spending is much lower: 0.4% and 0.8%. Baseline gap in probabilities of transiting to the good health between healthy and non-healthy children is 22.1% (1-2 periods) and 52.2% (3rd period). Additional $1,000 of medical spending decreases this gap by 8% (1-2 periods) and 3% (3rd period).

In the Table 1.14 I present baseline transition probabilities for ability levels and marginal effect of an additional $1,000 spending into education. Similar to Table 1.13, in th first line the baseline probabilities are reported for a child that gets an average amount of parental educational spending ($4,120) and grows up in a family with an average labor productivity ($109,000, which results in around $50,000 as an average household income that is very close to an estimate of the median US household income, $49,445 in 2010). In the first line I report the baseline probabilities of transiting into the high ability level conditional on current health and ability levels. Two important observations could be made. First, conditional on the level of health (bad/good), probability of having high ability next period is higher for those whose current ability is high: 20.2% versus 8.36% for bad health and 65.5% versus 20.3% for good health. Second, health contributes to the baseline probabilities. For the same level of ability, health produces almost three-fold difference in probability of having high ability next period. An additional parental investment of a size $1,000 increases baseline probabilities of transiting to the high ability next period. Both, current level of ability and current level of health are important. For the same level of health, high level of current ability means higher probability of having higher ability next period (35% versus 1.73% for bad health and 29.8% versus 4.14% for good health). The same level of ability for different level of health also reacts differently. Good health results in higher transition probability than bad health for the same level of ability. From this table we can make a conclusion, that health is an important determinant in ability production, and investing in education is just not enough to insure high productivity of children. One remark should be made here: ability production function is estimated for a binary ability variable, and the ability distribution is normal in shape (see Figure A.1). The robustness analysis should be made with respect to ability thresholds.

Table 1.13: Health production function. Baseline probabilities and marginal effects

	Periods 1,2 $\overline{m}$ =5.49			Period 3 $\overline{m}$ =9.22		
	$h_j = bad$	$h_j = good$	Δh	$h_j = bad$	$h_j = good$	Δh
Baseline probability ($Pr(h_{j+1} = good \mid h_j)$)	0.668	0.889	**0.221**	0.354	0.876	**0.522**
Marginal effect of $1,000 medical spending ($\overline{m} + \$1,000$)	0.0221	0.00387	**0.2028**	0.0252	0.00799	**0.505**

NOTE: Baseline probabilities and marginal effects are calculated from the estimates of the health production function for the average level of medical spendings in the model.

Table 1.14: Ability production function. Baseline probabilities and marginal effects

$\overline{e} = 4.12$, $\overline{A} = 109$	Health=bad			Health=Good		
	$a_i = low$	$a_i = high$	Δa	$a_i = low$	$a_i = high$	Δa
Baseline probability ($Pr(a_{j+1} = high \mid a_j = a_i, h)$)	0.0836	0.392	**0.308**	0.203	0.655	**0.452**
Marginal effect of $1,000 educational spending ($\overline{e} + \$1,000, \overline{A}$)	0.0173	0.15	**0.4411**	0.0414	0.298	**0.7086**

NOTE: Baseline probabilities and marginal effects are calculated from the estimates of the ability production function for the average level of educational spendings and the average level of parental income in the model.

Model Fit Table 1.15 presents all the elements of $\widehat{\pi}$ and correspondent values of $\pi(\Omega)$. As could be seen from the table, model provides a reasonably good fit. As I have more moments than parameters, it is not possible to match exactly all the moments at the same time. Overall the model gives pretty good match. Intergenerational income elasticity is slightly underestimated, however probability of upward mobility is captured pretty well. Gini coefficient is well reproduced; it was not, however, targeted. Model captures very well the fraction of children from different age groups who receive Medicaid. Unconditional health transition probabilities are also very much in line with the data, although the fraction of individuals in good health is increasing in income in the data, the model does not produce this trend well enough. The model overpredicts the share of college graduates in economy, however the average level college subsidies and the fraction of students with college subsidies are lower than in the data. Model replicates well the number of college educated individuals in lower income quintiles, but overestimates their numbers at the top quintile. Conditional transitional probabilities for ability during the childhood are slightly overestimated, however the monotonicity in these moments is captured very well. Model matches both the health and ability intergenerational correlations quite well. It underpredicts, however, probability of having good health if child's parent is in good health at the time of child's birth and probability of having high ability at birth conditional on income quintile of parents. Generally, there is a big trade-off between matching well intergenerational correlations and conditional and unconditional transitions for ability and health. The better is the match of intergenerational persistence in health and ability, the worse is the match of the transitions. In my opinion transitions moments are more important to match as they provide better information on the role of current levels of health and ability versus investments into education and medicine.

Table 1.15: Model Fit

Moment	Data	Model
Intergenerational income elasticity	0.4	0.273
Probability of Moving from Q1 to Q5	0.09	0.105
Probability of Moving from Q5 to Q5	0.32	0.279
Gini coefficient	0.4	0.424
Children with public insurance, j=1	0.304	0.358
Children with public insurance, j=2	0.237	0.245
Children with public insurance, j=3	0.156	0.132
$Pr(h = bad \| H == bad)$	0.218	0.439
$Pr(h = good \| H == good)$	0.912	0.547
$Pr(h_2 = good \| h_1 = bad)$	0.645	0.708
$Pr(h_2 = good \| h_1 = good)$	0.893	0.858
$Pr(h_3 = good \| h_2 = bad)$	0.653	0.673
$Pr(h_3 = good \| h_2 = good)$	0.836	0.974
$Pr(H_1 = good \| h_3 = bad)$	0.503	0.76
$Pr(H_1 = good \| h_3 = good)$	0.796	0.819
% of people in good health in Q1	0.864	0.789
% of people in good health in Q2	0.939	0.882
% of people in good health in Q3	0.949	0.666
% of people in good health in Q4	0.967	1
% of people in good health in Q5	0.978	0.771
% of children in good health	0.847	0.765
Share of students with federal grant	0.64	0.322
Share of college graduates	0.44	0.638
Average college subsidy	4.777	3.84
% of college educated people in Q1	0.18	0.26
% of college educated people in Q2	0.27	0.165
% of college educated people in Q3	0.349	0.819
% of college educated people in Q4	0.42	0.953
% of college educated people in Q5	0.65	0.956
$Pr(a = high \| Q_A = 1)$	0.368	0.512
$Pr(a = high \| Q_A = 2)$	0.543	0.522
$Pr(a = high \| Q_A = 3)$	0.618	0.529
$Pr(a = high \| Q_A = 4)$	0.677	0.529
$Pr(a = high \| Q_A = 5)$	0.737	0.529
$Pr(a_t + 1 = high \| a_t = low, h_t = bad, e = 1)$	0.076	0.206
$Pr(a_t + 1 = high \| a_t = low, h_t = good, e = 1)$	0.207	0.344
$Pr(a_t + 1 = high \| a_t = high, h_t = bad, e = 1)$	0.615	0.334
$Pr(a_t + 1 = high \| a_t = high, h_t = good, e = 1)$	0.686	0.502
$Pr(a_t + 1 = high \| a_t = low, h_t = bad, e = 2)$	0.218	0.314
$Pr(a_t + 1 = high \| a_t = low, h_t = good, e = 2)$	0.329	0.48
$Pr(a_t + 1 = high \| a_t = high, h_t = bad, e = 2)$	0.636	0.482
$Pr(a_t + 1 = high \| a_t = high, h_t = good, e = 2)$	0.796	0.653

4.3. Role Of Health

In the model health affects labor income in two ways. The direct effect comes through the determination of physical capacity to work, $T_t(H)$. The indirect effects comes from the accumulated effect of health in human capital accumulation process, that eventually affects productivity level.

In order to understand the importance of these two channels, I shut them one at a time and simulate the model economy while keeping all other parameters at their benchmark values. First, I disregard health differences in supplied working hours. I set the same working hours for healthy and not healthy individuals, i.e. $T_t(H) = T_t$ where T_t is the working hours for entire population of age t (I set them equal to working hours of healthy people). Second, in the human capital production functions I set coefficients on health to zero, i.e. I set α_2^a, α_5^a, α_{32}^a, α_{34}^a, and α_{35}^a equal to zero.

Table 1.16: Role of Health

Moment	Baseline	No Direct Effect $T_t(H) = T_t$	No Indirect Effect $\alpha_2^a, \alpha_5^a, \alpha_{32}^a, \alpha_{34}^a, \alpha_{35}^a = 0$
Intergenerational Elasticity and Inequality			
Intergenerational lifetime income elasticity	0.273	0.281	0.373
Probability of Moving from Q1 to Q5	0.105	0.117	0.0873
Probability of Moving from Q5 to Q5	0.279	0.265	0.269
Gini coefficient	0.424	0.394	0.433
Children in good health	0.776	0.706	0.742
Share of College Graduates	0.615	0.459	0.676
Medical Expenses			
Average Medical Expenditure	8.042	2.6	4.85
Educational Spendings			
Private Educational Expenditure	0.40	4.73	7.5
Tax rate	0.124	0.1087	0.12

The results of these experiments are presented in Table 1.16. In the first column the benchmark model results are presented, second column contains the results of the first simulation. If there are no health differences in hours supplied for the labor market, intergenerational income elasticity would increase just slightly, from 0.273 to 0.281, however as health is not as important for labor supply as in the benchmark, the probability of moving upwards would increase by 10%, from 10.6% to 11.7%. If independently of health everyone can work the same hours, relative income levels of those in poor health would increase (and low income people tend to have worse health), and on average they would invest slightly more into education of their children. As a result their children will have higher productivity and higher income. In turn, college will become not as important as in the benchmark, because the only way college affects later life outcomes is through higher initial productivity level.

The indirect effect of health is much more important. If health is not important for human capital accumulation (now it is important for labor supply only), average medical expenses decrease. As a result, the average health deteriorates. Now ability becomes the most important driver of the human capital production. For richer individuals, however, who possess higher ability, investments into education are more efficient than for poor less able individuals, thus the gap in ability between poor and rich increases, which results in higher intergenerational income elasticity (increases from 27.3% to 37.3%, by 36%), lower upward mobility (decreases from 10.5% to 8.73%, by 17%) and higher inequality.

5. Counterfactual Policy Experiments

In this section I present results of the main counterfactual experiments. These experiments highlight the effect of health and governmental health policies on intergenerational mobility. First, I eliminate all government spending on early education. Second, I eliminate governmental subsidies for college education. Third, I shut down Medicaid policy. As a result, poor households are left with the option of private insurance and since not all of them can afford it some households will choose to be uninsured. Finally, I eliminate different combinations of these three programs to understand the interaction effect: Medicaid together with early education, Medicaid with late education, and all three policies together.

Table 1.17: Counterfactual Experiments: Early and Late Education

Moment	Baseline	No Early Education	No College Subsidies
Intergenerational lifetime income elasticity	0.273	0.3	0.288
Probability of Moving from Q1 to Q5	0.105	0.098	0.0973
Probability of Moving from Q5 to Q5	0.279	0.273	0.299
Gini coefficient	0.424	0.425	0.432
Children in good health	0.776	0.75	0.769
Share of College Graduates	0.615	0.604	0.55
Insurance			
Children with Public Insurance	0.245	0.118	0.257
Children with Private Insurance	0.379	0.426	0.408
Children with No Insurance	0.376	0.456	0.335
Medical Expenses			
Average Medical Expenditure	8.042	7.4	8.0
Educational Spendings			
Private Educational Expenditure	0.408	2.8	1.6
Tax rate	0.124	0.0263	0.124

Table 1.17 shows the results when we shut down education policies. When there are no educational policies, parents are forced to spend money on education out of their pocket. However, there is a trade-off between spending on education and spending on health, and this trade-off is stronger for the poor households than for the rich. There is a big effect of early educational policy on intergenerational income elasticity (IIE): eliminating early childhood policies increases IIE by about 10%, from 0.273 in the benchmark model to 0.3 (column 2 of Table 1.17). Probability of reaching top income quintile by children of parents from the lowest income quintile decreases from 10.5% to 9.73%, by about 7.5%. On the other hand, for children of rich parents probability of staying in the top quintile slightly increases. Without any government subsidy for primary and secondary education, i.e. when $g = 0$, parents substitute spending on health for spending on education. As a result, due to lower medical spending average health of children in the first and second periods (correspond to early education periods) slightly decreases and share of college

graduates also slightly declines. When the college subsidies are eliminated, the share of college educated children decreases from 61.5% to 55%, and the probability of upward mobility for lower income quintile decreases (from 10.5% to 9.73%), however, probability of staying in the top income quintile increases for the reachest from 27.9% to 29.9%. Income elasticity increases by 5.5%.

Table 1.18: Counterfactual Experiments: Early and Late Education Policies, by Parental Income Quintile

Moment	Baseline	No Early Education	No College Subsidies
College Education by Parental Income Quintile			
Q1	0.0119	0.0116	0
Q2	0.299	0.25	0.166
Q3	0.782	0.774	0.633
Q4	0.98	0.982	0.96
Q5	1	1	1
Children in Good Health by Parental Income Quintile			
Q1	0.725	0.695	0.72
Q2	0.713	0.697	0.712
Q3	0.761	0.741	0.77
Q4	0.809	0.774	0.78
Q5	0.868	0.857	0.857
Effective Average Medical Expenses by Parental Quintile			
Q1	4.67	4.03	4.66
Q2	5.59	4.66	6.22
Q3	6.26	5.31	7.83
Q4	7.49	6.71	5.95
Q5	16.2	16.5	15.4
Average Medical Out-of-Pocket Expenses			
Q1	2.77	2.65	2.76
Q2	2.69	2.75	3.03
Q3	3.4	3.91	3.57
Q4	6.52	5.26	5.21
Q5	10.9	10.4	10.2
Average Educational Spending by Parental Quintile			
Q1	0	0	0
Q2	0	0	0
Q3	0	0	0
Q4	0	2.89	1.21
Q5	1.99	12.89	6.82

Households with different income might be affected differently by the same policy. In Table 1.18 I present households decisions, health and educational outcomes for by income level. All households decrease their spending in health, as a result, health deteriorates for children of all income quintiles, however the effect is stronger for lower income households. Educational spending in response to shutting down educational programs, on the contrary, increase, but only for reach households. Poor households just give up on educational investments. As we've seen from the Table 1.14, if the child is in bad health, additional educational investments do not increase a lot his probability of moving to the high ability level, thus this investments might not be efficient and parents can choose not to spend on education at all. Top income quintile, on the contrary, completely substitutes governmental educational spending with the private one. However, total spending on ability decrease even for the upper quintile. They do this because children of richer parents are more likely to be healthy as well as to be of high ability level, this will make educational investments very efficient for them (see Table 1.14).

In absence of college subsidies not a lot happens with medical investment for the lower quintiles (and as a result, with their health), while higher quintiles reduce medical expenses (in order to pay for college). Lower quintiles (1st, 2nd and 3rd) have the trade-off between investments into health and education, that is tighter than for upper income quintiles, this results in higher substitution rate of the lost college subsidies through out-of-pocket spending. Why does this happen? Highly able and healthy people additionally benefit from the college education as it guarantees them higher human capital in the beginning of the adult life. As we remember, there is a trade-off between investments in health and investments in education, so for richer families, this trade-off is resolved by sacrificing a little bit of their health in order to get higher human capital through investments into college.

Table 1.19: Counterfactual experiments: Medicaid

Moment	Baseline	No Medicaid
Intergenerational lifetime income elasticity	0.273	0.287
Probability of Moving from Q1 to Q5	0.105	0.1
Probability of Moving from Q5 to Q5	0.279	0.28
Gini coefficient	0.424	0.425
Children in good health	0.776	0.758
Share of College Graduates	0.615	0.604
Insurance		
Children with Public Insurance	0.245	0
Children with Private Insurance	0.379	0.431
Children with No Insurance	0.376	0.569
Medical Expenses		
Average Medical Expenditure	8.042	7.118
Educational Spendings		
Private Educational Expenditure	0.40	1.5
Tax rate	0.124	0.101

In the Table 1.19 the results of experiments with Medicaid are presented. Eliminating Medicaid means that now parents have to spend on health of their children out of their own pocket. It produces a 5% effect on intergenerational income elasticity. This is a pretty high number if we take into account that only about 1/3 of the entire population receives Medicaid while early educational spendings by government is received by the entire population and around 1/3 of population receive college subsidies (by the way, the results from Medicaid elimination are sizable with the effects of college subsidies). Probability of reaching the top income quintile decreases for the bottom income quintile from 10.5% to 10%. Average health decreases as a result of a decrease in medical spending.

An interesting result is that average investments into education increase. In Table 1.20 we see, however, that health deteriorates more for lower income quintiles and effectively medical spending for them decrease, even though out-of-pocket expenses increase to compensate for the lost medical insurance. Poor people loose more health than rich people. On top of that there is a separation in educational decisions of households. Rich people slightly decrease their medical spending in order to increase educational spending. They compensate a slight decrease in health towards an increase in ability, to ensure a better production process for their children as they know that there is no Medicaid in economy and consecutively, if their children do not have sufficiently high human capital, they will not have access to medical insurance.

Table 1.20: Counterfactual experiments: Medicaid, by Parental Income Quintile

Moment	Baseline	No Medicaid
College Education by Parental Income Quintile		
Q1	0.0119	0.0121
Q2	0.299	0.278
Q3	0.782	0.768
Q4	0.98	0.961
Q5	1	1
Children in Good Health by Parental Income Quintile		
Q1	0.725	0.679
Q2	0.713	0.701
Q3	0.761	0.752
Q4	0.809	0.8
Q5	0.868	0.858
Average Medical Expenses by Parental Quintile		
Q1	4.67	3.39
Q2	5.59	4.79
Q3	6.26	4.94
Q4	7.49	6.77
Q5	16.2	15.7
Average Medical OOP Expenses		
Q1	2.77	2.94
Q2	2.69	2.97
Q3	3.4	3.77
Q4	6.52	5.86
Q5	10.9	10.6
Average Educational Spending by Parental Quintile		
Q1	0	0
Q2	0	0
Q3	0	0
Q4	0	0.487
Q5	1.99	6.82

In Tables 1.21 and 1.22 I explore the case in which no policies are present in the economy, to understand what is the joint effect of policies. First, as a result of having no policies in the economy, parents try to maintain the level of out-of-pocket expenses on health, however their effective spending decrease, in relative terms decreases more for children of the lowest income quintile. As a result, health deteriorates, and it deteriorates more for the lower income children. Second, as in the case of shutting down the Medicaid only, there is a separation in educational policies. Lower income quintiles pay nothing, while upper income quintiles invest 4 times more than in the benchmark (however effectively the spending decrease as there is no government policy). As a result of lower early education investments and stronger budget constraint less people receive college education. Gini coefficient of inequality increases from 42.2% to 43.5%, intergenerational elasticity of income increases from 0.273 to 0.318 (by 16.5%).

Table 1.21: Counterfactual experiments: joint effect of educational and health policies

Moment	Baseline	No policies
Intergenerational lifetime income elasticity	0.273	0.318
Probability of Moving from Q1 to Q5	0.105	0.0906
Probability of Moving from Q5 to Q5	0.279	0.298
Gini coefficient	0.424	0.435
Children in good health	0.776	0.749
Share of College Graduates	0.615	0.542
Insurance		
Children with Public Insurance	0.245	0
Children with Private Insurance	0.379	0.439
Children with No Insurance	0.376	0.561
Medical Expenses		
Average Medical Expenditure	8.042	6.88
Educational Spendings		
Private Educational Expenditure	0.408	0.972
Tax rate	0.124	0

5.1. Future directions

Main experiments with shutting down educational and medical policies show that all policies are important for intergenerational mobility. If we knew that for educational policies from the previous literature, analysis of childhood medical policies is done for the first time, as well as the interaction effect of health and educational policies was not studied before. Although the results are interesting, there is still a lot of work to be done. First, I need to perform a lot of robustness checks, including robustness checks for definitions of health and ability. Estimation results should also be improved. Finally, several more experiments need to be done. First, these are experiments with different insurance schemes. I can analyze potential effects of changes in Affordable Care Health Act that were enacted in 2014 (my model is estimated for the year 2012), universal insurance coverage for all children, introduction of income-dependent insurance subsidies instead of a means-tested program, as well as substituting public insurance policy with

Table 1.22: Counterfactual Experiments: Joint Effect of Educational and Health Policies, by Parental Income Quintile

Moment	Baseline	No Policies
College Education by Parental Income Quintile		
Q1	0.0119	0
Q2	0.299	0.134
Q3	0.782	0.605
Q4	0.98	0.98
Q5	1	0.991
Children in Good Health by Parental Income Quintile		
Q1	0.725	0.674
Q2	0.713	0.691
Q3	0.761	0.749
Q4	0.809	0.779
Q5	0.868	0.854
Average Medical Expenses by Parental Quintile		
Q1	4.67	2.6
Q2	5.59	4.58
Q3	6.26	6.66
Q4	7.49	5.39
Q5	16.2	15.2
Average Medical OOP Expenses		
Q1	2.77	2.69
Q2	2.69	2.88
Q3	3.4	3.98
Q4	6.52	4.99
Q5	10.9	10.4
Average Educational Spending by Parental Quintile		
Q1	0	0
Q2	0	0
Q3	0	0
Q4	0	0
Q5	1.99	4.86

conditional cash transfers. Another experiment of interest is allocation of a limited budget between existing policies.

The model possesses high degree of heterogeneity that also can be studied. For example, I can analyze whether time of fertility or marital composition of the society is contributing to intergenerational mobility, and whether policies should take these degrees of heterogeneity into account while being designed.

6. Conclusions

In the U.S. government spends significant amount of resources on needs-based medical policies. In June 2013, over 28 million children were enrolled in Medicaid and another 5.7 million were enrolled in State Child Health Insurance Program (SCHIP). We know very little, however, how medical policies affect intergenerational mobility. This thesis chapter tries to fill this gap in the literature.

In this chapter, I develop and estimate a human-capital based overlapping generations model of household decisions that take into account multidimensionality and dynamic nature of human capital investments. I distinguish two forms of human capital: health capital and human capital, and model explicitly government policies in education and health.

Results show that Medicaid and education policies affect intergenerational mobility in the US. The important effect of health policy comes through interaction of health policy with educational policies. Changes in all policies together have a larger effect than of each policy in isolation. Especially this interaction effect is important for children of the lower income quintile. In general absence of any policy leads to deterioration of outcomes (health, college attainment) for poor households due to the stronger trade-off between investments into health and education, comparing to richer people, who have higher margin to adjust. As a result we observe separation in household educational decisions by the level of income.

Chapter 2

Marriage and Health: Selection, Protection, and Assortative Mating

Joint with Nezih Guner and Joan Llull

1. Introduction

Married individuals are healthier and live longer than unmarried ones. This fact was first documented by British epidemiologist William Farr more than 150 years ago, and has been established by many studies since then.[1] The question is, of course, why? Does the association between marriage and health indicate a *protective* effect of marriage, or is it simply an artifact of *selection*, as healthier people are more likely to get married in the first place? The answer to this question is critical as it has important implications for public policy.[2] Studies on the link between public policy and health suggest that "upstream social and economic determinants of health are of major health importance, and hence that social and economic policy and practice may be the major route to improving population health." (House, Schoeni, Kaplan and Pollack, 2008, p.22). The alarming increase in morbidity and mortality among white males in recent years in the U.S. highlighted once again the importance of socio-economic determinants of health (Case and Deaton, 2015). Marriage is often portrayed as a solution for many social problems in the U.S. (see Waite and Gallagher, 2000), and the effectiveness of pro-marriage policies depends on whether marriage indeed makes individuals healthier, wealthier and happier.

In this chapter we study the relationship between health and marriage using data from the Panel Study of Income Dynamics (PSID) and the Medical Expenditure Panel Survey (MEPS). In both data sets married individuals report to be healthier than unmarried ones, and they do so in remarkably similar levels. The gap in self-reported health persists after we control for observable characteristics such as education, income, race, gender and the presence of children; starting at about 3 percentage points at younger ages (20 to 39), and increasing continuously for older ages, reaching a peak of 10 percentage points around ages 55 to 59. A similar picture emerges when we consider objective instead of

[1] On Farr's study, see Parker-Pope (2010).

[2] "Between 1950 and 2011, real GDP per capita grew at an average of 2.0% per year, while real national health care expenditures per capita grew at 4.4% per year. The gap between the two rates of growth —2.4% per year— resulted in the share of the GDP related to health care spending increasing from 4.4% in 1950 to 17.9% in 2011." (Fuchs, 2013, p.108).

self-reported measures of health, or when we use the occurrence of chronic conditions as an indicator of poor health.

We define the *marriage health gap* as the difference between age-dependent health curves for married and single individuals, which we specify nonparametrically. Different studies in evolutionary biology suggest that several physical and personality traits that define a person as attractive for mating are associated with youth and health, and as a result, with reproductive capacity.[3] Hence, individuals with better innate health tend to be more attractive in the marriage market. If individuals with better innate health are more attractive marriage partners, and, as a result, more likely to get married in the first place and stay married afterwards, least squares estimation of these curves would provide biased estimates of the effect of marriage on health.

Using the panel structure of the PSID, we try to overcome this selection bias by accounting for individual heterogeneity in (unobserved) innate health, potentially correlated with the timing and likelihood of marriage. We consider three models. We first consider a standard fixed-effects specification, which allows for unobserved differences in permanent innate health. This is, however, a restrictive approach, since it assumes that the innate health is constant over time, while it is reasonable to expect that differences in innate health show up in a stronger manner at older ages. To allow for age-dependent effects of innate health, our second model follows a *grouped fixed-effects approach*, developed by Bonhomme and Manresa (2015). The grouped fixed-effects estimator that we implement allows for age-dependent patterns of unobserved heterogeneity that are common for a group of individuals (e.g. high and low innate health types). The two approaches give very similar results: the observed effect of marriage on health disappears for younger (20-39) ages, while about a 5 percentage point gap between married and unmarried individuals remains for older (55-59) ages. This is half of the total difference for this age group (10 percentage points). These results suggest that the association between marriage and health at younger ages is likely to be driven by selection of healthier individuals into marriage, while there might be a protective effect of marriage that shows up at older ages. Finally, since health shocks might affect the probability of getting or staying married in subsequent periods, we control for previous health shocks by using a dynamic panel data model with fixed effects. We estimate this model by the system-GMM approach in Arellano and Bover (1995). This approach delivers a larger marriage health gap (about 10 percentage points by for ages 50-59), and suggests that our fixed-effects and grouped fixed-effects estimates might be on the conservative side.

Next we provide evidence that is indicative of how selection and protection might show up in the data. On the selection side, we first document that individuals who are ever married by age 30 (or 40) have better average innate permanent health than those individuals who are never married by that age. The variance of permanent health, on the other hand, is larger for those who are never married. These facts are consistent with a world in which individuals look for healthy partners in the marriage market. In such a world, innate health should be a good predictor of marriage and divorce probabilities and individuals would mate assortatively in terms of innate health. We then corroborate that data supports both predictions. Having better innate health is associated with higher probability of marriage and lower probability of divorce, even after controlling for initial (pre-marriage and pre-divorce) health status. Likewise, the correlation between husbands' and wives' uncovered measures of innate health is about 37%, and remains large and significant (about 32%) even after controlling for college, race, and a measure

[3] For instance, see Buss (1994) and Dawkins (1989).

of permanent income.

On positive effects of marriage on health that are not captured by selection, we find that married individuals are more likely to engage in preventive medical care than singles are, even after controlling for observable characteristics (including health expenditures, health insurance, and socio-economic variables). Married individuals around ages 50 to 54, for example, are about 6% more likely to check their cholesterol or have a prostate or breast examination. Marriage also promotes healthy habits. We focus on smoking, a major health risk. Our results show that a single individual is about 23 percentage points more likely to quit smoking if he/she gets married than if he/she stays single. Furthermore, a majority (about 74%) of singles who get married and quit smoking do so while they are married. The importance of healthy behavior also shows up in health expenditure patterns. While married individuals spend more on their health when they are young and healthy, singles end up spending more than married individuals when they are older and less healthy.

A possible important factor behind these differences in healthy behavior is health insurance: while about 10% of married individuals do not have any public or private insurance, this share amounts to 20% for females and 25% for males when unmarried. Indeed, if we focus on individuals without health insurance, we do not find a significant marriage health gap. These findings suggest that the availability of health insurance is an important facilitator for positive effects of marriage on health. This result speaks to the debate surrounding to potential effects of the health care reform (the Affordable Heath Care Act) in the United States.

We finally show that the effect of marriage on health is cumulative. In particular, we estimate the effect of the total number of years an individual has been married (marriage capital) and find a positive and significant effect on health, especially at older ages. These results are very consistent with our baseline estimates. For example, they predict marriage health gaps for individuals who are continuously married since ages 25 and 40 that are very similar to the baseline.

This chapter is related to the large literature on the relation between socioeconomic status and health (Stowasser, Heiss, McFadden and Winter, 2012). It is well documented that marriage is associated with positive health outcomes. Wood, Avellar and Goesling (2009) and Wilson and Oswald (2005) provide reviews of existing evidence. Pijoan-Mas and Ríos-Rull (2014) estimate, using the Health and Retirement Study (HRS), age-specific survival probabilities conditional upon socio-economic characteristics and show that married females (males) are expected to live 1.2 (2.2) years longer than their single counterparts. The existing literature also documents that health outcomes and healthy behavior are correlated between spouses, see e.g. Clark and Etilé (2006), Oreffice and Quintana-Domenque (2010), Chiappori, Oreffice and Quintana-Domenque (2012, 2013) and Banks, Kelly and Smith (2014). There is also a large and positive effect of education on health (e.g. Lleras-Muney, 2005; Cutler and Lleras-Muney, 2010), which goes beyond the higher financial resources that it brings (Gardner and Oswald, 2004; Smith, 2007). Finally, there is a growing literature in labor economics and macroeconomics that introduce health shocks and expenditures into life-cycle models with heterogeneous agents. French (2005), De Nardi, French and Jones (2010b), Ozkan (2013), and Kopecky and Koreshkova (2014) are recent examples.

In the existing literature, one approach to estimate the effect of marital status on health (mortality or self-reported health) is to regress health outcomes on marital status (or history) with controls for health in early ages. This approach is used to mitigate the effects of the selection of healthier individuals into marriage. Murray (2000), who follows a sample of male graduates from Amherst College in Massachusetts, finds evidence both of selection of healthy individuals into marriage as well as of a protective effect of marriage on health outcomes. Another approach to control for selection is to estimate fixed-effects regressions. Using this approach on Canadian data, Averett, Argys and Sorkin (2013) find that while marriage has a positive effect on health in the form of better mental health and lower alcohol consumption, it is also associated with weight gain and less frequent exercising. Finally, an alternative approach is to find valid instruments that generate exogenous variation in health or marriage outcomes. Finding such instruments in not an easy task (Adams, Hurd, McFadden, Merrill and Ribeiro, 2003). Lillard and Panis (1996), using data on males from the PSID, take a simultaneous equations (instrumental variables) approach and find that there might be negative selection into marriage as less healthy men have more to gain from marriage.

In this chapter, we make three contributions to the existing literature. First, we study self-reported health status for working age (20 to 64) individuals and identify nonparametrically the marriage health gap as a function of age. Second, we allow for unobserved heterogeneity in innate health (permanent and age-dependent), potentially correlated with timing and likelihood of marriage. Our approach to deal with potentially correlated age-dependent unobserved heterogeneity is novel in this literature. In particular, we estimate the effect of marriage on health using a grouped fixed-effects estimator, which allows for a flexible and yet parsimonious specification of age-dependent unobserved heterogeneity. Finally, our exploration of the potential channels through which selection and protection may show up in the data is also a contribution. We find that our uncovered measures of innate health are associated with higher probabilities of marriage and lower probabilities of divorce; there is also strong assortative mating among couples by innate health; and we highlight preventive health care and health insurance as possible factors behind the protective effects of marriage on health.

The chapter is organized as follows. In Section 2, we describe data sources and provide descriptive statistics. We discuss our empirical strategy in Section 3. Section 4 presents main results. In Section 5, we document suggestive evidence on selection and protection. Section 6 concludes.

2. Data and Descriptive Statistics

We use two data sources to document the relationship between marriage and health. The first data source is the Panel Study of Income Dynamics (PSID). The PSID began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Extensive demographic and economic data on these individuals and their descendants have been collected continuously since then. Starting in 1984, the PSID has been collecting data on self-reported health of individuals. We use data from 1984 to 2013. The data is annual until 1997 and biannual afterwards. Sample selection and variable definitions are explained in Appendix B.1. Appendix B.2 shows descriptive statistics.

The main health variable we use in this analysis is self-rated health.[4] Each household head is asked to rate his/her as well as his/her spouse's health as excellent, very good, good, fair, or poor. We consider those with excellent, very good or good health as *healthy*

[4] Bound (1991) discusses the implications of using subjective and objective health measures.

and others as *unhealthy*. As Table B.1 in Appendix B.2 shows, throughout the sample period, about 88% of individuals are healthy according to this definition. Likewise, about 66% of individuals are married. We consider those who declare themselves married in the surveys as *married* and others (never married, divorced or widowed, separated, as well as cohabitants) as *unmarried*. In the sample, about 32% of individuals have a college degree. Per-adult household income is about 38,000 in 2005 U.S. dollars.

The second data source is the Medical Expenditure Panel Survey (MEPS). The MEPS is a set of surveys of families and individuals, their medical providers, and employers across the U.S. and is the most complete source of data on the cost and use of health care and health insurance coverage. The MEPS has two major components: the Household Component and the Insurance Component. The Household Component, which is used here, provides data from individual households and their members, which is supplemented by data from their medical providers. The Household Component contains detailed information for each person in the household on demographic characteristics, health conditions, health status, usage of medical services, charges and source of payments, access to care, satisfaction with care, health insurance coverage, income, and employment. The MEPS is a rotating panel where panel members are interviewed 5 times over a 2-year interval. In the analysis below we use pooled data from panels from 1996 to 2009.

Table B.2 in Appendix B.2 shows descriptive statistics for the MEPS sample.. The MEPS and the PSID samples are quite similar in terms of education and household income. A smaller fraction of the MEPS sample is married, which reflects the facts that it covers relatively more recent years than the PSID does. About 16% of individuals in the MEPS sample do not have any, public or private, insurance. Individuals on average spend about 3,000 per year on health in 2005 U.S. dollars, which is about 9% of their total income.

Table 2.1 documents the marital status of the population in the PSID and MEPS samples (Panel A) and marital transitions in the PSID (Panel B). In both samples, almost all individuals eventually marry. Less than 5% of individuals remain never-married by ages 60-64. The fractions of individuals who are married, divorced or widowed increase monotonically by age. The fraction of people who are married in younger ages is larger in the PSID, which, as we commented above, reflects the fact that the MEPS covers more recent years than the PSID. For younger ages, there is significant turnover in marital status (Panel B). About 5% of married individuals between ages 25 to 29 become unmarried each year (mainly divorced), and about 11% of singles in the same age group get married. The size of marital transitions declines as individuals age.

Figure 2.1 shows differences between married (dark brown lines) and unmarried (light brown lines) individuals in self-reported health from the PSID (dashed lines) and the MEPS (solid lines) for ages between 20 and 64. Age patterns of self-reported health as well as the health gap between married and unmarried agents are remarkably similar in the two data sets. On average for all ages considered (20-64), 90% of married individuals indicate that they are healthy, while only 85% of unmarried ones do so. Not surprisingly, in very early ages most individuals (more than 90%) are in good health and the marriage health gap is small. For older ages the marriage health gap widens, and among those who are 40 to 64 years old, 86% of married individuals are healthy in contrast to 76% of unmarried ones.

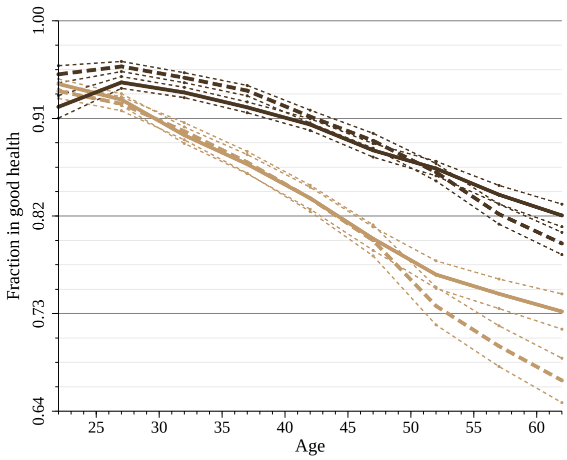
The fact that married agents are healthier than single ones could be due to a host of factors. Figure 2.2 reproduces Figure 2.1 conditional on a few observable characteristics

Table 2.1: Marriage Ratios and Transitions In and Out of Marriage by Age

	A. Marriage Ratios								**B. Marriage Transitions**	
	Married		Divorced/Sep.		Widowed		Never Married		Marr.	Single
Age:	PSID	MEPS	PSID	MEPS	PSID	MEPS	PSID	MEPS	Single	Marr.
20-24	36.9	16.4	7.1	2.5	0.1	0.0	55.8	81.1	8.1	11.6
25-29	52.1	43.4	10.8	7.3	0.3	0.2	36.9	49.1	5.3	11.3
30-34	63.5	60.3	14.7	10.8	0.5	0.2	21.2	28.7	3.9	10.1
35-39	69.3	65.2	17.2	14.9	0.8	0.6	12.7	19.4	3.1	7.2
40-44	70.8	66.2	19.1	18.4	1.0	1.1	9.1	14.4	2.7	7.0
45-49	71.5	68.0	19.8	19.8	1.6	1.8	7.1	10.5	2.1	4.4
50-54	73.0	68.8	18.1	20.2	3.3	2.8	5.7	8.2	1.9	4.5
55-59	74.1	69.1	16.3	19.3	5.5	5.0	4.0	6.5	1.4	2.2
60-64	73.7	68.2	14.2	17.1	9.0	9.7	3.1	4.9	1.8	2.2

Note: Panel A presents the weighted proportion of individual-year observations in each of four marital situations, and Panel B presents the proportion of married individuals getting unmarried in the following year (left column) and of unmarried individuals transiting into marriage (right column), within five-year age groups. Panel A is computed using the PSID and the MEPS as indicated; in Panel B, the PSID is used. PSID sample covers 1984-2013, annually until 1997, biannually since then; MEPS sample covers 1996-2009 annually. One-year transitions in Panel B are computed for 1984-1997, when yearly observations are available.

Figure 2.1: Health and Marital Status (PSID and MEPS)

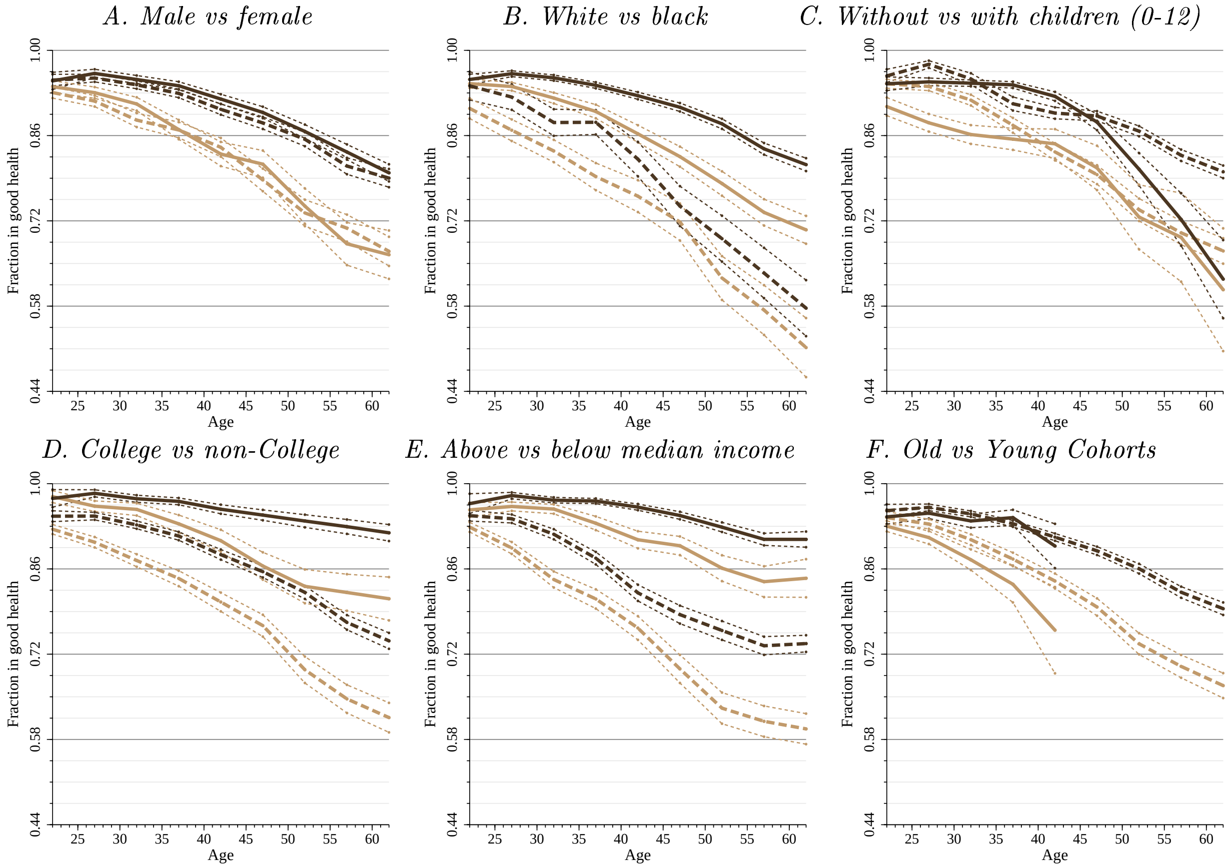


Note: Plotted lines represent the weighted fraction of married (dark brown) and unmarried (light brown) individuals that report being healthy, computed using the PSID (solid) and the MEPS (dashed). The horizontal axis indicates age, which is grouped in five-year categories (20-24 through 60-64). Dotted lines around point estimates indicate confidence bands of ± two standard errors, which are computed according to the corresponding survey design: sample weights are used for the PSID, and Taylor linearized standard errors are computed for the MEPS.

for the PSID sample.[5] In each sub-panel, dark brown lines indicate married individuals

[5]The results for the MEPS sample are in Figure B.1 in Appendix B.2.

Figure 2.2: Health and Marital Status for Different Socioeconomic Groups



Note: Plotted lines represent the weighted fraction of married (dark brown) and unmarried (light brown) individuals that report being healthy, obtained from the PSID. Fractions are reported for: top-left: male (solid) and female (dashed); top-center: white (solid) and black (dashed); top-right: without (solid) and with (dashed) children aged 0-12 living in the household; bottom-left: college graduates (solid) and non-college (dashed); bottom-center: above (solid) and below (dashed) median income; bottom-right: born after (solid) and before (dashed) 1970. The horizontal axis indicates age, which is grouped in five-year categories (20-24 through 60-64). Dotted lines around point estimates indicate confidence bands of ± two standard errors, which are computed using sample weights.

while light brown lines are for unmarried ones, and solid and dashed lines indicate different sub-populations. As Panel A of Figure 2.2 shows, males and females report very similar levels of health when they are married or single. According to Panel B, blacks have on average worse health than whites and the marriage health gap vanishes for blacks at older ages. In Panel C, the marriage health gap is visible and comparable whether or not one conditions on the presence of young (ages 0 to 12) children (estimates become imprecise at older ages, because few of those individuals have young children). Consistent with findings from the previous literature, individuals with better education and income have much better health. While the marriage health gap is similar conditional on college education (Panel D, the gap is larger for poorer individuals (Panel E). Finally, while younger cohorts report slightly lower levels of good health when unmarried, the marriage health gap is similar for individuals born before and after 1970 (Panel F).

3. Model Specification and Identification

In this section we describe our empirical strategy and discuss briefly how we aim to identify the effect of marriage on health. Our objective is to estimate how being married affects an individual's health at each point along his/her life cycle. Thus we are interested in heterogeneous treatment effect along the life cycle. The main challenge in identifying the effects of marriage on health is that married individuals might differ from unmarried ones along several observed and more importantly unobserved characteristics. As a result, if healthy individuals select themselves into marriage in the first place, simple correlations between marriage and health will capture a combination of selection and protection effects.

We estimate three different models that take unobserved heterogeneity and selection into account. First, we consider a fixed effects model that allows for individual-specific permanent innate health to be correlated with the treatment (i.e. with being married). Second, we study a less restrictive model that allows the individual-specific innate component of health to differ by age. Finally, since health shocks might also affect probabilities of getting or staying married later on in life, we consider a dynamic panel data model that controls for the lagged health status together with permanent innate health.

We start from the following model:

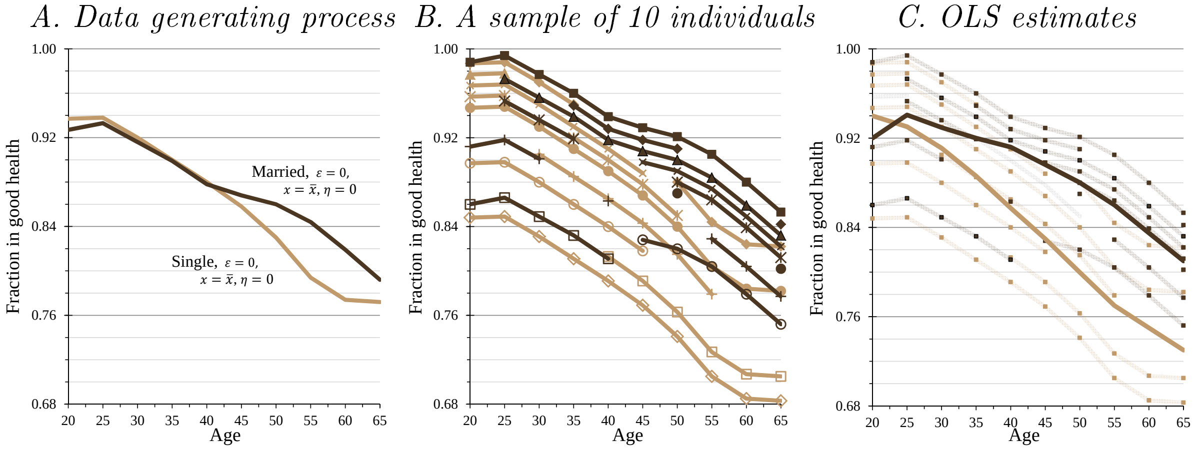
$$h_{it} = \alpha(a_{it}) + \beta(a_{it})m_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \delta_t + (\eta_i + \varepsilon_{it}), \tag{2.1}$$

for $i \in \{1, ..., N\}$ and $t \in \{1, ..., T\}$, where h_{it} is the health status of individual i in year t, a_{it} is his/her age, m_{it} is an indicator variable that equals one if the individual is married in period t, δ_t is a vector of time dummies, and $(\eta_i + \varepsilon_{it})$ is the error term, unobserved by the econometrician. The function $\alpha(a_{it})$ is the health curve for single individuals as a function of age, and $\alpha(a_{it}) + \beta(a_{it})$ is the one for married individuals. These functions are non-parametrically specified. Our main interest is in the marriage health gap, which is given by $\beta(a)$.

The unobserved error term includes an individual-specific permanent component η_i. This type of unobserved heterogeneity generates parallel health curves for different types of individuals, shifted by a different intercept. We interpret this as a permanent innate health component, which shifts health curves vertically, making them parallel across individuals. The term ε_{it} captures health innovations, which are assumed to be *iid* over time, and uncorrelated with observables. If certain types of individuals are more likely to get married in the first place (or, more generally, there are systematic differences in the timing and likelihood of marriage for different types), the error term $(\eta_i + \varepsilon_{it})$ will be correlated with the regressors, and Ordinary Least Squares (OLS) estimates will be biased, as we discuss below. Studies in evolutionary biology, for example, suggest that individuals with better innate health are more attractive mates in the marriage market, as better health is a clear indication of reproductive success. This is summarized in Buss (1994) as follows: "Our ancestors had access to two types of observable evidence of a woman's health and youth: features of physical appearance, such as full lips, clear skin, smooth skin, clear eyes, lustrous hair and good muscle tone, and features of behavior, such as bouncy, youthful gait, and animated facial expression, and a high energy level. These physical cues to youth and health, and hence reproductive capacity, constitute the ingredients of male standards of female beauty" (p.53).[6]

[6] Pointing in the same direction: "From the point of view of a female trying to pick good genes with which to ally her own, what is she looking for? One thing she wants is evidence of ability to survive" (Dawkins, 1989, p.157).

Figure 2.3: Unobserved Heterogeneity and the Self-Selection Bias: An Example



Note: This figure illustrates the bias from omitting unobserved heterogeneity in the estimation of the health curves. Panel A presents the data generating process. Married health curves are in dark brown and single health curves are in light brown. Panel B plots a hypothetical sample of 10 individuals simulated from the data generating process, all of them with $\boldsymbol{x} = \bar{\boldsymbol{x}}$ and $\varepsilon = 0$. Types of markers identify individuals. Panel C shows OLS estimates of the married and single curves on the simulated sample.

This pattern of self-selection would lead OLS to overestimate the marriage health gap in Equation (2.1). Furthermore, the size of the bias would differ at different ages. Since a majority of individuals eventually gets married at some point, the bias is likely to be larger at younger ages. We illustrate this bias in Figure 2.3. Consider the data generating process described in Figure 2.3A, which shows health curves for married (dark brown line) and single (light brown line) individuals. The curves are drawn with $\boldsymbol{x} = \bar{\boldsymbol{x}}$, $\eta = 0$, and $\varepsilon = 0$. As Figure 2.3A shows, this process does not generate a marriage health gap at younger ages, while it generates a marriage gap in later years. Our choice for particular health curves in Figure 2.3A is not random; they approximately reproduce the marriage health gap we obtain from a fixed effects estimation of Equation (2.1) on the PSID sample. As noted above, since innate health η enters as an additive shifter for given $\boldsymbol{x}_{it}$ and ε_{it}, individuals with different η values are represented by health curves that are parallel to those in Figure 2.3A and shifted by the corresponding η_i.

Figure 2.3B shows a simulated sample of 10 individuals generated by the process just described. Each individual is indicated by a different marker. There is, for example, an individual with the highest value of η who is always married (marked by dark brown squares at the top), and another individual with the lowest value of η who is always single (marked by empty light brown diamonds at the bottom). In between, there are individuals with different marital histories. The individual, who is indicated by empty circles, for example, is single before age 45 and then he/she gets married. In the generated sample, there is positive self-selection as individuals with higher η are more likely to get married and do so earlier.

If we average observed health of married and of singles (or, equivalently, we fit Equation (2.1) to those data by OLS), we obtain the health curves depicted in Figure 2.3C. Given the selection into early marriage by high η individuals, OLS overestimates the underlying marriage health gap. The health curves obtained in Figure 2.3C intentionally replicate the (unconditional) average health curves by marital status obtained from the PSID, depicted in Figure 2.1 in Section 2.

A fixed-effects estimation of Equation (2.1) provides consistent estimates of the health curves, as long as our assumption of additive separability of η is satisfied. It is important to note that since $\alpha(a)$ and $\beta(a)$ are time-varying for a given individual, as he/she is observed over different ages, identification does not rely exclusively on individuals who change their marital status. Individuals contribute to the identification of the shape of married health curves (up to their intercept) whenever they are married, even if they never switch marital status. Likewise, whenever they are single, individuals contribute to the identification of the singles health curve up to the intercept. Changes in marital status thus identify the gap between single and married intercepts.[7] Consequently, identification of the marriage health gap at a given age, say 60 to 64, is not identified exclusively by individuals who switch marital status within that age range.

As Figure 2.3C makes clear, we estimate Equation (2.1) under the assumption that innate health shifts health curves in a parallel way. It is, however, very likely that good or bad innate health maps into small differences in observed health early in the life cycle, while these differences might get magnified as one ages. In order to allow for age-dependent effects of innate health, we next consider the following model:

$$h_{it} = \alpha(a_{it}, \eta_{g(i)}) + \beta(a_{it})m_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \delta_t + \varepsilon_{it}, \tag{2.2}$$

for $i \in \{1, ..., N\}$ and $t \in \{1, ..., T\}$, where now $\alpha(a, \eta_g)$ is the unmarried health curve for type-$g \in \{1, ..., G\}$ individuals, with $G < N$, and $\alpha(a, \eta_g) + \beta(a)$ is the curve for married ones. Thus, Equation (2.2) allows for unobserved heterogeneity in the entire shape of the health curves through $\alpha(a, \eta_g)$.

Bonhomme and Manresa (2015) develop an estimator for models with grouped patterns of unobserved heterogeneity like the one specified in Equation (2.2), to which they refer as grouped fixed-effects estimation. The key intuition for self-selection and identification arguments are analogous to those illustrated in Figure 2.3. The main difference is that now the entire health curve is allowed to differ by type in a flexible way (over and above the different intercept). In order to identify such models, however, one needs to set a relatively small number of types. For example, in line with the results below, high types could have a higher intercept and a flatter decrease in their health status by age, while low types could have a lower intercept as well as a more steep health deterioration.

The models described in Equations (2.1) and (2.2) both assume that there is no feedback from health shocks to marriage probabilities, and that all self-selection occurs through innate unobserved heterogeneity. Health shocks, however, could affect the probability of getting or staying married in subsequent periods.[8] To account for this type of self-selection, we consider the following transformation of the model in Equation (2.1):

$$h_{it} = \varphi h_{it-1} + \alpha(a_{it}) + \beta(a_{it})m_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \delta_t + (\eta_i + \varepsilon_{it}), \tag{2.3}$$

for $i \in \{1, ..., N\}$ and $t \in \{1, ..., T\}$. By controlling for lagged health, h_{it-1}, Equation (2.3) analyzes the effect of marriage on health innovations. In this case, a fixed-effects estimation does not deliver consistent estimates, e.g. see Arellano and Bond (1991). Therefore, we use a generalized method of moments approach, in the way described in Arellano and

[7] Therefore, individuals who are, for example, always married (like the individual with the highest η in Figure 2.3B) contribute to the identification of the shape of the married health curve, despite not contributing to the identification of the gap between married and single intercepts.

[8] Medical literature documents that health shocks such as cancer, or unhealthy habits such as heavy drinking and smoking, are associated with divorce. See, for example, Kirchhoff, Yi, Wright, Warner and Smith (2012) and Torvik, Gustavson, Roysamb and Tambs (2015).

Bover (1995), often known as System-GMM. This procedure delivers consistent estimates if health shocks only affect marriage probabilities with some lag (i.e. η_i is predetermined to ε_{it}), and health innovations ε_{it} are serially uncorrelated. This assumption is plausible, since we focus on relatively younger ages.

4. Estimation Results: the Marriage Health Gap

In this section we present *OLS* and *fixed-effects estimates* of Equation (2.1), *grouped fixed-effects estimates* of Equation (2.2), and *system-GMM estimates* of Equation (2.3). We also show that the main results are robust to different definitions of two key variables, health and marriage.

4.1. Main Results

Panel A of Figure 2.4 presents OLS estimates of $\beta(a)$ from the PSID (dark blue) and the MEPS (light blue) samples.[9] In estimation, we use five-year age bins, from 20-24 to 60-64.[10] Health, h, is an indicator variable that takes a value of one whenever the individual is healthy. Control variables, $\boldsymbol{x}$, include income, gender (female dummy), race (black dummy), education (college dummy), children (dummies for presence of children ages 0-3, 4-12, and 13-18 in the household), and cohort (year of birth dummies).

The results show that after controlling for observable characteristics, there is a positive and significant difference between the reported health of married and unmarried individuals. The gap starts at about 3 percentage points at younger ages (20 to 39), and increases continuously for older ages, reaching a peak of 10 percentage points at age 55 to 59 in the PSID sample. Similar results are obtained from the MEPS sample when we estimate the model with the same controls. The gap is initially small and grows to about 8 percentage points for 55 to 59 age group.

Panel B of Figure 2.4 shows fixed-effects estimates for the PSID sample. Fixed-effects estimation reduces the size of the marriage health gap substantially. Indeed for ages up to 40 the marriage health gap disappears completely. After age 40, however, the positive effect of marriage on health starts to show up. At the peak of the gap (between ages 50-59), married individuals are about 5 percentage points more likely to be healthy than unmarried ones. This is about half of the OLS gap.[11]

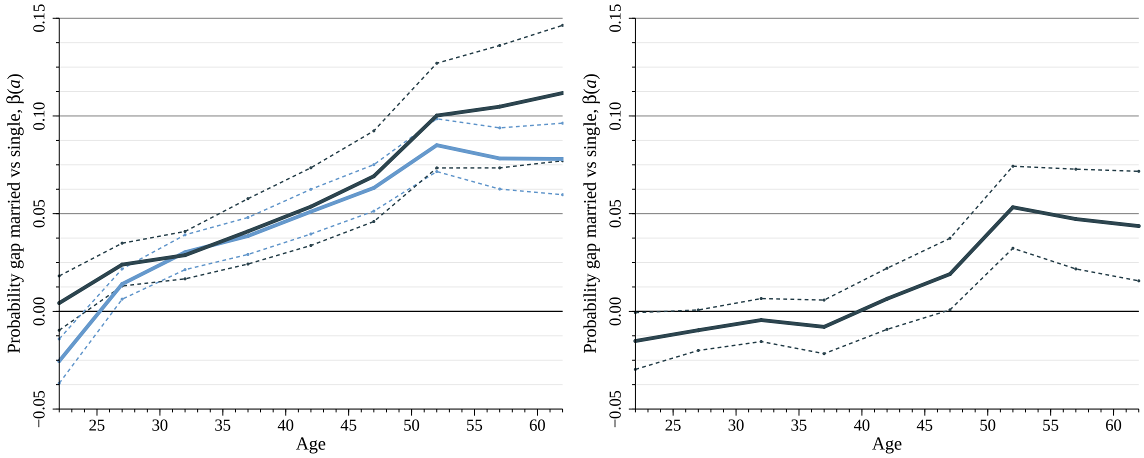
Next, we estimate Equation (2.2) that allows for age-dependent unobserved heterogeneity. We assume that unobserved heterogeneity is summarized by two (high and low innate health) types. Panel A of Figure 2.5 shows the health curves for single individuals of each type. It is apparent that two types are clearly separated with respect to their health curves. High types, who are about 81.3% of the sample, have consistently better health at all ages. On the other hand, low-type individuals, 18.7% of the sample, are less healthy to begin with and their health deteriorate faster. These results provide evidence of age-dependent patterns of unobserved heterogeneity in (innate) health.

Panel B of Figure 2.5 shows the resulting marriage health gap. Marriage health gap is negligible at younger age (below 40-45) and then grows to about 5% at around ages

[9] The full set of regression coefficients are shown in Table B.3 in Appendix B.3.
[10] Results are robust to different bin widths. Figures plot the mid point of the interval.
[11] We also checked whether health curves differ by several socioeconomic characteristics, such as gender, race, education, the presence of children, and income, as well as by different cohorts. Our results, which are available upon request, do not significantly different patterns across any of these dimensions.

Figure 2.4: Marriage Health Gap: OLS and Fixed-Effects Estimation Results

A. Ordinary Least Squares (OLS) *B. Fixed-Effects*



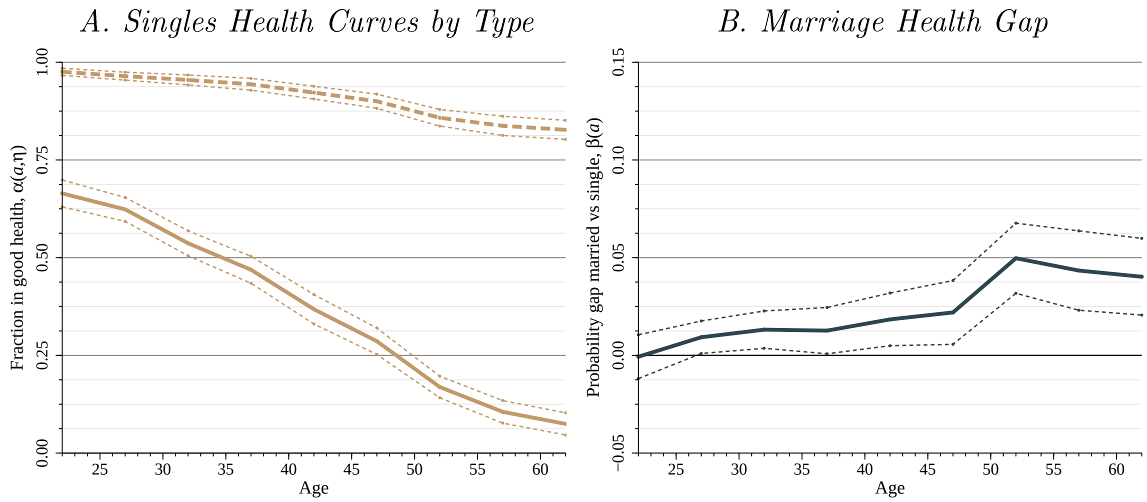
Note: Solid lines show estimated marriage health gaps $\beta(a)$ from Equation (2.1). The regression is fitted to the PSID (dark blue) and the MEPS (light blue). Left figure presents estimates from OLS regressions, and right figure presents fixed-effects estimates. The dependent variable is an indicator variable that takes a value of one if the individual is healthy. Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate $\alpha(a)$. The horizontal axis indicates age. In estimation, five-year age bins (20-24, through 60-64) are considered. The center point of the bin is represented in the figure. Weights are used in estimation. Dotted lines indicate $\pm$ two standard errors confidence bands around point estimates, which are clustered at the household level in the PSID, and Taylor linearized using survey stratification design in the MEPS.

50-55. This is again about half of the gap estimated by OLS for these ages. These results are almost identical to those in Panel B of Figure 2.4. This is remarkable as they are obtained from two models that are quite different. In particular, while the fixed-effects model assumes permanent unobserved heterogeneity, the grouped fixed-effects one allows for unobserved heterogeneity that is age-dependent. Additionally, estimates are obtained from very different techniques. While the first model is estimated using standard fixed-effects panel data tools, in the second one we allow for two unobserved types, and we use an estimation algorithm that classifies individuals into these types to minimize the predicted squared error for each individual (see Bonhomme and Manresa, 2015).

Finally, Figure 2.6 presents estimates for Equation (2.3). While the overall pattern of the marriage health gap is similar to what we obtain from fixed-effects and grouped fixed-effects estimates, the marriage health gap is now larger. This suggests that there is a negative correlation between lagged health shocks and the probability of being married. As a result, by not including lagged health in Equation (2.1), we underestimate the effect of marriage on health. Once this bias is corrected, the effect of marriage on health is estimated to be larger. In Figure 2.6, marriage health gap is already 5% for ages 40 to 49 and increases up to 10% for later years. These results suggest that the baseline results in Figures 2.4 and 2.5, are, if anything, conservative estimates of the effect of marriage on health.[12]

[12] There is another reason why these estimates might be conservative. If individuals make pre-marital investment in health to make themselves more attractive in the marriage market, the estimated effect of

Figure 2.5: Marriage Health Gap: Grouped Fixed-Effects Estimation Results



Note: Thick lines in the left plot show $\alpha(a, \eta_g)$, the estimated health curves for unmarried individuals of high (solid light brown) and low (dashed light brown) health types, and the solid line in the right plot shows $\beta(a)$, the estimated marriage health gap (dark blue), both of them from Equation (2.2). The model is fitted to the PSID, implementing the algorithm described in Bonhomme and Manresa (2015) for two types. The algorithm was started from 1,000 different random points, and it generally converged to the same minimum. It identified 81.3% healthy-type individuals (12,660), and 18.7% of unhealthy-type (2,909). The dependent variable is an indicator variable that takes the value of one if the individual is healthy. Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies. The horizontal axis indicates age. In estimation, five-year age bins (20-24, through 60-64) are considered. The center point of the bin is represented in the figure. Weights are used in estimation. Dotted lines indicate ± two standard errors confidence bands around point estimates, clustered at the household level.

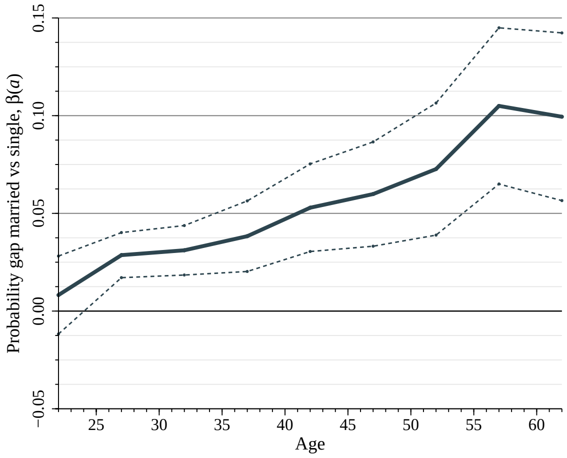
The results from these three specifications tell a very similar story: there is an important role for self-selection in explaining the observed marriage health gap, especially at earlier ages, while some protective effects of marriage on health remain at older ages. We next show that this result is robust to different definitions of the two key variables, health and marriage. In Section 5, we then explore both self-selection patterns and the potential remaining protective effects of marriage on health in further detail . In what follows, we focus on Equations (2.1) and (2.2), our more conservative estimates.

4.2. Robustness

The results in Figure 2.4 are based on self-reported measures of health. The MEPS contains another measure, SF12v2 (short form 12 version 2), that is constructed as an index from answers that respondents give to a set of health-related objective questions. The left panel of Figure 2.7 replicates the OLS estimates from the MEPS sample with this

marriage on health will be small as singles health will also be higher due to these premarital investment. In other words, marriage has an indirect effect on untreated individuals which makes them look healthier. Lafortune (2013) shows that worse marriage conditions indeed lead individuals to make higher pre-marital investment in education.

Figure 2.6: Marriage Health Gap: System-GMM Estimation Results



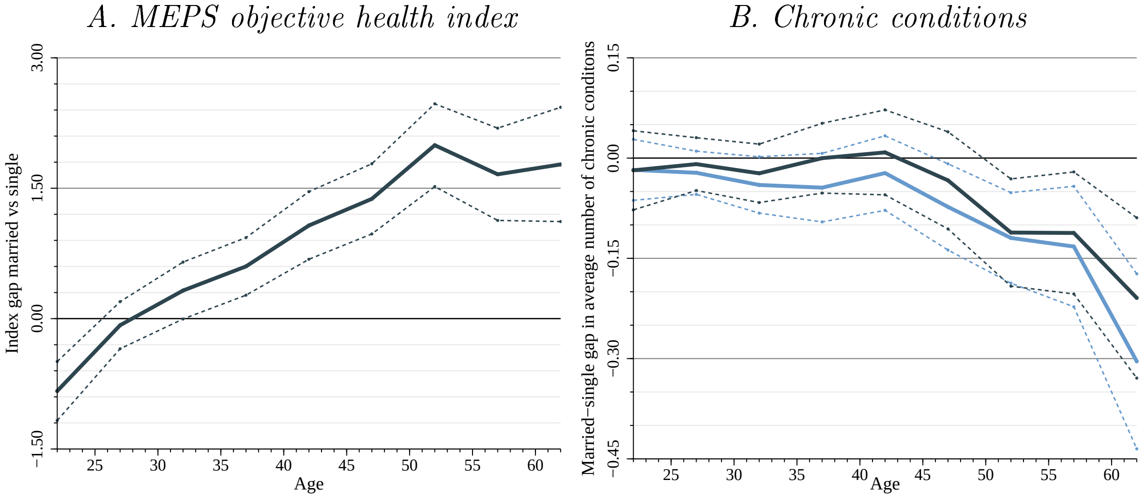
Note: The solid line shows the estimated marriage health gap $\beta(a)$ from the dynamic model in Equation (2.3). The regression is estimated by System-GMM (Arellano and Bover, 1995) from the PSID. The dependent variable is an indicator variable that takes a value of one if the individual is healthy. Control variables include the lagged dependent variable and a vector of controls that includes female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate $\alpha(a)$. The horizontal axis indicates age. In estimation, five-year age bins (20-24, through 60-64) are considered. The center point of the bin is represented in the figure. Weights are used in estimation. Dotted lines indicate $\pm$ two standard errors confidence bands around point estimates, which are clustered at the household level.

measure of health, and show that the basic qualitative picture remains the same (although it is hard to compare these results quantitatively).

Another objective measure of health is the presence of chronic conditions (such as cancer, hypertension, diabetes, stroke, hearth attack, etc.), which is provided in the PSID. The right panel of Figure 2.7 shows the fixed-effects and grouped fixed-effects and estimates of the marriage gap obtained from this health measure. The dependent variable is the number of different chronic conditions an individual ever had by any given age. Consistent with the other two measures of health, the difference between married and single individuals is very small for younger ages, but as individuals age, the model predicts that married individuals have a much smaller number of chronic conditions than singles do. Around ages 50 to 54, for example, a married individual is expected to have, all else equal, 0.15 fewer chronic conditions than if he/she was unmarried. As we summarize in Table B.1 in Appendix B.3, on average individuals have about 0.65 chronic conditions. Hence, the marriage gap is about 23% of the mean. Again the results from the two estimation strategies give very similar results.

We also check whether the way we define married and unmarried individuals affect the results. In our first check, we would like to understand whether divorce (in contrast to being never married) has a particularly adverse effect on health. To this end, we drop divorced agents from the pool of unmarried, and compare married individuals with those who are never married or widowed. Results in Panel A of Figure 2.8, are very much in line with our basic results. Indeed, the marriage health gap is now slightly larger, which suggests that divorced individuals have better, not worse, health than those who are never married or widowed. This could possibly reflects a positive effect of marriage capital (measured as the total number of years one is married) on health, which we explora

Figure 2.7: Alternative Health Measures



Note: Plotted lines show the estimated marriage health gaps $\beta(a)$ for two alternative measures of health: SF12v2 objective index of health (left), estimated by OLS from the MEPS, and the cumulative number of different chronic conditions suffered by the individual (right), which includes fixed-effects estimates (dark blue) and group fixed effects estimates (light blue), both obtained from the PSID. The following chronic conditions are considered: stroke, heart attack, hypertension, diabetes, cancer, lung disease, arthritis, asthma, memory loss, and learning disorder, as defined in the PSID. Group fixed effects estimates from the right plot are obtained implementing the algorithm described in Bonhomme and Manresa (2015) for two types. The algorithm was started from 1,000 different random points, and in general converged to the same global minimum. The algorithm identified 63% high-type individuals (9,804), and 37% of low-type (5,765). Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate $\alpha(a)$ or $\alpha(a, \eta_g)$. The horizontal axis indicates age. In estimation, five-year age bins (20-24, through 60-64) are considered. The center point of the bin is represented in the figure. Dotted lines indicate $\pm$ two standard errors confidence bands around point estimates, which are clustered at the household level in the PSID, and Taylor linearized using survey stratification design in the MEPS.

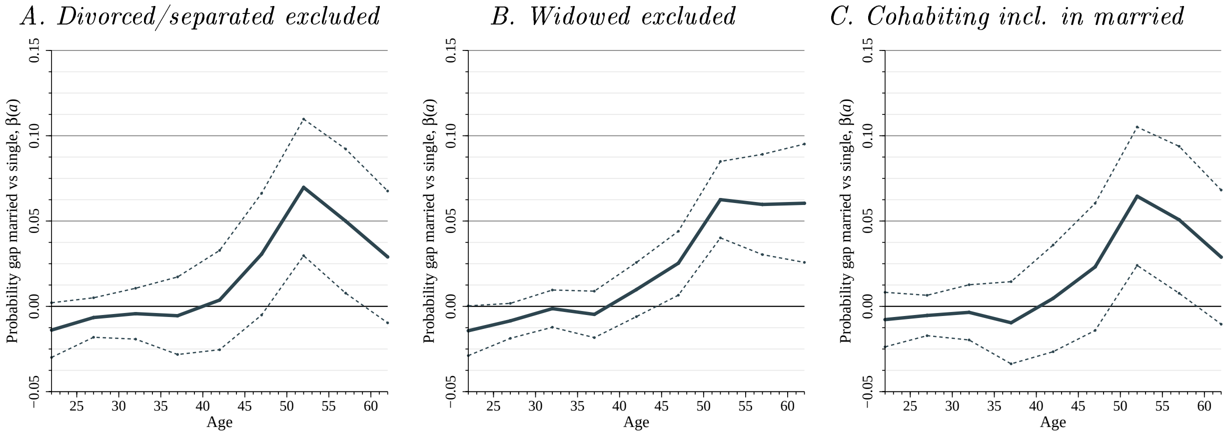
further below. Next, we exclude widows from the pool of single agents (Panel B). In this case, results are similar to our baseline results. Finally, we consider all cohabitants as married (Panel C). As documented in Table B.1 in Appendix B.3, this increases the fraction of married in the PSID from 65% to 72%. Point estimates of the marriage health gap are now slightly smaller, but not statistically different from baseline results.[13]

5. Exploring Selection and Protection Mechanisms

Results in previous section suggest that both selection of healthy individuals into marriage at early ages as well as protection and improvement of health within marriage at later

[13] The slightly lower effect could be the result of cohabitants being more similar to unmarried individuals than to married ones. This would be consistent with Schoenborn (2004), who document that "health limitations, conditions, and unhealthy behaviors among adults living with a partner resembled or exceeded prevalence among adults who are divorced or separated." (p.11).

Figure 2.8: Alternative Definitions of Married and Single



Note: Solid lines show within-groups estimated marriage health gaps $\beta(a)$ from Equation (2.1) for different definitions of married and unmarried populations: excluding divorced/separated (left) or widowed (center) from the sample, and including cohabitants in the married group (right). The regression is fitted to the PSID. Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate $\alpha(a)$. The horizontal axis indicates age. In estimation, five-year age bins (20-24, through 60-64) are considered. The center point of the bin is represented in the figure. Weights are used in estimation. Dotted lines indicate $\pm$ two standard errors confidence bands around point estimates, which are clustered at the household level.

ages play a role in generating the marriage health gap observed in the data. This section explores how selection and protection may show up in the data.

5.1. Self-Selection into Marriage and Divorce

We start by documenting the relation between permanent innate health and observed individual characteristics. The left panel of Table 2.2 shows the coefficients of a regression of when we regress innate health on several individual characteristics. In the first column, the dependent variable is η_i, the estimated fixed effects from Equation (2.1), while in the second column, it is a binary variable indicating whether an individual belongs to the healthy type in Equation (2.2). The two specifications give very similar results. Both educational attainment and race are strongly correlated with permanent innate health. A college degree is associated with about 0.05 higher value of η_i, about one-fifth of standard deviation of η_i (about 0.24), and being black is associated with 0.063 lower value of η_i, about one-fourth of a standard deviation. Similarly, a college graduate has about 8 percentage points higher chances of belonging to the healthy type, while a black individual has about 5.6 percentage points lower probability. Not surprisingly, higher height and lower weight are also associated with better innate health, and individuals with higher income are more likely to have higher innate health. For example, additional 10,000$ of income are associated with about 4 percentage points higher chances of belonging to the healthy type. There are, however, no significant differences by gender, i.e. females do not have higher innate health than males. In panel B of Table 2.2, we repeat the same exercise for chronic conditions. Individuals experiencing a chronic condition at one point along the life cycle are also much less likely to have higher levels of innate health. Having a stroke, for example, is associated with 18.4 percentage points lower probability

Table 2.2: Correlation between Innate Health and Observable Characteristics

A. Demographic characteristics	Innate permanent health (η_i)	Probability healthy type ($\eta_{g(i)}$)	**B. Chronic conditions**	Innate permanent health (η_i)	Probability healthy type ($\eta_{g(i)}$)
Height (inches)	0.009	0.013	Stroke	-0.135	-0.184
	(0.001)	(0.002)		(0.027)	(0.042)
Weight (pounds)	-0.001	-0.001	Hypertension	-0.034	-0.053
				(0.006)	(0.009)
	(0.000)	(0.000)	Diabetes	-0.101	-0.143
Female	0.008	0.007		(0.011)	(0.019)
	(0.008)	(0.014)	Cancer	0.002	-0.018
College	0.053	0.080		(0.011)	(0.020)
	(0.005)	(0.009)	Lung disease	-0.123	-0.173
Black	-0.063	-0.056		(0.013)	(0.021)
	(0.011)	(0.017)	Heart attack	-0.057	-0.084
Income	0.003	0.004		(0.016)	(0.029)
	(0.001)	(0.001)	Arthritis	-0.074	-0.115
Constant	-0.508	0.171		(0.008)	(0.013)
	(0.073)	(0.129)	Asthma	-0.049	-0.059
				(0.010)	(0.014)
			Memory loss	-0.206	-0.320
				(0.031)	(0.041)
			Learning disord.	-0.116	-0.183
				(0.017)	(0.030)
			Constant	0.042	0.937
				(0.002)	(0.004)

Note: The table presents the coefficients of a regression of innate health on the listed characteristics. Innate permanent health (η_i) indicates the estimated fixed effect from Equation (2.1). Probability healthy type ($\eta_{g(i)}$) indicates that the dependent variable of the regression is a dummy variable that takes the value of one if the individual is of the healthy type as defined in the estimation of Equation (2.2). The standard deviation of $\widehat{\eta}_i$ is 0.244. Regressions are fitted by to the PSID. Standard errors, clustered at the household level, are reported in parentheses.

of belonging to the healthy type.

We next document how innate permanent health is distributed among married and unmarried individuals. The upper panel of Table 2.3 shows innate health differences between individuals who are never and ever married by ages 30 and 40, measured by recovered individual fixed effects from Equation (2.1). For both ages, the average innate health of ever-married individuals is higher than never-married ones, but there is more

Table 2.3: Empirical Distribution of Innate Health

	Individuals that at age [...] are [...]:			
	Age 30		Age 40	
	Never married	Ever married	Never married	Ever married
Innate permanent health (η_i):				
Mean	-0.027	0.008	-0.039	0.008
Standard deviation	0.204	0.163	0.227	0.193
Number of individuals	2,207	4,827	810	4,963
Deciles:				
1st	-0.288	-0.175	-0.384	-0.228
2nd	-0.099	-0.013	-0.160	-0.043
3rd	0.021	0.056	-0.043	0.039
4th	0.055	0.062	0.009	0.072
5th	0.060	0.066	0.068	0.080
6th	0.065	0.071	0.081	0.088
7th	0.070	0.077	0.091	0.098
8th	0.078	0.084	0.108	0.113
9th	0.090	0.096	0.126	0.133
Innate health type ($\eta_{g(i)}$):				
Fraction of high type	0.845	0.895	0.824	0.884
Number of individuals	1,806	4,249	642	4,264

Note: The table reports statistics that summarize the empirical distribution of recovered fixed effects η_i in Equation (2.1), and of innate health types $\eta_{g(i)}$ in Equation (2.2) for different groups of individuals. Each block includes individuals that, at the indicated age, are in the indicated situation: never married and ever married. Statistics are computed from the PSID. Weights are used in the estimation. Three year windows are constructed around the indicated age to increase the number of observations.

dispersion among never married. At age 30, for example, coefficients of variation of innate permanent health are about 7.6 and 20 for married and unmarried individuals, respectively. Dispersion among unmarried is even higher at age 40. Additionally, the innate health distribution of ever-married individuals dominates that of never-married ones at lower deciles (below fourth), while the reverse is true for higher deciles. In the lower panel of Table 2.3, we report the fraction of individuals who belong to the healthy group by their marital status. Consistent with the results in the upper panel, individuals with higher permanent innate heath are more likely to marry with each other.

These patterns are consistent with selection of healthy individuals into marriage. Consider a world in which innate health is observable and singles look for healthy partners. In such world, given large variance of health among never married individuals, those with good health wait until they find a suitable partner. As a result, the average innate health among married is higher, while the dispersion of health is smaller (as in our data). Those

Table 2.4: Health and Marriage/Divorce Probabilities

	Never married by age 25 and married at age 30-40			Married at age 25 and divorced at age 30-40		
Health at 20-25	0.213	-0.140	0.085	-0.157	-0.014	-0.075
	(0.075)	(0.105)	(0.088)	(0.059)	(0.079)	(0.068)
Innate permanent health (η_i)		0.573			-0.236	
		(0.117)			(0.094)	
Innate health type ($\eta_{g(i)}$)			0.148			-0.094
			(0.052)			(0.041)

Note: The left panel presents the coefficients of three regressions of a dummy variable that takes the value of one if the individual is married at some point between ages 30 and 40 on the indicated health variables for a sample of individuals who had never been married by age 25. The right panel presents results from similar regressions where the dependent variable is a dummy variable that equals one if the individual gets divorced at some point between ages 30 and 40 on a sample of individuals that are married by age 25. These regressions are fitted to the PSID. Health at 20-25 indicates the average of the self-reported health variable used throughout the paper over ages 20 to 25. The innate permanent health variable (η_i) is the fixed individual effect recovered from the estimation of Equation (2.1); the standard deviation of $\widehat{\eta}_i$ is 0.244. Innate health type ($\eta_{g(i)}$) is a dummy variable that takes the value of one if the individual is of the healthy type from those obtained in the estimation of Equation (2.2). Robust standard errors in parenthesis.

with bad health are unattractive partners in the marriage market and those with better health are more selective. Hence, in such a world, health is a good predictor of entry into marriage and there is positive assortative mating by health among married individuals.[14] As we discuss next, the data supports both of these predictions.

We first explore whether health is a good predictor of entry into marriage in the PSID. We focus on individuals who remain never married by age 25 and analyze how their health in younger ages (average health between ages 20-25) and their innate permanent health (either the estimated fixed effect from Equation (2.1), $\widehat{\eta}_i$, or the health type in Equation (2.2)) affect their probability of getting married between ages 30 and 40.

The results are shown in Table 2.4. The first column shows that an unmarried individual who is in good health between ages 20-25 has about 21 percentage points higher chances of being married at some point between ages 30 and 40 than someone whose health is poor. When we include innate permanent health in the regression (measured by $\widehat{\eta}_i$), the latter absorbs all the positive association with marriage probability (second column): a one standard deviation increase in innate permanent health is associated with a 14 percentage points increase in the probability of getting married before age 40, and the remaining effect of being in good health at ages 20 to 25 becomes negative and not significant. These results suggest that selection into marriage is mostly captured by the

[14] There is evidence that husbands and wives sort by smoking behavior as well as by body-mass index. See Clark and Etilé (2006), Oreffice and Quintana-Domenque (2010) and Chiappori, Oreffice and Quintana-Domenque (2012, 2013). Domingue, Fletcher, Conley and Boardman (2014) compare genetic similarities between married and non-couple (random) pairs in the population and find genetic assortative mating.

individual fixed effects, and that, if anything, the remaining effect of past health on marriage would be negative. This is in line with the results from the estimation of the dynamic model described by Equation (2.3), presented in Figure 2.6 above, which show a steeper estimated health gap compared to the static models.

The third column of Table 2.4 shows the results when we measure innate health by an indicator variable that equals one if the individual is of healthy type in Equation (2.2). The results are again quite similar. Being of healthy type increases one's chances of getting married by about 15 percentage points, and once we control for innate health, the current health does not have a significant effect on marriage prospects. Given that, as we document in Table 2.1, about 55.8% of individuals between ages 20 and 24 are never married in the PSID sample, and 11.6% of singles get married between ages 25 and 30, a back-of-the-envelope calculation would suggest that $(11.6\%\times5)\times55.8\%=32.4\%$ of never married individuals get married at that age. The estimated coefficient for healthy types is almost a half of it.

Finally, we also analyze whether innate health has any effect on divorce. In columns fourth to sixth of Table 2.4, we consider individuals who are married at age 25 and analyze how their current and innate health correlate with the probability of being divorced by ages 30-40. Having a good current health lowers the probability of divorce by almost 16 percentage points. Once again, however, when we control for innate health, the effect of current health is not significant. A one-standard-deviation increase in innate health is associated with about 6 percentage points (0.236×0.244) lower divorce, and belonging to the healthy type lowers the probability of divorce by about 9 percentage points. For comparison, the same back-of-the-envelope calculation gives that about $36.9\%\times(8.1\%\times5)=14.9\%$ of married individuals would divorce in this age range.[15]

5.2. Assortative Mating by Health

The results in the previous section indicate that healthy individuals are more likely to get married and stay married. The marriage market outlined above would also predict assortative mating in health. To explore this possibility, the top left panel of Table 2.5 shows the contingency table for marriages formed by husbands and wives from different quintiles of the innate health distribution, together with marginal distributions of innate health for husbands and wives. Marriages in which both husbands and wives are from the bottom (top) health quintiles, for example, are about 8.1% (8.4%) of all marriages. By construction, the sum of all entries is 100% in a contingency table and due to positive assortative mating, almost half, 47.2%, of all the entries are along the diagonal. How would the contingency table look like if the matching was completely random by innate health? This is shown in the top right panel of Table 2.5. Entries in the random contingency table are obtained as a product of husbands' and wives' marginal distributions. The contingency table with random matching looks very different than the actual one. With random matching, there would be only 3.2% (in contrast to 8.1%) of marriages between husbands and wives from the bottom quintile. The fraction of marriages between husbands and wives from the top quintile would decline even more, from 8.4% to 2.5%. Overall, if the matching was random, the sum of diagonal elements in the contingency table would be 21.2%, a 26 percentage points decline from the observed 47.2%. The lower panel of Table 2.5 repeats the same exercise using the two types (high and low) from Equation (2.2).

[15] Table B.4 in Appendix B.4 repeats the analysis for alternative age ranges with similar results.

Table 2.5: Contingency Tables: Assortative Mating by Innate Health

		Innate permanent health (η_i)										
		Observed marital sorting %					Random matching %					
		Wife					Wife					
		1	2	3	4	5	1	2	3	4	5	Marginal
Husband	1	**8.1**	3.0	2.4	2.4	2.1	**3.2**	2.5	4.5	4.8	3.0	18.0
	2	2.6	**3.2**	3.2	3.4	1.7	2.5	**1.9**	3.5	3.8	2.3	14.1
	3	2.5	2.5	**14.7**	5.5	0.7	4.7	3.5	**6.5**	7.0	4.3	26.0
	4	2.6	3.3	4.3	**12.8**	3.6	4.8	3.6	6.7	**7.1**	4.4	26.5
	5	2.1	1.7	0.5	2.7	**8.4**	2.8	2.1	3.9	4.1	**2.5**	15.4
Marginal		18.0	13.6	25.1	26.8	16.5	18.0	13.6	25.1	26.8	16.5	100.0

	Innate health type ($\eta_{g(i)}$)				
	Observed sorting %		Random matching %		
	Wife		Wife		
Husband	Low	High	Low	High	Marginal
Low	**5.7**	8.2	**2.0**	11.9	13.9
High	8.6	**77.5**	12.3	**73.8**	86.1
Marginal	14.3	85.7	14.3	85.7	100.0

Note: In the left columns of the top panel, each cell gives the observed percentage of married households that lie in the indicated quintile of innate permanent health (η_i from Equation (2.1)) pairing between husbands and wives. In the right columns of the panel, each cell gives the predicted percentage from multiplying marginal distributions of husbands and wives, which are reported, respectively, at the last column and row. The bottom panel provides similar statistics computed for the innate health types ($\eta_{g(i)}$) obtained from the estimation of Equation (2.2).

Again individuals are more likely to marry some from their own health type.[16]

Table 2.6 shows that the simple correlation coefficient between innate permanent health of husbands and wives is about 0.37 (as a comparison, the correlation coefficient for years of education among husbands and wives is about 0.5).[17] When we control for education and race (by regressing recovered innate health, $\widehat{\eta}_i$, on these controls and looking at the correlations between residuals), the correlation remains almost unchanged. Even when we add a measure of permanent income (predicted fixed effects from a regression of taxable individual income on education, age, age squared, marriage and year dummies) as a further control, innate permanent health is still highly correlated between husbands

[16] Table B.5 in Appendix B.4 repeats the same exercises with innate health measures obtained from the regressions that use the number of chronic as a dependent variable with similar results.

[17] For the evidence on assortative mating by education and the related literature in economics, see Greenwood, Guner, Kocharkov and Santos (2014). Schwartz (2013) provides a review of the literature in sociology.

Table 2.6: Correlation of Husband's and Wife's Innate Permanent Health

Permanent health (η_i) from:	(1)	(2)	(3)
Self-reported health	0.374	0.347	0.318
	(0.019)	(0.020)	(0.019)
Chronic conditions	0.221	0.206	0.191
	(0.022)	(0.022)	(0.022)
College and race	No	Yes	Yes
Permanent income	No	No	Yes

Note: The table reports conditional correlation coefficients between husband and wife's estimated innate permanent health (η_i from Equation (2.1)). The first row corresponds to the baseline regression, in which the self-reported measure of health is used in the regression. The second row is computed using the number of chronic conditions as a dependent variable, as in Figure 2.7. To control for college and race, we introduce dummies for individuals and spouses having a college degree and being black, as well as the corresponding interactions. For the permanent income, we include husband's, wife's, and interacted individual fixed effects obtained from a regression of taxable individual income on years of education, age, age squared, marriage, and year dummies. All correlations are estimated from the PSID. Weights are used in the estimation. Bootstrapped standard errors in parenthesis.

and wives (0.32).

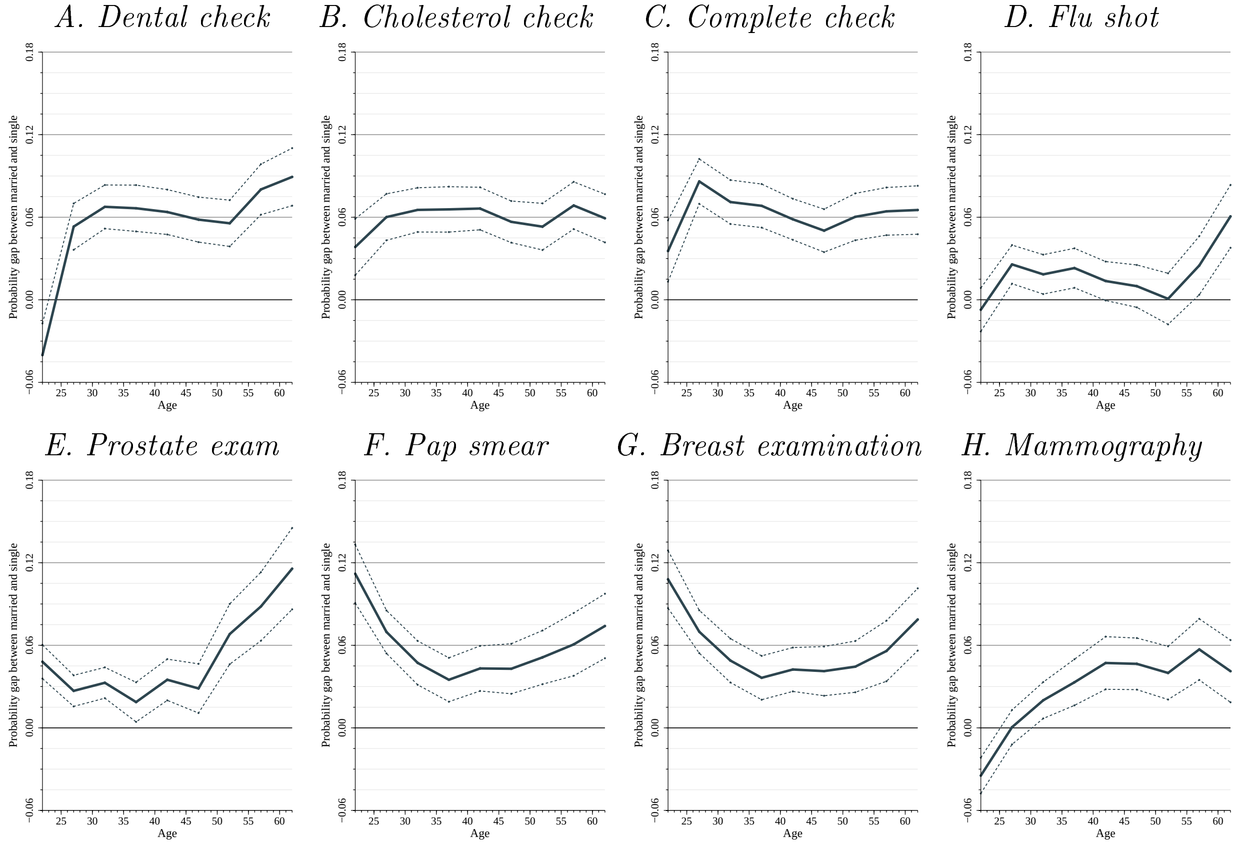
Since health status in the PSID is reported by the household head for both himself/herself and his/her spouse, one might wonder whether these correlations simply reflect this particular feature of the data collection.[18] In order to address this potential concern, we repeat our exercise with innate health estimates obtained using the presence of chronic conditions as a measure of health (second row of Table 2.6). Even if reported by the household head, chronic conditions, unlike a subjective measure of health, are much less likely to result in spurious correlations. We find that the correlation between innate healths of husbands and wives is again significant (estimated value is 0.22 in this case, which is while still large, somewhat smaller than 0.37 above). Moreover, the correlation remains again significant when we control for education, race and permanent income.

5.3. Healthy Behavior

What factors can explain the protective effect of marriage on health? In this section, we document that married individuals are much more likely to engage in healthy behavior than unmarried ones. Figure 2.9 shows differences between the probabilities that married and unmarried individuals do preventive health checks. The figure shows coefficients form regressions similar to Equation (2.1), where the dependent variable is an indicator that

[18]Banks, Kelly and Smith (2014) highlight this point. Using health data from the English Longitudinal Survey of Aging (ELSA) and the American Health and Retirement Survey (HRS), where health is reported by each individual, they still find that couples have similar health status and healthy behavior along several dimensions.

Figure 2.9: Preventive Health Checks and Marital Status



Note: Plotted lines show OLS estimates of the marriage gap in the probability of doing preventive checks. These differential curves are obtained from a regression that is similar to (2.1) but where the dependent variable is an indicator variable that takes the value of one if the individual did the indicated preventive check in previous years. The following preventive checks are considered: dental check at least once every year; cholesterol check, general physical examination, flu shot, prostate examination, Pap smear, breast examination, and mammography at least once in the last two years. The equation is fitted to data from the MEPS. Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies, as well as current health, health insurance (public and private insurance dummies) and total health expenditures; regressions also estimate probability curve for singles. Weights are used in the estimation. The horizontal axis indicates age. In estimation, five-year age bins (20-24 through 60-64) are considered. The center point of the bin is represented in the figure. Dotted lines indicate ± two standard errors confidence bands around point estimates, which are Taylor linearized using survey stratification design in the MEPS.

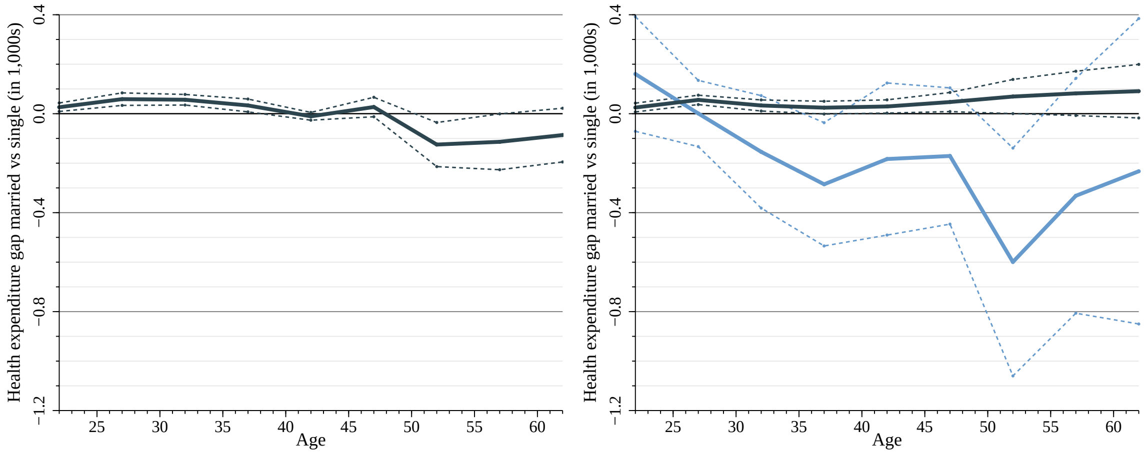
equals one if the individual performs a particular preventive check at a given age, and zero otherwise. This regression is fitted to the MEPS.

The results show that there are significant differences between married and single individuals for all categories of preventive care. Married individuals around ages 50 to 54, for example, are about 6 percentage points more likely to check their cholesterol or have a prostate or breast examination. Note that these differences come from regressions that control for education and income. Hence, the effect of marriage on healthy behavior goes beyond the well documented effect (see e.g. Cutler and Lleras-Muney, 2010) of education on healthy behavior.

Why would married individuals be more likely to do preventive care? One possible

Figure 2.10: Median Health Expenditures and Marital Status

A. Expenditure gap *B. Heterogeneous effects by health level*



Note: Solid line in the left plot shows the marriage gap in median health expenditures obtained from a regression to Equation (2.1), but with total health expenditures as the dependent variable. Solid lines in the right plot shows estimated heterogeneous marriage gaps in median expenditures by health level (healthy, dark blue, and unhealthy, light blue). Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies, as well as health insurance (public and private insurance dummies); regressions also estimate median expenditure curves for singles in each health level. The regressions are estimated from the MEPS. The horizontal axis indicates age. In estimation, five-year age bins (20-24 through 60-64) are considered. The center point of the bin is represented in the figure. Dotted lines represent $\pm$ two bootstrapped standard error confidence bands.

factor, which is well documented in the medical literature, is that having a partner encourages individuals to follow up on medical appointments, check-ups, etc.[19] Another factor, which we focus on in the next section, is the fact that married individuals are more likely to have health insurance than unmarried are.

Differences between married and unmarried individuals in healthy behavior are also reflected in their medical expenditures. To analyze differences in medical expenditures, we specify the conditional median of the total medical expenditure to be given by a similar expression to the right hand side of Equation (2.1).[20] Panel A of Figure 2.10 shows our estimates of the marriage gap in median health expenditure estimated from the MEPS. Results suggest that median health expenditure of married individuals aged below 40 is around 40-60$ larger per year than that of unmarried individuals at the same age range. This gap is quite significant and represents about 12% of the median medical expenditure

[19] There is a large medical literature that documents the link between marriage and specific health outcomes. In an interview to CNN, Dr. Paul L. Nguyen, summarizing his research published in Aizer, Chen, McCarthy, Mendu, Koo, Wilhite, Graham, Choueiri, Hoffman, Martin, Hu and Nguyen (2013), states that "You are going to nag your wife to go get her mammograms. You are going to nag your husband to go get his colonoscopy.... If you are on your own, nobody is going to nag you." Interview available at `http://thechart.blogs.cnn.com/2013/09/23/marriage-may-improve-cancer-survival-odds/?hpt=he_c2`, accessed on December 6, 2013. See Waite and Gallagher (2000) for further evidence on what they call "the virtues of nagging".

[20] Similarly, we consider regressions for mean expenditures as opposed to median, which deliver very similar results, with a different scale.

Table 2.7: Probability of Quitting Smoking and Marital Transitions

	Probability of quitting smoking	Probability of quitting smoking... while married	while single
Single → Single	0.298	0.005	0.293
	(0.024)	(0.003)	(0.024)
Single → Married	0.526	0.390	0.135
	(0.050)	(0.049)	(0.034)
Married → Single	0.312	0.084	0.228
	(0.045)	(0.027)	(0.041)
Married → Married	0.414	0.407	0.007
	(0.025)	(0.025)	(0.004)

Note: The table presents the probability that an individual quits smoking between 1999 and 2013 conditional on smoking in 1999, by type of marital status transition. These probabilities are calculated using data from the PSID. Weights are used in the estimation. In the left column, the numerator is the number of individuals in a given marital transition that were nonsmokers either in 2013 or in the last year for which smoking information is available, and were smokers in 1999. The denominator is the number of individuals that do the indicated marital transition who were smokers in 1999. In the right panel, the numerator is restricted to those individuals that were married/single in the first year they are observed as nonsmokers after their last smoking spell. The total number of observations is 1,373. Standard errors are in parenthesis.

by individuals below age 40 (about 420$). At older ages, though, unmarried individuals spend more than married ones; at ages 50-59, median expenditure of unmarried individuals is around 100-110$ larger. This is about 6.5% of the median medical expenditure for this age group (about 1,600$).

This higher expenditure by married individuals at earlier ages may be due to preventive motives, while the higher expenditure by unmarried at older ages may be due to curative motives, as a result of worse health. To further explore this hypothesis, we estimate marriage expenditure gaps for different health statuses. In particular, we extend the median expenditure model to account for heterogeneous expenditure curves for different health levels. Panel B of Figure 2.10 presents median regression estimates of the marriage health expenditure gap for healthy and unhealthy individuals. Married individuals consistently spend more when they are healthy, which is in line with the fact they they are more likely to do preventive checks. In contrast, unmarried individuals spend substantially more than married ones when they are unhealthy, which suggests that when the unmarried are unhealthy, they are more likely to face serious (and expensive) conditions.

Finally, we check whether marriage is associated with healthy habits. We focus on smoking, a key health factor. In particular, we look at all individuals who were smokers in 1999 and document how many of them quit smoking between 1999 and 2011 conditional on their marital transitions. As Table 2.7 shows, a single individual is about 23 percentage points points more likely to quit smoking if he/she gets married than if he/she stays single (53% versus 30%); additionally, a majority (about 74%) of singles who get married and quit smoking do so while they are married. Likewise, a married individual is more likely to quit smoking if he/she stays married than if he/she becomes single (41% versus 31%).

Overall, these results suggest that marriage goes together with healthy behavior. Even after controlling for observables (most importantly income, education and health insurance) preventive health care, measured both by frequency of preventive medical checks and by health expenditure while healthy, is more prevalent among married individuals than it is among singles. Marriage is also associated with a higher probability of quitting smoking.

5.4. Health Insurance

Health insurance status is a key determinant of health care utilization in the United States.[21] In the MEPS sample, about 16% of individuals, who are between 20 and 64 years old, do not have any public or private health insurance. Panel A in Figure 2.11 shows how health insurance status differ by marital status for males and females. For both genders, unmarried individuals are more likely to be uninsured than married ones. The gap is, however, larger for males. At ages 45 to 49, for example, about 10% of married individuals, male or female, do not have any health insurance. The fraction of uninsured among the unmarried of the same age is less than 20% for females, while it is higher than 25% for males.[22] The larger gap for males reflects the effect of Medicaid that provides health insurance for children and their parents, in particular single mothers, in low-income families. In the MEPS sample, 9.0% and 17.6% of unmarried males and females have public health insurance, respectively.

Panel B in Figure 2.11 documents how medical insurance affects the marriage health gap. We report OLS estimates of heterogeneous health curves for individuals with (dark blue) and without (light blue) health insurance. For individuals with health insurance, the results are similar to what we document in Panel A of Figure 2.4 for the MEPS sample. Married individuals are healthier and the estimated health gap grows by age. For uninsured individuals, however, we do not find any significant wedge between marriage and unmarried health. These results suggest that the availability of health insurance is an important facilitator for positive effects of health on marriage.

5.5. Health Accumulation Through Marriage

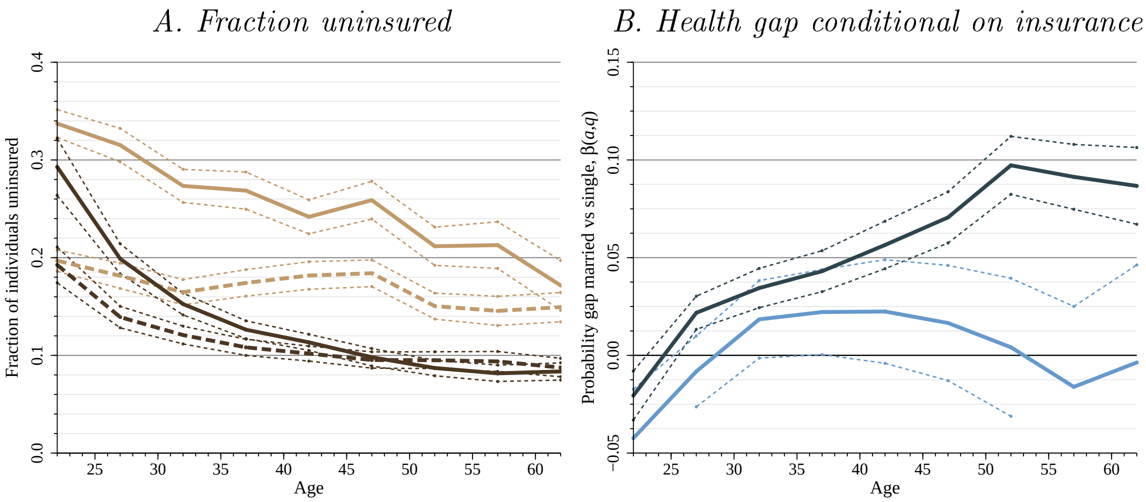
Finally, we investigate whether the benefits of marriage on health are cumulative, i.e. whether the duration of marriage matters. In Panel A of Figure 2.12, we show results from a regression that is very similar to Equation (2.1) except that m_{it} is replaced by a measure of marriage capital, defined as the total number of years an individual has been married by year t.[23] Hence $\beta(a)$ now measures the effect of one extra year of being married at a given age a on the probability of being healthy. The effect of an extra year of marriage is positive and significant and roughly constant after ages 35-39: having

[21] See e.g. Anderson, Dobkin and Gross (2012) and Finkelstein, Taubman, Wright, Bernstein, Gruber, Newhouse, Allen, Baicker and the Oregon Health Study Group (2012). Both papers document that changes in health insurance status has a large effect on health care utilization.

[22] Bernstein, Cohen, Brett and Bush (2008), using, National Health Interview Survey, report that 13% of married women between ages 25 and 64 were uninsured in contrast to 21% of unmarried women of the same age in 2007. For characteristics of uninsured population in the U.S., see Kaiser Family Foundation (2012).

[23] Independent of whether the person is married to the same partner.

Figure 2.11: Health Insurance, Health, and Marital Status



Note: Thick lines in the left plot show the weighted fraction of married (dark brown) and unmarried (light brown) males (solid) and females (dashed) that are covered by health insurance (public or private). Solid lines in the right plot are OLS estimates of the marriage health gap for insured (dark blue) and uninsured (light blue) individuals. Results are obtained from the MEPS. In the right figure, control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate health curves for singles with and without insurance. The horizontal axis indicates age. In estimation, age is grouped in five-year bins (20-24 through 60-64) and the center point of the bin is graphed. Dotted lines indicate ± two standard errors confidence bands around point estimates, which are Taylor linearized computed following the survey stratification design.

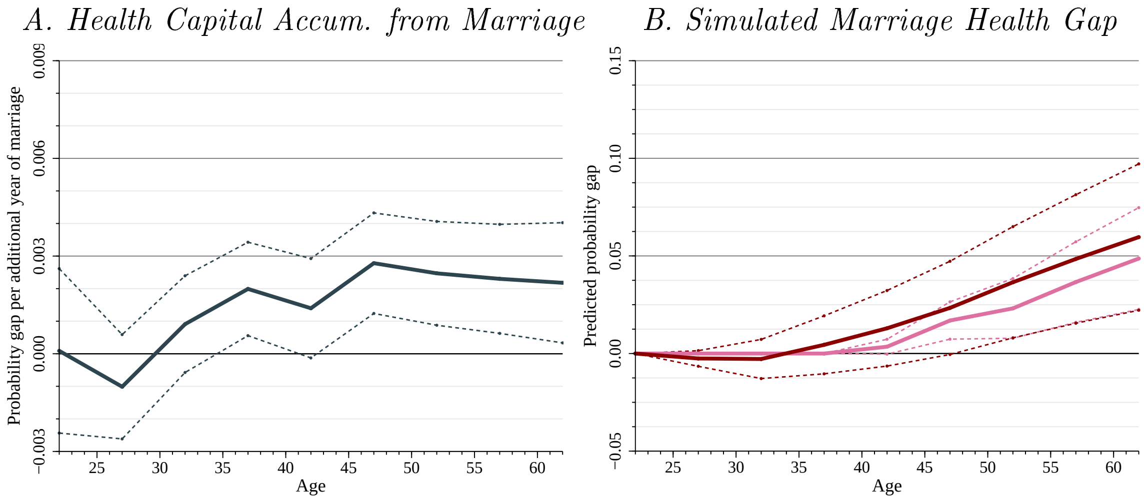
accumulated 10 extra years of marriage increases the probability of being healthy by about 3 percentage points. At earlier ages, the estimated effects are negligible.

Based on estimates from Panel A, in Panel B we show simulations for two possible marital histories and their cumulative effects on health. The red (dark) line shows the predicted marriage health gap for a person who gets married at age 25 and stay married afterwards compared to someone who never gets married. Hence, the simulated line is simply the cumulative sum of the estimates in Panel A. Consistent with our estimates in Section 4, marriage does not contribute to better health in early ages, but a health gap starts to emerge after around age 40. By ages 55-60, this individual is about 5 percentage points more likely to be healthy compared to someone who has never been married. Furthermore, since the effect of marriage on health appear only after around age 40, an individual who gets married at age 40, the pink (light) line, enjoys almost the same benefits from marriage compared to the individual who marries at age 25. This is very reassuring, since although they rely on a different estimation strategy, these simulations produce almost identical results to our estimates from Figures 2.4 and 2.5. Hence, it provides interesting insight for the interpretation of our main results in Section 4.

6. Conclusions

We use data from the Panel Study of Income Dynamics (PSID) and the Medical Expenditure Panel Survey (MEPS) to document differences in health between married and

Figure 2.12: Health Accumulation Through Marriage



Note: The left figure shows fixed-effect estimates of the health capital accumulated from marriage from a modified version of equation (2.1) in which the married dummy m is replaced by the number of years an individual have been married (zero if never married). Estimates are done with the PSID. The right figure plots the predicted marriage health gap for individuals married at age 25 (red line) and at age 40 (pink line). Control variables include female, black, and college dummies, income, dummies for 0-3, 4-12, and 13-18 year-old children at home, and year of birth dummies; regressions also estimate the health curve for singles. The horizontal axis indicates age. In estimation, five-year age bins (20-24 through 60-64) are considered and the center point of the bin is graphed. Dotted lines are ± two standard errors confidence bands around point estimates, clustered at the household level.

unmarried individuals. After controlling for observables (education, income, race and gender), there exists a marriage health gap of about 10 percentage points in both data sets. We estimate the marriage health gap as the difference between health curves for married and single individuals, nonparametrically specified as a function of age. Allowing for heterogeneity in innate health (both permanent and age-dependent), our results suggest that the marriage health gap disappears for younger (20-39) ages, while a positive gap of 5 percentage points remains for older (50-59) ages. We interpret these results as evidence that self-selection into marriage drives the observed marriage health gap at younger ages, while, at older ages, an important fraction of the observed gap is explained by protective effects of marriage on health.

We provide detailed evidence of self-selection patterns in the data, and on different mechanisms through which marriage exerts a beneficial effect on health. We observe that the distribution of innate permanent health of married individuals is shifted to the right, and less dispersed than that of unmarried individuals. This would be consistent with a marriage search model in which innate health is observable. Such model implies positive assortative mating by innate health, and that innate health is a good predictor of early entry into marriage. The data supports both of these predictions. On the other hand, we document that married individuals are much more likely to engage in preventive care and that the total years of being married (not just current marital status) has a positive effect on health. We interpret these results as indicators of better health production within marriage. We find that health insurance plays an important role in this difference.

Chapter 3

Household Labor Market Dynamics

Joint with Nezih Guner and Arnau Valladares-Esteban

1. Introduction

More than 60% of prime-age working population, between ages 25 and 54, consists of individuals who are married.[1] As a result, for a majority of workers, labor market decisions (whether to accept a job or keep looking for a better one; whether to quit and search for a new job; whether to move out of labor force; or whether to enter the labor force and search for a job) are not made in isolation but together with a partner. A key factor behind the growing number of two-earner households has been the dramatic increase in married female labor force participation since the 1950s. While only 35% of married women between ages 25 to 54 were in the labor force in 1960, today about 70% of them are.[2] As a result, today's married households mainly consist of two potential earners who make joint labor market decisions. Several recent papers, for example, Guler et al. (2012), Flabbi and Mabli (2012), and Choi and Valladares-Esteban (2015), study implications of joint search by husbands and wives for labor market dynamics and public policy.[3]

Yet, the large and growing empirical literature on labor market fluctuations, e.g. Blanchard et al. (1990), Fujita and Ramey (2009), Shimer (2012), and Elsby et al. (2015), focuses exclusively on individual transitions among different labor market states (employment, unemployment, and out of the labor force), and abstracts from joint transitions. Furthermore, the focus of this literature has been on transitions between employment and unemployment and how this affect cyclical movements in unemployment. Recent papers, e.g. Kudlyak and Schwartzman (2012) and Elsby et al. (2015), however, highlight the importance of the movements in and out of the labor force. In particular, Elsby et al. (2015) document that around one-third of cyclical variations in the unemployment rate

[1] The numbers are based on the Current Population Survey (CPS). For the 2000-2010 period, about 63% of males and 62% of females were married. For individuals who are in the labor force, married constitute about 64% for males and 60% for females.

[2] There is a large literature that studies the rise of married female labor force participation. See, among others, Greenwood et al. (2005), Jones et al. (2003), Fernandez et al. (2004).

[3] Besides labor market search and matching models, there is a growing literature that studies heterogenous agents models with two-earner households. Examples of these papers are Chade and Ventura (2002), Greenwood et al. (2003), Olivetti (2006), Kaygusuz (2015, 2010), Hong and Ríos-Rull (2007), Heathcote et al. (2010), Erosa et al. (2010), Guner et al. (2012a,b), Bick and Fuchs-Schündeln (2014), among others.

can be accounted for by transitions at the participation margin.[4] If the participation margin plays an important role for labor market fluctuations, then analyzing the joint labor market transitions of couples becomes even more important, as entry into and exit from the labor force of its members is one of the key decisions for a household.

In this paper, we study joint labor market transitions of husbands and wives among nine possible labor market states (both husband and wife being employed, husband being employed and wife being unemployed, etc.), and how these transitions affect individual states (employment, unemployment, and out of the labor force) of husbands and wives. We do this using data for 1976-2013 period from the Current Population Survey (CPS), which is the main data source to study labor market dynamics in the U.S.

The results show that joint labor market transitions are important to understand increase in labor force participation from mid-1970s until late 1990s and its subsequent decline, as well as the cyclical movements in unemployment. Married men and women differ in their labor market dynamics. The transitions between employment and unemployment are the key driver of the cyclical movements in unemployment for married males. For married females, however, transitions in and out of the labor force play a key role. Hence modeling out of labor force as a distinct state is key to understand joint labor market dynamics of married couples. The results also show that joint labor market transitions of husbands and wives imply an important degree of coordination between labor market activities of household members. In particular, we calculate "the added worker effect", increase in married women's labor supply in response to their partner's unemployment. Previous literature, e.g. Lundberg (1985), Stephens (2002) and Juhn and Potter (2007) show that women's labor supply is quite responsive to their partner's entry into unemployment. We find that without the added worker effect, female labor participation and unemployment rates in 2000-2010 period would be about 2.5 and 0.3 percentage points higher, respectively. This 0.3 percentage points represents about 6.16% of the female unemployment rate. On the other hand, the added worker effect lowers the fraction of households with no employed members by about 0.4 percentage points in the same period, which is a significant (about 13.3%) fraction of households with no employed members.

The rest of the paper is organized as follows. In Section 2, we describe the data we use and introduce key concepts. Section 3 documents how joint labor market states for married couples changed in the last four decades. Section 4 focuses on labor market flows and documents how joint labor market transitions affects cyclical and secular movements in employment, unemployment, and participation. In Section 5 we document how much the added worker effect affect aggregate labor market outcomes. We conclude in Section 6.

2. Data on Labor Market Stocks and Flows

We use monthly data from the Outgoing Rotation Groups of the CPS. Every household (address) that enters the CPS is interviewed for 4 consecutive months, then ignored (rotated out) for 8 months, and then interviewed again (rotated in) for 4 more months. This procedure implies that each month there are 8 *rotation groups* that are surveyed and 6

[4] Two-state (employment and unemployment) abstraction is also dominant in theoretical search and matching papers that follow the Diamond-Mortensen-Pissarides framework. For search and matching models with three states, see Alvarez and Veracierto (2000), Garibaldi and Wasmer (2005), Krusell et al. (2008, 2010a,b, 2011), Pries and Rogerson (2009), Veracierto (2008).

out of these 8 groups will be in the survey the following month as well. As a result, in principle, it is possible to follow 3/4 of individuals and match their information across two months. We follow a standard matching procedure, specified in Shimer (2012), based on matching households with the same identification code, as long as household members' characteristics (age, sex, race and education) are consistent between two months. This procedure allows use to compute *raw* flows of workers across states as the amount of workers transiting from state S_t to state S_{t+1} over the number of workers in state S_t. However, this *raw* data is potentially affected by two well-known problems: time aggregation bias and classification errors.

The time aggregation bias is a consequence of the frequency in which the data on labor market status is collected by the CPS. The CPS surveys the US population once a month. However, changes in labor market status can occur at any point in time between two surveys. Hence, if more than one transition occurs between two surveys, those would not be reflected in the *raw* flows. A simple example would be a worker who at time t is employed, then loses her job, that is, transits from employment to unemployment, and before the next survey takes places, finds a new job, transiting back from unemployment to employment. At time $t + 1$, the worker would be recorded as being employed and, thus, her transition into unemployment and back to employment would not be taken into account. To address this issue, we follow Shimer (2012) and we apply a decomposition technique to map the discrete *raw* flows into their continuos-time transitions probabilities counterparts.[5]

The issue of classification errors is related with to erroneous codification and/or misclassification of labor market statuses that has been identified in the CPS. Mainly, there is a concern about the distinction between unemployed and inactive (or out of the labor force) workers. As showed in Abowd and Zellner (1985) and Poterba and Summers (1986), the probability transitions between unemployment and out of the labor force might be importantly affected by classification errors. In order to address this issue we apply the method proposed in Elsby et al. (2015) which consist of, using the panel dimension of the CPS, identifying and correcting streams of labor market states that appear to be unlikely. For example, imagine an individual that is recorded to be out of the labor force for two consecutive months, then appears as unemployed in the third month, and is recorded as out of the labor force in the fourth month. The method of Elsby et al. (2015) identifies the recording in the third month as an error, and recodes the state of this individual as being out of the labor force for four consecutive months.

The final sample contains, for each month, individual demographic and labor market information associated to the previous and the current month, from February 1976 until December 2013. We restrict the sample to all couples who report to be married and living in the same household. We select only those couples for which one of the two members reports to be the head of the household. In order to minimize the effects of schooling and retirement decisions, we focus on prime age individuals, and restrict the sample to couples formed by individuals who are 25 to 54 years old. These restrictions result in a sample size of about 12,000 couples for each month.

We extend the standard concept of individual labor market states, Employment (E), Unemployment (U), and non-participation (O) to couples and consider nine different labor market states: both employed, husband employed - wife unemployed, husband employed - wife non-participant, etc. We label all these states using two letters. The first letter

[5] The main assumption is that within each month, at any point in time, inflows are equal to outflows in each state.

refers to the labor market status of the husband, while the second letter refers to the labor market status of the wife. For example, a couple with labor market status UO is a couple in which the husband is unemployed (U) and the wife is non-participant (O).

Given that any couple might be in 9 different labor market situations at any point in time (EE, EU, EO, UE, UU, UO, OE, OU, and OO), there are 72 labor market transitions, from one month to the following, that may occur (81, if one considers the diagonal terms). We denote the probability of a couple being in the state ij in a given month and transiting to state kl the following month by γ_{kl}^{ij}. For example γ_{EE}^{EO} denotes the probability that a couple is in state EO (the husband is employed and the wife is non-participant) in a given period and transits to state EE (both employed) next period. To compute these probabilities for each month, we simply calculate how many couples move from one state to another and divide this number by the total number of couples in the initial state. As a result, for each month we are able to construct a 9 by 9 Markov transition matrix across all possible labor market states.

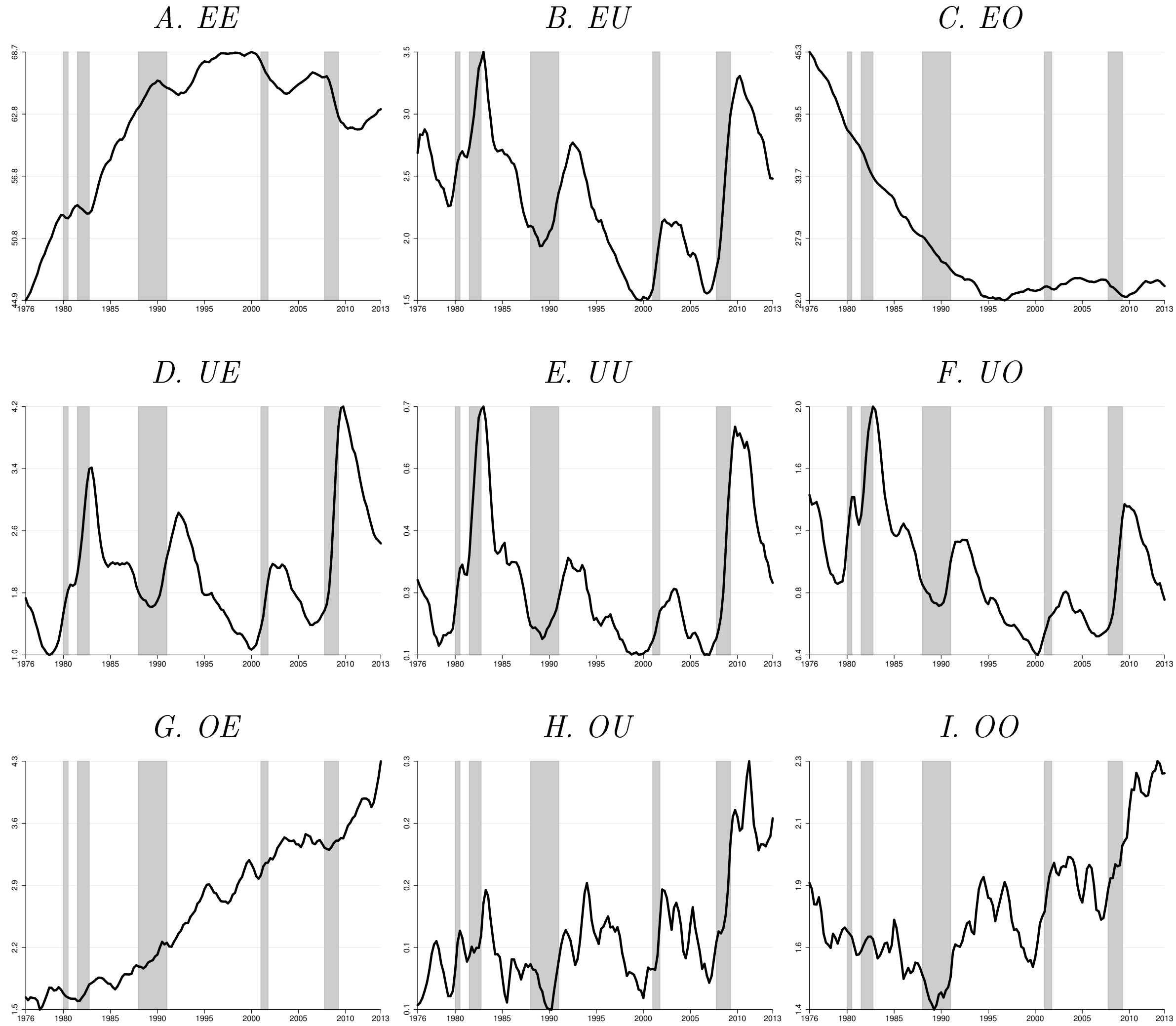
3. Labour Market Stocks

We start by documenting labor market stocks for married couples. For each possible labor market state and for each month, we compute the proportion of couples in the sample that are in that state. To compute the point estimate of the stocks for each month, we simply count (using sample weights in CPS) how many couples report to be in each state over the total number of couples in our sample. Figure 3.1 presents the labor market stocks, seasonally adjusted using a 12-month moving average, along with the National Bureau of Economic Research (NBER) recession dates. By construction, for each date, the fractions of households across nine panels in Figure 3.1 sum up to 100.

Figure 3.1 illustrates the dramatic decline in the number of traditional, a breadwinner husband and a housekeeper wife, households in recent decades. At the start of the sample in 1976, about 45% of households had an employed husband and an out-of-labor-force wife (panel 3.1C). By the end of the sample in 2013 less than 25% of married couples were traditional households. As women enter the labor force, these traditional households were replaced by households in which both members work (panel 3.1A). The fraction of such households increased by almost 20 percentage points, from 44% to 63%, between 1976 and 2013. The increase in the fraction of two-earner married couples was very significant until late 1990s. Since late 1990s, however, the fraction of households with two earners declined from about 69% to 63%. This coincides with the decline in the labor force participation in the U.S. population which have received lots of attention in the recent literature (see e.g. Barnichon and Figura (2015); Moffitt (2012); Aaronson et al. (2012)). Not surprisingly, the decline in households with two-earners was matched with an increase in households with at least one member who is not in the labor force. Finally, there was also a rise in the fraction of households in which traditional roles of husband and wives were reversed (panel 3.1G), where the husband is out of the labor force and the wife is employed. The fraction of such households increased from 1.7% to 4.2%.

Figure 3.1 also reveals well-known cyclical movements in labor markets. Recessions are periods in which one or both members of a household are more likely to be unemployed. The fraction of households with one unemployed member, states EU (panel 3.1B) and

Figure 3.1: Joint labor market stocks for married couples.



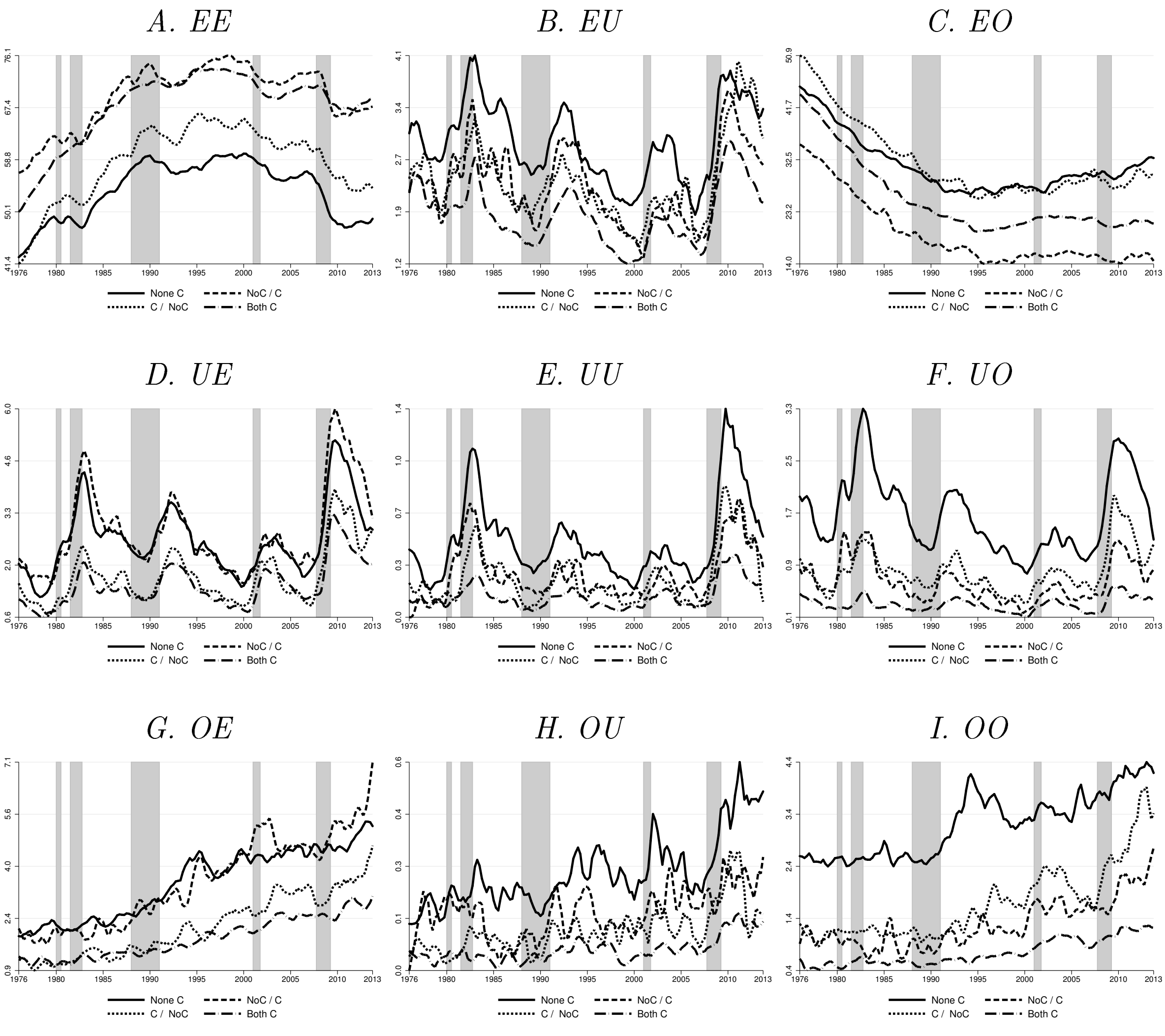
Note: CPS, time period 1976:Q1 to 2013:Q4. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recession periods.

UE (panel 3.1D), is strongly countercyclical. Interestingly, EU and UE states fluctuate around very similar magnitudes (about 2% to 3%), i.e., we do not observe more couples where the wife is unemployed and the husband is working than couples where the husband is looking for a job and the wife is working. Indeed, until the start of the Great Recession, there was a downward trend in the number of couples in the EU state.

The fraction of households in state UO (panel 3.1F) and, its mirror image, couples in state OU (panel 3.1H) increase in each recession as well. We also observe that there tend to be more couples in which the husband is unemployed and the wife is non-participant than the other way around (1% vs. 0.15%), reflecting the traditional roles in the household. The number of households where the wife is the one looking for a job and the husband is out of the labor force, OU state, however, increased from 0.1% at the beginning of the period to 0.2% at the end. This in line with the growing number of households in the OE state, and reflects the decline of traditional roles within marriages. Finally, panel 3.1E shows that the fraction of couples in which both members are unemployed (UU) has been fluctuating around 0.3% during the whole period. Such small number indicates that this is a very unlikely event for couples.

Figure 3.2 shows the labor market stocks for married couples by the educational attainment of husbands and wives. In Figure 3.2, we report joint stocks for four types of households: those with two members without a college degree, those with two members with a college degree, and those in which only one member (husband or wife) has a college degree. Less educated households are much less likely to have two working members (panel 3.2A). These households are also much more likely to have one or both members out of the labor force. Furthermore, the number of households with one or both members out of the labor force has been growing at least since the mid 1990s.

Figure 3.2: Joint labor market stocks for married couples by educational categories.

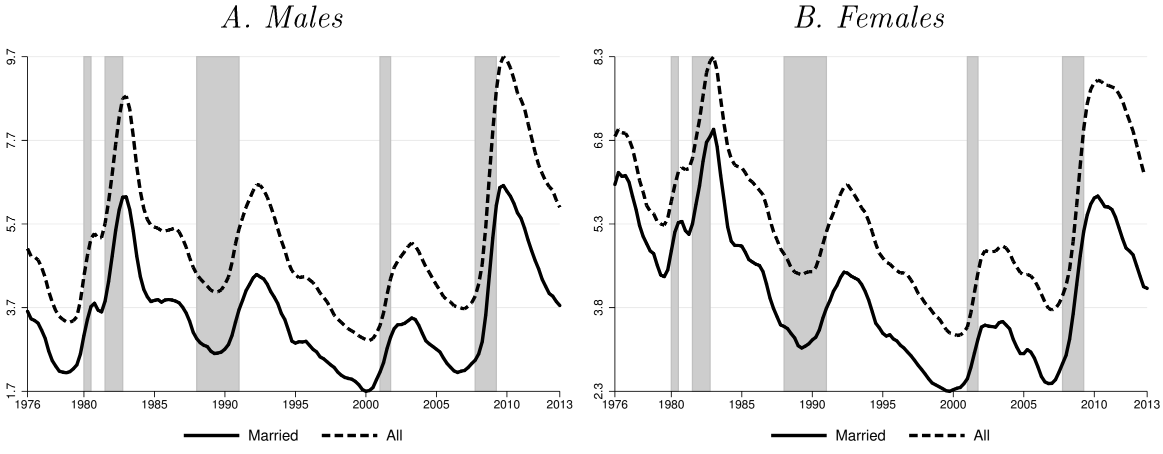


Note: CPS, time period 1976:Q1 to 2013:Q4. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. C denotes completed college education. Grey areas represent NBER recession periods.

The standard measure of unemployment rate is based on individual level data, i.e. the unemployment rate reports the number of individual who are unemployed as a fraction of the total labor force. Figure 3.3 shows the unemployment rate for males and females, both for the whole population as well as the married population. Married individuals have a lower unemployment rate but fluctuations in their unemployment rate mimic closely the fluctuations in the unemployment rate for the whole population. An important economic advantage of marriage is that individuals can insure each other against adverse labor market shocks.[6] As a result, more informative measures of unemployment for households with two potential earners are the fraction of households with at least one unemployed member and the fraction of households with no employed members.

Figure 3.4A shows these alternative measures of unemployment together with the standard unemployment rate. In the Great Recession, close to 10% of households had at least one unemployed member, while the fraction of households without any unemployed member was around 5%. Figure 3.4B shows the cyclical component of each time series.[7] The standard deviation of the cyclical component is about 0.7 for the fraction of household with at least one unemployed members, about 0.3 for the unemployment rate and about 0.09 for the fraction of households with two unemployed members. Hence, the fraction of household with at least one unemployed members moves quite more than the unemployment rate, while the fraction of households without any employed members is rather acyclical.

Figure 3.3: Individual Unemployment Rates of Males and Females

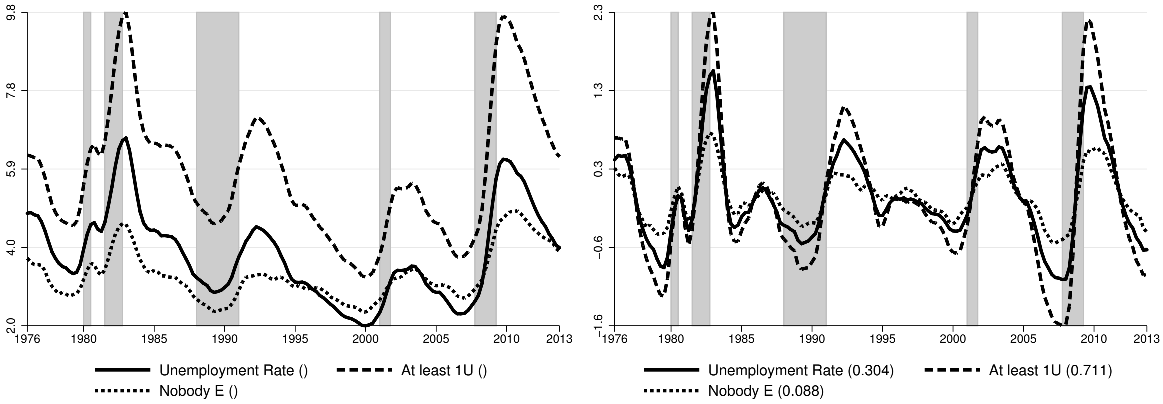


NOTE: CPS, time period 1976:Q1 to 2013:Q4. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recession periods.

[6]On differences in unemployment rate by marital status, see Choi and Valladares-Esteban (2015)
[7]We use Hodrick-Prescott filter with a smoothing factor of 1600.

Figure 3.4: Unemployment Measures and their Cyclical Components

A. Unemployment Measures *B. Cyclical Component*



Note: CPS, time period 1976:Q1 to 2013:Q4. Panel 3.4A presents proportion of couples in each labor market state, panel 3.4B presents the cyclical component of each state (standard deviations are presented in brackets). Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recession periods.

4. Labor Market Flows

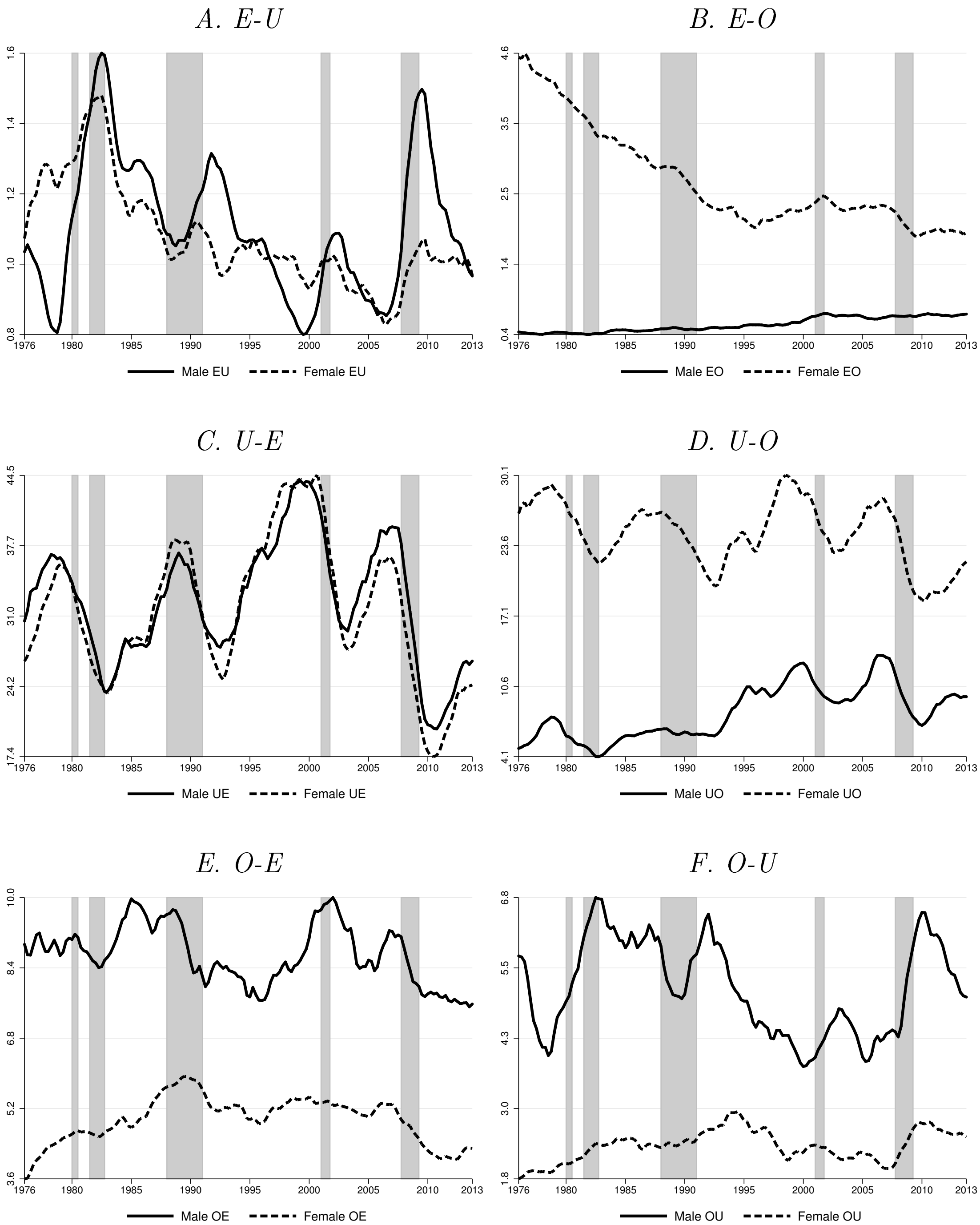
4.1. Individual Transitions

We next look at labor market transitions. We first revisit the analysis by Elsby et al. (2015) and report labor market transitions between three states (E, U and O) for individuals. We do so, however, separately for males and females.

Figure 3.5 shows labor market transitions for males and females. Both for males and females the transitions from employment (E) to unemployment (U) are countercyclical, panel 3.5A, and transitions from unemployment (U) to employment (E) are pro-cyclical, panel 3.5C. Employment to unemployment transitions are more cyclical for males than for females. This was particularly the case in the last recession in which E to U transitions increased much more for males than they did for females; it doubled for males while the increase was less than a half of that for females. In contrast, U to E transitions declined more strongly for females than they did for males in the last recession, for females the decrease was more than a half while for males it was only one third. Hence, while females were less likely to lose their jobs than males, they were at the same time less likely to move from unemployment to employment.

For both males and females, during recessions, movements from out of labor force to unemployment increase (panel 3.5F), and movements from unemployment to out of labor force decline (panel 3.5D). Hence, recessions are periods in which unemployed agents are more likely to remain unemployed rather than quitting the labor force, and those who are out of the labor force are more likely to enter to look for a job. The movements between unemployment and out of labor force are particularly large for females (panel 3.5D). Just before the last recession, about 30% of unemployed women decided to move out of the labor force from one month to the next. This number declined to about 22% during the recession. Similarly, while about 15% of employed men quit the labor market in a month, this number declined to 9% by the end of the recession. Figure 3.5 also shows that the increase in O to U transitions (panel 3.5F) during recessions is also very pronounced, especially for males.

Figure 3.5: Unconditional labor market transitions of males and females



NOTE:CPS, time period 1976:Q1 to 2013:Q4. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recession periods.

Both O to E and E to O transitions decline during recessions. While the decline in O to E transitions (panel 3.5E) is not surprising the decline in E to O transitions (panel 3.5B), which is stronger for females, suggest that individuals are less likely to quit their jobs during bad times or if they lose their jobs they are less likely to move out of the labor force. Lastly, the upward trend in E to O transition for males and the downward trend in the same transition for females (panel 3.5B) reflects the pattern, described in Section 3, that there is a growing number of households in which the traditional gender roles are reversed.

4.2. Joint Transitions

We next turn to joint labor market transitions for husbands and wives. Table 3.1 shows the 9 by 9 transition matrix for married couples for the whole sample period. Results in Table 3.1 illustrate very rich labor market dynamics that married couples exhibit. While states in which one or both partners are employed or out of labor force, such as EE, EO, OE, and OO are quite persistent, indicating that couples are likely to remain in those states for a long time, other states are more transitory.

Table 3.1: Joint average labor market transitions of married couples

	EE	EU	EO	UE	UU	UO	OE	OU	OO
EE	94.89	0.98	2.61	0.99	0.03	0.02	0.43	0.01	0.06
EU	32.43	38.88	25.13	0.50	2.43	0.48	0.36	0.62	0.32
EO	4.97	2.21	91.11	0.05	0.05	1.09	0.06	0.02	0.54
UE	31.51	0.69	0.65	56.13	2.08	1.83	7.97	0.32	0.32
UU	7.86	24.73	4.58	20.64	32.84	18.03	2.55	6.21	4.42
UO	1.74	1.44	34.31	3.83	7.13	44.81	0.83	0.98	9.18
OE	8.44	0.25	0.47	5.65	0.24	0.23	81.83	1.37	2.31
OU	4.72	10.05	3.92	3.99	9.82	4.63	26.07	37.39	27.00
OO	1.67	0.46	6.94	0.33	0.48	3.96	2.73	1.91	82.39

NOTE: CPS, age 25-54, 1976:Q1 to 2013:Q4. Adjusted for time aggregation and classification errors.

The transition probabilities in Table 3.1 differ significantly by the gender of the household member who is unemployed or out of the labor force. For example, a couple with an employed husband and an unemployed wife (EU) has about 32% chance to move to EE state, becoming both employed. For such a household, however, it also quite likely (about 25%) that the wife quits the labor force and the household moves to EO state. On the other hand, for a couple with an employed wife and an unemployed husband (UE), there is only a 8% probability that the husband moves out of labor force next month, and the household ends up in the state OE. The probability that both end up employed next month is 32%, identical to when to couples who are in the EU state in the previous month.

Similarly, for a couple in which the husband is unemployed and the wife is non-participant (UO), the probability that the husband finds a job and the wife remains unemployed the next month (EO) is 34%, while there is only around a 9% chance that the husband joins the wife and the household moves to OO state. However, in the opposite case, when the wife is unemployed and the husband is out of the labor force (OU), the probability of the wife finding a job and the husband staying out (OE) is 26% while there is around a 27% chance that the wife joins the husband in non-participation the following month (OO).

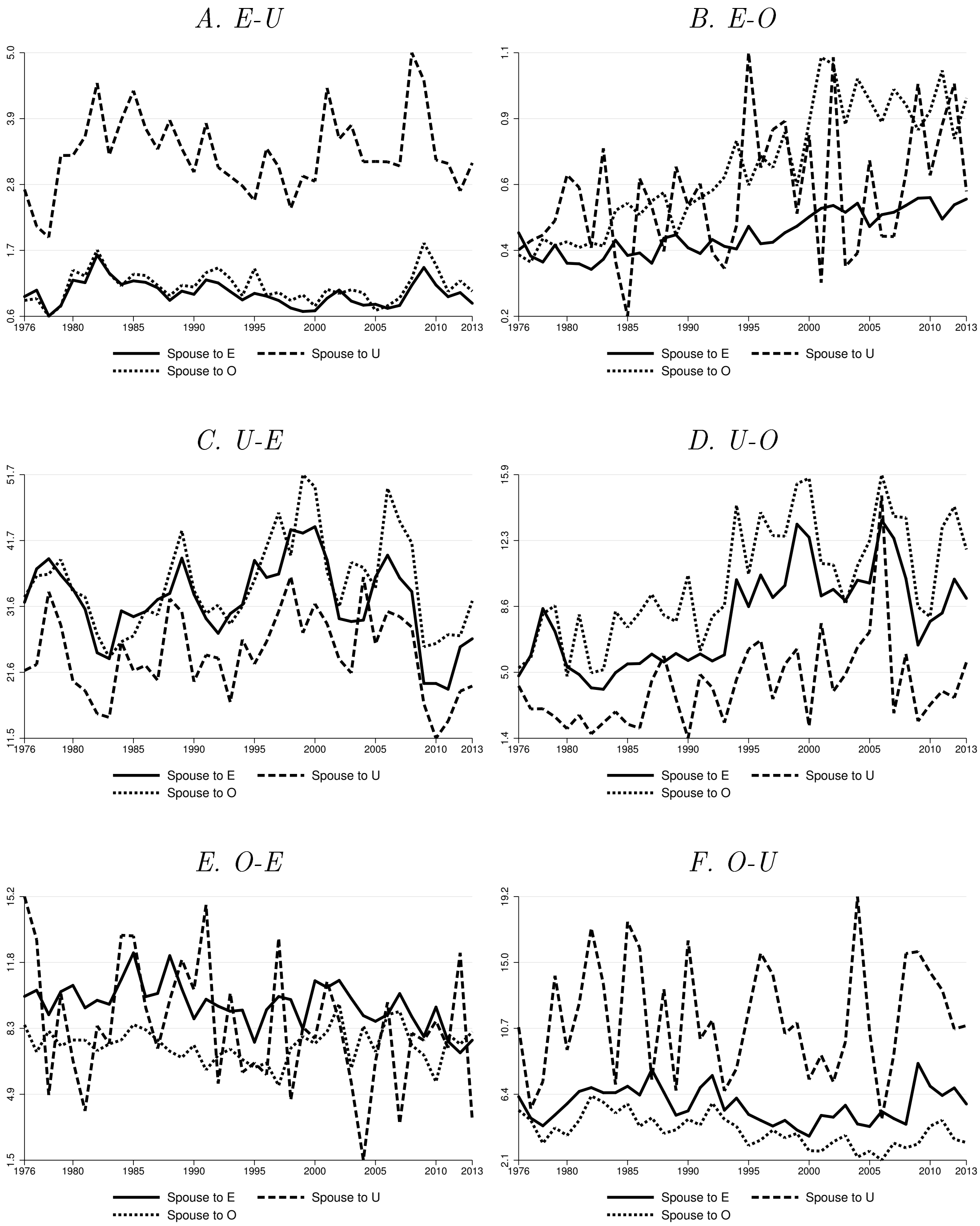
Figures 3.6 and 3.7 document individual transitions conditional on transitions that one's partner experiences. Each transition is reported conditional on the move of an individual's partner to employment, unemployment and out of labor force, respectively. Figures 3.6 and 3.7 show clearly that both the level and cyclicality of individual transitions depend critically on the labor market transitions of one's partner. For both males and females, transitions from employment to unemployment (panels 3.6A and 3.7A) is more likely when one's partner also moves to unemployment (either from employment or from out of labor force). This can reflect the fact that husbands and wives are facing similar labor market conditions and more likely to become unemployed together. It can also capture joint labor market search behavior of couples. Finally, both males and females are also much more likely to move from out of labor force to unemployment (O to U) when their partners move to unemployment (panels 3.6F and 3.7F). This can reflect the added worker affect.

Table 3.2 documents transitions of husbands and wives conditional on transitions of their partners, which makes the gender differences in labor market transitions more transparent. The results in Table 3.2 show that labor market transitions are quite different for married males and females, i.e., the two panels in Table 3.2 are not identical. Males are on average more attached to labor force than females. As a result, independent of their partners' labor market transitions, they are less likely to transit to out of labor force. Females, on the other hand, are more likely to move to out of labor force in any given month.

The results in Table 3.2 also suggest that there exist some coordination in the labor supply behavior of household members. First, we observe again the well-known added-worker effect. An out-of-the-labor-force female whose husband loses his job, i.e., moves from employment to unemployment, is twice as likely to enter the labor force, either as employed or unemployed, than an out-of-the-labor-force female whose husband keeps his job. Similarly, a husband with a wife that transits from employment to unemployment is 40% more likely to enter the labor force than a husband whose wife remains employed.

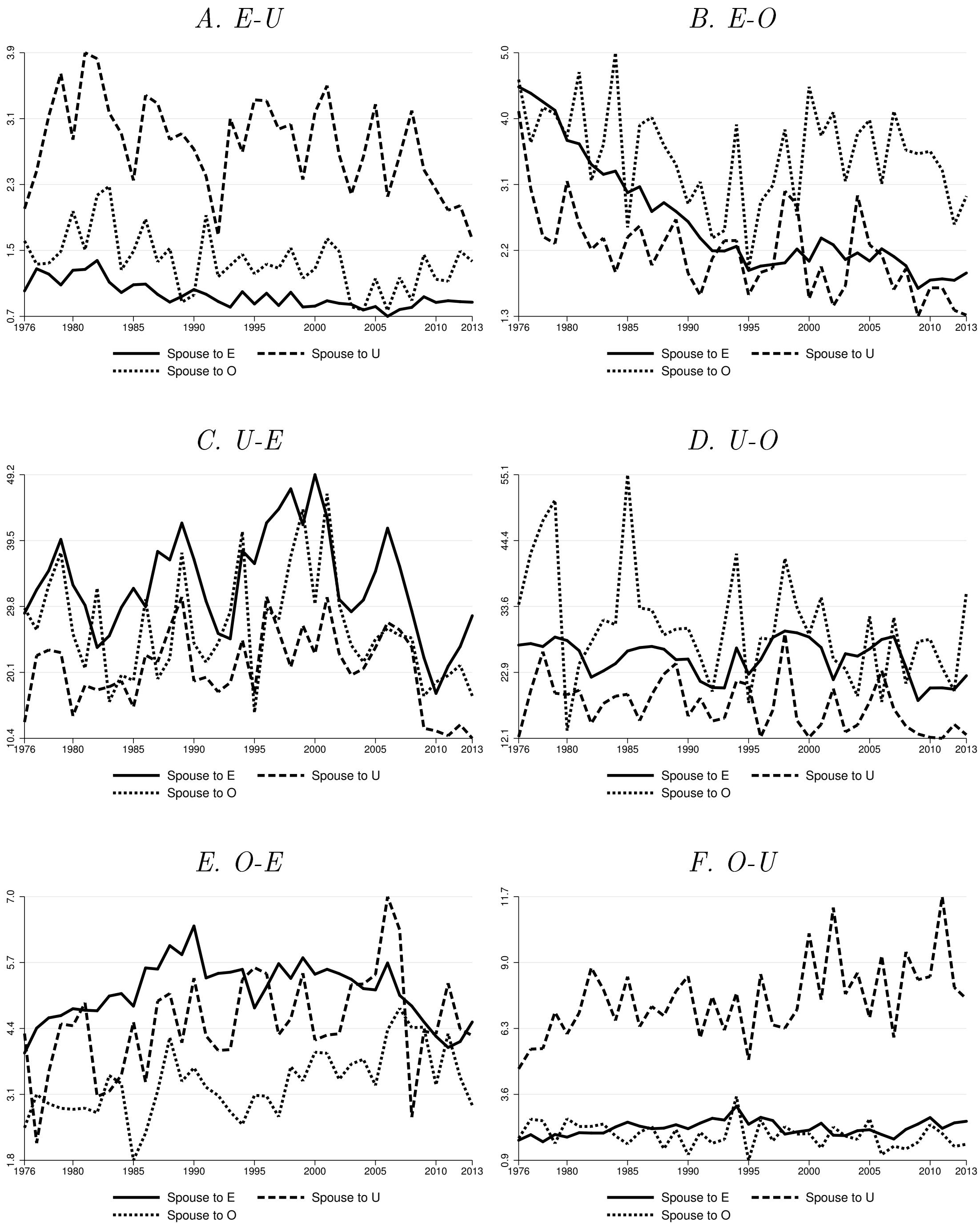
Second, wives are more likely to become unemployed if their husbands also become unemployed. When the husband moves from employment to unemployment, the wife has about 4% chance of moving from employment to unemployment as well. On the other hand, if the husband keeps his job, her chance of moving to unemployment is only 0.81%. We observe a similar pattern for husbands. One factor behind these patterns might be the fact that husband and wives face correlated labor market shocks. As a result, when the husband or wife becomes unemployed, chances that the other party looses his/her job is high. These patterns, however, can also result from the joint labor market decisions of husbands and wives. When one of the household members looses his/her job, the household might find it optimal to relocate and looks for new job opportunities for both partners in a new labor market.

Figure 3.6: Labor market transitions for married males conditional on spouse's state tomorrow



NOTE: CPS, time period 1976:Q1 to 2013:Q4. Yearly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recessions.

Figure 3.7: Labor market transitions for married females conditional on spouse's state tomorrow



NOTE: CPS, time period 1976:Q1 to 2013:Q4. Yearly average of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. Grey areas represent NBER recessions

Table 3.2: Conditional average labor market transitions for married couples

Female transitions		Male employed			Male unemployed			Male OLF		
		E	U	O	E	U	O	E	U	O
Male employed	E	96.40	0.99	2.61	91.73	4.93	3.34	83.12	2.22	14.75
	U	32.86	41.99	25.15	25.00	54.77	21.82	44.54	28.08	43.97
	O	5.00	2.22	92.78	6.41	7.42	86.17	9.87	2.91	87.22
Male unemployed	E	94.66	2.37	2.96	96.18	2.07	1.74	94.24	3.39	2.56
	U	46.03	31.50	23.59	19.77	63.91	16.33	36.32	19.57	62.18
	O	5.86	5.14	89.00	3.61	7.13	89.26	3.88	4.52	91.60
Male OLF	E	91.61	1.64	6.81	95.21	3.01	2.29	96.36	1.34	2.31
	U	38.49	35.96	38.08	17.93	54.56	30.62	24.48	49.41	26.11
	O	24.06	4.86	71.08	5.31	13.23	81.46	2.72	1.87	95.41

Male Transitions		Female employed			Female unemployed			Female OLF		
		E	U	O	E	U	O	E	U	O
Female employed	E	98.58	0.99	0.43	93.16	6.00	1.05	95.47	1.55	2.98
	U	31.64	60.50	7.87	31.66	60.32	8.02	48.00	40.93	12.47
	O	8.51	5.65	85.84	11.83	12.41	77.14	21.01	5.51	73.66
Female unemployed	E	97.05	2.17	0.79	96.84	2.59	0.57	96.81	2.32	0.87
	U	51.11	42.35	6.54	22.01	73.67	4.32	31.56	53.20	18.37
	O	12.74	8.90	79.47	6.77	7.52	85.71	9.58	8.54	81.88
Female OLF	E	96.77	1.64	1.60	95.94	3.51	0.58	98.37	1.08	0.55
	U	47.24	39.58	13.78	23.26	70.36	6.38	34.51	56.14	9.35
	O	52.26	7.38	40.35	13.23	23.22	64.17	6.92	3.94	89.14

NOTE: CPS, age 25-54, time period 1976 to 2013. Adjusted for time aggregation and classification errors

Finally, when a husband moves from any state to non-participation, his spouse is more likely to move to out of labor force as well. Notice that all female transitions into non-participation (ninth column) are higher than transitions into non-participation from other states (third and sixth columns). There is only one exception, when the husband transits from non-participation to employment the wife is more likely to transit from employment to out of the labor force than when the husband remains out of the labor force.

4.3. A Decomposition Exercise

To assess the importance of each labor market transition in determining the labor market states we extend the decomposition exercise proposed in Shimer (2012) to the case of couples. The exercise consists of three steps. First, for each month we use the monthly transitions calculated from the data to compute the steady state distribution of labor market stocks associated with these transitions, and check whether it provides a good approximation of actual stocks. The basic idea is that in each month there is a steady state distribution of couples across labor market stocks, and the number of couples moving out of each state to other states is equal to number of couples moving into each state from other states.

In our case, computing the steady state approximation of the labor market stocks requires solving a system of 9 equations with 9 unknowns (EE, EU, EO, UE, UU, UO, OE, OU, and OO) that defines the steady state. Basically, each equation states that, in the steady state, the flow of workers entering one state should be equal to the flow of workers leaving that state. Let $\mathcal{S}$ denote the set of all possible states, that is, $\mathcal{S} = \{EE, EU, EO, UE, UU, UO, OE, OU, OO\}$. Then, for any state $J \in \mathcal{S}$, we can write the steady state condition as

$$\left(\sum_{I \in \mathcal{S} \setminus J} \gamma_I^J \right) \pi(J) = \sum_{I \in \mathcal{S} \setminus J} \gamma_J^I \pi(I), \tag{3.1}$$

where $\pi(J)$ and $\pi(I)$ are the steady state probabilities of state J and I, respectively.

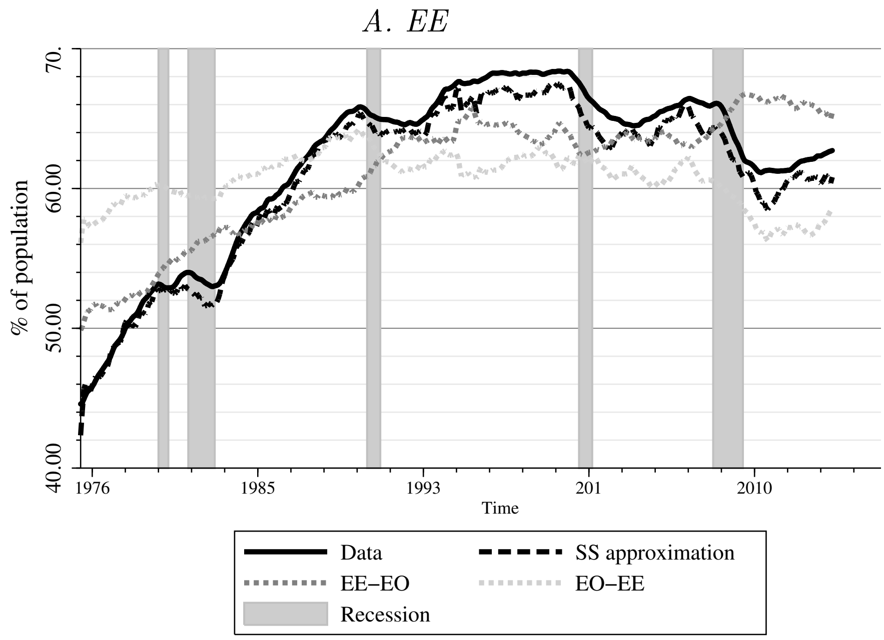
Second, we calculate the mean of all transitions across the entire period considered (from February 1976 until December 2013), which are reported in Table 3.1. The final step is to consider how important each transition is in determining each labor market stock. To that end, we set all transitions equal to their average values for the sample period and allow only one transition to vary as it does in the data. We then calculate the steady state approximation of labor market stocks associated to this counterfactual transitions which combines average values for all but one transition. As a result, for each labor market stock we have 72 counterfactual steady state distributions (associated to each possible transition). Obviously, some of the transitions do not affect steady state distributions, while others do. If one out of 72 possible transitions, accounts for all the variations in a particular joint labor market state for households, then the counterfactual associated with that particular transitions would coincide with the data. On the other hand if a particular transition has no effect on changes in a labor market states over time, the counterfactual associated with that particular transition would be a flat line.[8]

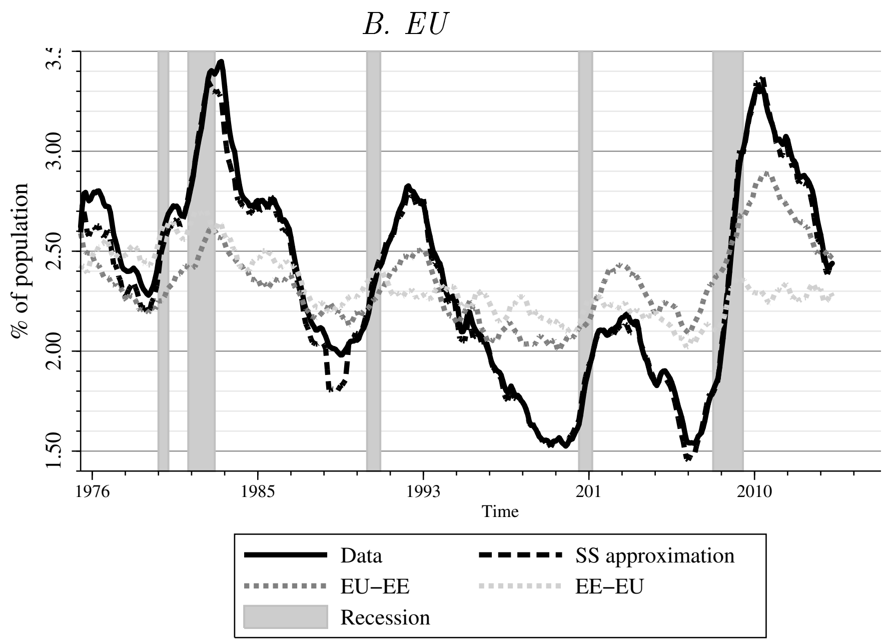
Joint Stocks In Figure 3.8, we present, for each joint labor market stock, the data (the same information as in Figure 3.1), the steady state approximations, and two counterfactuals that give the closest fit to the steady state approximations (out of the 72 counterfactuals that we compute for each stock, we select the two with highest covariation with the data). Table 3.3 shows how much of the variations in different labor market states can be accounted for by the two best counterfactuals and the transitions that were allowed to vary in these counterfactuals. Figure C.1 in Appendix C shows how some of the key transitions behave over time.

Changes in some labor market stocks are easy to understand. During the sample period, the fraction of traditional households, with a working husband and an out-of-labor-force wife declined, while the fraction of households with two workers increased (panels 3.9C and 3.8A in Figure 3.8). These changes were mainly driven by a large decline in EE to EO transitions and the corresponding increase in EO to EE transitions between 1976 and early 1990 (panels C.1A and C.1B in Figure C.1 in Appendix C). Since early 1990s, while EE to EO transitions have been rather stable, there was a decline in EO to EE transitions. As a result, since early 1990s the fraction of household with two workers declined slightly.

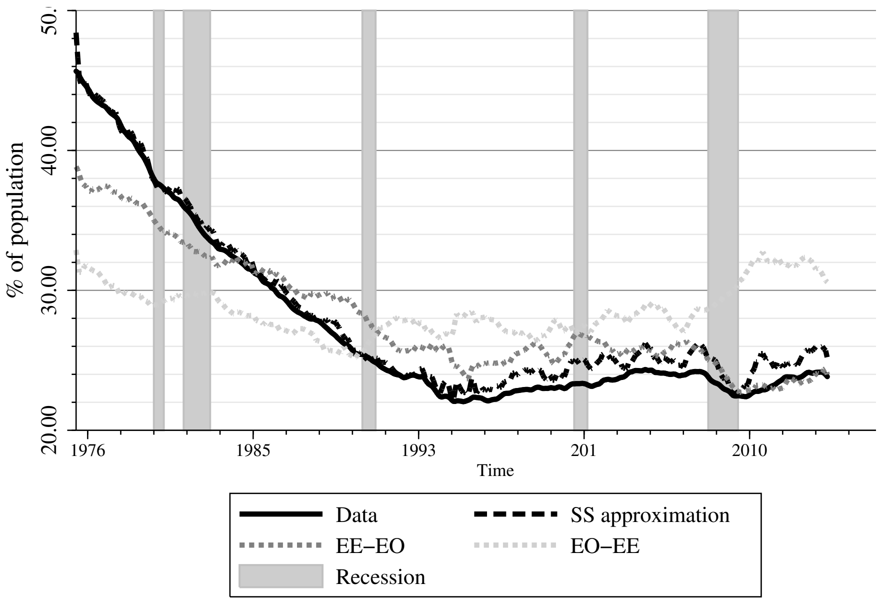
[8]Elsby et al. (2015) suggest an alternative decomposition procedure based on cumulative flows rather than stocks. Since we consider 72 transitions for a long period (1976-2013), the transitions between some states in some periods have very few observations, which results in unreliable estimates. As Elsby et al. (2015) focus on individual data with only 6 possible transitions, this problem does not arise.

Figure 3.8: Decomposition exercise for joint labor market states

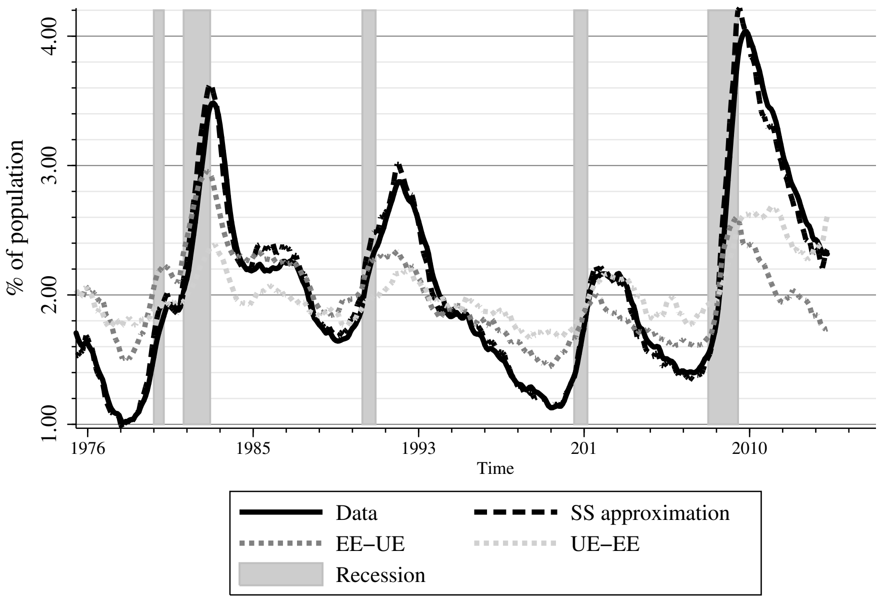




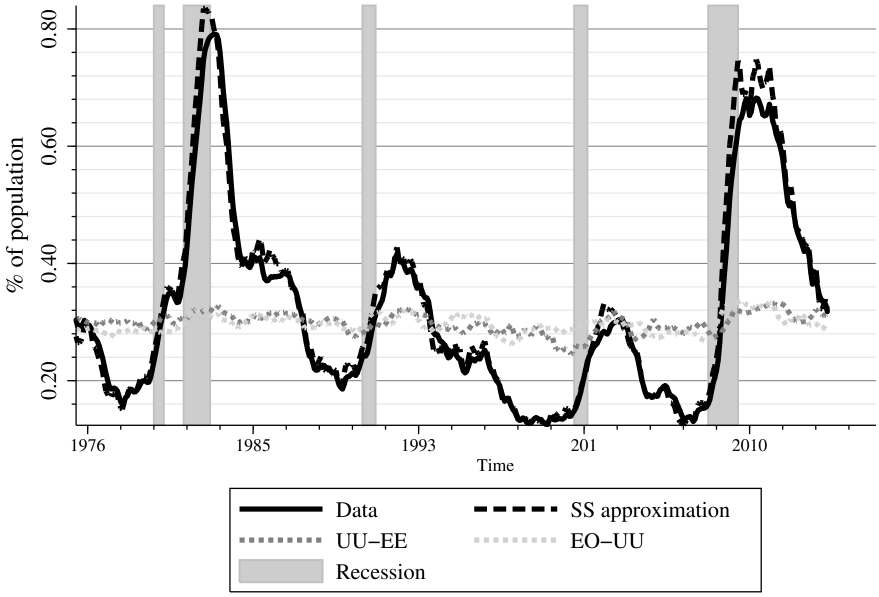
C. EO


% of population
50.
40.00
30.00
20.00
1976
1985
1993
201
2010
Time
Data
SS approximation
EE−EO
EO−EE
Recession

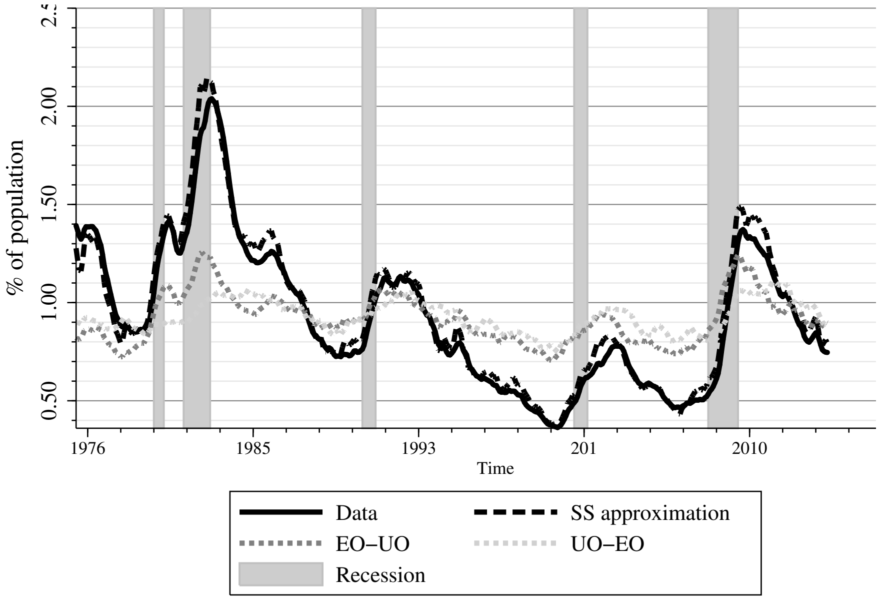
D. UE

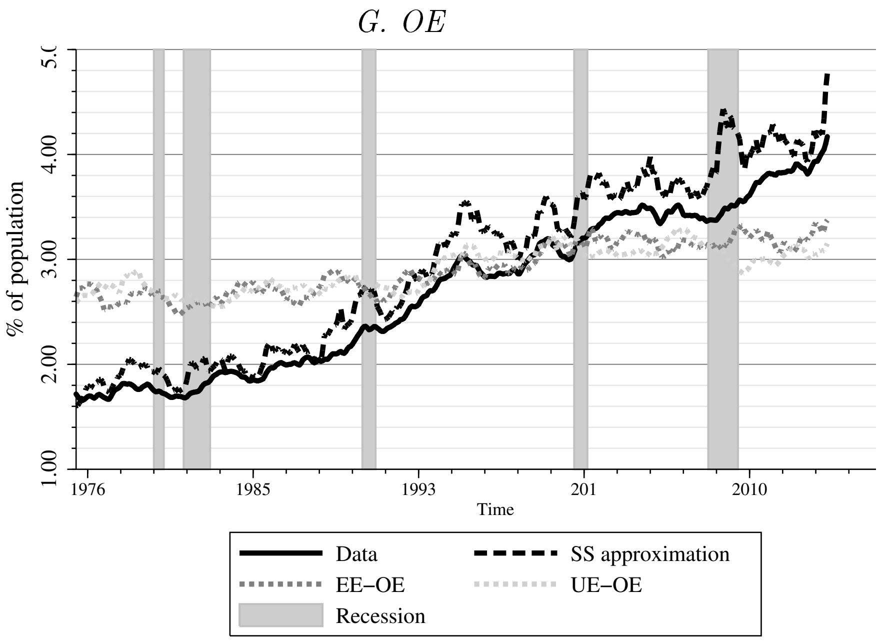

% of population
4.00
3.00
2.00
1.00
1976
1985
1993
201
2010
Time
Data
SS approximation
EE−UE
UE−EE
Recession

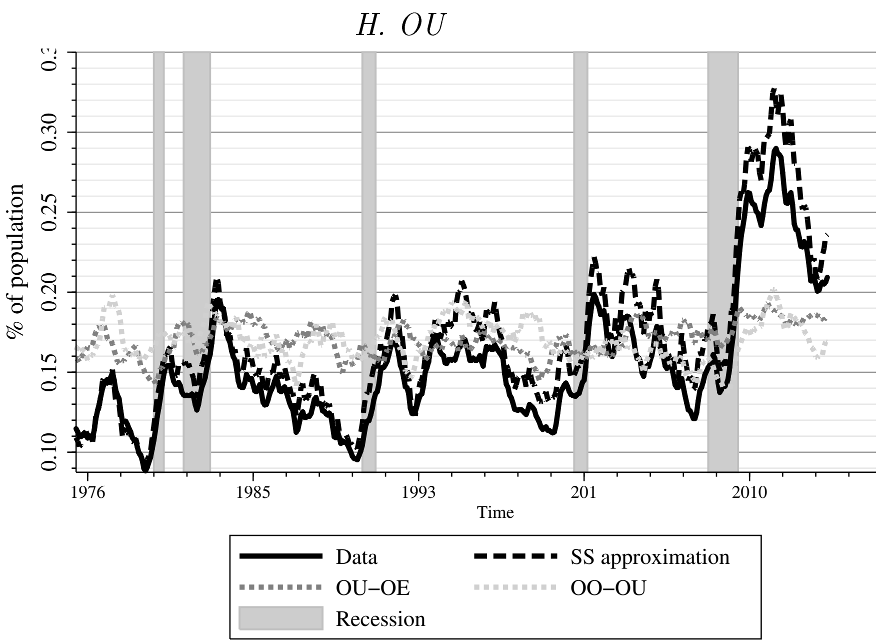
E. UU

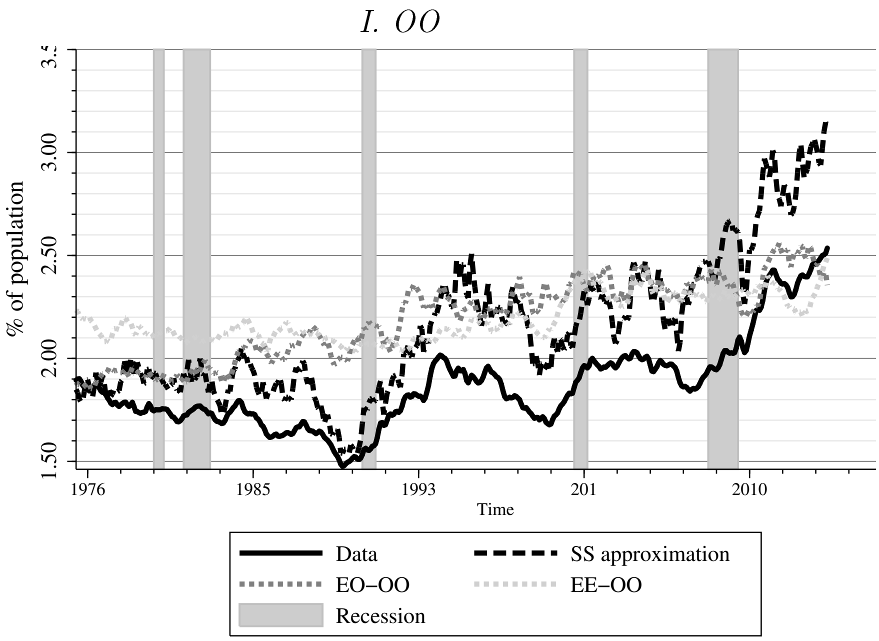

% of population
0.20
0.40
0.60
0.80
1976
1985
1993
201
2010
Time
Data
SS approximation
UU−EE
EO−UU
Recession

F. UO


% of population
0.50
1.00
1.50
2.00
1976
1985
1993
201
2010
Time
Data
SS approximation
EO−UO
UO−EO
Recession


G. OE
% of population
1.00
2.00
3.00
4.00
1976
1985
1993
2010
Time
Data
SS approximation
EE−OE
UE−OE
Recession


H. OU
% of population
0.10
0.15
0.20
0.25
0.30
1976
1985
1993
2010
Time
Data
SS approximation
OU−OE
OO−OU
Recession



NOTE: Decomposition exercise for joint labor market states, from 1976:2 to 2013:12. The solid line represents the seasonally adjusted fraction of the population in state XY, where X refers to the male and Y to the female. X and Y can stand for: E - employed, U - unemployed, O - out of the labor force. The dashed black line corresponds to the stationary distribution of couples in state XY associated with the transition probabilities. The dashed dark and light gray lines correspond to the two most important transitions which contribute to the stock XY. The legend contains the description of these transitions. Grey areas represent NBER recession dates (taken from http://www.nber.org/cycles/cyclesmain.html).

Table 3.3: Explained variation (in %) of joint labor market stocks by the two most important transitions.

Transition	%	Transition	%	Transition	%
EE		**EU**		**EO**	
EE-EO	64.11	EU-EE	35.25	EE-EO	66.18
EO-EE	18.70	EE-EU	22.00	EO-EE	10.50
UE		**UU**		**UO**	
EE-UE	37.35	UU-EE	7.14	EO-UO	28.20
UE-EE	29.62	EO-UU	6.80	UO-EO	15.17
OE		**OU**		**OO**	
EE-OE	26.60	OU-OE	13.46	EO-OO	44.09
UE-OE	19.84	OO-OU	9.69	EE-OO	22.51

The transitions that account for the fraction of households with one employed and one unemployed member differ depending on who the unemployed member is. For households in UE state (panel 3.9D), with an unemployed husband and an employed wife, the transitions of husbands from employment to unemployment and vice versa (EE to UE and UE to EE transitions) play the key role. As Figure C.1 (panels C.1C and C.1D) shows EE to UE transitions are very pro-cyclical while those from UE to EE are countercyclical. When it is the female member who is unemployed, i.e., household is in the EU state (panel 3.8B), the transitions of wife between employment and unemployment are important, but for couples in UE state husband's movements between employment and unemployment are important.

For those couples in which one member is out of the labor force while the other is looking for a job, states UO in panel 3.9F and OU in panel 3.9H, we also see differences depending on whether it is the husband or the wife who is looking for a job. When the husband is the one unemployed, panel 3.9F, the relevant transitions are EO to UO and UO to EO, that is, the husband losing his job and the husband finding a job, conditional on the wife remaining out of the labor force. However, when the the wife is the one looking for a job (panel 3.9H), the important transitions are EO to UO, as for the husband, and OO to OU, that is, the wife entering the labor force from a situation in which both members are not participating. Although, this OO to OU transition accounts for only 10% of the variation in the OU stock (see Table 3.3), it reflects the fact that the participation margin is important to understand the unemployment of females.

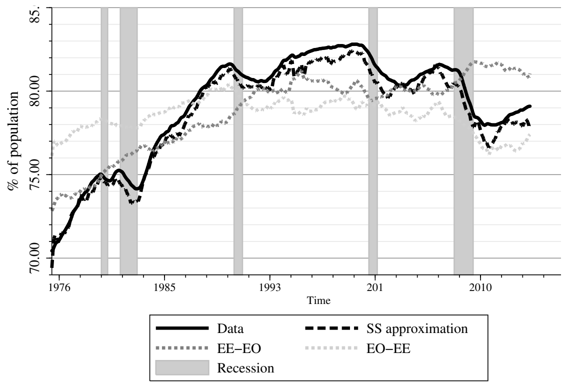
Individual Stocks Figures 3.9, 3.10, and 3.11 show movements in employment, unemployment, and participation rates for married males, married females and the whole married population. Table 3.4 documents the role of different joint labor market transitions in explaining these movements. Looking at the evolution of the employment rate of all married population over the period (panel 3.9A), we can observe a well known pattern: the remarkable increase in the employment rate between the 1970s and the 2000s has been mainly driven by the increase in the participation of married females. In particular, the decrease in the transition from EE to EO (panel C.1A) accounts for 61% of the movement in the employment rate while the increase in the the EO to EE (panel C.1B) accounts for 21% of the variation (Table 3.4). In panel 3.9B we observe a slight downward trend in the employment rate of married males over the period. However, the employment rate of males is mainly affected by the cyclicality of their job-finding and job-losing rates (conditional on employment of the wife), that is, the transitions from UE to EE (panel C.1D) and from EE to UE (panel C.2H).

Table 3.4: Explained variation (in %) of employment, unemployment, and participation by the two most important transitions.

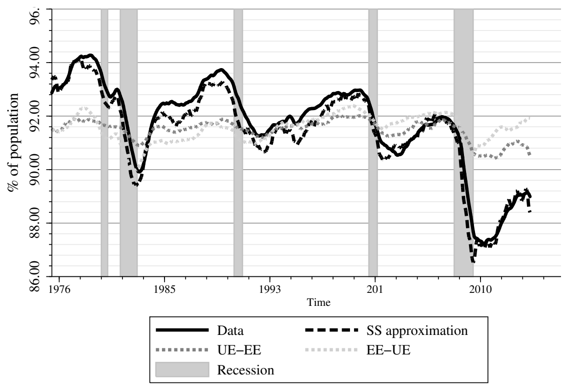
Transition	All	Transition	Males	Transition	Females
Employment					
EE-EO	61.05	UE-EE	20.27	EE-EO	66.40
EO-EE	20.73	EE-UE	13.45	EO-EE	14.22
Unemployment					
EE-UE	17.00	EE-UE	26.18	EU-EE	22.44
UE-EE	11.49	UE-EE	18.41	EE-EO	19.81
Participation					
EE-EO	72.71	EE-OE	21.49	EE-EO	68.19
EO-EE	18.77	EO-OO	17.93	EO-EE	12.69

Figure 3.9: Decomposition of employment rates: everyone, males and females

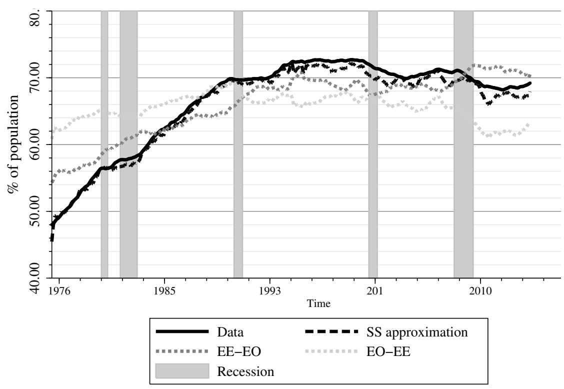
A. All married population



B. Males



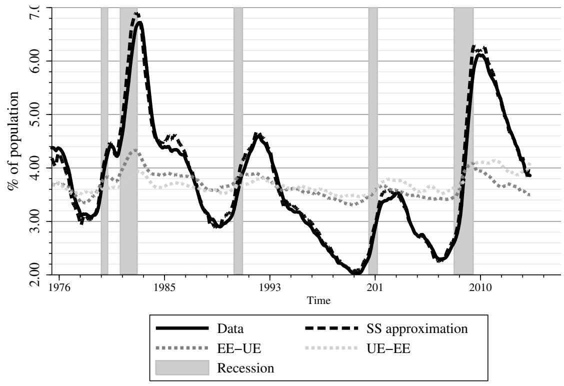
C. Females



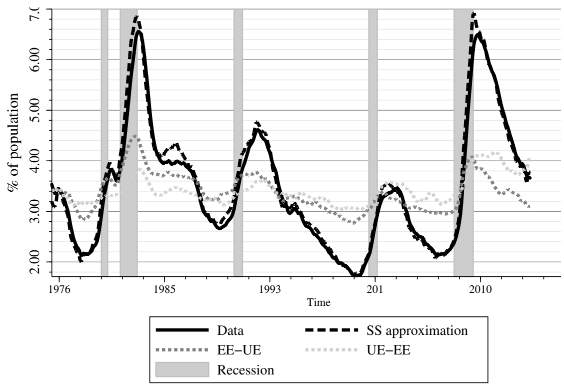
NOTE: CPS, time period from 1976:2 to 2013:12. The solid line represents the seasonally adjusted data. The dashed black line corresponds to the employment rate in the steady associated with the transition probabilities. The dashed dark and light gray lines correspond to the two most important transitions which contribute to the employment rate. The legend contains the description of these transitions. Grey areas represent NBER recession dates.

Figure 3.10: Decomposition of unemployment rates: everyone, males and females

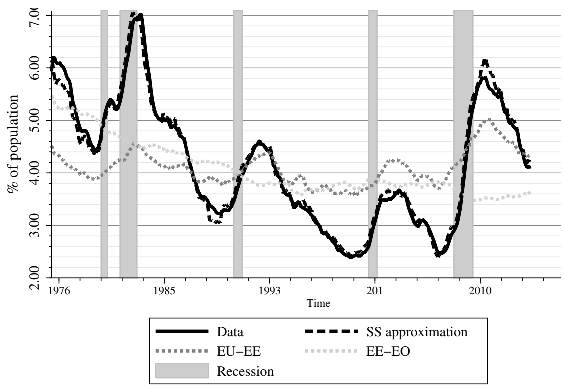
A. All married population



B. Males



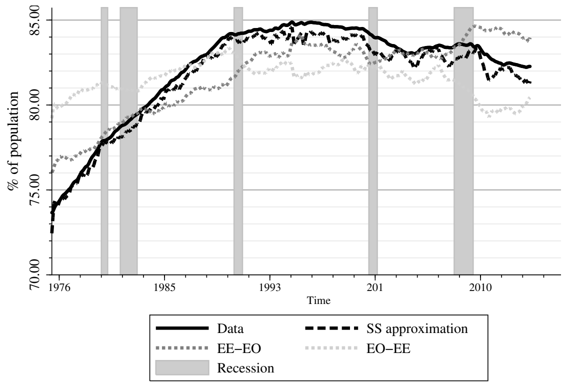
C. Females



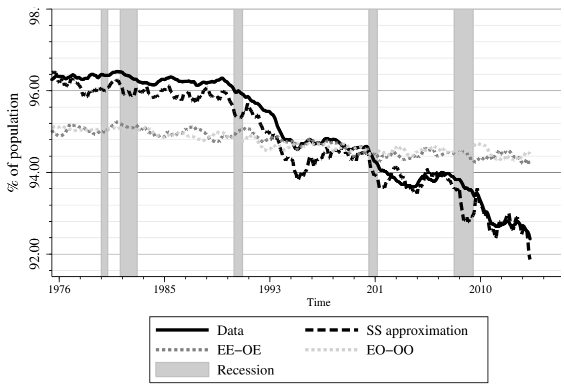
Note: CPS, time period from 1976:2 to 2013:12. The solid line represents the seasonally adjusted data. The dashed black line corresponds to the unemployment rate in the steady associated with the transition probabilities. The dashed dark and light gray lines correspond to the two most important transitions which contribute to the unemployment rate. The legend contains the description of these transitions. Grey areas represent NBER recession dates.

Figure 3.11: Decomposition of participation rates: everyone, males and females

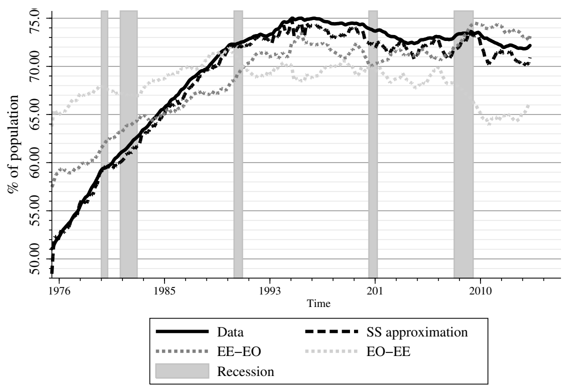
A. All married population



B. Males



C. Females



NOTE: CPS, time period from 1976:2 to 2013:12. The solid line represents the seasonally adjusted data. The dashed black line corresponds to the participation rate in the steady associated with the transition probabilities. The dashed dark and light gray lines correspond to the two most important transitions which contribute to the participation rate. The legend contains the description of these transitions. Grey areas represent NBER recession dates.

In Figure 3.10, we observe that the variation of the unemployment rate of married males and married females are affected by different channels. While, for males the most important transitions are the job-losing and job-finding rates (conditional on the wife being employed), for females the important transitions are the job-finding rate and the transition from employment to out of the labor force (conditional on the male being employed). In this sense, our findings for married males are in the line of those of Shimer (2012), while what we observe for married females is more in line with the findings of Elsby et al. (2015). Note that the transitions that we consider explain *less* of the volatility of the unemployment rate than those analyzed by Shimer (2012) or Elsby et al. (2015) (see Table 3.4). The reason is that, since we look at joint transitions, we are further disaggregating the effect of the transitions considered in these papers. Consider, for example, the transition from U to E, which in Shimer (2012) accounts for three-quarters of the variation in the unemployment rate. In our analysis, this transition, for example for males, would correspond to the aggregated effect of those nine transitions in which the husband moves from unemployment to employment irrespective of what the wife does (transitions from UE to EE, from UU to EE, from UO to EE, from UE to EU, from UU to EU, from UO to EU, from UE to EO, from UU to EO, and from UO to EO).

Finally, in Figure 3.11 we observe that the patterns described for the employment rate of married individuals also are the driving force for the participation rate. That is, the increase in the participation of married individuals is mainly explained by the increase in the employment of married females. Interestingly, in panel 3.11B, we see a clear downward trend in the participation of married males over the period. This trend is driven by the increase in the transitions from EE to OE (panel C.2E) and from EO to OO (panel C.2O). It seems that the decline of the participation of married males is mainly due to the increase of households in which the traditional roles are reversed and the increase in couples in which non of the members participate in the labor market.

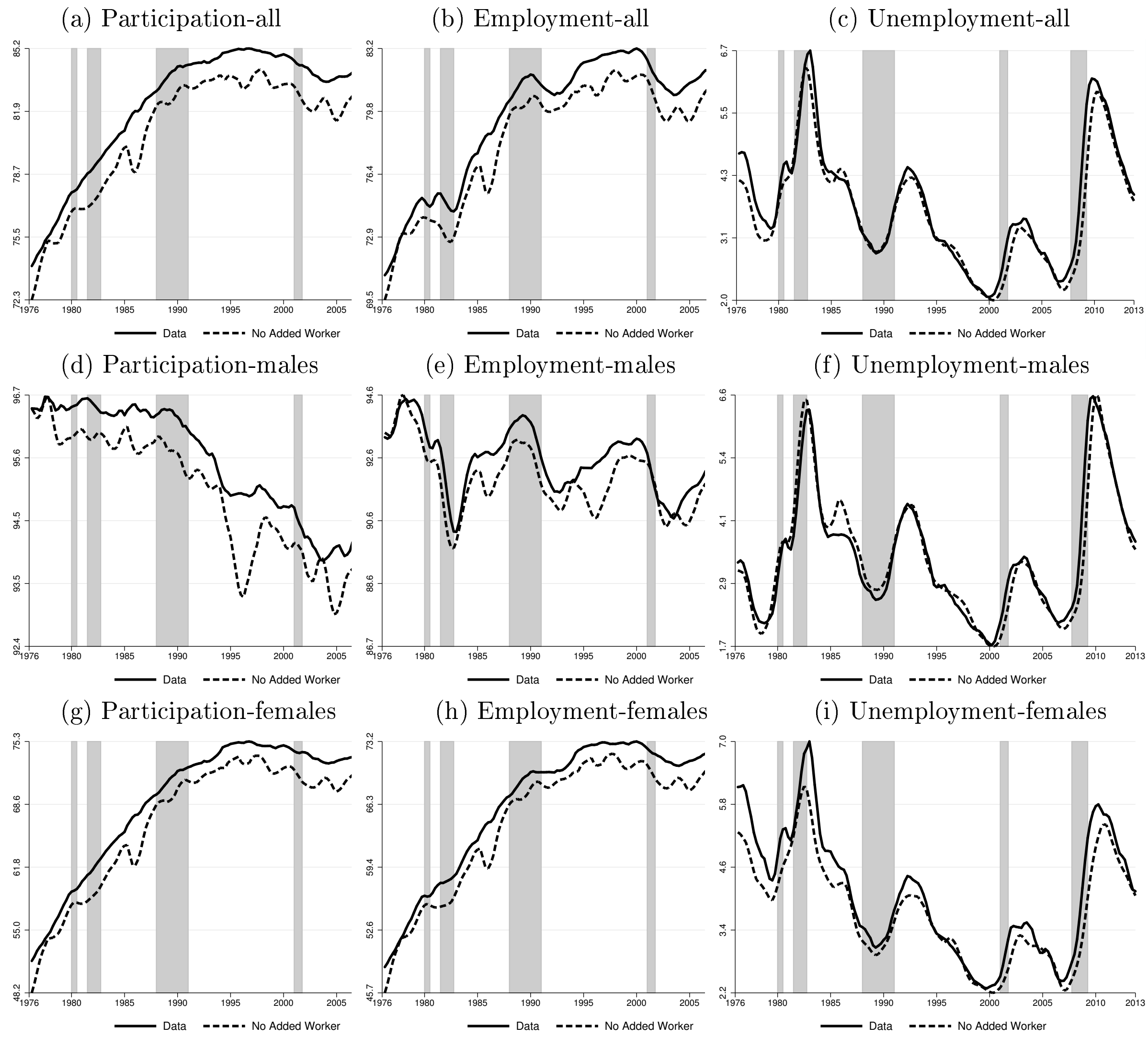
5. Added Worker Effect

In this section, we document the importance of the added worker effect, increase in married women's labor supply in response to their partner's unemployment. Our focus on joint transitions provides us with a natural way of calculating the importance of added worker affect. We focus on joint labor market transitions in which one partner moves from employment to unemployment or remains unemployed and the other partner enters the labor force and becomes unemployed. If the wife is the one who is entering the labor force, we focus on EO to UU and UO to UU transitions, while if the husband is the added worker the relevant transitions are OE to UU and OU to UU. To be able to compute the importance of the added worker effect, we set all these transitions, as well as OO to UU transitions to zero for the entire period, and recalculate the implied labor market statistics.

Figure 3.12 shows the impact of the added worker effect on participation, employment and unemployment. Table 3.5 documents the contribution of the added worker, i.e. the difference between data and counterfactual time series without the added worker effect. Table 3.6 shows the same statistics for recessions and normal times. The added worker effect increases female labor force participation by about 2-2.5 percentage points and the effect is stronger since 2000. The effect of the added workers on unemployment is not negligible either. In the absence of added worker effect, the female unemployment rate would be about 0.3 percentage points higher for the 2000-2010 period. This 0.3 percentage points represents about 6.16% of the female unemployment rate.

Finally, Figure 3.13 and Table 3.7 show how added worker effect contributes to household level measures of unemployment. Results highlight clearly the insurance role of the added worker effect. On the one hand, with the added workers, the fraction of households in which any household member is unemployed is about 0.4 percentage points higher in 2000-2010 period. On the other hand, the added workers reduce the fraction of household in which nobody is employed by about 0.4 percentage point during the same period, which is close to 13.3% of the total households with none of the members employed.

Figure 3.12: Added Worker Effect and Participation rate, Employment and Unemployment



NOTE: Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, and presented averaged across quarters from 1976:Q1 to 2013:Q4. Grey areas represent NBER recession periods.

Table 3.5: Counterfactual participation rate, employment and unemployment

	1976-2013	1980-1990	1990-2000	2000-2010
All				
Participation Rate	1.37	1.47	1.29	1.56
Emplyment Rate	1.20	1.39	1.23	1.28
Unemployment Rate	0.17	0.08	0.03	0.29
Males				
Participation Rate	0.63	0.55	0.71	0.60
Employment Rate	0.59	0.75	0.73	0.35
Unemployment Rate	0.02	-0.23	-0.04	0.24
Females				
Participation Rate	2.11	2.38	1.87	2.53
Emplyment Rate	1.82	2.03	1.74	2.21
Unemployment Rate	0.33	0.39	0.11	0.33

NOTE: Difference between data (mean) and counterfactual (mean) in percentage points.

Table 3.6: Counterfactual participation rate, employment and unemployment during recessions and normal times

	Normal times						
	1976Q1 1979Q4	1980Q4 1981Q2	1983Q1 1987Q4	1991Q2 2000Q4	2002Q1 2007Q3	2009Q3 2013Q4	Total
All							
Participation Rate	0.95	1.43	1.68	1.32	1.54	1.34	1.35
Employment Rate	0.68	1.31	1.55	1.25	1.39	0.83	1.20
Unemployment Rate	0.39	0.12	0.14	0.04	0.13	0.54	0.16
Males							
Participation Rate	0.26	0.52	0.53	0.71	0.53	0.49	0.63
Employment Rate	0.15	0.59	0.71	0.71	0.43	0.02	0.60
Unemployment Rate	0.11	-0.09	-0.21	-0.02	0.09	0.48	0.01
Females							
Participation Rate	1.64	2.34	2.83	1.93	2.55	2.20	2.08
Employment Rate	1.20	2.02	2.39	1.79	2.35	1.65	1.80
Unemployment Rate	0.68	0.34	0.49	0.10	0.16	0.61	0.31

	Recessions					
	1980Q1 1980Q3	1981Q3 1982Q4	1988Q1 1991Q1	2001Q1 2001Q4	2007Q4 2009Q2	Total
All						
Participation Rate	0.94	1.73	1.13	1.50	1.86	1.42
Employment Rate	0.80	1.76	1.11	1.11	1.14	1.21
Unemployment Rate	0.23	-0.06	0.01	0.41	0.79	0.23
Males						
Participation Rate	0.50	0.53	0.62	0.45	0.77	0.61
Employment Rate	0.67	0.99	0.77	0.04	-0.05	0.54
Unemployment Rate	-0.19	-0.51	-0.17	0.43	0.85	0.06
Females						
Participation Rate	1.38	2.94	1.64	2.54	2.95	2.24
Employment Rate	0.94	2.53	1.46	2.19	2.32	1.88
Unemployment Rate	0.65	0.38	0.18	0.39	0.72	0.40

NOTE: Difference between data (mean) and counterfactual (mean) in percentage points.

Table 3.7: Contribution of the added worker effect to the household unemployment measures

	1976-2013	1980-1990	1990-2000	2000-2010
Any Unemployed	0.20	-0.00	0.02	0.44
Nobody Employed	-0.41	-0.53	-0.44	-0.38

NOTE: Difference between data (mean) and counterfactual (mean) in percentage points.

Figure 3.13: Added Worker Effect and the Data

A. Any Unemployed *B. Nobody Employed*

NOTE: Proportion of couples in each situation: data and implied by the counterfactual exercise, without added worker effect in economy. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, and presented averaged across quarters from 1976:Q1 to 2013:Q4. Grey areas represent NBER recession periods.

6. Conclusions

We study joint labor market transitions of husbands and wives among three labor market states (employment, unemployment and out of labor force) between 1976 and 2013. Our results show that joint labor market transitions are important to understand cyclical movements in unemployment as well as the secular rise in aggregate employment. Married men and women differ in their labor market dynamics. Transitions in and out of labor force play a more important role for unemployment dynamics of females than they do for those of males. As a result, modeling out of labor force as a distinct state is critical to understand joint labor market dynamics of married couples. Our results also show that joint labor market transitions of husbands and wives imply an important degree of coordination between labor market activities of household members. Without the added worker effect, female labor participation and unemployment rates in 2000-2010 period would be about 2.5 and 0.3 percentage points higher, respectively. This 0.3 percentage points represents about 6.16% of the female unemployment rate.

Bibliography

Aaronson, Daniel, Johnathan Davis, and Luojia Hu, "Explaining the Decline in the U.S. Labor Force Participation Rate," *FRB Chicago Chicago Fed Letter 296*, March 2012.

Abowd, John M and Arnold Zellner, "Estimating Gross Labor-Force Flows," *Journal of Business & Economic Statistics*, June 1985, *3* (3), 254–83.

Adams, Peter, Michael D. Hurd, Daniel McFadden, Angela Merrill, and Tiago Ribeiro, "Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status," *Journal of Econometrics*, January 2003, *112* (1), 3Ű56.

Aizer, Anna, "Rising Inequality and Intergenerational Mobility: The Role of Public Investments in Human Capital," *CESifo Economic Studies*, 2014.

Aizer, Ayal A., Ming-Hui Chen, Ellen P. McCarthy, Mallika L. Mendu, Sophia Koo, Tyler J. Wilhite, Powell L. Graham, Toni K. Choueiri, Karen E. Hoffman, Neil E. Martin, Jim C. Hu, and Paul L. Nguyen, "Marital Status and Survival in Patients With Cancer," *Journal of Clinical Oncology*, November 2013, *31* (31), 3869–3876.

Alvarez, Fernando and Marcelon Veracierto, "Labor-market policies in an equilibrium search model," *NBER Macroeconomics Annual 1999*, 2000, *14*, 265–316.

Anderson, Michael, Carlos Dobkin, and Tal Gross, "The Effect of Health Insurance Coverage on the Use of Medical Services," *American Economic Journal: Economic Policy*, February 2012, *4* (1), 1–27.

Araujo, Maria Caridad, Pedro Carneiro, Yyannú Cruz-Aguayo, and Norbert Schady, "A Helping Hand? Teacher Quality and Learning Outcomes in Kindergarten," 2014.

Arellano, Manuel and Olympia Bover, "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, July 1995, *68* (1), 29–51.

_ **and Stephen Bond**, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, April 1991, *58* (2), 277–297.

Attanasio, Orazio, Sagiri Kitao, and Giovanni L. Violante, *Financing Medicare: A General Equilibrium Analysis in Demography and the Economy (Ed. John B. Shoven)*, University of Chicago Press, 2010.

Averett, Susan L., Laura M. Argys, and Julia Sorkin, "In Sickness and in Health: An examination of Relationship Status and Health using Data from the Canadian National Public Health Survey," *Review of Economics of the Household*, December 2013, *11* (4), 599–633.

Banks, James, Elaine Kelly, and James P Smith, "Spousal Health Effects: the Role of Selection," in David A. Wise, ed., *Discoveries in the Economics of Aging*, University of Chicago Press, 2014, chapter 7, pp. 255–279.

Barnichon, Regis and Andrew Figura, "Declining Desire to Work and Downward Trends in Declining Desire to Work and Downward Trends in Unemployment and Participation," *NBER Macroeconomics Annual*, 2015, *30.*

Becker, Gary S. and Nigel Tomes, "An Equilibrium Theory of Disribution of Income and Intergenerational Mobility," *The Journal of Political Economy*, December 1979, *87* (6), 1153–1189.

_ **and** _ , "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 1986, *4* (3), S1–S39.

Becker, Gary, Scott Duke Kominers, Kevin M. Murphy, and Jörg L. Spenkuch, "A Theory of Intergenerational Mobility," Working paper, 2015.

Bernstein, Amy B., Robin A. Cohen, Kate M. Brett, and Mary Ann Bush, "Marital Status is Associated With Health Insurance Coverage for Working-age Women at all Income Levels, 2007," National Center for Health Statistics Data Brief 11, U.S. Department of Health and Human Services, Center for Disease Control and Prevention December 2008.

Bick, Alexander and Nicola Fuchs-Schündeln, "Taxation and Labor Supply of Married Couples across Countries: A Macroeconomic Analysis," *Mimeo*, 2014.

Blanchard, Oliver Jean, Peter Diamond, Robert E. Hall, and Kevin Murphy, "The Cyclical Behavior of the Gross Flows of U.S. Workers," *Brookings Papers on Economic Activity*, 1990, *1990* (2), 85–155.

Bonhomme, Stéphane and Elena Manresa, "Grouped Patterns of Heterogeneity in Panel Data," *Econometrica*, May 2015, *83* (3), 1147–1184.

Bound, John, "Self-Reported Versus Objective Measures of Health in Retirement Models," *Journal of Human Resources*, Winter 1991, *26* (1), 106–138.

Brown, David W., Amanda E. Kowalski, and Ithai Z. Lurie, "Medicaid as an Investment in Children:What is the Long-Term Impact on Tax Receipts?," January 2015.

Browning, Martin, Pierre-André Chiappori, and Yoram Weiss, *Family Economics*, Cambridge University Press, 2014.

Buss, David M., *The Evolution of Desire: Strategies of Human Mating*, New York: Basic Books, 1994.

Carneiro, Pedro and James Heckman, *Human Capital Policy in Inequality in America: What Role for Human Capital Policies?*, James J. Heckman, Alan B. Krueger and Benjamin M. Friedman, editors. Cambridge, MA: MIT Press., 2003.

Case, Anne and Angus Deaton, "Rising Morbidity and Mortality in Midlife Among White Non-Hispanic Americans in the 21St Century," *Proceedings of the National Academy of Sciences*, December 2015, *112* (49), 1–6.

_ , Darren Lubotsky, and Christina Paxton, "Economic Status and Health in Childhood: The Origins of the Gradient," *American Economic Review*, December 2002, *92* (5), 1308–1334.

Caucutt, Elizabeth M. and Lance Lochner, "Early and late human capital investments, borrowing constraints, and the Family," Working paper, October 2012.

Chade, Hector and Gustavo Ventura, "Taxes and Marriage: A Two-Sided Search Analysis," *International Economic Review*, 2002, *43* (3), 955–985.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez, "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States," *The Quarterly Journal of Economics*, November 2014, *129* (4), 1553–1623.

Chiappori, Pierre-Andre, Sonia Oreffice, and Climent Quintana-Domenque, "Fatter Attraction: Anthropometric and Socioeconomic Matching on the Marriage Market," *Journal of Political Economy*, August 2012, *120* (4), 659–695.

_ , _ , and _ , "Bidimensional Matching with Heterogeneous Preferences: Smoking in the Marriage Market," IZA Discussion Paper 5392, November 2013.

Choi, Sekyu and Arnau Valladares-Esteban, "On Households and Unemployment," Mimeo, 2015.

Clark, Andrew E. and Fabrice Etilé, "Don't Give up on Me Baby: Spousal Correlation in Smoking behaviour," *Journal of Health Economics.*, September 2006, *25* (5), 958–978.

Clark, Gregory, *The Son Also Rises: Surnames and the History of Social Mobility*, Princeton, NJ: Princeton University Press, 2014.

Coşar, A. Kerem, Nezih Guner, and James Tybout, "Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy," *American Economic Review*, March 2016, *106* (3), 625–663.

Cohodes, Sarah, Samuel Kleiner, Michael F. Lovenheim, and Daniel Grossman, "The effect of child health insurance access on schooling: evidence from public insurance expansions," NBER Working paper 20178, May 2014.

Corak, Miles, "Income Inequality, Equality of Opportunity, and Intergenerational Mobility," *Journal of Economic Perspectives*, Summer 2013, *27* (3), 79–102.

Creel, Michael and Montserrat Farell, "On the Production of Cognitive Achievement and Gaps in Test Scores," *Oxford Bulletin of Economics and Statistics*, 2015, *77* (5).

Cunha, Flavio and James Heckman, "The technology of skill formation," *American Economic Review, AEA papers and proceedings*, 2007, *97* (2), 31–47.

—, —, **and Susanne Schennach**, "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, May 2010, *78* (3), 883–931.

—, —, **Lance Lochner, and Dmitiy V. Masterov**, *Interpreting the Evidence on Life Cycle Skill Formation in Handbook of the Economics of Education, Ed. Eric A. Hanushek and Finis Welch*, Vol. 1, Elsevier B.V, 2006,

Currie, Janet and Jonathan Gruber, "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women," *Journal of Political Economy*, 1996a, *104* (6), 1263–1296.

— **and** —, "Health Insurance Eligibility, Utilization of Medical Care, and Child Health.," *The Quarterly Journal of Economics*, May 1996b, *111* (2), 431–466.

Cutler, David M. and Adriana Lleras-Muney, "Understanding Differences in Health Behaviors by Education," *Journal of Health Economics*, January 2010, *29* (1), 1–28.

— **and Jonathan Gruber**, "Does public insurance crowed out private insurance?," *The Quarterly Journal of Economics*, May 1996, *111* (2), 391–430.

Dawkins, Richard, *The Selfish Gene*, second ed., New York City: Oxford University Press, 1989.

De Nardi, Mariacristina, Eric French, and John B. Jones, "Why Do the Elderly Save? The Role of Medical Expenses," *Journal of Political Economy*, February 2010, *118* (1), 39–75.

De Nardi, Mariacristina, Eric French, and John Bailey Jones, "Why Do the Elderly Save? The Role of Medical Expenses," *Journal of Political Economy*, February 2010, *118* (1), 39–75.

Domingue, Benjamin W., Jason Fletcher, Dalton Conley, and Jason D. Boardman, "Genetics and Educational Assortative Mating Among US Adults," *Proceedings of the National Academy of Sciences of the United States of America*, June 2014, *111* (22), 7996–8000.

Elsby, Michael, Bart Hobijn, and Aysegu Sahin, "On the Importance of the Participation Margin for Labor Market Fluctuations," *Journal of Monetary Economics*, May 2015, *72*, 64–82.

Erosa, Andres, Luisa Fuster, and Diego Restuccia, "A general equilibrium analysis of parental leave policies," *Review of Economic Dynamics*, October 2010, *13* (4), 742 – 758.

Fernandez, Raquel, Alessandra Fogli, and Claudia Olivetti, "Mothers and Sons: Preference Formation and Female Labor Force Dynamics," *The Quarterly Journal of Economics*, 2004, *119* (4), 1249–1299.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and the Oregon Health Study Group, "The Oregon Health Insurance Experiment: Evidence from the First Year," *Quarterly Journal of Economics*, August 2012, *127* (3), 1057–1106.

Flabbi, Luca and James Mabli, "Household Search or Individual Search: Does it Matter? Evidence from Lifetime Inequality Estimates," IZA Discussion Paper No. 6908, 2012.

French, Eric, "The Effects of Health, Wealth and Wages on Labor Supply and Retirement Behavior," *Review of Economic Studies*, April 2005, *72* (2), 395–427.

Fuchs, Victor R., "The Gross Domestic Product and Health Care Spending," *The New England Journal of Medicine*, July 2013, *369* (2), 107–109.

Fujita, Shigeru and Garey Ramey, "The Cyclicality of Separation and Job Finding Rates," *International Economic Review*, 2009, *50* (2), 415–430.

Gardner, Jonathan and Andrew J. Oswald, "How is mortality affected by money, marriage, and stress?," *Journal of Health Economics*, November 2004, *23* (6), 1181–1207.

Garibaldi, Pietro and Etienne Wasmer, "Equilibrium search unemployment, endogenous participation and labor market flows," *Journal of the European Economic Association*, 2005, *3* (June), 851–882.

Gourinchas, Pierre-Olivier and Jonathan A. Parker, "Consumption over the Life Cycle," *Econometrica*, January 2002, *70* (1), 47–89.

Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu, "Engines of Liberation," *The Review of Economic Studies*, 2005, *72* (1), 109–133.

_ , Nezih Guner, and John A. Knowles, "More on Marriage, Fertility, and the Distribution of Income," *International Economic Review*, 2003, *44* (3), 827–862.

_ , _ , Georgi Kocharkov, and Cezar Santos, "Marry Your Like: Assortative Mating and Income Inequality," *American Economic Review: Papers and Proceedings*, May 2014, *104* (5), 348Ű353.

Grossman, Michael, "On the Concept of Health Capital and the Demand for Health," *The Journal of Political Economy*, March-April 1972, *80* (2), 223–255.

Güell, Maia, José V. Rodríguez Mora, and Christopher I. Telmer, "The Informational Content of Surnames, the Evolution of Intergenerational Mobility and Assortative Mating," *The Review of Economic Studies*, 2015, *82* (2), 693–735.

Guler, Bulent, Faith Guvenen, and Giovanni Violante, "Joint-Search Theory: New Opportunities and New Frictions," *Journal of Monetary Economics*, 2012, *54* (4), 352–369.

Guner, Nezih, "Gary Becker's Legacy on Intergenerational Mobility," *Journal of Demographic Economics*, March 2015, *81* (1), 33–43.

_ , Remzi Kaygusuz, and Gustavo Ventura, "Taxation and Household Labour Supply," *The Review of Economic Studies*, December 2012, *79* (3), 1113–1149.

_ , _ , and _ , "Taxing women: A macroeconomic analysis," *Journal of Monetary Economics*, 2012, *59* (1), 111–128.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante, "The Macroeconomic Implications of Rising Wage Inequality in the United States," *Journal of Political Economy*, 2010, *118* (4), 681–722.

Heckman, James J., Junjian Yi, and Junsen Zhang, "Early Health Shocks, Intrahousehold Resource Allocation, and Child Human Capital," Working paper, 2013.

Herrington, Christopher M., "Public Education Financing, Earnings Inequality, and Intergenerational Mobility," Working paper, 2015.

Hong, Jay and José-Víctor Ríos-Rull, "Social security, life insurance and annuities for families," *Journal of Monetary Economics*, January 2007, *54* (1), 118–140.

House, James S., Robert F. Schoeni, George A. Kaplan, and Harold Pollack, "The Health Effects of Social and Economic Policy: The Promise and Challenge for Research and Policy," in James S. House, Robert F. Schoeni, George A. Kaplan, and Harold Pollack, eds., *Making Americans Healthier: Social and Economic Policy as Health Policy*, Russell Sage Foundation, 2008.

Huggett, Mark, Gustavo Ventura, and Amir Yaron, "Sources of Lifetime Inequality," *American Economic Review*, December 2011, *101*, 2923–2954.

Jones, Larry E., Rodolfo E. Manuelli, and Ellen R. McGrattan, "Why Are Married Women Working So Much?," *Staff Report no. 317, Federal Reserve Bank of Minneapolis, Minneapolis, MN*, 2003.

Juhn, Chinhui Juhn and Simon Potter, "Is There Still an Added-Worker Effect?," Staff Report no. 310, Federal Reserve Bank of New York, August 2007.

Jung, Juergen and Chung Tran, "Medical Consumption over the Life Cycle: Facts from a U.S. Medical Expenditure Panel Survey," *Empirical Economics*, 2014, *47* (3), 927–957.

Kaiser Family Foundation, "The Uninsured: A Primer. Key Facts About Americans Without Health Insurance," Technical Report, October 2012.

Kaygusuz, Remzi, "Taxes and female labor supply," *Review of Economic Dynamics*, October 2010, *13* (4), 725 – 741.

_ , "Social Security and Two-Earner Households," *Journal of Economic Dynamics and Control*, October 2015, *59*, 163–178.

Keane, Michael P. and Kenneth I. Wolpin, "The Career Decisions of Young Men," *Journal of Political Economy*, June 1997, *105* (3), 473–522.

Kirchhoff, Anne C., Jaehee Yi, Jennifer Wright, Echo L. Warner, and Ken R. Smith, "Marriage and Divorce among Young Adult Cancer Survivors," *Journal of Cancer Survivorship*, December 2012, *6* (4), 441–450.

Kopecky, Karen A. and Tatyana Koreshkova, "The Impact of Medical and Nursing Home Expenses on Savings," *American Economic Journal: Macroeconomics*, July 2014, *6* (3), 29–72.

Krusell, Per, Toshihiko Mukoyama, and Aysegul Sahin, "Labor-Market Matching with Precautionary Savings and Aggregate Fluctuations," *The Review of Economic Studies*, 2010, *77* (4), 1477–1507.

_ , _ , Richard Rogerson, and Aysegul Sahin, "Aggregate implications of indivisible labor, incomplete markets, and labor market frictions," *Journal of Monetary Economics*, July 2008, *55* (5), 961–979.

_ , _ , _ , and _ , "Aggregate labor market outcomes: The roles of choice and chance," *Quantitative Economics*, 2010, *1*, 97–127.

_ , _ , _ , and _ , "A three state model of worker flows in general equilibrium," *Journal of Economic Theory*, May 2011, *146* (3), 1107–1133.

Kudlyak, Marianna and Felipe Schwartzman, "Accounting for Unemployment in the Great Recession: Nonparticipation Matters," Richmond FED WP No. 12-04, 2012.

Lafortune, Jeanne, "Making Yourself Attractive: Pre-marital Investments and the Returns to Education in the Marriage Market," *American Economic Journal: Applied Economics*, April 2013, *5* (2), 151–78.

Lee, Sang Yoon (Tim) and Ananth Seshadri, "On the Intergenerational Transmission of Economic Status," Working paper, 2014.

Lefgren, Lars, Matthew J. Lindquist, and David Sims, "Rich Dad, Smart Dad: Decomposing the Intergenerational Transmission of Income," *Journal of Political Economy*, April 2012, *120* (2), 268–303.

Lillard, Lee A. and Constantijn W. A. Panis, "Marital Status and Mortality: The Role of Health," *Demography*, August 1996, *33* (3), 313–327.

Lleras-Muney, Adriana, "The Relationship Between Education and Adult Mortality in the United States," *Review of Economic Studies*, January 2005, *72* (1), 189–221.

Loury, Glenn C., "Intergenerational transfers and the distribution of earnings.," *Econometrica*, 1981, *49* (4), 843–867.

Lundberg, Shelly, "The Added Worker Effect," *Journal of Labor Economics*, 1985, *3* (1), 11–37.

Mayer, Susan E. and Leonard M. Lopoo, "Government Spending and Intergenerational Mobility," *Journal of Public Economics*, 2008, *92*, 139–158.

Mazumder, Bhashkar, "Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data," *The Review of Economics and Statistics*, 2005, *87* (2), 235–255.

Moffitt, Robert, "The U.S. Employment-Population Reversal in the 2000s: Facts and Explanations," *Brookings Papers on Economic Activity*, Fall 2012, pp. 201–264.

Murray, John E., "Marital Protection and Marital Selection: Evidence from a Historical-Prospective Sample of American Men," *Demography*, November 2000, *37* (4), 511–521.

O'Brien, Rourke L. and Cassandra L. Robertson, "Medicaid and Intergenerational Economic Mobility," Working paper, 2015.

Olivetti, Claudia, "Changes in Women's Aggregate Hours of Work: The Role of Returns to Experience," *Review of Economic Dynamics*, October 2006, *9* (4), 557–587.

Oreffice, Sonia and Climent Quintana-Domenque, "Anthropometry and Socioeconomics among Couples: Evidence in the United States," *Economics and Human Biology*, December 2010, *8* (3), 373–384.

Ozkan, Serdar, "Preventive vs. Curative Medicine: A Macroeconomic Analysis of Health Care over the Life Cycle," mimeo, Federal Reserve Board, July 2013.

Palumbo, Michael G., "Uncertain Medical Expenses and Precautionary Saving Near the End of the Life Cycle," *The Review of Economic Studies*, April 1999, *66* (2), 395–421.

Parker-Pope, Tara, "Is Marriage Good for Your Health," *The New York Times Magazine*, April 14 2010.

Parman, John, "Gender and Intergenerational Mobility: Using Health Outcomes to Compare Intergenerational Mobility Across Gender and Over Time," Working paper, 2012.

Pijoan-Mas, Josep and José-Víctor Ríos-Rull, "Heterogeneity in Expected Longevities," *Demography*, December 2014, *51* (6), 2075–2102.

Poterba, James M. and Lawrence H. Summers, "Reporting Errors and Labor Market Dynamics," *Econometrica*, 1986, *54* (6), pp. 1319–1338.

Prados, María José, "Health and Earnings Inequality Over the Life Cycle: The Redistributive Potential Of Health Policies," mimeo, Columbia University, July 2013.

Pries, Michael and Richard Rogerson, "Search frictions and labor market participation," *European Economic Review*, 2009, *53* (5), 568–587.

Rauh, Christopher, "The Political Economy of Early and College Education - Can Voting Bend the Great Gatsby Curve?," Working paper, 2015.

Restuccia, Diego and Carlos Urrutia, "Intergenerational Persistence of Earnings: The Role of Early and College Education," *American Economic Review*, December 2004, *94* (5), 1354–1378.

Schoenborn, Charlotte A., "Marital Status and Health: United States, 1999-2002," Advance Data from Vital and Health Statistics 351, U.S. Department of Health and Human Services, Center for Disease Control and Prevention December 2004.

Schwartz, Christine R., "Trends and Variation in Assortative Mating: Causes and Consequences," *The Annual Review of Sociology*, July 2013, *39* (1), 451–70.

Shimer, Robert, "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, April 2012, *15* (2), 127–148.

Smith, James P., "The Impact of Socioeconomic Status on Health over the Life-Course," *Journal of Human Resources*, Fall 2007, *XLII* (4), 739–764.

Solon, Gary, "Cross-Country Differences in Intergenerational Earnings Mobility," *Journal of Economic Perspectives*, Summer 2002, *16* (3), 59–66.

_ , *A Model of Intergenerational Mobility Variation over Time and Place*, Generational Income Mobility in North America and Europe, edited by Miles Corak. Cambridge, UK: Cambridge University Press., 2004.

Stephens, Melvin, "Worker Displacement and the Added Worker Effect," *Journal of Labor Economics*, 2002, *20* (3), 504–537.

Stowasser, Till, Florian Heiss, Daniel McFadden, and Joachim Winter, "Healthy, Wealthy and Wise?Ť Revisited: An Analysis of the Causal Pathways from Socioeconomic Status to Health," in David A. Wise, ed., *Investigations in the Economics of Aging*, Chicago: University of Chicago Press, 2012.

Torvik, Fartein Ask, Kristin Gustavson, Espen Roysamb, and Kristian Tambs, "Health, Health Behaviors, and Health Dissimilarities Predict Divorce: Results from the HUNT Study," *BMC Psychology*, May 2015, *3* (13), 1–9.

Veracierto, Marcelo, "On the cyclical behavior of employment, unemployment and labor force participation," *Journal of Monetary Economics*, 2008, *55* (6), 1143–1157.

Waite, Linda J. and Maggie Gallagher, *The Case for Marriage: Why Married People are Happier, Healthier and Better Off Financially*, New York: Doubleday, 2000.

Wilson, Chris M. and Andrew J. Oswald, "How Does Marriage Affect Physical and Psychological Health? A Survey of the Longitudinal Evidence," IZA Discussion Paper n. 1619, May 2005.

Wood, Robert G., Sarah Avellar, and Brian Goesling, *The Effects of Marriage on Health: A Synthesis of Recent Research Evidence*, New York: Nova Science Publishers Inc., 2009.

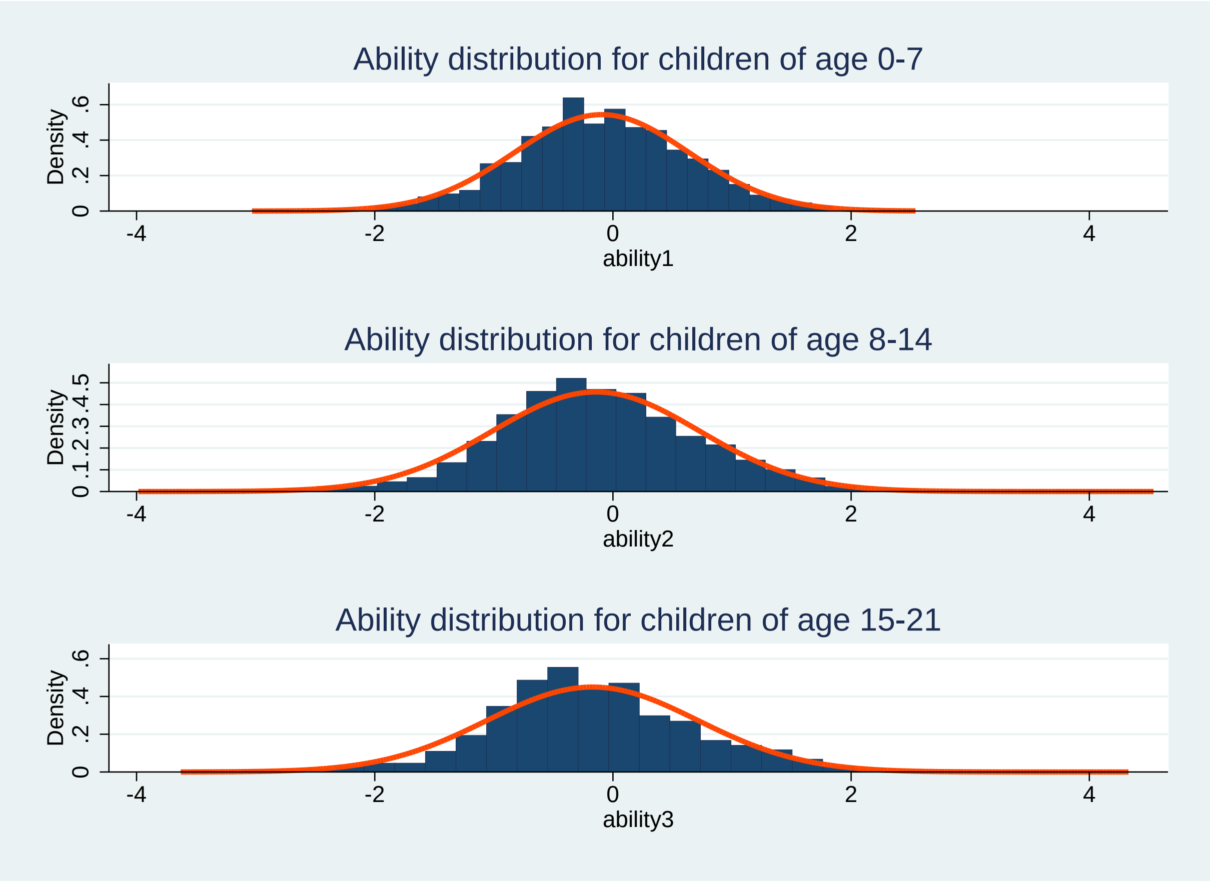
Zimmerman, David J., "Regression Toward Mediocrity in Economic Stature," *American Economic Review*, 1992, *82* (3), 409–429.

Appendix A

Appendix to Chapter 1

A.1. Children Ability Distribution

Figure A.1: Ability distribution for different age groups



Note: Ability distribution comes from the measure of ability that is constructed in the paper. To construct this measure, subtests of Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R) were used, in particular, standardized measures of Letter-Word identification, Passage Comprehension and the Applied Problems test. For each model period a factor analysis was performed and the first factor is taken as the resulting ability measure.

Appendix B

Appendix to Chapter 2

B.1. Data Description and Variable Definitions

B.1.1. Sample Selection

Panel Survey of Income Dynamics (PSID) The Panel Study of Income Dynamics (PSID) is administered by the Survey Research Center in the Institute for Social Research at the University of Michigan. The study began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Extensive demographic and economic data on these individuals and their descendants have been collected continuously since then, yearly until 1997 and biannually after that. The PSID started to collect data on health in 1984. We use data from 1984 to 2013 (the latest year of the survey). The analysis is based on the core PSID sample. While the PSID has extensive data on heads and spouses, available data for other household members is limited. Our analysis focuses on heads and spouses based on "sequence number" 1 (head) or 2 (wife).

Medical Expenditure Panel Survey (MEPS) The Medical Expenditure Panel Survey began in 1996 and it is the most complete source of data on the cost and use of health care and health insurance coverage in the United States. The survey has two major components: the Household Component and the Insurance Component. We use the Household Component, which contains extensive information on demographic characteristics, health conditions, health status, usage of medical services, access to care, satisfaction with care, health insurance coverage, income, and employment, at both individual and household levels, supplemented by information from their medical providers. The survey has a rotating panel structure in which each individual is interviewed 5 times during a 2-year period and then replaced. The sample includes about 31,000 individuals per year, with some variation across years, and it is representative of the U.S. population. As we do not exploit the short panel dimension of the data set, for each year we consider the cross-section of available individuals. Some of the variables are only available at a yearly basis. Others are available at each of the five interviews over the two-year period. In the latter case, for each individual, we consider his/her first interview of the year. We use survey years 1996 to 2009.

Both in the PSID and in the MEPS, we clean our samples by dropping observations that have no compete information on self-reported health, marital status, gender, race, or income. We focus on working-age individuals, so we consider individuals aged 20 to 64.

B.1.2. Variable Definitions

Self-Reported Health Our main health variable is constructed from the reported self-rated health. Individuals rate their health as “excellent”, “very good”, “good”, “fair” or “poor”. We create a health dummy where 1 (healthy) corresponds to the first three grades, and 0 (unhealthy) to the other two.

Marital Status Marital status is defined as one of four possible status as reported by individuals: “married”, “divorced/separated”, “widowed”, “separated” and “never married”. In the PSID, if a respondent reported to be widowed, divorced or separated in a previous period, but reports to be never married in current one, he/she is assigned his/her previously-reported marital status. The MEPS contains two questions on marital status: “what is your current marital status?” and “what was your marital status in previous round” (which means after the previous interview, but before the current one). Whenever available, marital status is determined based on the first question; the second question is used otherwise.

Age We create five-year age bins: 20-24, 25-29, 30-34, etc.

Gender Gender is self-reported.

Race Based on self-reported race, we create a “black” dummy, which we use as a control in most of the regressions. Additionally, we also create a “white” dummy that is used when we compute heterogeneous health gaps by race (Figures 2.2 and B.1).

Education Our main education variable is a dummy that takes the value of one if the individual received a college degree, based on the responses to “did you receive a college degree?” or “did your wife receive a college degree?” in the PSID or “highest degree attained” in the MEPS (in which case, college degree is defined as bachelor’s degree or more). In the PSID, if a person reported that he/she has a college degree in a previous year, but the answer to this question is missing in a later year, we use previous answer to fill the missing observation. In the last column of Table 2.6, we use the number of years of education of the individual to compute our measure of permanent income. This information is based on the response to the question “what is the highest grade or year of school that you have completed?”. For that particular exercise, observations with DK/NA codes are dropped. Whenever possible, missing or zero observations are imputed from valid answers to this questions from preceding or following interviews. If a respondent reports a lower completed grade in an interview after he/she reports a higher one in a previous interview, we consider the higher value.

Children Presence of children in the household is identified from the question “children under 18 in the family unit”. From the record of each child in the household, we identify their age and create dummy variables for the presence of children of the ages 0 to 3, 4 to 12, and 13 to 18.

Income Our definition of income is “taxable income” in the PSID or “total person’s income” in the MEPS. For couples (married or cohabiting), we calculate household taxable income by summing the total taxable incomes of the head and the spouse and then divide the total taxable income by 2. This variable is deflated using 2005 Consumer Price Index (CPI), obtained from the Bureau of Labor Statistics.

Marital capital (PSID) Marital capital is defined as the sum of the durations of all (past and present) marriages. Duration of a given marriage is calculated as the difference between either the year of divorce/separation/widowhood or the current year (depending on whether the marriage ended or is ongoing), and the starting year of the marriage. This information is obtained from the Marriage History Supplement of the PSID.

Chronic conditions (PSID) We consider the following chronic conditions: stroke, hypertension, diabetes, cancer, lung disease, heart attack, heart disease, arthritis, asthma, memory loss, and learning disorder. For each of them, we create a dummy that equals one if you ever suffered that condition. Our chronic conditions variable is defined as the sum of these dummies across all conditions. Hence, it measures the number of different conditions the individual ever suffered.

Smoking (PSID) An individual is classified as a smoker if he answered the question "do you smoke cigarettes?" affirmatively or the household head did so for the question "does your wife smoke cigarettes?". Smoking transitions conditional on marital transitions are then computed as described in the main text.

Cohabitation (PSID) Cohabitants are identified from the variable "relationship to head". This variable takes the following values: 10 (head), 20 (legal wife), 90 (legal husband of head, if in rare cases the head is a female), 22 (female cohabitant who has lived with the head for 12 months or more), 88 (first-year cohabitant, boyfriend or girlfriend, of head). To identify cohabitants we use codes 22 and 88.

Objective Health Index (MEPS) We use the Physical Summary Component of the Short Form 12 version 2 (SF-12v2) as an objective index of health. In 2000, 2001, and 2002, MEPS used Version 1 of the SF-12. Therefore for these years, Version 1 scores are converted to Version 2 scores by adding 1.07897. Further details are available at `http://meps.ahrq.gov/data_stats/download_data/pufs/h147/h147doc.pdf`.

Preventive checks (MEPS) For each preventive check (dental, cholesterol, general, flu shot, prostate check, pap smear, breast examination and mammography), we create a dummy variable that is equal to 1 if a person did the corresponding check within the preceding two years and zero otherwise.

Medical expenditure (MEPS) We use total medical (health care) expenditures. Expenditures are defined as the sum of direct payments for care provided during the year, including out-of-pocket payments and payments by private insurance, Medicaid, Medicare, and other sources. Payments for over the counter drugs and for alternative care services are not. Indirect payments not related to specific medical events, such as Medicaid Disproportionate Share and Medicare Direct Medical Education subsidies, are not included either. Whenever medical expenditure is used, we drop observations with unavailable medical expenditure. Expenditures are deflated by 2005 medical CPI, available at `http://data.bls.gov/cgi-bin/surveymost?cu`.

Insurance (MEPS) We use the insurance coverage variable and distinguish between "any private insurance", "any public insurance" and "no insurance". Whenever indicated, we create two dummies, public or private, which take the value of one if the individual holds the corresponding insurance (public and private insurance are not mutually exclusive). Otherwise, we create an indicator variable that equals one if the individual holds any insurance, public or private. Whenever insurance information is used, observations with unavailable insurance are dropped.

B.2. Descriptive Statistics

Table B.1: Descriptive Statistics: Panel Study of Income Dynamics (PSID)

	Mean	St. dev.	Min	Max	N.obs.
i. Baseline					
Healthy	0.88	0.33	0.0	1.0	150,062
Married	0.66	0.47	0.0	1.0	150,062
Age	41.63	11.82	20.0	64.0	150,062
Female	0.53	0.50	0.0	1.0	150,062
Black	0.12	0.33	0.0	1.0	150,062
College	0.32	0.47	0.0	1.0	150,062
Children 0-3 years	0.16	0.36	0.0	1.0	150,062
Children 4-12 years	0.28	0.45	0.0	1.0	150,062
Children 13-18 years	0.21	0.41	0.0	1.0	150,062
Taxable income (in 1000$)	37.76	50.03	-590.2	5,500.0	150,062
ii. Robustness and further explorations					
Married+cohabiting	0.72	0.45	0.0	1.0	150,062
Divorced/separated	0.16	0.36	0.0	1.0	150,062
Widowed	0.02	0.15	0.0	1.0	150,062
Never Married	0.16	0.37	0.0	1.0	150,062
Marriage capital	18.65	11.97	0.0	52.0	114,627
Height (inches)	67.21	3.86	51.0	82.0	111,397
Weight (pounds)	175.11	42.77	75.0	400.0	42,975
Smoke	0.22	0.42	0.0	1.0	61,360
Num. of chronic conditions	0.73	1.09	0.0	10.0	54,466
Chronic conditions:					
Stroke	0.02	0.13	0.0	1.0	54,443
Hypertension	0.22	0.41	0.0	1.0	54,430
Diabetes	0.07	0.26	0.0	1.0	54,432
Cancer	0.04	0.20	0.0	1.0	54,430
Lung disease	0.04	0.20	0.0	1.0	54,432
Heart attack	0.02	0.14	0.0	1.0	54,444
Arthritis	0.14	0.35	0.0	1.0	54,435
Asthma	0.10	0.30	0.0	1.0	54,437
Memory loss	0.01	0.11	0.0	1.0	54,433
Learning disord.	0.03	0.16	0.0	1.0	54,433

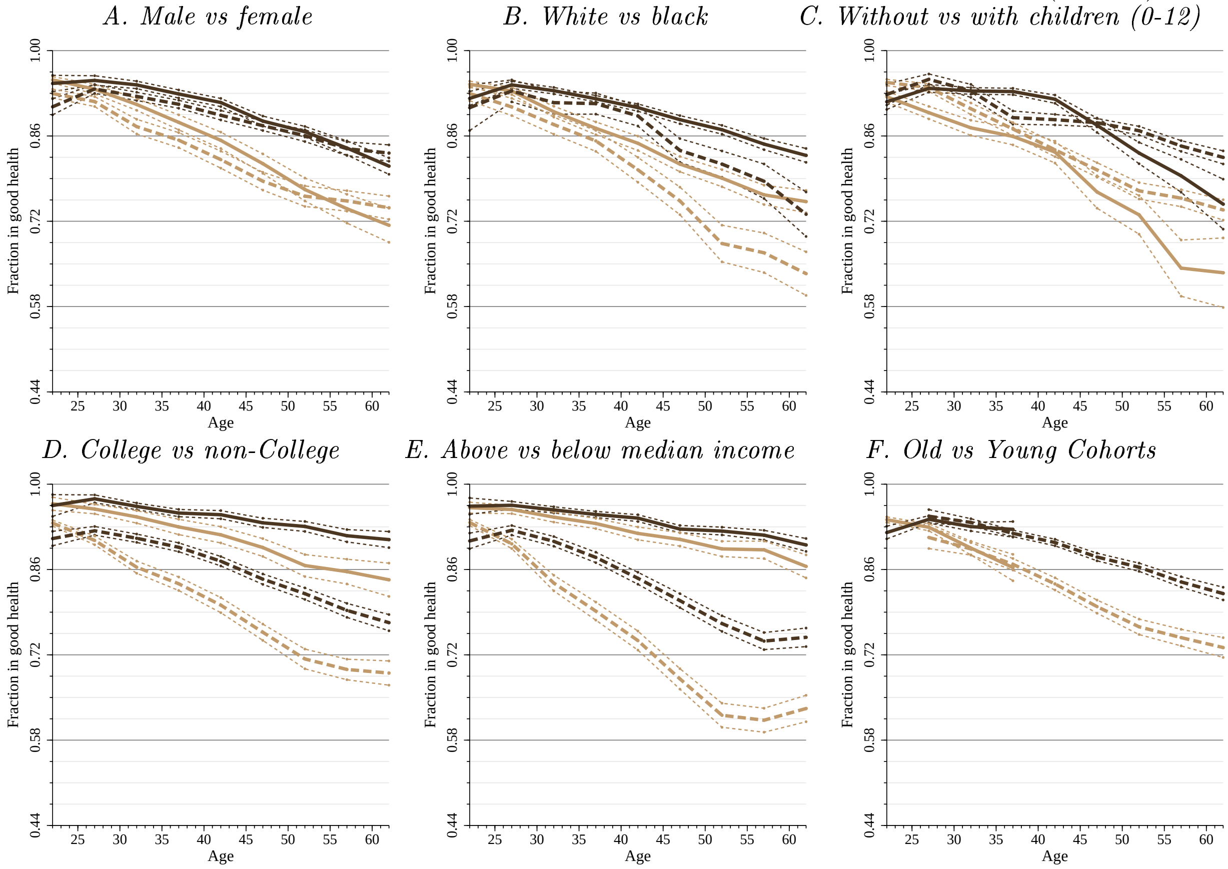
Note: Means and standard deviations are computed using weights. The sample covers 1984-2013, annually until 1997, bianually since then. Chronic conditions and smoking data is only available starting in 1999. Tacable income is deflated by 2005 CPI.

Table B.2: Descriptive Statistics: Medical Expenditure Panel Survey (MEPS)

	Mean	St. dev.	Min	Max	N.obs.
i. Baseline					
Healthy	0.88	0.31	0.0	1.0	235,094
Married	0.58	0.47	0.0	1.0	235,094
Age	40.66	11.70	20.0	64.0	235,094
Female	0.51	0.48	0.0	1.0	235,094
Black	0.12	0.31	0.0	1.0	235,094
College	0.35	0.46	0.0	1.0	235,094
Children 0-3 years	0.15	0.34	0.0	1.0	235,094
Children 4-12 years	0.26	0.42	0.0	1.0	235,094
Children 13-18 years	0.38	0.46	0.0	1.0	235,094
Taxable income (in 1000$)	34.61	30.70	0.0	658.6	235,094
ii. Robustness and further explorations					
Objective health index	51.15	9.26	4.6	76.1	160,057
Total health expenditure	3.04	9.47	0.0	1,051.5	235,094
Uninsured	0.16	0.35	0.0	1.0	235,094
Preventive checks:					
Dental	0.50	0.48	0.0	1.0	231,873
Cholesterol	0.51	0.48	0.0	1.0	221,942
Complete	0.57	0.47	0.0	1.0	227,623
Flu shot	0.26	0.42	0.0	1.0	229,296
Prostate	0.22	0.38	0.0	1.0	90,412
Pap smear	0.54	0.48	0.0	1.0	140,965
Breast	0.55	0.48	0.0	1.0	136,720
Mammography	0.36	0.46	0.0	1.0	119,403

Note: Means and standard deviations are computed exploiting sampling stratification design. The sample covers 1996-2009 annually. Taxable income is deflated by 2005 CPI.

Figure B.1: Health and Marital Status, Different Socioeconomic Groups (MEPS)



Note: This figure reproduces the results in Figure 2.2 using the MEPS sample. Plotted lines represent the weighted fraction of married (dark brown) and unmarried (light brown) individuals that report being healthy, obtained from the MEPS. Fractions are reported for: top-left: male (solid) and female (dashed); top-center: white (solid) and black (dashed); top-right: without (solid) and with (dashed) children aged 0-12 living in the household; bottom-left: college graduates (solid) and non-college (dashed); bottom-center: above (solid) and below (dashed) median income; bottom-right: born after (solid) and before (dashed) 1970. The horizontal axis indicates age, which is grouped in five-year categories (20-24 through 60-64). Dotted lines around point estimates indicate confidence bands of $\pm$ two standard errors, which are computed using sample stratification design.

B.3. Detailed Baseline Results

Table B.3: Estimated Coefficients from Baseline Regressions

	PSID					MEPS
		Fixed-	Grouped F.E.		System-	
	OLS	Effects	Type I	Type II	GMM	OLS
Marriage gap $\beta(a)$:						
20-24	0.004	-0.015	-0.001		0.008	-0.025
	(0.007)	(0.007)	(0.006)		(0.010)	(0.006)
25-29	0.024	-0.010	0.009		0.029	0.014
	(0.005)	(0.005)	(0.004)		(0.006)	(0.004)
30-34	0.029	-0.004	0.013		0.031	0.030
	(0.006)	(0.006)	(0.005)		(0.006)	(0.004)
35-39	0.041	-0.008	0.013		0.038	0.039
	(0.008)	(0.007)	(0.006)		(0.009)	(0.005)
40-44	0.054	0.006	0.018		0.053	0.051
	(0.010)	(0.008)	(0.007)		(0.011)	(0.006)
45-49	0.069	0.019	0.022		0.060	0.063
	(0.012)	(0.009)	(0.008)		(0.013)	(0.006)
50-54	0.100	0.053	0.050		0.073	0.085
	(0.013)	(0.010)	(0.009)		(0.017)	(0.007)
55-59	0.105	0.047	0.043		0.105	0.078
	(0.016)	(0.013)	(0.010)		(0.020)	(0.008)
60-64	0.112	0.044	0.040		0.099	0.078
	(0.017)	(0.014)	(0.010)		(0.021)	(0.009)
Singles health curve $\alpha(a)$:						
20-24	0.914	0.948	0.975	0.664	0.747	0.914
	(0.008)	(0.006)	(0.004)	(0.017)	(0.014)	(0.004)
25-29	0.883	0.936	0.964	0.624	0.736	0.873
	(0.009)	(0.005)	(0.005)	(0.015)	(0.014)	(0.005)
30-34	0.859	0.918	0.955	0.537	0.727	0.836
	(0.010)	(0.005)	(0.006)	(0.016)	(0.014)	(0.007)
35-39	0.828	0.904	0.944	0.469	0.711	0.804
	(0.012)	(0.007)	(0.008)	(0.017)	(0.015)	(0.008)
40-44	0.785	0.868	0.922	0.368	0.687	0.771
	(0.014)	(0.008)	(0.008)	(0.019)	(0.015)	(0.008)
45-49	0.743	0.834	0.900	0.286	0.656	0.729
	(0.015)	(0.009)	(0.009)	(0.017)	(0.017)	(0.009)
50-54	0.687	0.779	0.858	0.169	0.617	0.687
	(0.016)	(0.010)	(0.011)	(0.014)	(0.019)	(0.010)
55-59	0.656	0.752	0.837	0.106	0.549	0.670
	(0.018)	(0.012)	(0.012)	(0.014)	(0.020)	(0.011)
60-64	0.646	0.736	0.827	0.075	0.531	0.660
	(0.019)	(0.013)	(0.012)	(0.014)	(0.021)	(0.013)
Lagged health					0.150	
					(0.013)	
College	0.069	0.002	0.020		0.060	0.055
	(0.006)	(0.008)	(0.002)		(0.005)	(0.002)
Female	-0.004		-0.001			0.000
	(0.005)		(0.002)			(0.002)
Black	-0.087		-0.038			-0.020
	(0.011)		(0.005)			(0.003)
Children 0-3 years	0.001	0.000	0.000		0.001	0.001
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Children 4-12 years	-0.004	0.006	0.000		-0.003	0.001
	(0.003)	(0.003)	(0.002)		(0.004)	(0.002)
Children 13-18 years	-0.000	0.006	-0.001		-0.002	0.001
	(0.004)	(0.003)	(0.002)		(0.004)	(0.003)
Taxable income (in 1000$)	-0.012	0.006	-0.003		-0.015	0.001
	(0.004)	(0.003)	(0.003)		(0.005)	(0.003)
Birth year dummies:	Yes	Yes	Yes		Yes	Yes

Note: The table presents point estimates and standard errors for the coefficients of the regressions in Figures 2.4 through 2.6. Standard errors are clustered at the household level in the PSID and follow survey design in the MEPS.

B.4. Self-Selection into Marriage and Divorce, and Assortative Mating: Additional Results

Table B.4: Health and Marriage/Divorce Probabilities: Additional results

	Never married by age $t-5$ and married at age t to $t+10$			Married at age $t-5$ and divorced at age t to $t+10$		
A. Older reference ages ($t = 40$):						
Health at 30-35	0.182	-0.130	0.141	-0.174	-0.080	-0.141
	(0.097)	(0.166)	(0.137)	(0.071)	(0.115)	(0.093)
Innate permanent health (η_i)		0.446			-0.146	
		(0.169)			(0.134)	
Innate health type ($\eta_{g(i)}$)			0.037			-0.035
			(0.080)			(0.063)
B. Wider period for current health ($t = 30$):						
Health at 20-29	0.229	-0.113	0.123	-0.131	0.008	-0.078
	(0.070)	(0.119)	(0.088)	(0.051)	(0.087)	(0.064)
Innate permanent health (η_i)		0.419			-0.175	
		(0.125)			(0.089)	
Innate health type ($\eta_{g(i)}$)			0.099			-0.049
			(0.049)			(0.036)
C. Innate health from chronic conditions ($t = 30$):						
Health at 20-25	0.213	0.140	0.194	-0.157	-0.097	-0.129
	(0.075)	(0.083)	(0.076)	(0.059)	(0.066)	(0.060)
Innate permanent health (η_i)		-0.051			0.040	
		(0.024)			(0.018)	
Innate health type ($\eta_{g(i)}$)			0.036			-0.051
			(0.033)			(0.025)

Note: This table reproduces estimates in Table 2.4 for alternative age ranges. In the top panel, the reference ages are moved forward 10 years. Thus, the left panel is for a sample of individuals who had never been married by age 35, and the right panel is for the sample of individuals married at age 35; similarly, the current health variable is measured over ages 30 to 35. In the central panel, the samples are changed respectively to individuals never married or currently married by age 29, and current health is measured as the average for ages 20 through 29 as opposed to ages 20 through 25. The bottom panel differs from the baseline in that the innate health variables are obtained from chronic conditions. Note that in the case of chronic conditions, the larger η_i, the lower the health, so signs of the second line of the bottom panel are expected to revert.

Table B.5: Contingency Tables: Assortative Mating from Chronic Conditions

Innate permanent health (η_i)

		Observed marital sorting %					Random matching %					
		Wife					Wife					
		1	2	3	4	5	1	2	3	4	5	Marginal
Husband	1	**8.6**	3.6	1.3	3.5	2.4	**3.9**	4.7	3.7	3.8	3.2	19.3
	2	3.6	**8.6**	3.5	4.4	3.0	4.7	**5.7**	4.4	4.6	3.8	23.2
	3	1.6	4.0	**7.4**	3.6	3.0	4.0	4.8	**3.7**	3.9	3.2	19.7
	4	3.7	5.2	3.8	**4.4**	3.6	4.2	5.1	3.9	**4.1**	3.4	20.7
	5	2.6	3.2	3.0	3.9	**4.5**	3.5	4.2	3.3	3.4	**2.8**	17.2
Marginal		20.1	24.6	19.0	19.8	16.4	20.1	24.6	19.0	19.8	16.4	100.0

Innate health type ($\eta_{g(i)}$)

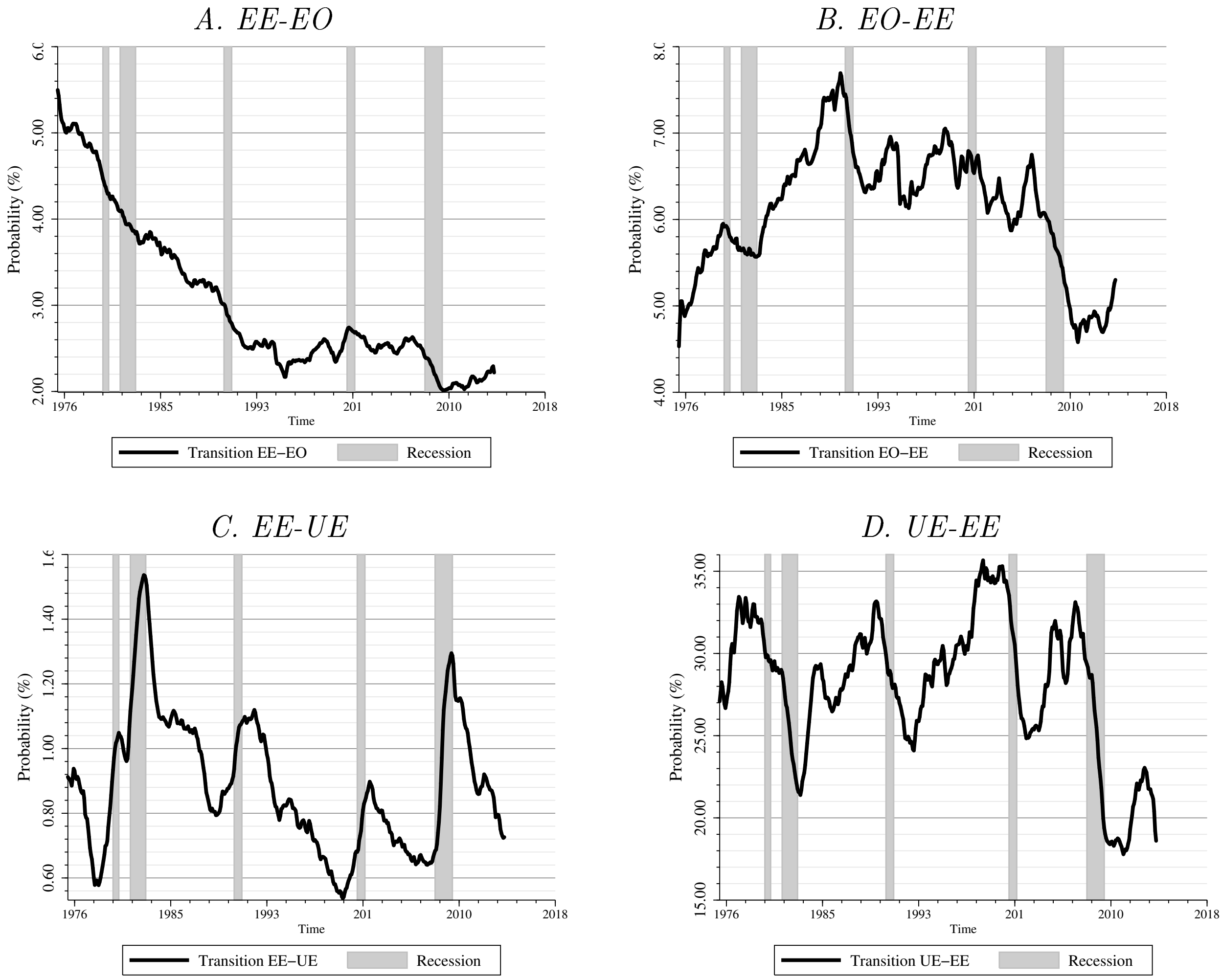
	Observed sorting %		Random matching %		
	Wife		Wife		
Husband	Low	High	Low	High	Marginal
Low	**20.0**	17.4	**17.3**	20.1	37.4
High	26.2	**36.4**	28.9	**33.7**	62.6
Marginal	46.2	53.8	46.2	53.8	100.0

Note: The table replicates the results in Table 2.5 using innate health measures obtained from the regressions for chronic conditions presented in Figure 2.7B.

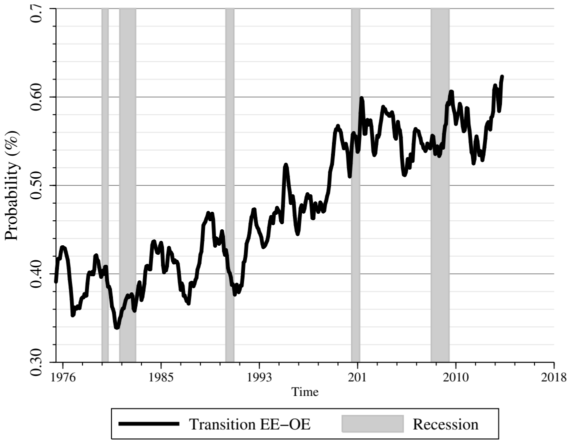
Appendix C

Appendix to Chapter 3

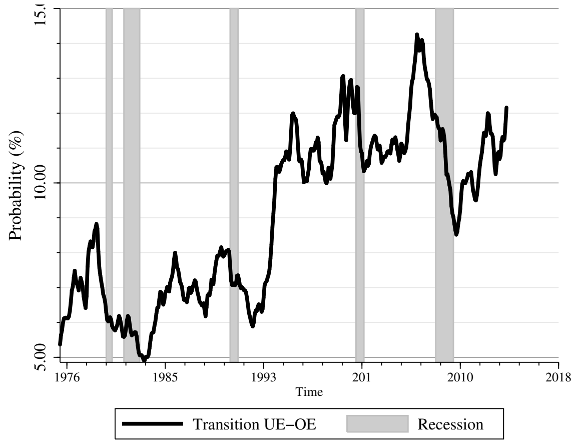
Figure C.1: Important joint labor market transitions



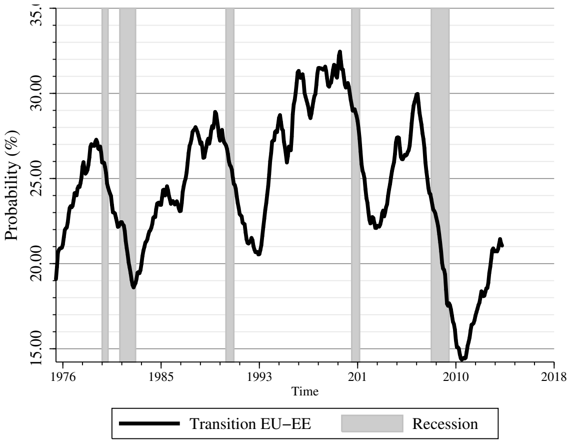
E. EE-OE



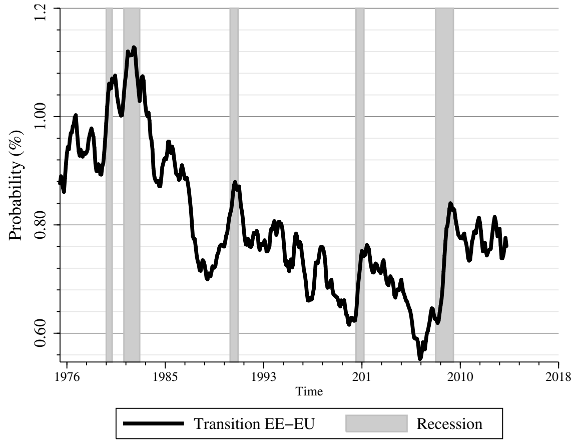
F. UE-OE



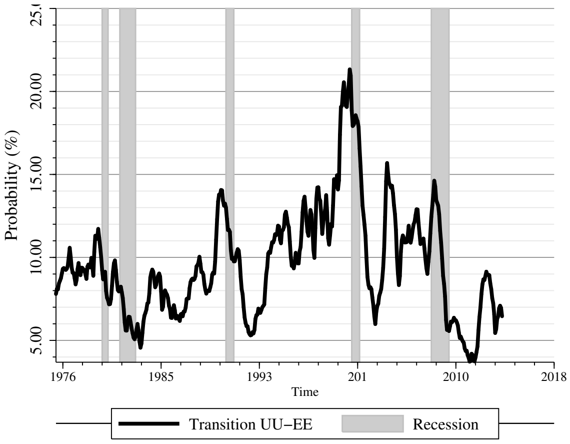
G. EU-EE



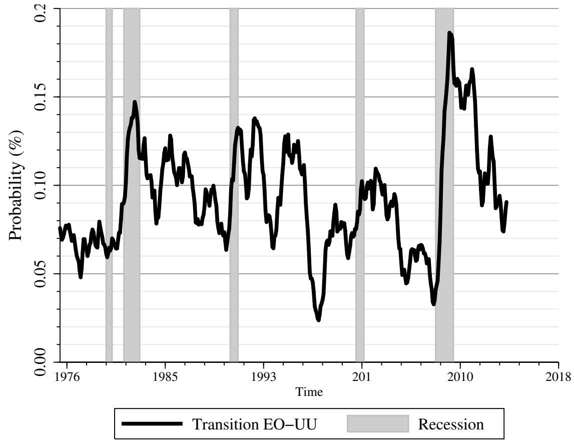
H. EE-EU

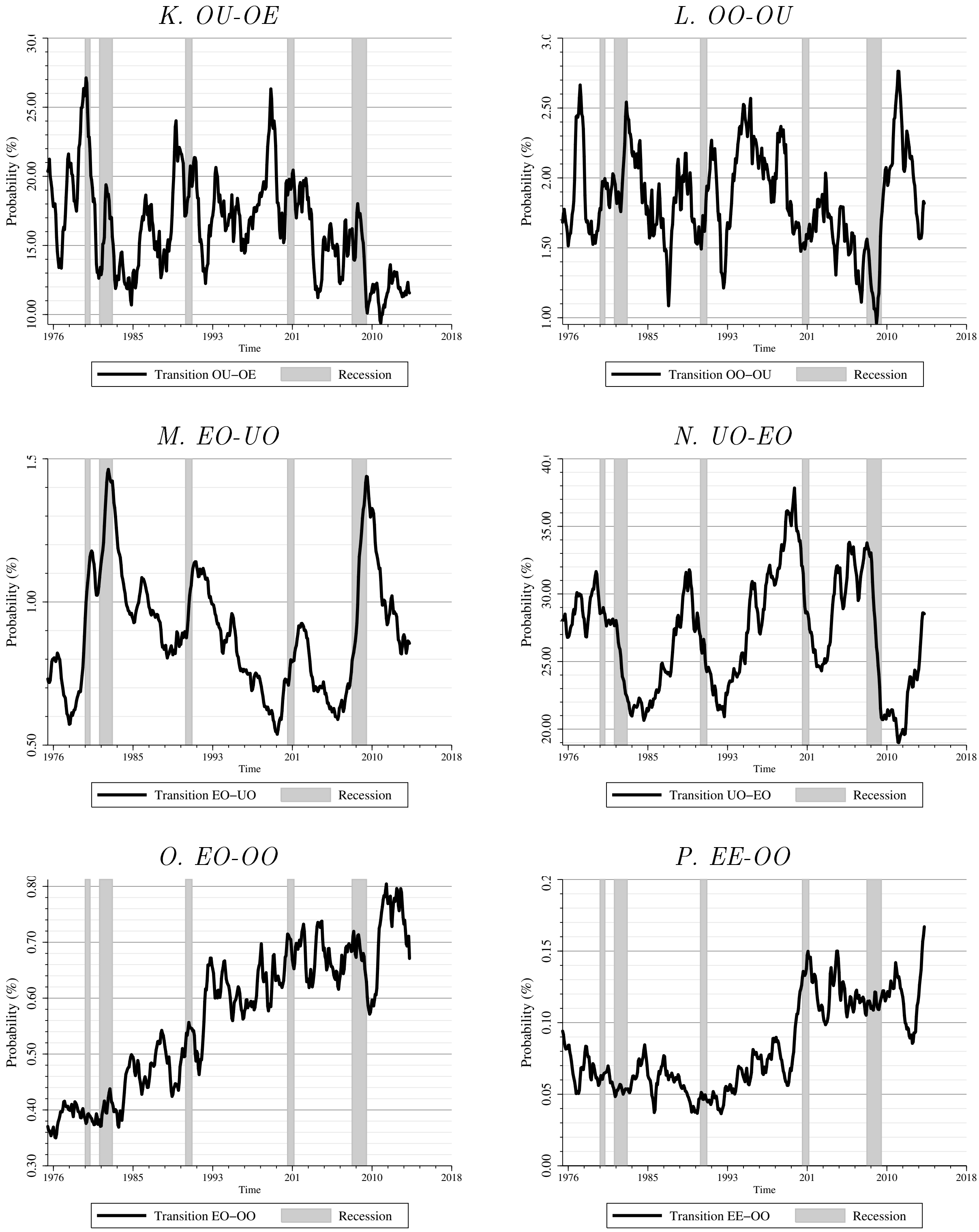


I. UU-EE



J. EO-UU





NOTE: CPS, time period from 1976:2 to 2013:12. The solid line represents the seasonally adjusted probability of being in state XX in the current month, having been in YY in the previous month. X and Y can stand for: E - employed, U - unemployed, O - out of the labor force. Grey areas represent NBER recession dates.