Title
Essays in Applied Microeconomics

Author
Severnini, Edson Roberto

Publication Date
2013

Peer reviewed|Thesis/dissertation

Essays in Applied Microeconomics

By

Edson Roberto Severnini

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor David Card, Chair

Professor Enrico Moretti

Professor Patrick Kline

Professor Steven Raphael

Spring 2013

Essays in Applied Microeconomics

By

Edson Roberto Severnini

Abstract

Essays in Applied Microeconomics

By Edson Roberto Severnini

Doctor of Philosophy in Economics

University of California, Berkeley

Professor David Card, Chair

This dissertation consists of three studies analyzing causes and consequences of location decisions by economic agents in the U.S.

In Chapter 1, I address the longstanding question of the extent to which the geographic clustering of economic activity may be attributable to agglomeration spillovers as opposed to natural advantages. I present evidence on this question using data on the long-run effects of large scale hydroelectric dams built in the U.S. over the 20th century, obtained through a unique comparison between counties with or without dams but with similar hydropower potential. Until mid-century, the availability of cheap local power from hydroelectric dams conveyed an important advantage that attracted industry and population. By the 1950s, however, these advantages were attenuated by improvements in the efficiency of thermal power generation and the advent of high tension transmission lines. Using a novel combination of synthetic control methods and event-study techniques, I show that, on average, dams built before 1950 had substantial short run effects on local population and employment growth, whereas those built after 1950 had no such effects. Moreover, the impact of pre-1950 dams persisted and continued to grow after the advantages of cheap local hydroelectricity were attenuated, suggesting the presence of important agglomeration spillovers. Over a 50 year horizon, I estimate that at least one half of the long run effect of pre-1950 dams is due to spillovers. The estimated short and long run effects are highly robust to alternative procedures for selecting synthetic controls, to controls for confounding factors such as proximity to transportation networks, and to alternative sample restrictions, such as dropping dams built by the Tennessee Valley Authority or removing control counties with environmental regulations. I also find small local agglomeration effects from smaller dam projects,

and small spillovers to nearby locations from large dams. Lastly, I find relatively small costs of environmental regulations associated with hydroelectric licensing rules.

In Chapter 2, I study the joint choice of spouse and location made by individuals at the start of their adult lives. I assume that potential spouses meet in a marriage market and decide who to marry and where they will live, taking account of varying economic opportunities in different locations and inherent preferences for living near the families of both spouses. I develop a theoretical framework that incorporates a collective model of household allocation, conditional on the choice of spouse and location, with a forward-looking model of the marriage market that allows for the potential inability of spouses to commit to a particular intra-household sharing rule. I address the issue of unobserved heterogeneity in the tastes of husbands and wives using a control-function approach that assumes there is a one-to-one mapping between unobserved preferences of the two spouses and their labor supply choices. Estimation results for young dual-career households in the 2000 Census lead to three main findings. First, I find excess sensitivity of the sharing rule that governs the allocation of resources among couples to the conditions in the location they actually choose, implying that spouses cannot fully commit to a sharing rule. Second, I show that the lack of commitment has a relatively larger effect on the share of family resources received by women. Third, I find that the failure of full commitment can explain nearly all of the gap in the interstate migration rates of single and married people in the U.S.

Finally, in Chapter 3, I examine unintended consequences of environmental regulations affecting the location of power plants. I present evidence that while hydroelectric licensing rules do conserve the wilderness and the wildlife by restricting the development of hydro projects in some counties, they lead to more greenhouse gas emissions in those same locations. Such environmental regulations aimed to preserve natural ecosystems do not seem to really protect nature. Basically, land conservation regulations give rise to a replacement of hydropower, which is a renewable, non-emitting source of energy, with conventional fossil-fuel power, which is highly pollutant. Restrictions imposed by hydroelectric licensing rules might be used as leverage by electric utilities to get permits to expand thermal power generation. Each megawatt of hydropower potential that is not developed because of those regulations induces the production of the average emissions of carbon dioxide per megawatt of U.S. coal-fired power plants. Environmental regulations focusing only on the preservation of ecosystems appears to stimulate dirty substitutions within electric utilities regarding electricity generation.

Acknowledgements

I especially want to thank David Card for being the best advisor I could wish for. I am deeply grateful for his continuous guidance, dedication, patience, and encouragement. His mentorship was paramount in providing me a well-rounded experience consistent with my long-term career and personal goals. He encouraged me to not only grow as an economist and a researcher but also as an independent thinker.

I would also like to thank Enrico Moretti and Patrick Kline for their invaluable advice during these projects, for their support, and for their excitement with my research topics. Steven Raphael and Frederico Finan also offered very valuable suggestions.

I also acknowledge generous financial support from this University, especially from the Center for Labor Economics.

This acknowledgements section would not be complete without thanking my colleagues and friends. I would like to thank my cohort of labor economists Monica Deza, Valentina Paredes, and Issi Romem for going through this journey with me, listening to my research and presentation several times, and providing very valuable advice at each stage of these projects. Usree Bhattacharya, Mayssa Dabaghi, Thembi Anne Jackson, Tarso Mori Madeira, and Joana Naritomi also provided continuous support, encouragement and comments. I feel so blessed I have them around. I also thank Ana Rute Cardoso, Momen El-Husseiny, Willa Friedman, Francois Gerard, Tadeja Gracner, Hedvig Horvath, Attila Lindner, Markus Pelger, Michaela Pagel, Gisela Rua, Michel Serafinelli, Reed Walker, and Tom Zimmermann for their support and comments.

Finally, I would like to thank my beloved parents, Beto and Lola, for their unconditional love and support.

Contents

Chapter 1

The Power of Hydroelectric Dams: Agglomeration Spillovers

1.1 Introduction

Economic activity is geographically concentrated (e.g., Ellison and Glaeser, 1997, 1999; Duranton and Overman 2005, 2008; Ellison, Glaeser and Kerr, 2010; and Moretti, 2011). However, the mere occurrence of agglomeration does not imply the existence of agglomeration spillovers. The location of economic agents in space might be due to agglomeration economies (increasing returns, knowledge spillovers, and pooling of specialized skills) and/or natural advantages (topography, climate, and resource endowments). Although there is recent evidence that locational choices are not uniquely determined by fundamentals (e.g., Redding, Sturm, and Wolf, 2011; Bleakley and Lin, 2012; and Kline and Moretti, 2012), influential studies have found a major role for natural advantages by examining growth in the aftermath of war bombing (e.g., Davis and Weinstein, 2002, 2008; Brakman, Garretsen and Schramm, 2004; and Miguel and Roland; 2011). Despite significant losses during war, bombed cities almost all returned to their prewar growth paths. In this paper, I present new evidence on the importance of agglomeration spillovers in population density by keeping natural advantages constant, and evaluate whether such spillovers are strong enough to generate long-run effects. Instead of bombing, I use installation of large hydroelectric dams.

Throughout my analysis, I use a unique database of U.S. counties with similar natural endowments associated with comparable suitability for hydroelectric projects. In the 1990s, a team of engineers determined the hydropower potential across the nation at the request of the U.S. Department of Energy. I define counties with hydroelectric dams as "treated" counties, and counties with no dams but with hydropower potential as "control" counties. To identify agglomeration spillovers, I split the treated counties into two groups: (i) those which have a dam constructed before 1950, and (ii) those which have a dam constructed after 1950. The time horizon of my analysis is the entire twentieth century. I argue that counties hosting dams in the first half of the century have a temporary advantage because of the local availability of cheap electricity.

This advantage gives rise to a strong concentration of economic activity around dam sites. In the second half of the century, technological improvements in thermal power generation make fossil fuels (mostly coal and natural gas) and nuclear energy almost as competitive as hydropower in producing electricity. In addition, the construction of high-voltage transmission lines weakens the need for electricity generation next to consumers. Therefore, the appeal of local cheap hydroelectricity reduces considerably after 1950.

The growth in population density of counties with pre-1950 dams over and above the growth of counties with post-1950 dams, in post-1950 years, when the advantage of cheap local electricity is attenuated, provides an estimate of agglomeration externalities[1]. The subtraction of the impact of post-1950 dams refines the identification of spillovers, since it eliminates any direct impact of changes in stock of capital[2]. At the same time, though, it removes any potential agglomeration effects of post-1950 dams. In this sense, my estimate represents a lower bound of agglomeration spillovers. To illustrate my approach, Figure 1.1 plots the log population density from 1900 to 2000 for two counties: one with a hydroelectric dam built before 1950, and the other with a dam built after 1950. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a counterfactual county, as I explain below.

The left chart, for Blount County, Tennessee, shows a high degree of agglomeration after the construction of the Calderwood Dam, in the 1930s. There is also clear evidence of agglomeration spillovers, over and above the agglomeration accumulated until 1950 (dotted line with hollow triangles), which one could see as arising solely from the advantage of cheap local hydroelectricity in the first half of the twentieth century. In addition, there seems to be strong evidence of path dependence. While the local economic advantage of nearby hydroelectricity is decreasing in the second half of the century, population density is still increasing. It is fair to say that the trend flattens out after 1950, but the upward slope is still unequivocally positive. The right chart, for Lincoln County, North Carolina, depicts a low degree of agglomeration, even right after the installation of the Cowans Ford Dam, in the 1960s, when increases in the stock of capital were still recent. As mentioned above, this feature of the data helps to strengthen the interpretation of the effects of pre-1950 dams in post-1950 years as agglomeration spillovers. Though less extreme, I find similar patterns for the impact of a broad sample of large hydroelectric dams on the economic activity of U.S. counties.

To obtain average estimates of agglomeration spillovers, I need credible impact estimates of hydroelectric dams. Despite the number of large hydro dams in the U.S. -

[1] In a related study, Bleakley and Lin (2012) use a fading locational advantage - obsolescence of portage sites - to examine the role of path dependence in the spatial distribution of economic activity the U.S.

[2] This is related to Greenstone, Hornbeck and Moretti's (2010) strategy to identify agglomeration economies. They examine whether attracting a Million Dollar Plant (MDP) leads to increases in total factor productivity (TFP) of incumbent manufacturing plants, over and above the mechanical effect of the new plant on the TFP of the winning county.

185 dams with a capacity of 100 megawatts or more - there is surprisingly little research on their local economic impacts. Hence, in this paper, I also present the first evaluation of the short- and long-run effects of new hydropower facilities on local economies[3]. To estimate the causal effects of hydro dams, I employ a novel empirical strategy. I combine synthetic control methods (Abadie and Gardeazabal, 2003; and Abadie, Diamond and Hainmueller, 2010) with event-study techniques (Jacobson, LaLonde, and Sullivan, 1993). First, I use the synthetic control estimator to generate a counterfactual for each treated county. Each counterfactual, which I refer to as a "synthetic control county", is a weighted average of the originally defined control counties that reproduces more closely the outcome trajectory that the affected county would have experienced in the absence of dams. Then, I pool all pairs of treated and synthetic control counties, and proceed with my event-study analysis. A byproduct of the synthetic control approach is the estimation of the impact of hydro dams for each treated county separately. This allows me to examine heterogeneity in dam effects by plotting the distribution of effects across treated counties for each decade after dam installation.

My impact estimates of hydro dams show that counties with dams built before 1950 have population density increased by approximately 51 percent after 30 years, and 139 percent after 60 years, indicating substantially different short- and long-term effects. Kline's (2010) theoretical argument that assessing place-based policies requires understanding the long-run effects of temporary interventions finds clear empirical support here. On the other hand, counties with dams built after 1950 have no statistically significant effects. I argue that the large difference in the impact of pre- and post-1950 hydro dams can be accounted for by the attenuation of the advantage of cheap local hydroelectricity in the second half of the twentieth century, as mentioned above.

Regarding agglomeration spillovers, the causal effects of hydro dams imply an average lower bound of up to 45 percent five decades after dam construction (three decades after spillovers kick in). This long-run estimate represents almost half of the full impact of hydro dams over the same time span. Interestingly, my short-run estimate of agglomeration externalities is very close to that of Greenstone, Hornbeck and Moretti (2010). My lower bound nearly a decade after spillovers kick in is around 11.5 percent, while their estimate five years after the opening of a Million Dollar Plant is 12 percent. Taken together, my short- and long-run estimates point to an amplification of spillovers over time. This suggests that spillovers may sustain high levels of local development in the long-run.

I also find that the estimated short- and long-run effects are highly robust to alternative procedures for selecting synthetic controls, to controls for confounding factors such as proximity to transportation networks, and to alternative sample restrictions, such as dropping dams built by the Tennessee Valley Authority or removing control counties with environmental regulations. I also provide evidence of small local agglomeration effects from smaller dam projects, and small spillovers to nearby locations from

[3]Other studies that examine long-term adjustments to temporary shocks are, for example, Blanchard and Katz (1992), Davis and Weinstein (2002, 2008), Redding and Sturm (2008), Miguel and Roland (2011), Hornbeck (2012), and Kline and Moretti (2012).

large dams.

Lastly, I use the causal effects of hydro dams to also obtain a novel estimate of costs of environmental regulations associated with preservation of wilderness and wildlife. Based on the long-run estimates of hydro dams built before 1950, I uncover the forgone earnings of workers that would have come to the counties with hydropower potential had land regulations not inhibited the installation of hydroelectric facilities. (I do not include forgone gains of landowners because I find no statistically significant effects of dams on the average value of farmland.) My decadalized estimate turns out to be \$1.3 billion, or 26,708 jobs, for all the 55 control counties in my sample. This represents a third of a comparable estimate based on the effects of air quality regulations on manufacturing plants in the U.S. found in Greenstone, List and Syverson (2012).

The remainder of the paper is organized as follows. Section 1.2 provides a historical discussion of the process of electrification in the U.S., focusing on the local importance of hydroelectricity in the first half of the twentieth century. Section 3.2 presents a simple theoretical framework to identify agglomeration spillovers. Section 1.4 discusses the research design and related issues. Section 2.5 describes the databases used in the study. Section 1.6 outlines the methodology for the empirical analysis. Section 2.6 reports and discusses results regarding the impact estimates of hydro dams, the estimate of agglomeration spillovers, and the persistence of dam effects. Section 1.8 presents my novel estimate of costs of environmental regulations. Section 2.7 provides some concluding remarks.

1.2 Historical Background

The invention of the continuous direct current (D.C.) dynamo in 1870 was a breakthrough in the history of electrification. Lighting and traction (i.e., electric streetcars) were among the first benefits of the new technology, but the most important consequence of the dynamo revolution was the process of industrial electrification following the invention of the polyphase alternating current (A.C.) motor in 1888 (see chronology in table 1.1). Between 1880 and 1930, the production and distribution of mechanical power rapidly evolved from water and steam-driven line shafts connected by belts to electric motors that drove individual machines.

During this rapid transition in energy use, the U.S. power industry became highly specialized and electric utilities gained prominence. In early 1900s, around 60 percent of the electricity used in manufacturing was generated by the establishments themselves. By 1917, however, eletric utilities were already generating more power than industrial plants. By the late 1950s, their production had reached almost 90 percent of total generation, as shown in table 1.2. This shift of electricity generation to the power sector led manufacturing to become sensitive to local availability of power.

In the beginning, hydroelectricity prevailed as a source of motive power. This was probably due to familiarity with water power and the high cost of coal to drive steam turbines. The availability of (cheap) hydroelectricity significantly affected the locational decisions of industrial plants. After the first hydroelectric generating station was built near Niagara Falls in 1881, manufacturing flourished around hydro dam sites. Although "*its supply is limited and plants have to locate where favourable sites exist*" (Schramm, 1969, p.220), hydroelectricity continued having a large comparative advantage in the U.S. until the 1950s. The costless energy content of falling water, and the high mechanical efficiency of hydraulic turbines, were among the key factors maintaining that advantage.

Important innovations, however, took place in the field of thermal power generation. Technological improvements increased boiler temperatures and operating pressures substantially, attaining greater thermal efficiencies. As depicted in figure 1.2, thermal efficiencies increased gradually until the early 1940s, and rapidly in the post-World War II years, reaching their current level around 1960. At the same time, electric utilities started constructing larger generating plants to capture economies of scale. As a result, steam power gave location flexibility to firms. Thermal power plants could be built almost anywhere, provided that fuels and a minimum amount of boiler and cooling water were available.

Summarizing the transformation of the electricity industry around the middle of the twentieth century, Schramm (1969) states that "*the historical cost advantage of hydropower vis-à-vis other generating methods has been (...) drastically reduced. (...) Fifteen to twenty years ago [1949-1954], power-intensive industries found it advantageous to move their plants to sites where cheap hydropower was still available. Today, with generating cost differentials reduced so drastically, these advantages have all but disappeared.*" (p.225-226). The tremendous post-1950 growth of steampower relative to hydropower, presented in figure 1.3, corroborates his conclusions.

Yet another major change happened in the electricity sector in the 1950s: the emergence of higher voltage transmission lines. The nineteenth century inventors who first began to harness electricity to useful purposes did so by putting their small generators right next to the machines that used electricity. The development of the A.C. system allowed power lines to transmit electricity over much longer distances. In 1896, for instance, an eleven-kilovolt A.C. line was built to connect a hydroelectric generating station at Niagara Falls to Buffalo, twenty miles away. From then on, the voltage of typical transmission lines grew rapidly.

Nevertheless, until 1950, the number of circuit miles of high-voltage transmission lines - 230 kilovolts and above - was extremely small in the U.S. That number more than tripled to over 60,000 circuit miles in the 1960s (Brown and Sedano, 2004). This was a huge expansion: approximately 40 percent of all high-voltage transmission lines installed in the U.S. at the end of the twentieth century had been constructed in the 1950s and 1960s. Such developments gave utilities access to ever more distant power sources, further reducing the appeal of cheap local hydroelectricity[4].

Advances in hydropower, steampower, and transmission lines all contributed to the

[4]In subsection 7.2, I provide empirical evidence on the advantage of cheap local hydropower using historical data.

rise of the power sector. At first, private electric utility companies dominated the market. The proliferation, consolidation, and complexity of such companies coincided with a number of financial and securities abuses, sometimes inflating costs that were passed through to the retail customers. As a response, "*Georgia, New York and Wisconsin established State public service commissions in 1907, followed quickly by more than 20 other states. Basic state powers included the authority to franchise the utilities, to regulate their rates, financing, and service, and to establish utility accounting systems*" (EIA, n.d.).

The foundations for strong federal involvement in the electricity industry were also established between 1900 and 1930 (EIA, n.d.). First, the electric power industry became recognized as a natural monopoly in interstate commerce subject to federal regulation (Supreme Court Ruling of 1927 - see chronology). Second, the federal government owned most of the nation's hydroelectric resources. Third, federal economic development programs accelerated, including electricity generation. After 1930, the federal government became a regulator of private utilities, and a major producer of electricity. Both regulation and production were aimed at generating less expensive electricity for customers.

Federal participation also increased because of national efforts to overcome the Great Depression in the 1930s, and to meet the massive electricity requirements for wartime production in the 1940s. Considerable funding was provided for the construction of large federal dams and hydroelectric facilities. This is the period known as the Big Dam Era (Billington, Jackson and Melosi, 2005). Bonneville Dam, completed in 1938, was a public works project to help relieve regional unemployment during the Great Depression. Grand Coulee Dam, opened in 1942, supplied the electricity needed to produce planes and other war material in support of World War II efforts. Later on, to meet escalating electricity needs in response to the dramatic expansion of consumer demand and industrial production throughout the decades of the 1950s, 1960s, and 1970s, many new electric generating facilities, including hydroelectric developments, were constructed.

From this discussion, it is clear that many hydroelectric projects in the first half of the century can be characterized as shocks of federal investment to local economies. By generating benefits in the hosting localities, federal funds created rents to be exploited by local consumers and firms. Indeed, Billington, Jackson and Melosi (2005) notice that "*power production, in particular, gave dams a great reach well beyond the site of their construction, transforming hinterland into cities.*" (p.384).

1.3 Theoretical Framework

In this section, I enrich Greenstone, Hornbeck and Moretti's (2010) framework with insights from Duflo and Pande (2007) to illustrate how the installation of hydroelectric dams could affect the attractiveness of hosting counties through advantage of local cheap electricity and agglomeration spillovers. I focus on the profitability of firms in hosting counties, and I assume factor-neutral spillovers related to the impact of hydro dams. Then, I provide a case study to show that the framework seems to match historical evidence.

1.3.1 Simple model

Assume that all firms have a production technology that uses labor, capital, and electricity to produce a nationally traded good whose price is fixed and normalized to one. Firms choose their amount of labor, L, capital, K, and electricity, E, to maximize profits:

$$\max_{L,K,T,E} f(A, L, K, E) - wL - rK - sE,$$

where w, r and s are input prices, and A is a productivity shifter (TFP). I ignore local land inputs. As noted below, I find little or no effect of dams on the local price of land, so this simplification is innocuous.

More specifically, A includes all factors that affect the productivity of labor, capital, and electricity equally, such as technology and agglomeration spillovers of hydro dams, if they exist. To explicitly allow for such agglomeration externalities, I let A depend on the population density in a county, N:

$$A = A(N).$$

Factor-neutral agglomeration spillovers exist if A increases in N: $\partial A/\partial N > 0$.

Let $L^*(w, r, s)$ be the optimal level of labor inputs, given the prevailing wage, cost of capital, cost of electricity, and population density. Similarly, let $K^*(w, r, s)$ and $E^*(w, r, s)$ be the optimal level of capital and electricity, respectively. In equilibrium, L^*, K^* and E^* are set so that the marginal product of each of the three factors is equal to its price. I assume that capital is internationally traded, so its price r does not depend on local demand or supply conditions. On the other hand, I allow the wage to depend on local economic conditions: $w(N)$. In particular, I allow the supply of labor to be less than infinitely elastic at the county level. Hence, $w(N)$ represents the inverse of the reduced-form labor supply function that links population density in a county, N, to the local wage level, w (Greenstone, Hornbeck and Moretti, 2010).

Regarding the (inverse of the) electricity supply function, I assume it is infinitely elastic until a threshold E^M, and then perfectly inelastic, as shown in figure 1.4. E^M represents the maximum amount of electricity that a county can generate using its cheapest source of motive power. Since the electricity supply function has a "hockey stick" shape, this simplifying assumption is not restrictive. Also, I suppose s does not depend on local economic conditions. Indeed, most U.S. retail electricity prices are determined through rate hearings where regulated firms can recover rates through average cost pricing. Recall from the historical section that regulated electric utilities have been monopolies in their service areas since the beginning of the twentieth century.

The equilibrium level of profits, Π^*, can be written as

$$\Pi^* \; = \; f[A(N),\, L^*(w(N), r, s),\, K^*(w(N), r, s),\, E^*(w(N), r, s)]$$

$$-w(N)L^*(w(N),r,s) - rK^*(w(N),r,s) - sE^*(w(N),r,s),$$

where now I make explicit the fact that TFP and wages depend on the population density in a county.

Consider the total derivative of profits with respect to a change in electricity price and in population density:

$$\frac{d\Pi^*}{ds} = \frac{\partial L^*}{\partial s}\left(\frac{\partial f}{\partial L} - w\right) + \frac{\partial K^*}{\partial s}\left(\frac{\partial f}{\partial K} - r\right) + \frac{\partial E^*}{\partial s}\left(\frac{\partial f}{\partial E} - s\right) - E^*, \tag{1.1}$$

$$\begin{aligned}\frac{d\Pi^*}{dN} &= \left(\frac{\partial f}{\partial A} \times \frac{\partial A}{\partial N}\right) - \left(\frac{\partial w}{\partial N}L^*\right) \\ &\quad + \frac{\partial w}{\partial N}\left\{\frac{\partial L^*}{\partial w}\left(\frac{\partial f}{\partial L} - w\right) + \frac{\partial K^*}{\partial w}\left(\frac{\partial f}{\partial K} - r\right) + \frac{\partial E^*}{\partial w}\left(\frac{\partial f}{\partial E} - s\right)\right\}.\end{aligned} \tag{1.2}$$

If all firms are price takers and all factors are paid their marginal product, equations (1.1) and (1.2) simplify to

$$\frac{d\Pi^*}{ds} = -E^* < 0, \tag{1.3}$$

$$\frac{d\Pi^*}{dN} = \left(\frac{\partial f}{\partial A} \times \frac{\partial A}{\partial N}\right) - \left(\frac{\partial w}{\partial N}L^*\right). \tag{1.4}$$

Equation (1.3) is just Hotelling's lemma, implying that profits are higher when local electricity prices are lower. Equation (1.4) points out that the effect of an increase in N is the sum of two opposing forces. The first term, $\left(\frac{\partial f}{\partial A} \times \frac{\partial A}{\partial N}\right)$, represents the effect of positive agglomeration spillovers, if they exist. Agglomeration spillovers of hydro dams allow firms to produce more output using the same amount of inputs. On the other hand, the second term, $\left(\frac{\partial w}{\partial N}L^*\right)$, represents negative effects from increases in the cost of production, specifically, wages. Intuitively, an increase in N is an increase in the level of economic activity in the county and therefore an increase in the local demand for labor ($\partial w/\partial N > 0$). Unlike the beneficial effects of agglomeration spillovers, the increase in factor prices is costly for firms because they now have to compete more for locally scarce resources[5].

Equations (1.3) and (1.4) provide useful guidance on what would happen after installation of hydroelectric dams. Assuming free entry, firms would move to counties hosting hydro dams to exploit rents arising from cheaper electricity ($d\Pi^*/ds < 0$). Supposing imperfect substitution between labor and electricity, firms would hire lots of workers. This would potentially pull individuals from other locations, leading to an increase in population density. In the presence of strong agglomeration spillovers, this

[5] In many standard models, the supply of labor to a location is infinitely elastic in the real wage, which includes a local component due to the local cost of housing. As discussed below, I find no evidence that dams affect land prices. In this case, it may be reasonable to assume that $\partial w/\partial N$ is small or even zero.

increase in population density would trigger a positive feedback mechanism that would continue attracting both firms and workers to those places ($d\Pi^*/dN > 0$). Strong spillovers would keep attracting businesses even when cheap electricity had become available everywhere.

The same story is evident in figure 1.4. There, the dashed curve E_{S0} represents power supply in a county with no hydro dams, and the solid curve E_{S1} the supply in a county with dams. Because large hydropower facilities generate cheap and abundant electricity, E_{S1} has a lower intercept and a larger maximum. If firms had electricity demand curves like E_D, they could exploit rents by moving to counties with dams. Rents are represented by the shaded trapezoid. Hence, it is reasonable to think that before 1950 firms would move to counties hosting dams mainly to take advantage of lower costs of electricity[6].

After 1950, technological improvements in thermal power generation and construction of high-voltage transmission lines made cheap electricity available to most counties across the country. E_{S0} and E_{S1} became just one curve within a grid area, which is much larger than a county. Currently, there are only three power grids in the U.S.: Eastern, Western, and Texas. Therefore, rents may have reduced considerably. As a result, if firms still move to counties with hydroelectric facilities, they might do so to take advantage of agglomeration spillovers, as shown in equation (1.4). Indeed, $d\Pi^*/dN > 0$ only if spillovers are sufficiently large.

1.3.2 Case Study

To illustrate the predictions of the model with some historical evidence, I provide a case study about the Bonneville Dam, a hydropower plant built in the 1930s. In an effort to prevent extortion against the public by giant electric utilities, and to provide employment during the Great Depression, the U.S. government started large hydroelectric projects in the West. One of them was the Bonneville Dam, on the Columbia River between the states of Washington and Oregon. Construction began in June 1934, and commercial operation was achieved in 1938.

In 1937, Congress created the Bonneville Power Administration (BPA) to deliver and sell the power from Bonneville Dam (see important historical facts in table 1.1). The first line connected the dam to Cascade Locks, a small town just three miles away. Major construction from the 1940s through the 1960s created networks and loops of high-voltage wire touching most parts of BPA's current service territory, which includes Idaho, Oregon and Washington, and small portions of California, Montana, Nevada, Utah and Wyoming (BPA, n.d.). During that time, Congress authorized BPA

[6] It is important to mention that, in the context considered here, free entry would not drive electricity prices up so rapidly. First, the hydroelectric dams were very large: there was capacity enough to accommodate many additional firms in the local economy. Second, the federal government wanted to keep electricity prices as low as possible, as discussed in the historical section. Acting as regulator and major producer, the federal government managed to provide cheap electricity for many years. In the case study that follows, for example, the price of electricity was kept constant for 28 years.

to commercialize power from other federal dams on the Columbia and its tributaries. By 1940, however, the federal pricing policy was set: all federal power was marketed at the lowest possible price while still covering costs.

The initial wholesale cost of power from Bonneville Dam was \$17.50/kW year (0.2 cents/kWh), a rate that was maintained for 28 years. To take advantage of this cheap and abundant electricity, the Aluminum Company of America (ALCOA) and Reynolds Metals started to mobilize to build aluminum smelters in the Northwest. ALCOA purchased property in Vancouver, Washington, in December 1939 and poured the first ingot on September 23, 1940 (Voller, 2010). Reynolds Metals purchased the property for a smelter in Longview, Washington, in 1940. By this time, with war raging in Europe, the U.S. government saw a strategic need to increase aluminum production for the impending defense effort and agreed to underwrite the construction of the Longview facility. The smelter opened in September 1941, just in time to meet the aircraft industry's increased need for aluminum (McClary, 2008).

Hydroelectric dams brought prosperity to their hosting locations, attracting hundreds of workers. Vancouver, for instance, saw an industrial boom in the 1940s, including the Kaiser shipyard and the Boise Cascade paper mill, besides ALCOA (Jollata, 2004). Over the years, though, as many heavy industries left the U.S., Vancouver's economy has largely changed to high tech and service industry jobs. The city contains the corporate headquarters for Nautilus, Inc. and The Holland (parent company of the Burgerville, U.S. restaurant chain). It seems that nowadays other forces attract people to Vancouver. They might be agglomeration spillovers.

1.4 Location Decisions and Research Design

In testing for the presence of agglomeration spillovers, a key econometric challenge is that concentration of economic activity also can be generated by natural advantages. Specific geographical features that bring people and businesses to an area, such as detailed topography, resource endowments, and climate, are often unobserved, but they are problematically correlated to those location decisions.

Therefore, a naive comparison of population growth across counties with distinct natural endowments is likely to yield biased estimates of agglomeration spillovers. Some places might attract people because of such externalities, but some others might pull people in just because of an unobserved geographical attribute. Credible estimates of spillovers require the identification of locations which are similar in natural advantages.

The first appealing characteristic of my research design is the narrowing of my sample to encompass counties that are comparable in some natural features. Indeed, I compare only counties that have similar potential to generate hydroelectricity, as determined by an engineering team in the beginning of the 1990s, at the request of the U.S. Department of Energy. As is well-known in the engineering literature, suitability of sites for hydro dams depends on parameters associated with topography and inflow in the catchment area, morphology of the river valley, geological and geotechnical conditions, and climate and flood regime. Therefore, I believe my approach controls for important geographical peculiarities of counties in my sample.

Locations with similar geography tend to have similar economic activity. It would then be desirable to have temporary shocks that would make some of these areas more attractive than others. In that case, workers and firms would concentrate in certain areas even if they could enjoy the same geographical features in other places. After the interruption of the shocks, affected areas would have higher population density. If they continued having higher population growth after the cessation of the shocks, this would be an indication of the presence of agglomeration spillovers.

The second valuable feature of my research design is the use of the appeal of cheap local hydroelectricity in the first half of the twentieth century as such a shock. Not every county with suitable dam sites ever had hydropower plants constructed. Therefore, not every county with appropriate dam sites had access to the cheapest source of electricity until 1950. By the middle of the century, however, such advantage was reduced considerably, as argued in previous sections. As thermal power generation was enjoying major technological improvements, and high-voltage transmission lines were being constructed, cheap electricity was becoming available to most counties across the nation.

Obviously, the validity of my research design depends on the assumption that places with hydro potential where dams were not built provide a valid counterfactual for similar places where dams were built. This in turn requires a clearer understanding of why dams were not built in some counties with hydroelectric potential. Prior to World War I, hydroelectric power development was mostly a private venture. However, with private hydro plants increasingly interfering with navigation in the East and Midwest, government regulation evolved to become stricter. Congress initially attempted to regulate dam construction through the Rivers and Harbors Acts of 1890 and 1899, requiring that dam sites and plans for dams on navigable rivers be approved by the U.S. Army Corps of Engineers and the Secretary of War. Then, the Right-of-Way Act of 1901 gave the Secretary of the Interior the authority to grant rights-of-way over public lands for dams, reservoirs, waterpower plants, and transmission lines (see table 1.1 for key historical facts related to hydroelectricity in the U.S.).

Although "*between 1894 and 1906 Congress issued 30 permits for private dams, mostly along the Mississippi River*" (Billington, Jackson and Melosi, 2005, p.37), the federal government began to reserve waterpower sites for conservation and wise use, and to enter the business of hydroelectricity. Indeed, "*in the 1903 veto of private construction of a dam and power stations on the Tennessee River at Muscle Shoals, Alabama, Roosevelt protected the site for later government development, but he also helped to establish the principle of national ownership of resources previously considered only of local value.*" (Billington, Jackson and Melosi, 2005, p.37).

The General Dam Act of 1906 was, perhaps, the legislation that most discouraged the entrance of private enterprise into the hydroelectric sector. It "*standardized regulations concerning private power development, requiring dam owners to maintain and operate navigation facilities - without compensation - when necessary at hydroelectric* *power sites."* (Billington, Jackson and Melosi, 2005, p.38). Private companies fought for more favorable legislation, but ended up accepting the permit system. At the same time, the federal government started to link hydropower to plans for waterway improvements. A 1910 amendment to the 1906 act, for instance, underscored hydropower as a mechanism for navigation and flood control projects. The connection between hydropower and local development grew considerably until the 1930s and 1940s, when the federal government gained prominence in the construction of large hydro dams, as pointed out in the historical section above.

As we can see, the decision of where to construct hydroelectric dams basically changed from the private sector to the federal government in the first quarter of the twentieth century. Environmental issues, which became very salient in the second half of the century, and regional development concerns frequently guided the allocation of dams throughout the nation. Therefore, counties with higher economic growth potential have not always attracted more investments than counties with lower growth potential. Instead, Hansen et al. (2011) argue that politics might have shifted the eventual location of major water infrastructure projects away from what otherwise might have been the optimal location. They provide evidence suggesting that membership in congressional committees for water resources, agriculture, and appropriations, often times unrelated to population pressures, generally has a positive and significant impact on the number of dams and the proportion of dams constructed in a state.

As the discussion above attests, my research design may be valid under relatively mild assumptions. In my main estimation, I end up using the group of counties with hydropower potential that was not developed as my potential control group. Nevertheless, I also control flexibly for climate variables and geographic coordinates, allowing them to vary with time, and use synthetic control methods to match treated and control counties more closely (details are presented in section 6). In my robustness checks, I include other sets of controls such as proximity to transportation networks, and consider alternative definitions for my potential control group, such as counties with hydropower potential but no environmental regulations.

A third and last notable feature of my research design is its ability to control for the effect of direct investment in the estimation of agglomeration externalities. Counties that hosted hydroelectric dams in the first half of the twentieth century might have had another important initial stimulus in their local economies, on top of the appeal of cheap local hydroelectricity. The construction of hydropower plants might have increased the local stock of capital substantially, and might have attracted workers and firms as well. Because not all counties with hydro dams had their facilities built at the same time, I use the counties with dams built after 1950 to refine my identification of spillovers. Since these counties experienced the same infusion of capital as the counties with pre-1950 dams, but did not enjoy the advantage of cheap local power, they can be used to purge the estimates of agglomeration economies of this source of confoundedness.

1.5 Data Description

My basic dataset is a balanced panel of 154 U.S. counties covering the period from 1900 to 2000. It includes all counties with a hydropower potential of 100 megawatts or more. This choice of sample ensures that counties are similar with respect to natural endowments. County-level data on population and employment are drawn from the U.S. census of population (Haines and ICPSR, 2010; Minnesota Population Center - NHGIS, 2011). Variables of interest include population density and employment density, which have usually been used as proxies for economic activity. Other data sources include climate data from Schlenker and Roberts (2009), market access data from Donaldson and Hornbeck (2012), and hydropower data from INL (1998) and eGRID (2010), as presented below. To account for county border changes, data are adjusted in later periods to maintain the 1900 county definitions (Hornbeck, 2010).

A natural measure of hydropower potential is capacity installed in hydro plants plus undeveloped capacity. A unique feature of my database is the inclusion of a measure for the undeveloped capacity. It comes from the 1998 U.S. Hydropower Resource Assessment, prepared by the Idaho National Engineering and Environmental Laboratory (INL) for the U.S. Department of Energy (DOE) (Conner, Francfort, and Rinehart, 1998; INL, 1998). A measure of installed capacity comes from the U.S. Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID) for 2007 (eGRID, 2010).

The INL report presents DOE's efforts to produce a more definitive assessment of undeveloped hydropower resources within the U.S. No agency had previously estimated the undeveloped hydropower capacity based on site characteristics, stream flow data, and available hydraulic heads. Initial efforts began in 1989 and information from the last state was received in 1998. State agencies such as departments of dam safety, water resources, environmental quality, fish and game, history, and commerce, contributed information about hydropower resources within their states. The report summarizes and discusses the undeveloped *conventional* hydropower capacity for the 5,677 sites within the country. It does not include the capacity produced by pumped storage sites. However, for conventional hydropower, the resource assessment contains site identification information, geographic coordinates, and crucially the estimated nameplate capacity[7].

The eGRID is a comprehensive inventory of the generation and environmental attributes of all power plants in the U.S. Much of the information in this database, including plant opening years, comes from DOE's Annual Electric Generator Report compiled from responses to the EIA-860, a form completed annually by all electric-generating plants. In addition, eGRID includes plant identification information, geographic coordinates, number of generators, primary fuel, plant nameplate capacity, plant annual net generation, and whether the plant is a cogeneration facility.

My sample consists of counties that have either (i) non-cogeneration plants with installed capacity of 100 megawatts or more, generating electricity only through con-

[7]Nameplate capacity refers to the intended technical full-load sustained output of a facility.

ventional hydropower, or (ii) undeveloped sites with estimated nameplate capacity of 100 megawatts or more. Because often capacity builds up gradually, I assume that a county has hydroelectric dams only when it reaches the 100-megawatt nameplate. I use the same cut-off to determine the year in which a dam is completed. Counties with hydroelectric facilities are my "treated" counties, and those with undeveloped sites are my "control" counties. Here, "undeveloped" means with no dams at all, or with dams for purposes other than power generation (e.g., flood control, irrigation, and navigation).

Figure 1.5 displays the sample counties. As we can see clearly, most of them are located in two regions of the country: South (44.8 percent) and West (38.3 percent). Because they have similar hydropower potential, they likely have comparable topography. However, because they are somewhat spread within regions, climate variables (50-year average rainfall and 50-year average temperature for each season of the year) and geographic coordinates (latitude and longitude) are included in the empirical analysis to control for other possible natural advantages.

Table 1.3 reports county statistics for my main outcomes (population and employment density) and some hydroelectric-related variables. Among the reported statistics, notice that pre-1950 treated counties have the highest levels of outcomes throughout the twentieth century, followed by post-1950 treated counties, and then by control counties. (Figures A1 and A2, in the Appendix, display outcome trajectories from decade to decade.) Also, observe that most of the hydroelectric dams were constructed from the 1920s to the 1980s, with a boom around the 1950s. In the beginning of the century, they were small, then became larger to tap economies of scale in electricity generation, and finally came to be small again because of environmental concerns. Last, note the increase in hydroelectricity capacity after installation of the first plants. In some cases, hydropower facilities were upgraded; in others, new plants were constructed. Because these changes in installed capacity may affect outcomes directly, I control for them in my empirical analysis.

1.6 Empirical Framework

In this section, I present my novel empirical approach to obtain impact estimates of hydroelectric dams in the short and long run and my strategy to estimate agglomeration spillovers. My new approach is a two-step procedure that combines synthetic control methods and event-study techniques. In the first step, I use synthetic control analysis to uncover the effect of dams for each treated county separately and, more importantly, to construct counterfactuals, which I refer to as "synthetic control counties". In the second step, I pool all pairs of treated and synthetic control counties, and run an event-study analysis to find the average treatment effect of dams across all treated counties. My strategy to estimate agglomeration spillovers follows the intuition provided by figure 1.1 in the introduction.

1.6.1 Estimation by County - Synthetic Control Analysis

Initially, I estimate the impact of hydroelectric dams on population density for each treated county separately. I use synthetic control methods (Abadie and Gardeazabal, 2003; and Abadie, Diamond and Hainmueller, 2010), which basically compare the evolution of population density for a treated county to the evolution of the same outcome for a synthetic control county. The synthetic control county is a weighted average of potential control counties chosen to approximate the treated county in terms of the outcome predictors. The evolution of the outcome for the synthetic control county is an estimate of the counterfactual of what would have been observed for the affected county in the absence of dam installation. Once treated and synthetic control counties have similar outcome behavior over extended periods of time before dam installation, a discrepancy in the outcome variable following installation is interpreted as produced by the dam itself.

To provide a more formal summary of this approach, suppose that there is a sample of $C+1$ counties indexed by c, among which unit $c = 1$ is the treated county and units $c = 2$ to $c = C + 1$ are potential controls. Also, assume a balanced panel which includes a positive number of pre-intervention periods, T_0, as well as a positive number of post-intervention periods, T_1, with $T_0 + T_1 = T$.

Let Y_{ct} be the outcome of unit c at time t. For a post-intervention period t (with $t \geq T_0$), the synthetic control estimator of the effect of dam installation is given by the comparison between the outcome for the treated county and the outcome for the synthetic control at that period:

$$Y_{1t} - \sum_{c=2}^{C+1} w_c^* Y_{ct}.$$

Let $W = (w_2, ..., w_{C+1})'$ be a $(C \times 1)$ vector of positive weights that sum to one. Also, let X_1 be a $(k \times 1)$ vector containing the values of the pre-intervention characteristics of the treated county, and let X_0 be the $(k \times C)$ matrix collecting the values of the same variables for the counties in the "donor pool"[8]. Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010) choose W^* as the value of W that minimizes

$$\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)},$$

where an optimal choice of V assigns weights to linear combinations of the variables in X_0 and X_1 to minimize the mean squared error (MSE) of the synthetic control estimator.

The matching variables in X_0 and X_1 are meant to be predictors of post-intervention outcomes, which are not themselves affected by the intervention. Notwithstanding, using a linear factor model, Abadie, Diamond, and Hainmueller (2010) argue that if the number of pre-intervention periods in the data is large, the inclusion of pre-intervention

[8] "Donor pool" is defined as the set of potential control counties out of which the synthetic control unit is constructed.

outcomes in X_0 and X_1 helps control for unobserved factors affecting the outcome of interest as well as for heterogeneity of the effect of the observed and unobserved factors. This approach ends up extending the traditional difference-in-differences framework, allowing the effects of unobserved variables on the outcome to vary with time. In my analysis, I use the following matching variables in X_0 and X_1 : (i) pre-dam log of population density up to the year before installation, (ii) dummies for the four regions of the country (Northeast, Midwest, South, and West), (iii) cubic function in latitude and longitude, and (iv) 50-year average rainfall and 50-year average temperature for each season of the year.

A byproduct of the synthetic control estimation is the construction of synthetic control counties. Using the weights that minimize the MSE of the synthetic control estimator, I generate a counterfactual for each treated county in my sample. Each counterfactual, or synthetic control county, represents a weighted average of the counties contained in the donor pool. Hence, it has outcomes and characteristics representing weighted averages of outcomes and characteristics, respectively, of the originally defined control counties. In the end, I obtain a pair of treated and synthetic control counties for each county hosting hydroelectric dams.

1.6.2 Pooled Estimation - Event-Study Analysis

To provide an average estimate of the impact of hydroelectric dams on population density, with dams built in different decades, I pool all pairs of treated and synthetic control counties, and use an event-study research design (e.g., Jacobson, LaLonde, and Sullivan, 1993; McCrary, 2007; and Kline, 2012). An event-study analysis can recover the dynamics of the impact of those dams in the short and long run, and test whether hydro dams were constructed in response of county-specific trends in population density. I follow Kline's (2012) exposition of such an approach here.

Consider the following econometric model of population density:

$$Y_{ct} = \sum_y \beta_y D^y_{ct} + \alpha_c + \gamma_{rt} + Z^{'}_c \phi_t + X^{'}_{ct}\lambda + \varepsilon_{ct}, \tag{1.5}$$

where Y_{ct} is the log of population density in county c in calendar year t, α_c is a county effect, γ_{rt} is a region-by-year fixed effect, Z_c is a vector of time-invariant county characteristics (cubic function in latitude and longitude, and 50-year average rainfall and 50-year average temperature for each season of the year) whose coefficients are allowed to vary in each year, X_{ct} is a vector of time-varying county attributes (cubic function in dam size and in capacity of thermal power plants), and ε_{ct} is an error term that may exhibit arbitrary dependence within a county but is uncorrelated with the other right-hand side variables[9].

The D^y_{ct} are a series of event-time dummies that equal one when dam installation is y years away in a county. Formally, we may write

$$D^y_{ct} \equiv I[t - e_c = y],$$

[9]The reason for this exact specification will be clear in section 7, subsection "Specification Issues".

where $I[.]$ is an indicator function for the expression in brackets being true, and e_c is the year a dam is installed in county c.

Thus, the β_y coefficients represent the time path of population density relative to the date of dam installation, conditional on observed and unobserved heterogeneity. If dams are randomly assigned to counties, the restriction $\beta_y = 0$ should hold for all $y < 0$. That is, dam installation should not, on average, be preceded by trends in county-specific population density. Because not all of the β's can be identified due to the collinearity of D's and county effects, I normalize $\beta_0 = 0$, so that all post-installation coefficients can be thought of as treatment effects. Lastly, I impose the following endpoint restrictions:

$$\beta_y = \begin{cases} \overline{\beta}, & \text{if } y \geq 80 \\ \underline{\beta}, & \text{if } y \leq -80, \end{cases}$$

which simply state that any dynamics wears off after eighty years. This restriction helps to reduce some of the collinearity between the region-by-year and event-time dummies. As explained in Kline (2012), because the sample is unbalanced in event time, these endpoint coefficients give unequal weight to counties installing hydro dams early or late in the sample. For this reason, I focus the analysis on the event-time coefficients falling within an eighty-year window that are identified off of a nearly balanced panel of counties.

Reweighting/Matching Empirical Strategy

My two-step procedure to obtain impact estimates of hydroelectric dams can be seen as a reweighting/matching strategy to estimate treatment effects that accounts for time-varying unobserved heterogeneity. First, I find a synthetic control unit for each treated county using synthetic control methods. As discussed above, a synthetic control is a weighted average of potential control counties that replicates the counterfactual outcome that the treated county would have experienced in the absence of the treatment (dam installation). Recalling that time-varying unobserved heterogeneity is taken into account in the estimation of the synthetic-control optimal weights (Abadie, Diamond and Hainmueller, 2010), synthetic control counties represent reweighted aggregations of the originally defined control counties that account for time-varying unobserved heterogeneity.

Second, I match each treated county with its corresponding synthetic control to generate the sample with which I run the event-study analysis. Because synthetic controls are objects intrinsically associated with their treated counterparts, I conduct hypothesis testing using standard errors clustered at the case level, where a case is a pair of a treated and its corresponding synthetic control county[10].

[10] In Appendix C, I discuss an alternative approach to this reweighting-matching strategy. I consider the "synthetic propensity score reweighting".

1.6.3 Agglomeration spillovers

Having described my methodology to estimate the effects of hydroelectric dams on population density over a long period of time, I present my strategy to uncover lower bound estimates of agglomeration spillovers. As exemplified in the introduction, my measure of spillovers is the growth in population density in pre-1950 treated counties over and above (i) the growth experienced by them until 1950, which is mostly due to the advantage of cheap local hydroelectricity, and (ii) the growth experienced by post-1950 treated counties, which probably results from changes in stock of capital, given the attenuation of the appeal of cheap local hydropower in the second half of the twentieth century. Hence, this measure reflects the dynamics of population growth that might arise when the effects of cheap electricity and direct investment fade away. It represents a lower bound for the agglomeration spillovers of pre-1950 dams because the subtraction of the impact of post-1950 dams eliminates not only the effects of changes in stock of capital, but also any potential agglomeration effects of those dams.

Although my measure of agglomeration economies is easily illustrated in figure 1.1, it can be less clear when I average it across pre-1950 treated counties because of different dam completion dates. For any number of years y after dam installation, I can express it as

$$\widehat{AS}_y = \widehat{\beta}_y^{CTB1950} - \widehat{G}^{CTB1950until1950} - \widehat{\beta}_y^{CTA1950}, \tag{1.6}$$

where $\widehat{\beta}_y^{CTB1950}$ is the coefficient of an event-time dummy for Counties Treated Before 1950 ($CTB1950$), $\widehat{G}$ is the estimate of the average growth of population density from the time of dam installation until 1950 for $CTB1950$, and $\widehat{\beta}_y^{CTA1950}$ is the coefficient of an event-time dummy for Counties Treated After 1950 ($CTA1950$).

To accommodate treated counties with hydroelectric plants built in different decades, $\widehat{G}$ is a weighted average of the impact of dams up to forty years after installation of the facilities, depending on the county-specific completion date. That is,

$$\widehat{G}^{CTB1950until1950} = (d_{1910s} * \widehat{\beta}_{40}) + (d_{1920s} * \widehat{\beta}_{30}) + (d_{1930s} * \widehat{\beta}_{20}) + (d_{1940s} * \widehat{\beta}_{10}), \tag{1.7}$$

where d_{19_0s} is the number of counties with dams built in a specific decade.

1.7 Results

In this section, I present two sets of results. First, I discuss the effects of hydro dams case by case for a representative group of treated counties. These are my county-specific estimates, found through synthetic control methods. Then, I discuss the average impact of hydroelectric facilities for all treated counties in my sample. These are my pooled estimates, arising from event-study analyses. The evidence of agglomeration spillovers is examined within this last subsection.

1.7.1 Synthetic Control Approach: County-Specific Estimates

Pre-1950 Dams

Emblematic Case. In figure 1.1, I have introduced the synthetic control estimator for Blount County, Tennessee, where Calderwood Dam was installed in the 1930s. In that figure, population density grows rapidly from dam completion until 1950, and then slows down afterwards. Had the dam not been constructed, there would have been just slight growth after 1930s, probably due to the Great Depression. Therefore, the impact of the hydropower plant until 1950 was approximately 0.40 log points (49 percent). From 1950 to 2000, the effect was roughly 0.50 log points (65 percent). This second number is also an approximate measure of agglomeration spillovers for Blount County, since the advantage of cheap local hydroelectricity weakened around 1950.

No Agglomeration Economies. Figure 1.6, panel A, displays a case of strong short-run effect of hydroelectric facilities, but almost no agglomeration economies. From completion in the 1930s until 1950, Norris Dam induced growth of approximately 1.17 log points (223 percent) in population density of Anderson County, Tennessee, relative to the counterfactual. Despite this enormous short-run impact, Anderson County grew only 0.12 log points (13 percent) afterward. Thus, the dam generated virtually no agglomeration externalities once cheap electricity spread around the country.

Reversion. A disturbing result of a public investment is illustrated by Hawks Nest Dam, installed in the 1930s in Fayette County, West Virginia. Following dam completion, the county experienced a growth of almost 0.15 log points (16 percent) in population density relative to its counterfactual, as shown in figure 1.6, panel B. Nevertheless, in the second half of the twentieth century, when the appeal of cheap local hydroelectricity became attenuated, that trend reversed and the county had a drop of 0.45 log points (36 percent) in population density. This is an emblematic case of lack of path dependence. Once the advantage of cheap local power reduces, and capital depreciates, people fly away.

Constant Growth. An interesting outcome is the one exemplified by Travis County, Texas, which had Mansfield Dam (formerly Marshall Ford Dam) constructed in the 1940s. As displayed in figure 1.7, panel A, once the dam was built, the county embarked on a stable path of population density growth, with a rate that remained constant until the end of the twentieth century. In the first decade, Travis County expanded nearly 0.39 log points (48 percent) relative to its counterfactual. From 1950 to 2000, that trend did not become flatter, and the county grew approximately 1.07 log points (191 percent). From a local perspective, this is what every policymaker would like to witness. After the initial push, agglomeration spillovers kicked in vigorously, producing a sustainable dynamic of growth.

Indifference. An unattractive situation from a policymaking point of view is the one portrayed by Fort Loudoun Dam, built in the 1940s in Loudoun County, Tennessee. The trajectories of population density of treated and synthetic control counties, shown in figure 1.7, panel B, do not differ significantly after the installation of the plant. Apparently, the county would have grown steadily even without the hydropower facilities.

Timing of Attenuation of Cheap Local Power Advantage

In the emblematic example of figure 1.1, the path of population density flattens out in 1950. As discussed in the historical section, this might be a good estimate of the period in which the appeal of cheap local hydroelectricity started to fade away. However, most of the high-voltage transmission lines were constructed in the 1950s and 1960s, and thermal efficiency increased gradually from the 1940s to the 1960s, as displayed in figure 1.2. So it is possible that some counties experienced the compression in growth rates earlier or later than 1950. Indeed, figure 1.8 presents two emblematic cases of such possibilities. Haywood County, North Carolina, for instance, witnesses the flattening in 1940, just a decade after Walters Dams was completed. San Bernardino County, California, on the other hand, sees its growth rates in population density reduce only in 1960, two decades after Parker Dam had been completed. Therefore, the use of 1950 as the turning point of the attenuation of the advantage of cheap local hydroelectricity must be seen as an approximation only.

Post-1950 Dams

Figures 1.9 and 1.10 display the dynamics of population density for four counties where hydroelectric plants were installed in the second half of the twentieth century. These cases illustrate the typical effects that I find in my analysis with post-1950 dams: moderately positive, small but positive, nonexistent, and somewhat negative.

First, consider the case of Lewis County, Washington, which had both Mayfield Dam and Mosyrock Dam constructed in the 1960s (Figure 1.9, Panel A). Notice that the initial jump in population density, representative of the impact of pre-1950 dams, was relatively small here: around 0.16 log points (17 percent) relative to the counterfactual, after a decade. This small effect seems to reinforce hydroelectricity as an advantageous local attribute in the first half of the century. Moreover, it indicates that direct investment might also play a role in generating growth following dam completion. The impact grew gradually to nearly 0.35 log points (42 percent) in 2000. It is quite possible that some agglomeration spillovers are present here, over and above the effect of changes in stock of capital, but I cannot separate them out.

In the second case (Figure 1.9, Panel B), the initial impact is even smaller, and potential agglomeration externalities look negligible. Indeed, after installation of Keowee Dam in the 1970s, Pickens County, South Carolina, grew only approximately 0.09 log points (10 percent) in the first decade. Subsequently, the growth was minimal. In 2000, three decades after dam completion, the impact was just under 0.17 log points (18 percent). Therefore, agglomeration economies seem insignificant.

The third case, of Detroit Dam (Figure 1.10, Panel A), concluded in the 1950s in Marion County, Oregon, shows no effect at all. It appears that the county would have grown as much as it did without the hydro plant. Lastly, the fourth case (Figure 1.10, Panel B) depicts a decrease in population density. After completion of Roanoke Rapids Dam, in the 1950s, and Gaston Dam, in the 1960s, people started to leave Halifax County, North Carolina. Part of such population decline might be due to displacement, but it seems odd that the county had not recovered even its pre-dam level of population density as of 2000.

Distribution and Heterogeneity of County-Specific Dam Impacts

The cases mentioned above illustrate reasonably well typical dynamics of population density growth in my sample. To provide a summary of all counties, I plot the distribution of pre-1950 dam effects in figure 1.11, and of post-1950 dams in figure 1.12. When we examine each column of figure 1.11, we can see clearly that the distribution of impacts of hydroelectric plants is shifting to the right. This movement happens despite the attenuation of the appeal of cheap local hydroelectricity and the fading of the direct investment effect. It is then quite plausible that agglomeration spillovers kick in at some point, and give rise to such a path dependence.

Figure 1.12, on the other hand, portrays a rather different story. Each column shows a distribution of dam effects somewhat inert around zero even after fifty years. This observation reinforces the idea of cheap local hydroelectricity as a driving force of concentration of economic activity and subsequent agglomeration externalities.

Besides allowing me to plot the distribution of effects, county-specific estimates give me the possibility of analyzing the heterogeneity of dam impact in a very simple and direct way. All that is necessary is to run panel data regressions of dam effects on characteristics of dams or locations hosting them, for example, controlling for years relative to dam completion. Doing so, I find that pre-1950 dam effects are, on average, nearly 6 percent stronger (coefficient: 0.0575; s.e.: 0.0210) when dam size at completion is a hundred megawatts larger. In my sample, dam size at completion ranges from one to approximately nine hundred megawatts for pre-1950 dams. On the other hand, I do not find any statistically significant heterogeneity regarding population density a decade before dam completion (coefficient: -0.0499; s.e.: 0.0385).

1.7.2 Event-Study Analysis: Pooled Estimates

Short- and Long-Run Impact of Hydro Dams

When I pool all pairs of treated and synthetic control counties and estimate equation (1.5), I find quite interesting results[11]. First, the timing of dam installation appears to be crucial to the pattern of observed effects. Hosting hydropower facilities in the first half versus the second half of the twentieth century means enjoying a period of great prosperity versus no detectable changes, as depicted in figure 1.13 and table 1.4. Indeed, counties with pre-1950 dams experience average increases in population density

[11] I discuss my results using the group of synthetic control counties. As explained in the methodology section, because both observed and unobserved heterogeneity are taken into account in the estimation of synthetic controls, and are allowed to vary flexibly over time, the comparison between treated counties and these controls might provide a more accurate estimate of the treatment effect. Nevertheless, for comparison purpose, I present results using the originally defined control counties as well. Both sets of estimates are shown side-by-side in tables and figures.

of approximately 0.41 log points (51 percent) after 30 years[12], and 0.87 log points (139 percent) after 60 years, as shown in table 1.4. On the other hand, counties with post-1950 dams experience no statistically significant effects.

Second, the enormous magnitude of the impact of hydroelectric plants seems somewhat remarkable. On average, county sizes more than double five decades after dam completion. Actually, population density grows nearly 0.79 log points (120 percent) after 50 years of pre-1950 dam installation. Third, the difference in short- and long-term effects is revealing. The 30-year estimate presented above is less than half its 60-year counterpart. This suggests that the assessment of large infrastructure projects does require understanding of long-run effects, as advocated by Kline (2010). The comprehensive report of the World Comission on Dams, in 2000, does provide some evidence of long-term effects of a few dams around the world, but my study seems to provide the first systematic evaluation of impact of dams in the long run. Fourth, and last, the strength of economic growth in the long run looks rather surprising. The annualized growth rate of population density is roughly 1.6 percent in the first 40 years, and still 1 percent in the following 40 years. This might indicate the presence of either slow adjustment of capital stock to shocks or strong agglomeration economies. Below, I provide evidence that agglomeration spillovers may explain a great part of the late growth in population density.

Specification Issues

The first specification that I estimate in this study is equation (1.5), but without X_{ct}. Such specification, which I refer to as the "basic specification", includes event-time dummies, county effects, region-by-year fixed effects, and time-invariant county characteristics (cubic function in latitude and longitude, and 50-year average rainfall and 50-year average temperature for each season of the year) interacted with year effects. Because this set of covariates does not seem enough to eliminate all pre-treatment trends, as evident in table 1.5 and in figure 1.14, I add controls for dam size to the basic specification. As explained in section 5, dams above the 100-megawatt cutoff still differ in size, and might expand over time. When I include a cubic function in dam capacity, the post-treatment estimates remain unchanged, and the coefficients of such controls are statistically insignificant. What seems to drive the effects of hydro dams is timing, not size. However, the inclusion of controls for dam size does remove any pre-treatment trends.

Next, I add controls for the size of thermal power plants present in my sample counties. My concern is that counties with lower hydropower potential might respond

[12]Duflo and Pande's (2007) pioneer study of the impact of large irrigation dams on agricultural production and poverty rates in India provides estimates over a time span of only three decades. Notwithstanding, their work produces credible estimates of the impact of irrigation dams. Instead of just comparing outcomes of districts with and without irrigation dams, they use variation in dam construction induced by differences in river gradient across districts within Indian states to obtain instrumental variable estimates.

to this natural constraint by building fossil fuel and/or nuclear power plants. In that case, the impact of hydro dams would be underestimated. My estimates do increase when I include such controls, but just a little bit.

Also, I add controls for the interaction of year effects with three county-specific measures of market access in 1890: mileage of railroad tracks, distance to closest waterway, and log of market access as estimated by Donaldson and Hornbeck (2012). One could argue that my control group, while appealing in some respects, does not necessarily have the same natural advantages simply because they have the same hydropower potential. A concern will be that if a county has good hydro potential and is near a river or a rail line, the value of installing hydroelectric facilities there would be higher because then local manufacturers could easily ship out their products. That could lead to bribes and political deals that would get the dams built in those places, and not in isolated places where, even if a dam was built, it would be hard to get manufacturers to move in. In such case, the impact of hydro dams would be overestimated. After controlling for pre-dam proxies of market access, my post-dam estimates do decrease, but not significatively. However, pre-treatment trends seem to be slightly more pronounced than in the previous specification.

Lastly, I check how state-by-year fixed effects versus region-by-year fixed effects would change my findings. One can argue that most energy policies are made at the state level, so the impact of hydro dams may reflect only state-specific effects. As evident in the chart with original control counties, this is not the case here. (I could not run this specification with the synthetic control group because there were fewer observations than parameters to be estimated.) In the end, the specification that I use to report my findings throughout the paper - my main specification: equation (1.5) in the text - is the one with region-by-year fixed effects, controls for dam size, and controls for capacity of thermal power plants.

Placebo Tests

In order to check whether my research design is capturing the impact of hydroelectric dams rather than the effect of some unobserved intervention, I run placebo tests. The estimated impact of dams would be undermined if I obtained effects of similar or even greater magnitudes in cases where/when the intervention did not take place (Heckman and Hotz, 1989; Abadie and Gardeazabal, 2003; Bertrand, Duflo, and Mullainathan, 2004; and Abadie, Diamond and Hainmueller, 2010). Therefore, I pool all counties and select randomly treated before 1950, treated after 1950, and controls, and redo my analysis fifty times. For artificially treated counties, I also set the year of dam completion at random.

The estimated effects of artificial treatments are shown in figures 1.15 and 1.16. For comparison purposes, I plot the impact of the real treatment as well. As we can see clearly, the effect of pre-1950 hydro plants in counties that actually hosted them are distinguished from the placebo effects. This effect is higher than any other effect in figure 1.15. On the other hand, the impact of post-1950 dams is completely mixed with placebo impacts. These pieces of evidence reinforce the importance of pre-1950 hydroelectric dams in driving my results.

Evidence on the Advantage of Cheap Local Hydroelectricity

The difference in findings based on the timing of dam installation might be due to the appeal of cheap local hydroelectricity in the first half of the twentieth century, as discussed in the historical section. In fact, electricity was much cheaper in counties hosting pre-1950 dams than in counties with hydropower potential but no hydroelectric facilities. When I regress the log of the unit value of electricity purchased by manufacturing in 1947 (Bureau of the Census, 1949) on a dummy for pre-1950 treatment, controlling for state fixed effects, a cubic function on latitude and longitude, and 50-year average rainfall and 50-year average temperature for each season of the year, I find a coefficient of approximately -0.60 (s.e. 0.22). This means that electricity price was roughly 45 percent lower in pre-1950 treated counties relative to controls. This was not the case, however, for counties which had hydropower plants constructed only in the second half of the century. The estimated coefficient for the post-1950 treatment in a regression similar to the one described above was not statistically significant (-0.28, with s.e. 0.34)[13].

Indirect evidence that may reinforce cheap electricity as the force driving my results comes from the dispersion of prices across counties. If electricity could be transmitted costlessly from suppliers to consumers, and electricity markets were nationally competitive, then we would observe no difference in prices over the country. Because there was no major change in regulation around the middle of the century, variations in dispersion in that period might be associated with transmission costs. The standard deviation of the log of the unit value of electricity purchased by manufacturing decreased from nearly 0.46, in 1947, to 0.38 (Davis et al., forthcoming), in 1972. As mentioned in the historical review, most of the high-voltage transmission lines were built in the 1950s and 1960s, so this 17 percent drop in the standard deviation may reflect a higher degree of spatial interconnection of the electrical grid. Thus, improvements in the power network may help explain the difference in the effects of pre-1950 versus post-1950 hydro dams.

Agglomeration Spillovers

The effects of hydroelectric dams long after dam completion suggest that economic growth may be amplified by additional forces such as agglomeration spillovers. The installation of large hydropower facilities combined with the local appeal of hydroelectricity in the first half of the twentieth century might have induced a process of cumulative causation in counties hosting pre-1950 dams. The initial investments and

[13] I run similar regressions using electricity prices in 2000, constructed from data available from the Energy Information Administration (EIA) form 861, as in Kahn and Mansur (2012). Relative to the control group, neither pre-1950 nor post-1950 treated counties have lower prices that are statistically significant. For pre-1950, the coefficient of the dummy of treatment is approximately -0.10 (s.e. 0.06), and for post-1950, it is nearly -0.07 (s.e. 0.05).

the resulting cheap electricity might have set in motion a chain reaction with multiple changes in population density.

As illustrated by figure 1.1, and described in the methodology, in order to provide evidence of agglomeration economies I make two simplifying assumptions. First, I attribute any growth in population density until 1950 to the advantage of cheap local hydroelectricity. Second, I suppose that the effects of post-1950 dams are driven mostly by changes in the stock of capital associated with dam installation, and, potentially, small agglomeration externalities. Hence, a lower bound of agglomeration economies can be found by subtracting any impact of post-1950 dams from the post-1950 population density growth of counties hosting pre-1950 dams.

Figure 1.17 displays the impact of pre- and post-1950 dams in the top charts, and the difference of those effects in the bottom charts[14]. The dotted line in the bottom charts represents the growth of population density from the completion of pre-1950 dams until 1950. Therefore, the lower bound of agglomeration spillovers (or the magnitude of "pure" agglomeration externalities) is up to 45 percent (0.37 log points) five decades after dam installation. The advantage of cheap local hydroelectricity might explain most of the concentration of economic activity in the first 20 years after dam completion. Subsequently, spillovers seem to kick in, and may account for roughly 47 percent of the 50-year impact of hydroelectric dams.

My lower bound for agglomeration economies seems to be very large compared to other estimates in the literature. For instance, Greenstone, Hornbeck and Moretti (2010) find that, five years after the opening of a Million Dollar Plant, incumbent plants' TFP is 12 percent higher in hosting counties. Thus, my estimate appears to be almost four times larger than theirs. Most of the difference, however, is due to the time horizons of our analyses. Theirs is a short-run estimate, mine is a long-run one. When I consider the lower bound nearly a decade after spillovers kick in, my estimate is around 11.5 percent (0.11 log points), which is close enough to theirs. (My estimate then becomes 34 percent (0.29 log points) after two decades of prominence of spillovers, and 45 percent (0.37 log points) after three decades.)

Potential Mechanism: Manufacturing

Although I have described my results in terms of population density, I find similar patterns for employment density. As depicted in figure 1.18, and reported in tables 1.4 and 1.6, the effects of hydroelectric dams on population and employment are closely related, but there is a lot of heterogeneity in the impact on different sectors of the economy. In fact, the sectoral decomposition in table 1.7 and figure 1.18 shows construction and trade (trade defined as wholesale plus retail) with the weakest effects, manufacturing and agriculture with intermediate effects, and other sectors with the strongest effects. "Other sectors" consists basically of the nontradable sector of local economies. It includes employment in industries that provide local goods and services such as real estate, cleaning services, legal services, medical services, and personal services.

[14] Differences are shown in columns 5 and 6 of table 1.4.

The patterns of sectoral employment after dam installation seem to make sense. In many hydro projects, dams serve multiple purposes such as navigation, flood control, irrigation and hydropower. So, it is expected that agriculture benefits from them, especially in the West, where agricultural production depends heavily on irrigation. It is also not surprising that construction goes up when dams are being built, and down afterwards. The dynamics of employment in trade is the only puzzling result. In general, it follows the pattern of other industries in the nontradable sector. The strong long-run impact on the nontradable sector might reflect a local multiplier induced by manufacturing growth, which in turn might have been driven by cheap hydroelectricity. Indeed, Hornbeck and Keskin (2012) provide evidence that agricultural production does not appear to generate local economic spillovers. On the other hand, Moretti (2010) finds that, for each additional job in manufacturing in a given city, 1.6 jobs are created in the nontradable sector in the same city. My results indicate a local multiplier of 1.5 five decades after dam completion, very close to Moretti's estimate. Therefore, it is likely that the main mechanism generating agglomeration spillovers is the concentration of manufacturing next to hydropower plants.

Neighboring Counties

Because hydroelectricity seems to be the main driving force of agglomeration, and power could be transmitted to neighboring areas at low cost, even in the first half of the twentieth century, we should see some impact of hydroelectric dams in contiguous counties as well. Figure 1.19 displays the short- and long-term effects of dams in contiguous counties. As expected, they look strong enough: they represent more than half of the effects in the treated counties 10 years after dam completion, nearly a third 50 years after, and roughly a fifth 80 years after. Detailed estimates are presented in table 1.8.

Notice, however, that there is a steep upward trend before dam completion. This might be due to two things. First, my definition of completion refers to the point at which a dam reaches 100 megawatts of capacity. So, it is possible to observe some effects in decades before "completion", especially if hydropower facilities are expanded step-by-step. Indeed, it is common to see a generator being installed in a year, and the next ones years later. Second, during dam construction population might be temporarily or permanently displaced, and then economic activity might flourish in neighboring locations. Upon dam completion, though, people might return to their original counties, flattening the trend.

Smaller Hydro Dams (30-100 Megawatts)

The focus of my analysis is large hydroelectric dams: 100 megawatts or more of capacity. The goal of my study is to estimate the impact of new, independent hydropower plants on the economic activity of local economies. Plants smaller than 100 megawatts were excluded because they tend to be built in connection with existing industrial facilities.

It is interesting, however, to check how the results change when we use these smaller dams as treatment. It can give us some insights about potential nonlinearities of the agglomeration effects. If larger dams induce proportionately larger effects than smaller dams, one might infer that larger interventions are more efficient than smaller ones from the point of view of a social planner.

Table 1.9 reports and figure 1.20 plots the results of my main analysis along with the effects of smaller dams. I estimate the impact of smaller plants using two different groups of controls: (i) original control counties, and (ii) counties with hydropower potential between 30 and 100 megawatts but with no hydroelectric facilities. The analysis with the first control group reveals effects proportionally larger than the difference in average dam size. The average size of smaller dams is a quarter of the average size of larger dams, but the impact of smaller dams is up to half of the impact of larger dams. This suggests the presence of nonlinear agglomeration effects but with direction opposite to that expected. Taken seriously, this would imply diminishing agglomeration returns to investments in hydropower plants. Nevertheless, when I use the second control group, which makes treated and control counties more comparable in the estimation, I find effects proportional to the difference in average dam size. Therefore, larger dams appear not to induce larger agglomeration effects. If anything, potential nonlinearities indicate dispersion forces prevailing against agglomeration.

Tennessee Valley Authority (TVA) versus Non-TVA Counties

As we can see in figure 1.5, many counties treated before 1950 are located in the TVA region. The TVA was one of the most ambitious place-based economic development policies in the history of the U.S. It was created in the 1930s to boost economic activity in the region by investing in large scale infrastructure programs, particularly hydroelectric dams, and in an extensive network of new roads, canals, and flood control systems. Kline and Moretti (2012) conduct an evaluation of the dynamic effects of the TVA on local economies. They find that it led to short-run gains in agricultural employment that were eventually reversed, but impacts on manufacturing employment that continued to intensify well after the program's subsidies had lapsed.

Given that my results mirror the amplifying effects of the TVA, and that in my sample a third of counties with pre-1950 dams are situated in the TVA region, one can argue that my findings are driven by the TVA. One can attribute most of my results to infrastructure projects not related to hydroelectricity. However, as shown in table 1.10 and in figure 1.21, when I estimate the effects of hydro dams without TVA counties, the pattern is very similar to the one with the counties all together. Hence, hydropower may indeed be the main force behind my findings.

All versus No Control Counties with Environmental Regulations

One concern with my impact estimates of hydro dams is that my originally defined control counties may be subject to environmental regulations. If a county has sites suitable for hydroelectric dams, but construction is not allowed by law or by pressure of civil society, population changes in that county may be severely constrained. As a consequence, my estimates would be overestimated[15].

It is true that most of my originally defined control counties - 78 percent - have some kind of land regulation aimed at preserving wilderness and wildlife. However, only two out of 55 would have hydro projects completely forbidden under hydroelectric licensing rules. Being extremely conservative, and eliminating all control counties with some environmental regulations from my analysis, I find no significative changes in my estimates, as shown by figure 1.22 and table 1.11. The number of originally defined control counties, however, decreases considerably.

To make sure that my results are not driven by environmental constraints in my originally defined control counties, I redefine my control group to include every county with hydropower potential above ten megawatts but with no land regulations. Although geographical features of treated and control counties might be less comparable than before, when both groups had 100 megawatts or more of capacity, this procedure increases my sample size substantially - from 55 to 192 control counties. Nevertheless, the new estimates are still within the 95 percent confidence of my main analysis.

Hydroelectric Dams as Big Push?

In order to shed light on the sustainability of the higher steady states reached with dam installation, I construct an empirical agglomeration function. Basically, I compute decadal increments of log population density after treatment for counties treated before 1950, and plot a smoothed version of them against time relative to dam completion. The increments are derived from my short- and long-run estimates, and the smoothing is done with locally weighted regressions (lowess). Figure 1.23 displays the shape of the resulting function: concave until approximately 60 years, and positive flat afterwards. This implies that the rate of population growth decreases as investments depreciate, but not indefinitely. At a certain point, the declines in that rate stop, and population continues growing at a smaller constant rate. Given the high degree of agglomeration spillovers found previously, it is not surprising that local economies tend to keep their higher/better steady states reached with the help/push of large hydro dams.

1.8 Costs of Environmental Regulations

The economic costs of environmental regulations have been widely debated in the U.S. Most of the discussion, however, revolves around pollution restrictions that began more than four decades ago through the Clean Air and Water Acts. Instead, I attempt to shed light on such costs based on hydroelectric licensing rules. I assume that my originally

[15] Even more troublesome would be the fact that regulations have become stricter over time. Nevertheless, this has already been considered in the analysis: my empirical strategy takes into account time-varying unobserved heterogeneity.

defined "control" counties were, in fact, "treated" with land regulations constraining hydroelectric projects. Then, I use the effects of hydro dams to infer how much those counties would have prospered had the regulations not restricted the development of dams. The forgone prosperity is my measure of the costs of environmental regulations.

Land regulations have been long enacted in the U.S. to preserve wilderness and wildlife. They have protected the natural habitat of many threatened/endangered species. At the same time, they have limited the development of new hydroelectric dams, which are renewable, non-emitting sources of energy, and an important force pulling economic activity to a location, as found previously. I use a crucial piece of information from the 1998 U.S. Hydropower Resource Assessment, introduced in section 5, to proceed with my analysis. That report provides a list of all land regulations that reduce the viability of potential hydroelectric sites, as well as the probability of development of each site based on each regulation.

I focus on the regulations meant to preserve wilderness and wildlife, presented in Appendix B. I assume that the regulations in place in the 1990s are informally in effect since the beginning of the twentieth century. In fact, although the designation of wilderness areas became official only with the Wilderness Act of 1964, preservation has been carried out by the National Park Service since its creation in 1916 (U.S. Department of the Interior, 2011). All designated wilderness areas so far are within the National Park System. Wilderness designation has not added or removed land from the parks: it has just ensured they are kept free from permanent improvements or human habitation.

1.8.1 Suitability Factor Determination

A key element of my analysis here is the suitability factor of a potential hydropower site. Such a factor reflects the probability that environmental considerations might make a project site unacceptable, prohibiting its development. Suitability factors were developed by the Idaho National Engineering and Environmental Laboratory (INL), in conjunction with Oak Ridge National Laboratory staff who are experienced in hydropower licensing cases. Five potential values were selected, as shown in table 1.13. (The discussion that follows is heavily based on Conner, Francfort, and Rinehart [1998].)

The crucial step in evaluating the environmental suitability of each project site is to combine the suitability factors for the individual environmental attributes into a single factor for each project site. This overall suitability factor is an estimate of the probability of a project's successful development, considering all the attributes described in Appendix B. The presence of more than one environmental attribute means that more than one environmental concern affects a project. The overall suitability factor should obviously be no greater than the lowest factor for individual attributes, and it should be less than the lowest factor if multiple significant environmental constraints are present. For example, if an undeveloped project has both fish values (suitability factor = 0.25) and wildlife values (suitability factor = 0.25), the cumulative effects of these two concerns will make its overall suitability even less than 0.25, so an overall suitability factor of 0.1 is assigned.

If the environmental suitability factors for individual attributes were truly the probability of the project's being developed, then the overall probability of development could be mathematically calculated. And, if the individual suitability factors were true and independent probabilities, then the probability of developing the project site because of environmental concerns would be equal to the product of all the individual factors. However, the Federal Energy Regulatory Commission's (FERC's) licensing process is not a statistical probability function, and it cannot be assumed that suitability factors can be handled as independent probabilities (for example, there is a strong correlation between the scenic, recreational, and fishing values of a stream). The procedure outlined in table 1.14 is used for assigning overall suitability factors. It was developed by the laboratories mentioned above and assumes that the lowest suitability factor dominates the likelihood of a project's development. However, it also considers the reduced likelihood of development resulting from the occurrence of multiple low suitability factors.

After finding the overall suitability factor for each potential hydropower site, I obtain the probability of development at the county level. First, I weight the potential capacity of each site with its own probability, and sum the weighted capacities over all sites in the county. Then, I divide this weighted sum by the total potential capacity. This quotient is my county suitability factor.

1.8.2 Cost estimates

To obtain an estimate of the costs of environmental regulations, I crucially use the probability that development of hydroelectric projects will not happen, which is one minus the county suitability factor. This probability of non-development is then multiplied by my estimates of the long-run impact of hydro dams. I assume that the potential capacity of each control county in my sample could have been installed before 1950, but part of it was not developed because of the environmental regulations. Recall that I have supposed that such regulations were informally in effect since the first half of the twentieth century. In order to provide a conservative estimate of the costs of those regulations, I further assume that hydropower facilities would have been constructed right before 1950 had the regulations not been in place. Because I compute the costs for 2000, I use the effect of hydro dams 50 years after installation.

The estimate that I focus on in this exercise is the impact of hydro dams on employment density. Hence, the 50-year effect from column 1 of table 1.6 multiplied by the average wage at the county level in 2000, and weighted by the probability of non-development, gives us the forgone earnings of the extra residents per square mile that a large hydropower plant would have attracted. I then multiply this amount by the land area of each county to get a county-specific estimate of the costs induced by environmental regulations. My final estimate is just the sum of the county-specific costs. It is important to mention that, in principle, I could have included the effect of hydro dams on the average value of farmland in my cost estimate, since it reflects gains of landowners. However, as shown in table 1.12, that effect is broadly not statistically significant at conventional levels.

The point estimate of the 50-year effect of dams on employment density implies an estimated cost of \$6.3 billion (dollars of 2000) for all the 55 controls counties in my sample. This represents a loss of approximately 133,541 jobs. Decadalized estimates are \$1.3 billion and 26,708 jobs, respectively. They represent a third of a 55-county decadal equivalent estimate of the effects of air quality regulations on manufacturing plants in the U.S. found in Greenstone, List and Syverson (2012). Therefore, it seems that land regulations associated with preservation of the wilderness and the wildlife also induce sizable costs to regulated entities, but not as large as the costs induced by air quality regulations.

1.9 Concluding Remarks

How much of the geographic clustering of economic activity is attributable to agglomeration spillovers as opposed to natural advantages? I present evidence on this question using data on the long-run effects of large scale hydroelectric dams built in the U.S. over the twentieth century, obtained through a unique comparison between counties with or without dams but with similar hydropower potential. Using a novel combination of synthetic control methods and event-study techniques, I show that, on average, counties with dams built before 1950 have population density increased by approximately 51 percent after 30 years, and 139 percent after 60 years, indicating substantially different short- and long-term effects. This suggests that the assessment of large infrastructure projects does require understanding of long-run effects, as advocated by Kline (2010). On the other hand, counties with dams built after 1950 have no statistically significant effects. I argue that the large difference in the impact of pre- and post-1950 hydro dams can be accounted for by the attenuation of the advantage of cheap electricity in the second half of the twentieth century. Until mid-century, the availability of cheap local power from hydroelectric dams conveyed an important advantage that attracted industry and population. By the 1950s, however, these advantages were weakened by improvements in the efficiency of thermal power generation and the advent of high tension transmission lines.

By using a unique sample of counties with or without hydroelectric dams but with similar hydropower potential, as determined by a team of engineers at the request of the U.S. Department of Energy, I hold natural advantages constant and provide evidence that the persistence and amplification of the dam effects in the long-term is due in great part to agglomeration spillovers. In fact, my lower bound of agglomeration spillovers is up to 45 percent five decades after dam construction, representing almost half of the full effect of hydro dams over the same time span. Interestingly, my short-run estimate of agglomeration externalities is very close to that of Greenstone, Hornbeck and Moretti's (2010). My lower bound nearly a decade after spillovers kick in is around 11.5 percent, while their estimate five years after the opening of a Million Dollar Plant is 12 percent.

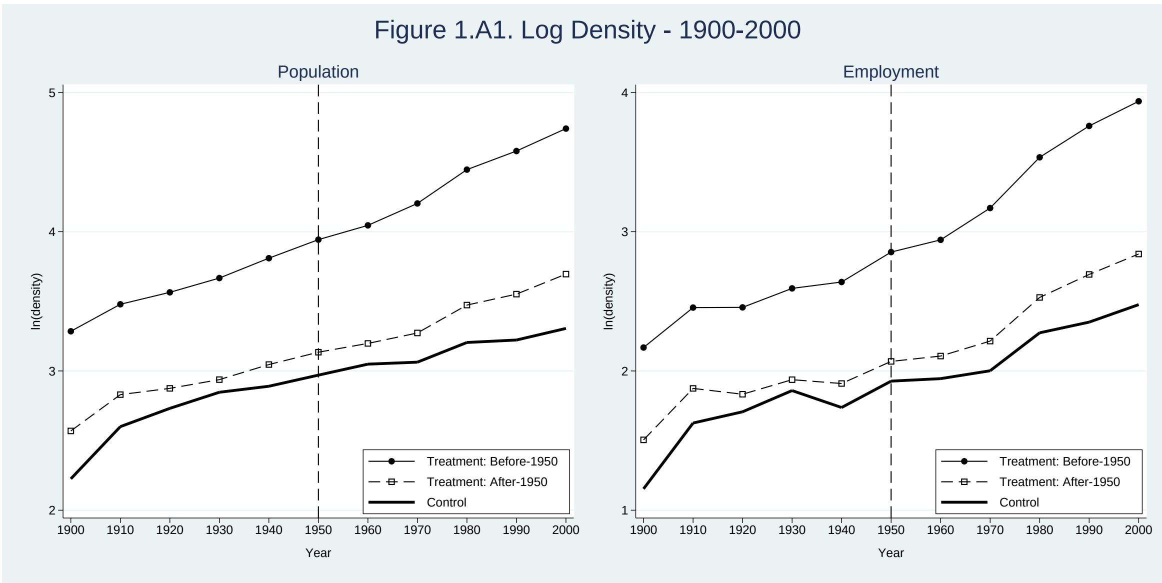
I also find that the estimated short- and long-run effects are highly robust to alternative procedures for selecting synthetic controls, to controls for confounding factors such as proximity to transportation networks, and to alternative sample restrictions, such as dropping dams built by the Tennessee Valley Authority or removing control counties with environmental regulations. I also provide evidence of small local agglomeration effects from smaller dam projects, and small spillovers to nearby locations from large dams.

Given that many counties with hydropower potential but with no hydroelectric facilities could not develop their dam sites because of environmental regulations aiming to preserve wilderness and wildlife, I also use the long-run estimates of hydro dams to obtain a novel estimate of costs of environmental regulations. My estimate turns out to be sizable, but smaller than recent estimates based on air quality regulations. It is \$1.3 billion, or 26,708 jobs, per decade for all the 55 control counties in my sample. This represents a third of a comparable estimate based on the effects of air quality regulations on manufacturing plants in the U.S. found in Greenstone, List and Syverson (2012).

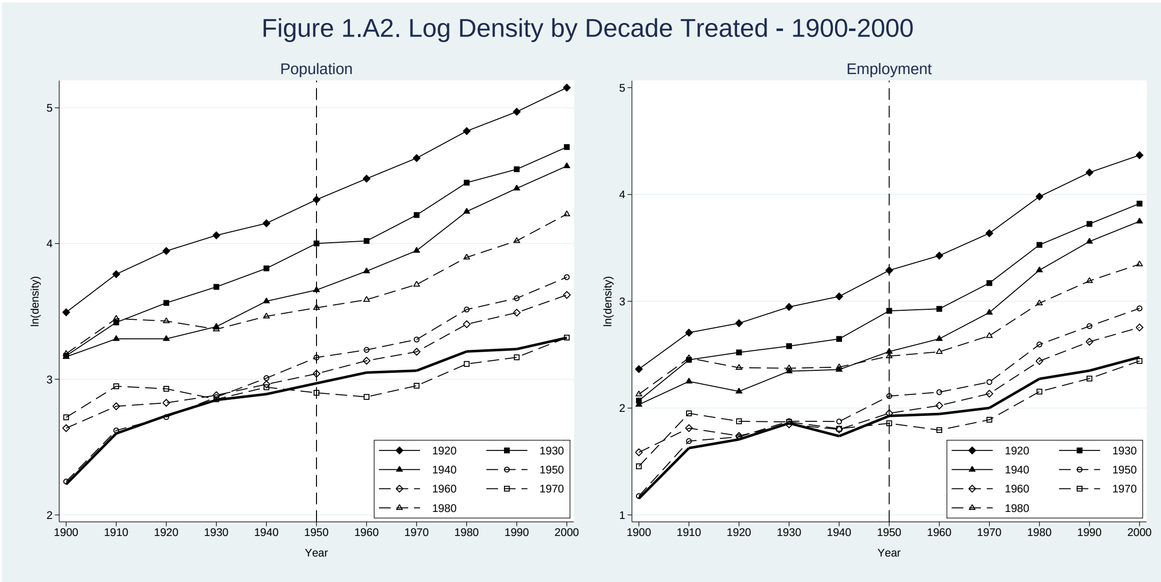
This study opens up the possibility of some other research projects. First, a similar evaluation of short- and long-run impacts can be done with flood control dams. Because the U.S. Army Corps of Engineers has flood maps available for most of the country, a control group can be constructed in the same spirit as this paper. Second, further investigation on the shape of the agglomeration function may be feasible with my database. Given that the eGRID has information of hydro dams of all sizes, and the INL report contains hydropower potential of all possible capacities as well, variation in dam size could be used to identify potential nonlinearities of that function. Third, an analysis of the tradeoff between land conservation regulations and air quality regulations can also be done with my dataset. The eGRID also contains information about air emissions for pollutants such as nitrogen oxides, sulfur dioxide, carbon dioxide, methane, and nitrous oxide. Thus, it is possible to examine whether land regulations that restrict the development of new hydroelectric dams, which are renewable, non-emitting sources of energy, induce electricity generation by highly polluting firms: the conventional fossil-fuel power plants. These are interesting questions for future research.

1.10 Appendix

1.10.1 Appendix A: Trends of Population and Employment



Notes: This figure displays time series of log density of population (panel A) and employment (panel B) throughout the twentieth century. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. In each panel, the solid line with solid circles depicts the dynamics for counties that have hydroelectric dams built before 1950. The dashed line with hollow squares depicts the dynamics for counties that have dams built after 1950. Lastly, the thick solid line shows the dynamics of log density for counties in the control group.



Notes: This figure displays time series of log density of population (panel A) and employment (panel B) throughout the twentieth century. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. In each panel, the solid lines with solid symbols (circles, squares, and triangles) depict the dynamics for counties that have hydroelectric dams built before 1950. The dashed lines with hollow symbols (circles, squares, triangles, and diamonds) depicts the dynamics for counties that have dams built after 1950. Lastly, the thick solid line shows the dynamics of log density for counties in the control group.

1.10.2 Appendix B: Description of Environmental Regulations

The assessment report provides information about a handful of environmental, legal, and institutional attributes associated with land regulations. In my analysis, I use only the ones directly related to preservation of wilderness and wildlife. They are summarized/reproduced below.

Wild/Scenic Protection. This attribute identifies project sites that are included in the federal wild and scenic rivers system, under consideration for inclusion in the federal system, included in a state river protection program, in a designated wilderness area, or protected from development under another program. Relatively few sites have this status, but those that do are highly unlikely to be developed. The suitability factor assigned to all such projects at undeveloped sites is 0.1. It is highly unlikely that a project at an existing dam would be on a wild and scenic river since rivers are usually designated as wild and scenic only if they are free of developments such as dams. A suitability factor of 0.5 is assigned for such unusual cases.

Wild and Scenic Tributary or Upstream or Downstream of a Wild and Scenic Location. This attribute is assigned to a project if it is at the upstream or downstream end of a wild and scenic river reach or is on a tributary of a wild and scenic river. A project at a developed site would affect a downstream wild and scenic river if additional alterations to the flow regime resulted. A suitability factor of 0.75 is assigned for such projects. Projects at undeveloped sites are highly likely to alter the flow regime and may cause changes in downstream water quality, so a suitability factor of 0.5 is assigned to undeveloped sites.

Fish Presence Value. A stream reach may or may not have legally protected fisheries. In either case, however, strong state opposition to new development must be expected if a valuable fishery resource exists. Relatively high instream flow release requirements can mitigate the impact on fisheries, but a high instream flow release would reduce the economic viability of the project. Projects at developed sites could have some impact, such as increased turbine mortality. A suitability factor of 0.75 is assigned to projects at developed sites. Development at undeveloped sites could have a major impact on aquatic habitat through inundation, migration blockage, turbine mortality, water quality, and altered flows. Some of these can be mitigated, but such mitigation could be expensive. A suitability factor of 0.25 is assigned to undeveloped sites.

Wildlife Value. Terrestrial wildlife and wildlife habit are protected by fish and game agencies that are influential in determining mitigation requirements for hydropower projects. Development at existing sites would have little effect on wildlife unless reservoir pool elevations are altered or construction of major facilities is required. A suitability factor of 0.75 is assigned for projects at existing sites. Development at undeveloped sites could inundate wildlife habitat, and construction would cause a great deal of disturbance. It is difficult to mitigate for such impacts, so opposition to such a project could be strong. Undeveloped projects are assigned a suitability factor of 0.25.

Threatened and Endangered Fish or Wildlife. The presence of threatened and endangered species near a project site requires additional consultations with wildlife agencies and can result in additional studies and mitigation requirements. The presence of threatened and endangered fish species may preclude development of new storage projects because new projects can involve the greatest alteration of aquatic habitat. Terrestrial threatened and endangered species are unlikely to be highly affected by run-rivers projects, but storage reservoirs could affect terrestrial habitat. For existing sites, a suitability factor of 0.75 is assigned when threatened and endangered species are present. For projects at undeveloped sites, a suitability factor of 0.5 is assigned when threatened and endangered species are present.

Federal Land Code 104. National Forest or Grassland. These lands are not legally protected from development, but the managing agency has the right to impose additional mitigation requirements on projects. A suitability factor of 0.75 is assigned to projects at existing sites, since these projects typically have fewer impacts. A suitability factor of 0.5 is assigned for undeveloped sites.

Federal Land Code 105. National Wildlife Refuge, Game Preserve, or Fish Hatchery. These lands are managed for fish and wildlife habitats, and hydropower development would almost always be incompatible. A suitability factor of 0.1 is assigned for such projects.

Federal Land Code 106. National Scenic Waterway or Wilderness Area. These lands are legally protected from development. A suitability factor of 0.1 is assigned for such projects.

1.10.3 Appendix C: Synthetic Propensity Score Reweighting

As an alternative to my reweighting-matching strategy, we can use a propensity score reweighting approach with weights from the synthetic control method (Abadie and Gardeazabal, 2003; and Abadie, Diamond and Hainmueller, 2010). I refer to such an approach as the "synthetic propensity score reweighting". If we treat the synthetic control weights as non-random, then we can just average the weights each untreated county gets across the synthetic control estimation of all treated counties and run the event-study analysis by weighted least squares in the full sample, giving each treated county a weight of one. Intuitively, the synthetic control weights provide us with a set of propensity score weights, and we can use them to compute average treatment effects on the treated.

An advantage to this approach over the reweighting-matching strategy is that we can easily cluster for more aggregated levels, such as state, in the estimation of standard errors. In the reweighting-matching case, the "location" of each synthetic control county is a weighted average of all originally defined control counties. On the other hand, in the reweighting-matching strategy we do not have to assume non-random weights in the estimation of standard errors. Each pair of treated and synthetic control counties is allowed to have arbitrary within-pair dependence, including the one arising from the uncertainty in the estimation of the synthetic control. Furthermore, because each synthetic control is matched to its treated county by construction, the comparison between synthetic control and treated counties becomes much more transparent.

In the table C1 below, I compare four sets of estimates: (i) reweighting-matching with standard errors clustered at the case level[16], as in my main analysis; (ii) standard event-study with standard errors clustered at the county level (all treated and control counties are assumed to have weight one); (iii) synthetic propensity score reweighting with standard errors clustered at the county level; and (iv) synthetic propensity score reweighting with standard errors clustered at the state level. As we can see, the synthetic propensity score reweighting estimates are similar to the reweighting-matching ones. Regarding the cluster at the state level versus the county level, observe that there is a loss of power when using the state level but the long run estimates are still statistically significant at conventional levels.

[16]Recall that a case is just a pair of a treated and its corresponding synthetic control county.

Table 1.C1. The Impact of Pre-1950 Hydro Dams on Population Density - Comparison of Methodologies

ln(Pop Density)	TS	TC	TC_SPSR_C	TC_SPSR_S
	(1)	(2)	(3)	(4)
40 years before dam	-0.2428	-0.1441	0.1993	0.1993
	(0.2365)	(0.2740)	(0.2771)	(0.2497)
30 years before dam	-0.2564	-0.1493	-0.0547	-0.0547
	(0.1893)	(0.1941)	(0.2062)	(0.1649)
20 years before dam	-0.1536	-0.1253	-0.0614	-0.0614
	(0.1528)	(0.1740)	(0.1626)	(0.1305)
10 years before dam	-0.0398	-0.0337	-0.0248	-0.0248
	(0.1445)	(0.1544)	(0.1267)	(0.1080)
10 years after dam	0.1103**	0.0652	0.0603	0.0603
	(0.0451)	(0.0461)	(0.0524)	(0.0564)
20 years after dam	0.3063***	0.1574*	0.2146*	0.2146
	(0.0979)	(0.0811)	(0.1120)	(0.1332)
30 years after dam	0.4129***	0.2207**	0.2962**	0.2962
	(0.1131)	(0.0942)	(0.1332)	(0.1749)
40 years after dam	0.6551***	0.4118***	0.5194***	0.5194**
	(0.1408)	(0.1138)	(0.1586)	(0.2000)
50 years after dam	0.7897***	0.5176***	0.6693***	0.6693***
	(0.1681)	(0.1293)	(0.1840)	(0.2177)
60 years after dam	0.8699***	0.6036***	0.7835***	0.7835***
	(0.2047)	(0.1514)	(0.2179)	(0.2494)
70 years after dam	0.9584***	0.6026***	0.8759***	0.8759***
	(0.2454)	(0.1663)	(0.2663)	(0.2964)
80 years after dam	1.0494***	0.6448***	0.9246***	0.9246**
	(0.3052)	(0.2094)	(0.3382)	(0.3611)
Observations	660	935	935	935
R-squared	0.9837	0.9781	0.9836	0.9836

Notes: This table presents the short- and long-run effects of pre-1950 hydroelectric dams on population density. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, and "SPSR" synthetic propensity score reweighting. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In column 1, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In columns 2 and 3, they are clustered at the county level ("C"). In column 4, they are clustered at the state level ("S"). "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Chapter 2

Who to Marry and Where to Live: Estimating a Collective Marriage Market Model

2.1 Introduction

Since Mincer (1978)'s seminal work on family migration, many researchers have studied the implications of the location choices made by couples. A key reason for such long-lasting interest is the enormous increase in female labor participation over the past four decades, which has made the dual-career concerns associated with locational choices more salient. Another important reason is Mincer's insight that family mobility may reinforce observed differences in labor market outcomes of men and women. Curiously, though, few studies treat the household as a collection of agents rather than a single unit, and deal with spousal bargaining behind locational decisions [e.g., Costa and Kahn (2000), Lundberg and Pollak (2003), and Gemici (2011)]. Even more surprising, very few studies try to link locational and marital choices [e.g., Compton and Pollak (2007)]. As shown in table 2.1, however, the locational choices of couples who are born in the same state are quite different from those who are not. Marrying someone from another state substantially reduces the probability that a man or a woman will live in their own state of birth. In this paper, I develop a framework to study the joint spouse/location choices in the presence of intra-household transfers and of both observable and unobservable preferences for location. Secondly, I develop a simple test to check if in equilibrium spouses can commit to *ex-ante* Pareto-efficient household decisions associated with those choices. Thirdly, I analyze potential implications of (no-)commitment on the observed migration behavior of married individuals.

My theoretical framework is, essentially, a *collective marriage market model.* It combines Chiappori's (1988, 1992) collective approach to modelling households with Choo and Siow's (2006) matching model of the marriage market, and Choo, Seitz and Siow's (2008a, 2008b) model of the determination of the individual share of household resources in the equilibrium of the marriage market. I assume that in the marriage market potential spouses anticipate utilities from the choice of spouse and location that reflect the payoffs from a collective household allocation model. As a result, such framework allows me to test full commitment in intra-household allocations associated with spouse/location arrangement choices. Indeed, it makes it possible to investigate if the sharing rule that rationalizes the *ex-post* equilibrium in the model is identical to the one that would rationalize the *ex-ante* Pareto-efficient equilibrium. I borrow the idea for this test from Mazzocco's (2007) test of full commitment in household intertemporal behavior. His basic insight is that, if family members can commit formally or informally to future plans, only the individual decision power at the time of household formation affects household decisions. By contrast, in the absence of commitment, such decisions depend on the decision power in each period. My similar idea here is that, under full commitment, only a sufficient statistic representing the earnings potential in all arrangements (e.g., the mean) is relevant to the determination of the sharing rule within the household. Under limited commitment, on the other hand, arrangement-specific deviations from that mean also affect the sharing rule. That is, the earnings potential of the particular arrangement the individual is in also influences the share of resources he/she can get within the household.

To implement my theoretical framework empirically, I assume a functional form for the individual indirect utility, and I estimate its key parameters through standard discrete choice techniques originally developed by McFadden (1974). However, before estimating my parameters of interest, I must overcome an important data-driven obstacle. While spouses observe the preferences of each other regarding marriage and locations, researchers do not so. To get over the potentially serious selection problem in spouse/location arrangement choices arising from the unobservability of preferences, I extend Olley and Pakes's (1996) control function approach to a two-dimensional setting. I show that conditional on observed covariates there is a one-to-one relationship between the observed labor supply choices of the two spouses and the unobserved preference variables of the two spouses. Then, I use a function of labor supplies plus covariates to control for unobserved preferences.

I estimate the parameters of the individual indirect utility in three steps. Noticing that wage, non-labor income, and labor supply are observed only in the arrangement that individuals have chosen, in my first step I predict these variables for all arrangements using a novel approach to control for self-selection. I estimate outcome equations using a selection-correction term that is a functional of a parametric function arising from the multinomial logit structure. Basically, I estimate conditional choice probabilities for all arrangements using a nonparametric sieve logit method [see Bajari, Hong and Nekipelov (2010)], assuming that spouse's state of birth and individual's and spouse's preferences for locations are excluded from the outcome equations. Based on the relationship between unobserved preferences and observed labor supplies mentioned above, I implement such estimation using labor supplies. Then, I estimate the outcome equations semiparametrically using a power series approximation for the selection-correction term [Newey (2009)]. This correction term ends up depending on a simple parametric function, whose arguments are the predicted conditional choice probabilities. Although derived in such a different manner, this selection-correction term turns out to be very similar to Dahl's (2002).

With predicted wage, labor supply and non-labor income in hand, I proceed to the estimation of the parameters of the indirect utility function using a non-linear conditional logit. Following Olley and Pakes's (1996), in my second step I replace the unobserved preference terms of both spouses with a function of labor supply of both spouses plus covariates. This procedure makes the coefficients of many variables to reflect not only their own effect on the arrangement choice, but also part of the impact of unobserved preferences on that choice. Since the main variable of interest - the share of the earnings potential - is among those covariates, in my third step I develop an instrumental variable approach to isolate its own effect from its impact through unobserved preferences. Basically, I rearrange the non-linear conditional logit probabilities and generate new estimable equations which have only the covariates with biased coefficients in the R.H.S. It turns out that the only endogeneity left in those equations comes from the correlation between three variables - wage, share of earnings potential, and non-labor income - with labor supplies, which are the only elements of the control function representing unobserved preferences that are excluded from the R.H.S. of such equations. Then, I construct instruments for those three variables by regressing each of them on labor supply of both spouses, and taking the residuals. Such technique ends up being an extension to cross-sections of the Hausman and Taylor's (1981) approach to generate instruments for endogenous variables in panel data settings.

I implement my three-step methodology using the 2000 Census data. My sample includes only U.S.-born, white, non-hispanic, heterosexual couples, with both spouses 20-35 years old, not attending school anymore, working, and present in households of only one family. Estimation results lead to three main findings. First, there seems to be no full commitment in intra-household decisions associated with broad locational choices. Arrangement-specific deviations from the sharing rule that incorporates information of all arrangements do appear to affect allocations within the household. The following might be happening: at the outset of the marriage, spouses agree to a place of residence and a rule to split the household resources regardless of the place they eventually live. That rule is supposed to reflect their potential bargaining positions in all outside options. Yet, upon settling down in the selected location, they let such rule change because of the particularities of the local labor market. Second, limited commitment related to locational decisions tends to be deleterious to females. Indeed, women have higher probability to live in arrangements where their share of the couple's earnings potential is smaller. Consequently, they end up getting a smaller portion of the household resources. Third, those commitment issues seem to inhibit couple migration considerably. They can actually explain all the difference between migration rates of single and married individuals observed in U.S. data.

This paper is organized as follows. In Section 2.2, I discuss the literature associated with my study. In Section 2.3, I introduce my theoretical framework: a collective marriage market model. In Section 2.4, I present my empirical strategy, which is a three-step procedure aimed to take into account all the information that spouses use in their decision process. In Section 2.5, I proceed to the presentation of my sample, and in Section 2.6, I report my results. Finally, in Section 2.7, I present some concluding remarks.

2.2 Related Literature

The present paper is related to at least four branches of the economic literature: family migration, commitment in household behavior, interdependence between intra-household allocations and marriage-market conditions, and matching models of marriage. Starting with family migration, the seminal contribution is Mincer (1978), as mentioned before. In such original work, Mincer treats households as single agents making a lifetime decision of where to settle down. He then advances the idea that family ties represent negative "personal" externalities which are not always internalized within the household. He argues that such ties tend (i) to deter migration, (ii) to reduce employment and earnings of migrating wives, who are generally tied spouses in the households, (iii) to increase the employment and earnings of their husbands, and (iv) to contribute to marital instability. In addition, he points out that tied migration can adversely affect women's wage growth even in the absence of after-moving unemployment spells. In his own words, *"tied migration ranks next to child rearing as an important dampening influence in the life-cycle wage evolution of women"* (p.771). The large literature following Mincer's influential insights just provide empirical evidence corroborating his main theoretical predictions. Despite of describing the implications of family mobility in many details, unfortunately most of the evidence suffers with the biases originating from self-selection. Furthermore, most of the papers disregard the family aspect of migration by treating households as single units rather than groups of agents. A notable exception is Gemici (2011).

Gemici (2011) models household migration decisions in a dynamic framework with intra-household bargaining. She assesses the implications of joint location constraints on migration patterns, labor market outcomes, and marital stability of men and women. Her results depict a rich portrait of how family ties related to migration decisions affect mobility, wage growth, and marital stability[1]. Nevertheless, her model excludes an important decision that my model incorporates: the marriage decision. Since rational agents antecipate the joint location constraints they might face within marriage, there might be some effects of location ties on the timing of marriage and sorting patterns that her model does not capture. In this study, I consider the sorting patterns explicitly, but I still ignore timing-of-marriage issues. And last but not least, my framework also differs from Gemici's in a crucial aspect: it allows each spouse to have his/her own home location. In her general model, Gemici defines home as being just an attractive

[1]Without family ties 25 percent of men and 23 percent of women move, whereas when married only 18 percent move. Without family ties men's and women's wages are 10 and 3 percent higher, respectively, compared to when they are married. Finally, without location ties divorce rates fall from 24 to 16 percent.

location that gives the couple a higher utility. In her empirical implementation using data from the Panel Study of Income Dynamics (PSID), she strongly assumes that, for both spouses, home is the place (Census Division) where the head of the household grew up. This assumption clearly rules out spousal compensations associated with family migration, which is in the heart of my research questions.

Other studies that consider location decisions of two-earner couples are Costa and Kahn (2000) and its "companion" Compton and Pollak (2007). These papers try to explain the mechanisms behind the increased concentration of the so-called "power couples", couples whose both spouses have college education, in large metropolitan areas[2]. Costa and Kahn (2000) advance the idea that such change in the locational choice of the college educated emerges from the growth of dual career households and the consequent severity of the "colocation problem", defined as the difficulty of finding two jobs commensurate with the skills of each spouse within a reasonable commute from home. Implicitly, those authors are arguing that, because of their diversified labor markets, large metropolitan areas offer dual career households an opportunity to preserve their marriages and to reduce the degree to which both husband and wife must compromise in their individual gains from marriage. If at all true, such explanation would be consistent with power couples being more likely to migrate to the largest cities than part-power couples or power singles. However, when testing such Costa and Kahn's colocation hypothesis using data from the PSID, Compton and Pollak (2007) find no support for their hypothesis. Instead, they provide evidence that observed location trends are better explained by higher rates of power couple formation in larger metropolitan areas. In light of this result, it is encouraging that my framework focuses on understanding sorting patterns on the basis of location in the marriage market.

Now, let us move to the second area that the present study is associated with: the commitment in household behavior. The first paper worth mentioning is Lundberg and Pollak (2003), which investigates the efficiency of bargaining in family migration decisions under limited commitment. Such authors argue that current location decisions affect future bargaining power, and, consequently, inefficient outcomes are plausible. Their theory shows that if spouses could make binding commitments - commitments to refrain from exploiting the future bargaining advantage -, then the inefficiency would disappear. Discussing some anecdotal evidence, they claim that spouses can seldom make such binding commitments in modern societies. My study, on the other hand, tests the household ability to commit to future plans in location decisions.

Lich-Tyler (2004) also examines the plausability of household commitment. He presents three different models of intertemporal household bargained decisions: a repeated static collective model, a model with commitment, and a model without commitment. He derives a unique modified Euler equation for each model, and then uses such competing specifications to determine which procedure, if any, accurately describes household behavior in the PSID. He shows that, except for newlyweds and couples with

[2]Indeed, using data from the U.S. censuses, Costa and Kahn (2000) show that in 1970, 39 percent of such couples lived in metropolitan areas with a population of at least 2 million. In 1990, this number had jumped to 50 percent.

many children, few households seem to commit to bargained decisions. For some, marriage appears to be a repeated game: each year's decision is made on its own, with no regard for the future, as if agents know that they can easily change partners. For others, especially households with children, multi-period household bargaining problems are solved by backwards induction, knowing that renegotiations can and will occur. Despite advancing interesting ideas, Lich-Tyler does not provide a test of household commitment. Mazzocco (2007), in the most important paper of this literature, does derive and perform a formal test of intra-household commitment in intertemporal behavior. He shows that the full-efficiency household Euler equations are nested in the no-commitment Euler equations. Using this result, he tests the full commitment hypothesis using data from the Consumer Expenditure Survey, and strongly rejects it. As discussed previously, apart from its static characterization, my test of full commitment in location decisions follows Mazzocco's insights.

Another topic that my paper is closely related to is the interdependence between intra-household allocations and marriage market conditions. The study of intra-household allocations begins with, among others, Becker (1973, 1974; summarized in 1991), the bargaining models of Manser and Brown (1980) and McElroy and Horney (1981), McElroy (1990), and the collective model of Chiappori (1988, 1992). The study of the relationship between marriage market conditions and marriage rates is also pioneered by Becker (1973). Moving towards integration, Grossbard-Schectman (1984) builds a model where marriage market conditions affect the bargaining power within the household. One important implication is that improvement in the marriage market conditions for women translates into greater allocation of household resources towards them. Such implication has received extensive empirical support in the literature [e.g., Grossbard-Schectman (1984), and Chiappori, Fortin and Lacroix (2002)]. More recently, researchers have formally integrated the collective model and the marriage market [e.g., Choo, Seitz and Siow (2008a, 2008b)] and have extended the integrated model to consider pre-marital investiments [e.g., Iyigun and Walsh (2007)]. In all of these recent papers, the sharing rule arises endogenously in the marriage market. My approach is associated with Iyigun and Walsh's (2007) in the sense that it also considers pre-marital attributes in the determination of the bargaining power. However, my emphasis is on birthplace, an attribute not chosen by the individuals. Now, the paper I am mostly indebted here is Choo, Seitz and Siow (2008a, 2008b): my framework depends heavily from theirs. Choo, Seitz and Siow (2008a, 2008b) develop and estimate an empirical collective model with endogenous marriage formation, participation, and family labor supply. By introducing the marriage market in the collective model, they are able to independently estimate transfers from labor suplies and from marriage decisions. Using 2000 U.S. Census data, they then find that estimates of the model using marriage data are more consistent with the theoretical predictions than estimates derived from labor supply. In light of these results, my approach goes in the right direction by modelling spouse/location choices along with intra-household decisions.

Lastly, the present study relates to the literature dealing with matching models of marriage. Since the seminal contribution of Becker (1973), economists have modeled marriage markets as a matching problem in which each potential match generates a marital surplus. As is well-known, if the types of the partners are one-dimensional and are complementary in producing surplus, then the socially optimal matches exhibit positive assortative matching. While this result is both simple and powerful, it is at odds with the imperfect assortative matching observed in the data. Therefore, researchers have long felt the need to accomodate such imperfect matching. Shimer and Smith (2000) introduce search frictions, but their model is hard to handle empirically. Choo and Siow (2006), on the other hand, propose a simpler solution: to allow the joint surplus of a match to incorporate heterogeneity that is unobserved by the analyst. Such pioneer study has influenced more theoretical and empirical work since then. Chiappori, Salanie and Weiss (2010), for example, extend Choo and Siow's approach to study partner choice and the marital college premium. Galichon and Salanie (2010, 2011) enrich Choo and Siow's framework to study identification in matching models more generally, and to analyze matching with competing characteristics. As will be clear next section, I take great advantage of Choo and Siow's and these new insights.

2.3 Modelling Marriage/Migration Decisions: Guidance to Empirical Analysis

In this study, I model the individual decision of spouse/location arrangement. My ultimate goals are (i) to test full commitment in household decisions in the context of spouse/location arrangement choice, (ii) to provide evidence of transfers between spouses arising from that choice, and (iii) to examine some implications of commitment issues on the observed migration behavior of married individuals. To elucidate the mechanisms behind those spousal transfers, I develop a collective marriage market model based on Chiappori (1988, 1992), Chiappori, Fortin and Lacroix (2002), Choo and Siow (2006), and Choo, Seitz and Siow (2008a, 2008b).

To explain the idea of my model intuitively, I use figure 2.1. First notice that when individual are searching for spouses, in knot A, they consider people from their home state, defined here as the state of birth (SOB), or other states. If they cope with potential partners from their birth state, at knot B they have to jointly decide if they live there or elsewhere. If they become involved with someone from other state, at knot C they have three options regarding place of residence: their SOB, their spouse's SOB, or a third state. As a result, the choice set has five possible arrangements:

(1) to marry someone from SOB and to live there,
(2) to marry someone from SOB and to live in other state,
(3) to marry someone from other state and to live in SOB,
(4) to marry someone from other state and to live in spouse's SOB,
(5) to marry someone from other state and to live in a third state (neither spouse's SOB).

Each arrangement a is associated with a sharing rule $\phi_a \equiv \phi(S_a, Y_a | Z_a, Q_a, \eta_a)$. S denotes share of earnings potential within the household, and Y couple non-labor income. Z represents observable preference shifters such as education, age, and SOB of both spouses, as well as rent and amenities of each arrangement. Q represents distribution factors - variables that affect the division of resources inside the household, but not shift individual preferences - such as sex ratio and divorce laws. Last but not least, η represents individual preferences which are observed by both spouses, but not by the researchers.

The sharing rules are determined in the equilibrium of the marriage market. Given their definition, it is then possible to observe transfers between spouses in equilibrium. For instance, we might see individuals living in locations really appreciated by their spouses but with a large advantage in terms of earnings potential. Indeed, it is very likely that spousal transfers arise from the trade-off between taste for "hometown" kinships and earnings. Assuming that individuals have good information of relevant variables in all arrangements, those negotiations might be based on the best share of earnings potential, and then there might be only one sharing rule for all arrangements: $\phi_a = \overline{\phi}$ for all a. Now, if agents abide by those agreements, i.e., commit to those decisions, then arrangement-specific deviations from $\overline{\phi}$ do not affect arrangement choices in equilibrium. If we do observe such effect, then it might be an evidence of lack of commitment in the household behavior.

2.3.1 Collective marriage market model

To start setting things up formally, I consider a society where all agents get married and work, and have *perfect foresight*. Each person is supposed to decide whom to marry and where to live, and within a spouse/location arrangement, how much to consume and work. Although this is a simultaneous model of intra-household allocations and marriage matching, it is convenient to discuss it as if decisions are made in two stages. In the first stage, individuals make partner/place of residence tied decisions, knowing wages and non-labor incomes for each alternative. In the second stage, within a spouse/location choice, they choose household labor supplies and consumption allocations to realize the indirect utilities which were anticipated by their first stage choices. I now begin by discussing the second-stage intra-household decisions. Notice that I will be using the terms man/woman or husband/wife to refer to spouses in the discussion below. I do that because I focus on heterosexual couples in the empirical part of this study.

2.3.1.1 Collective model of intra-household allocations

Assume the (second-stage) intra-household allocation process is described by the familiar Chiappori's (1988, 1992) collective model. That is, suppose agents are characterized by their own preferences, and household decisions are Pareto efficient. Even though it seems natural to employ such assumption in the context of spouse/location arrangement choices, it has been rarely used in the family migration literature, as I mentioned in the introduction. In my framework, it is crucial. Indeed, in order to examine transfers between spouses and test full commitment in household behavior, it is imperative that each spouse have his/her own utility function. In addition, it is somewhat realistic that the household decision-making process is cooperative, at least conditional on an arrangement choice.

Now, under the the collective model, the problem facing a couple is to choose a level of consumption and labor supply for each spouse. As the household is assumed to make conditionally Pareto-efficient decisions, for any (W_a^m, W_a^f, Y_a), there exists some $\overline{U}^m$ such that $(C_a^f, H_a^f, C_a^m, H_a^m)$ is the solution to the programme

$$\max_{\{C_a^f, H_a^f, C_a^m, H_a^m\}} U^f(C_a^f, 1 - H_a^f) \tag{2.1}$$

$$\text{subject to } \begin{cases} U^m(C_a^m, 1 - H_a^m) \geq \overline{U}^m \\ \text{and} \\ C_a^m + C_a^f \leq W_a^m H_a^m + W_a^f H_a^f + Y_a, \end{cases}$$

where$U$ represents utility, W wage, Y household non-labor income, C consumption, and H hours of work. In addition, the superscripts m and f distinguish between male and female variables, respectively. Also, U^f and U^m are assumed to have diminishing marginal utilities in consumption and leisure. Finally, the function $\overline{U}^m$ defines the level of utility that a husband can command conditional on all the exogenous variables. Indeed, besides wages and non-labor income, $\overline{U}^m$ might also depend on observed and unobserved attributes of both spouses, and on distributions factors (sex ratios and divorce laws, for example, as in Chiappori, Fortin and Lacroix (2002)).

Underlying the determination of $\overline{U}^m$ there is some mechanism (such as a bargaining model) that leads to Pareto-efficient allocations. I will not be explicit about it: the collective model does not rely on specific assumptions on the precise way couples share household resources. However, the ideas behind the bargaining context can help to understand which wages and non-labor incomes might be included in $\overline{U}^m$. Since couples make consumption-leisure decisions within one arrangement, but have knowledge of relevant exogenous variables of all other arrangements, the threat point might depend on wages and non-labor income in other arrangements as well. The exact wages contained in $\overline{U}^m$, though, depend ultimately on the degree of commitment of the household in the allocation of resources, as will be discussed later on.

A seminal insight of Chiappori (1988, 1992) is that, if household decisions are Pareto efficient, the above program can be decentralized into each spouse solving an individual maximization problem with their own shadow budget constraint. A wife acts as if she was facing a shadow budget constraint characterized by her earnings and a *lump sum transfer* or *sharing rule,* denoted by ϕ_a^f, which depends on the same variables as $\overline{U}^m$. Likewise, a husband acts as if he was facing a shadow budget constraint characterized by his earnings and household nonlabor income net of the transfer, $\phi_a^m \equiv Y_a - \phi_a^f$. *Notice that the sharing rule is the fundamental element driving intra-household allocations in this model. Even more, it is the element that generates spousal transfers in this framework.* Observe also that such sharing rule is treated as pre-determined at the point consumption and labor supply allocations are chosen. The large literature on collective models is, with few exceptions, agnostic regarding its origins. In this basic model, it will emerge from the market clearing in the marriage market.

Having said that, the decentralized problem for husbands in this second stage is

$$M_a \equiv \max_{\{C_a^m, H_a^m\}} U^m(C_a^m, 1 - H_a^m)$$
$$\text{subject to } C_a^m \leq W_a^m H_a^m + \phi_a^m,$$

which gives us

$$\begin{aligned} H_a^{m*} &\equiv h^m(W_a^m, \phi_a^m), \\ C_a^{m*} &\equiv c^m(W_a^m, \phi_a^m), \end{aligned} \tag{2.2}$$

where h and c denote Marshallian labor supply and Marshallian consumption functions, respectively.

Similarly for wives,

$$F_a \equiv \max_{\{C_a^f, H_a^f\}} U^f(C_a^f, 1 - H_a^f)$$
$$\text{subject to } C_a^f \leq W_a^f H_a^f + \phi_a^f,$$

which gives us

$$\begin{aligned} H_a^{f*} &\equiv h^f(W_a^f, \phi_a^f), \\ C_a^{f*} &\equiv c^f(W_a^f, \phi_a^f). \end{aligned} \tag{2.3}$$

As a result, the indirect utility of each spouse in the second stage, M_a and F_a, must be a function of the variables $(W_a^m, W_a^f, Y_a, \phi_a^f)$.

As a last remark, observe that the utility functions considered in the household programme (2.1) are defined over consumption and leisure only. They simplify the exposition of the model and are standard in collective models since Chiappori (1988, 1992), but they imply that consumption and labor supply are the only variables that matter in intra-household allocations. Consequently, other potential dimensions that couples could consider in household allocations, such as commuting time[3] and time

[3]Indeed, Black, Kolesnikova and Taylor (2010) provide empirical evidence that labor force participation rates of married women are negatively correlated with the MSA commuting time. In particular, they show that a 10-minute increase in an MSA's commute time is associated with an approximately 3% decline in the labor force participation of women with a high school education.

devoted to home production[4], are ruled out. They could be easily included in the analysis, yet for the sake of simplicity and/or data unavailability I do not incorporate them here.

2.3.1.2 Marriage market

Having discussed the household decision-making process conditional on spouse/location arrangement choices, I now turn to the marriage matching process. I consider a simplified version of the Choo, Seitz and Siow's (2008a, 2008b) nontransferable utility (NTU) model of the marriage market, which is a generalization of the influential transferable utility (TU) model of Choo and Siow (2006). I use an NTU model because the TU assumption is not suitable for studying the impact of spousal transfers on household outcomes. As shown by Chiappori (2009), TU implies that households behave as single agents, and that redistribution among spouses cannot alter household aggregate behavior[5]. Besides NTU, which here means U^f and U^m having diminishing marginal utilities in consumption, I assume that there is only one type of man and one type of woman in the society, and that each individual chooses one out of the five possible arrangements mentioned previously. I also assume that the number of men is identical to the number of women in the society, and each man must be matched with one and only one woman. As in Choo and Siow (2006), matching here is frictionless, and there is no asymmetric information.

In this framework, when a man i marries a woman of arrangement a, he agrees to divide household resources according to a sharing rule ϕ_a, formally defined as the amount of household non-labor income gotten by the woman, as discussed above. *This is the kind of spousal transfer I am interested in.* The marriage market clears when, given equilibrium sharing rules ϕ_a, the demand for men of arrangement a is equal to the supply of women of that same arrangement, for all $a \in \{1, ..., A = 5\}$. Following Choo and Siow (2006), I adopt the extreme-value (logit) random utility model of McFadden (1974) to generate market demands for marriage partners.

Starting with the specification of preferences, the utility of a man i marrying any woman of arrangement a is assumed to

$$V_{ia} = M_a + \Gamma_a + \varepsilon_{ia}. \tag{2.4}$$

$M_a \equiv M(\phi_a)$ represents the return to arrangement a that emerges from intra-household consumption and leisure allocations. As formally defined last section, it is the indirect utility originating from the second-stage collective setting. Γ_a represents invariant gains to arrangement a associated with sources separable from intra-household allocations, such as social status and companionship. Choo, Seitz and Siow (2008a,

[4] In fact, gender disparity in family and household responsabilities have reduced over time but are still in play. Lundberg and Pollak (2007) document that in the 2005 American Time Use Survey, married women have an average of 16 hours per week of "household activities" compared to less than 11 hours for men.

[5] In Appendix A, I discuss why redistribution affects household behavior under the NTU assumption.

2008b) point out that such term allows the model to fit the observed marriage matching patterns in the data. Lastly, ε_{ia} is an independently and identically distributed random variable with a type I extreme-value distribution. Importantly, ε_{ia} is individual-specific but it does not depend on the particular identity of the spouse. That is, it is assumed that an individual treats all potential spouses of the same arrangement as perfect substitutes, as in Choo and Siow (2006). Although clearly restrictive, such indifference assumption makes it possible to use price taking behavior (equilibrium sharing rules) to clear the marriage market. Chiappori, Salanie and Weiss (2010) call this crucial assumption "separability", for the reasons discussed at the end of this section.

Now, man i chooses arrangement according to

$$V_i = \max\{V_{i1}, ..., V_{i5}\}. \tag{2.5}$$

Assuming that the number of men and women in the society is large, and letting μ_a^d be the number of arrangement-a marriages demanded by men, then following McFadden (1974) the demand equation for arrangement-a marriages can be written as

$$\begin{aligned} \ln\mu_a^d &= \ln\mu_1^d + (M_a - M_1) + (\Gamma_a - \Gamma_1) \\ &= \ln\mu_1^d + \widetilde{M}(\phi_a) + \widetilde{\Gamma}_a. \end{aligned} \tag{2.6}$$

Similarly, the utility of a woman j who marries a man of arrangement a can be written as

$$V_{ja} = F_a + \tau_a + \varepsilon_{ja}, \tag{2.7}$$

where $F_a \equiv F(\phi_a)$. From it, we can write the supply of women for arrangement-a marriages as

$$\begin{aligned} \ln\mu_a^s &= \ln\mu_1^s + (F_a - F_1) + (\tau_a - \tau_1) \\ &= \ln\mu_1^s + \widetilde{F}(\phi_a) + \widetilde{\tau}_a. \end{aligned} \tag{2.8}$$

The marriage market clears when, given equilibrium sharing rules ϕ_a, demand and supply of spouses are equal for all arrangements. That is, for all a, $\mu_a^d = \mu_a^s = \mu_a$. Substituting this into equations (2.6) and (2.8) and adding the two equations yields

$$\ln\left(\frac{\mu_a}{\mu_1}\right) = \frac{\left[\widetilde{M}(\phi_a) + \widetilde{F}(\phi_a)\right] + \left[\widetilde{\Gamma}_a + \widetilde{\tau}_a\right]}{2} \equiv \pi_a. \tag{2.9}$$

This equation is called the marriage matching function and is the equilibrium condition in the marriage market. Indeed, Choo, Seitz and Siow (2008a, 2008b) prove that such equilibrium exists. Now, equation (2.25) makes it clear two key implications. The first is Choo and Siow's (2006) main result: the observed marriage patterns μ directly identify the total gains to marriage π in such a model. The second is Choo, Seitz and Siow's (2008a, 2008b) main insight: the sharing rule ϕ_a can be derived from the marriage market clearing, upon assuming functional forms for M and F. Therefore, to sum up, in equilibrium individuals choose spouse/location optimally, the sharing rules clear the marriage market, and conditional on the sharing rules, agents choose consumption and labor supply optimally.

As promised, I now discuss some implications of a crucial assumption in Choo and Siow's (2006) model: that the utility of man i who marries a woman of arrangement a does not depend on who this woman really is, with a similar assumption for women. As already mentioned, Chiappori, Salanie and Weiss (2010) call this assumption "separability". Given its relevance, I state it here, adapting it from Galichon and Salanie (2011).

Assumption S (Separability). Let Θ_{ija} denote the joint surplus created by a match between a man i and a woman j in arrangement a. If two men i and i' are both in arrangement a, and two women j and j' are also both in arrangement a, then

$$\Theta_{ija} + \Theta_{i'j'a} = \Theta_{ij'a} + \Theta_{i'ja}.$$

Under this assumption, Θ_{ija} must decompose into

$$\Theta_{ija} = 2\pi_a + \varepsilon_{ia} + \varepsilon_{ja},$$

which does not include the term ε_{ija}, a matching-specific component of unobserved heterogeneity. Therefore, as pointed out by Galichon and Salanie (2011), "*[t]his assumption rules out interactions between unobserved characteristics in the marital output from a match, given the observed characteristics of both partners. On the other hand, it does not restrict group preferences in any way; and it also allows for variation in marital output within groups, as long as they do not interact across partners. For instance, men of a given group may differ in the marital outputs they can form, but only as relates to the group of their partner.*" (p.5). Finally, it simplifies the analysis enormously. Chiappori, Salanie and Weiss (2010) have shown that given such assumption, the matching problem boils down to a set of single-agent choice problems for each type of man and of woman.

2.3.1.3 Testing full commitment in household decisions

To test full commitment in the household behavior, I rely on the sensitivity of the sharing rule ϕ_a^f to variation in arrangement-specific exogenous variables. Under the assumption of perfect-foresight agents, if there is *full commitment*, i.e., if there is *ex-ante* efficiency in household decisions, then the outside-option utility $\overline{U}^m$ in the household problem (2.1) is the same for all arrangements and is a function of wages of both spouses and couple non-labor income of all arrangements. Since the sharing rule depends on the same variables as $\overline{U}^m$, it is also constant across arrangements and also reflects the realization of the exogenous variables of all possible arrangements. Hence, $\phi^f = \overline{\phi}^f \equiv \phi(W_a^m, W_{(-a)}^m, W_a^f, W_{(-a)}^f, Y_a, Y_{(-a)})$, with $(-a)$ representing all other arrangements. On the other hand, if there is *no full commitment*, then $\overline{U}^m$ varies with arrangement and is a function of wages of both spouses and couple non-labor income of only arrangement

a. As a result, $\phi^f = \phi^{fa} \equiv \phi(W_a^m, W_a^f, Y_a)$. In order to generate a direct test of full versus limited commitment, I nest the former into the latter by decomposing the arrangement-specific sharing rule ϕ^{af} in the following way:

$$\begin{aligned}\phi^{af} &= (\phi^{af} - \overline{\phi}^f) + \overline{\phi}^f \\ &= \widetilde{\phi}^{af} + \overline{\phi}^f.\end{aligned}$$

As a consequence, my test of full commitment is the test of the importance of $\widetilde{\phi}^{af}$ in the determination of intra-household allocations. In principle, this test is very similar to Mazzocco's (2007). Indeed, he tests full commitment in the intertemporal behavior of households by assessing how the realization of distribution factors in a given year affects intra-household allocations in that same period. Recall that distribution factor is a variable that affects exclusively the decision power of an individual: it does not affect preferences. Under *ex ante* efficiency, only the individual decision power at the time of household formation can influence household decisions. Hence, the only set of distribution factors relevant to explain household behavior is the set containing the variables known or predicted at the time the household was formed. If the assumption of full commitment is relaxed, the individual decision power in each period can also influence the behavior of the household. That is, the realization of the distribution factors in each period can also affect household decisions. Now, going back to my context, such realizations can be seen as deviations of the distribution factors in a given year from the ones at the year of marriage.

2.3.1.4 Allowing covariates in the analysis

So far, the indirect utilities in arrangement a, M_a and F_a, and the invariant gains to arrangement a, Γ_a and τ_a, have been constrained to be identical among all men and among all women in that arrangement. I now relax this assumption to allow the marital output from a match to vary with observed characteristics of both spouses. It is easy to see that the separability assumption is not violated when marital output varies with individual attributes. Therefore, the matching problem still boils down to a set of single-agent choice problems for each individual. However, in order to also include spousal characteristics in the set of those individual attributes, I must make an additional assumption. I have to suppose that the optimal partner's characteristics are part of the set of variables that define an individual's preference. (In the empirical analysis, the actual spouse will be considered the optimal partner.) As a consequence, the set of covariates that I use in the analysis from now on contains attributes of both spouses.

Letting $Z \equiv (Z^m, Z^f)$ denote observed preference factors, and $\eta \equiv (\eta^m, \eta^f)$ a bidimensional unobserved preference component, we can now express the utility functions in the household programme (2.1) as

$$U^m(C_{ia}^m, 1 - H_{ia}^m | Z_{ia}, \eta_{ia}) \text{ and } U^f(C_{ja}^f, 1 - H_{ja}^f | Z_{ja}, \eta_{ja}).$$

As a result, the indirect utilities resulting from the intra-household allocations must be written with the individual subscript: M_{ia} and F_{ja}. Furthermore, the sharing rule ϕ_a^f must also be expressed with the individual subscript, because it is also conditional on Z and η. That is, the sharing rule also depends on the characteristics of the individual and on the attributes that such individual values in an optimal partner. (Recalling that the sharing rule is also a function of distribution factors Q, we can now express it as $\phi_a^f \equiv \phi(W^m, W^f, Y|Z, Q, \eta)$.) In addition, the invariant gains to arrangement a can also be written with the individual subscript: Γ_{ia} and τ_{ja}. Lastly, the demand and supply functions of spouses, equations (2.6) and (2.8), respectively, and the marriage matching function (2.25), must be seen as averages across all the covariation within arrangements.

Notice that the assumption of type-I extreme value distribution for ε in equations (2.4) and (2.7) is extremely useful here. As well-known, it underlies the standard multinomial logit model of discrete choice, and implies the independence of irrelevant alternatives (IIA). In turn, the IIA greatly simplifies the analysis. In the words of Galichon and Salanie (2010), "*without it, the odds ratio of the probability that a man with observable type x ends up in a match with a woman of observable type y rather than with z would also depend on the types of other women, and the model would be unmanageable.*" (p.14).

Finally, for the sake of clarity, I explain which kinds of variables Z, Q and η represent. The observed preference factors Z are generally considered in the literature of household behavior, and include attributes of both spouses, households, and locations (education, age, rent in a, and amenities in a, for example). The distribution factors are also oftenly taken into account in the literature, and consist of sex ratios and divorce laws, for example, as in Chiappori, Fortin and Lacroix (2002). The unobserved preference component η, however, is rarely considered in collective models. Indeed, Browning, Chiappori and Lechene (2006) argue that *"(...) the issues arising from observable heterogeneity are conceptually clear. This is not the case for unobserved heterogeneity. This important but tricky question has received little attention so far, and unobserved heterogeneity is most often introduced in an* ad hoc *fashion. Errors are usually introduced additively to parametric demand equations without attempt or possibility to trace their origin to the structural elements of the model. [...] [T]o date very little has been done to assess the implications of allowing for unobserved heterogeneity in preferences (...)"* (p.12). Here, I assume that η represents atributes unobserved by the researcher, but observed by the spouse. It represents, for example, attachment to family, friends and places, distribution of relatives across locations, preference for arrangement a, preference towards parenthood, and aesthetic beauty. Here, I focus on what I have called the taste for hometown kinships. Such element is arguably observable by the other household member; since spouses interact very often, they end up learning a lot of personal information about each other. Importantly, observe that I do not make any distributional assumption for η: it can have any arbitrary distribution, even conditional on the observables.

2.3.2 Understanding the driving forces of arrangement choices

With the collective marriage market model set up, let us analyze the driving forces of arrangement choices using a simple framework with a specific functional form for the indirect utilities and small sets of possible arrangements (two or three arrangements). The functional form for the indirect utilities used here arises from the assumption of linear labor supply. The reason for such choice is simplicity and will be clearer in the empirical section later on. That said, let us start by supposing that a husband i's indirect utility of choosing arrangement a is

$$V_{ia}^m = e^{m_1 W_{ia}^m}(m_2 W_{ia}^m + m_3\phi_{ia}^m + \eta_{ia}^m) + \Gamma_{ia} + \varepsilon_{ia},$$

where again W represents wage, ϕ sharing rule, η distribution-free preference for arrangement $a \in \{1, .., A\}$ observed only by the partner, Γ invariant gain to an arrangement choice, and ε preference component independently and identically distributed with a type I extreme-value distribution. Recall that by definition, $\phi_{ia}^m = Y_{ija} - \phi_{ja}^f$, where Y is the couple's nonlabor income.

Similarly, suppose that a wife j's indirect utility of choosing arrangement a is

$$V_{ja}^f = e^{f_1 W_{ja}^f}(f_2 W_{ja}^f + f_3\phi_{ja}^f + \eta_{ja}^f) + \tau_{ja} + \varepsilon_{ja}.$$

2.3.2.1 Two arrangements

Let the husband i's indirect utility of choosing arrangements 1 and 2 be

$$\begin{aligned} V_{i1}^m &= e^{m_1 W_{i1}^m}(m_2 W_{i1}^m + m_3\phi_{i1}^m + \eta_{i1}^m) + \Gamma_{i1} + \varepsilon_{i1}, \\ V_{i2}^m &= e^{m_1 W_{i2}^m}(m_2 W_{i2}^m + m_3\phi_{i2}^m + \eta_{i2}^m) + \Gamma_{i2} + \varepsilon_{i2}. \end{aligned}$$

Such man chooses arrangement 2 iff

$$\begin{aligned} A(V_{i2}^m - V_{i1}^m) &\geq 0 \\ A(\varepsilon_{i2}^m - \varepsilon_{i1}^m) + m_2(W_{i2}^m - BW_{i1}^m) + m_3(\phi_{i2}^m - B\phi_{i1}^m) + (\eta_{i2}^m - B\eta_{i1}^m) + A(\Gamma_{i2} - \Gamma_{i1}) &\geq 0, \end{aligned}$$

where $A = e^{-m_1 W_{i2}^m}$ and $B = e^{-m_1(W_{i2}^m - W_{i1}^m)}$.

Similarly, let the wife j's indirect utility of choosing arrangements 1 and 2 be

$$\begin{aligned} V_{j1}^f &= e^{f_1 W_{j1}^f}(f_2 W_{j1}^f + f_3\phi_{j1}^f + \eta_{j1}^f) + \tau_{j1} + \varepsilon_{j1}, \\ V_{j2}^f &= e^{f_1 W_{j2}^f}(f_2 W_{j2}^f + f_3\phi_{j2}^f + \eta_{j2}^f) + \tau_{j2} + \varepsilon_{j2}. \end{aligned}$$

Such woman chooses arrangement 2 iff

$$\begin{aligned} C(V_{j2}^f - V_{j1}^f) &\geq 0 \\ C(\varepsilon_{j2}^f - \varepsilon_{j1}^f) + f_2(W_{j2}^f - DW_{j1}^f) + f_3(\phi_{j2}^f - D\phi_{j1}^f) + (\eta_{j2}^f - D\eta_{j1}^f) + C(\tau_{j2} - \tau_{j1}) &\geq 0, \end{aligned}$$

where $C = e^{-f_1 W^f_{j2}}$ and $D = e^{-f_1(W^f_{j2} - W^f_{j1})}$.

Assume both husband and wife live in the same location. Then, both must choose the same arrangement. Let us say that both choose arrangement 2, so the following inequalities must be satisfied simultaneously:

$$\begin{aligned} A(\varepsilon^m_{i2} - \varepsilon^m_{i1}) + m_2(W^m_{i2} - BW^m_{i1}) + m_3(\phi^m_{i2} - B\phi^m_{i1}) + (\eta^m_{i2} - B\eta^m_{i1}) + A(\Gamma_{i2} - \Gamma_{i1}) &\geq 0 \\ C(\varepsilon^f_{j2} - \varepsilon^f_{j1}) + f_2(W^f_{j2} - DW^f_{j1}) + f_3(\phi^f_{j2} - D\phi^f_{j1}) + (\eta^f_{j2} - D\eta^f_{j1}) + C(\tau_{j2} - \tau_{j1}) &\geq 0. \end{aligned}$$

Given that $\phi^m_{ia} = Y_{ija} - \phi^f_{ja}$, these inequalities imply that both husband and wife choose arrangement 2 iff

$$\begin{aligned} A(\varepsilon^m_{i2} - \varepsilon^m_{i1}) + C(\varepsilon^f_{j2} - \varepsilon^f_{j1}) \geq\; & -m_2(W^m_{i2} - BW^m_{i1}) - f_2(W^f_{j2} - DW^f_{j1}) \\ & -m_3(Y_{ij2} - BY_{ij1}) \\ & -(\eta^m_{i2} - B\eta^m_{i1}) - (\eta^f_{j2} - D\eta^f_{j1}) \\ & +m_3(\phi^f_{j2} - B\phi^f_{j1}) - f_3(\phi^f_{j2} - D\phi^f_{j1}) \\ & -A(\Gamma_{i2} - \Gamma_{i1}) - C(\tau_{j2} - \tau_{j1}). \end{aligned} \tag{2.10}$$

Notice that expression (2.10) contains elements emphasized in the literature of family migration (e.g., wages of both spouses), but also adds elements not underscored in that literature (e.g., non-labor income, preferences, and spousal transfers). In fact, expression (2.10) combines wage advantages of the two spouses using the relative weights m_2 and f_2, includes the household non-labor income advantage with relative weight m_3, combines preference terms, combines the sharing rule in intra-household allocations with relative weights m_3 and f_3, and, lastly, combines the invariant gains to an arrangement choice with relative weights A and C. Therefore, the arrangement decision is driven by a myriad of forces.

To stress the importance of the new driving forces on the spouse/location arrangement choices, and to better understand the implications of full versus limited commitment in such choices, I shut down the wage differentials in expression (2.10) yielding

$$\begin{aligned} A(\varepsilon^m_{i2} - \varepsilon^m_{i1}) + C(\varepsilon^f_{j2} - \varepsilon^f_{j1}) \geq\; & -m_3(Y_{ij2} - Y_{ij1}) \\ & -(\eta^m_{i2} - \eta^m_{i1}) - (\eta^f_{j2} - \eta^f_{j1}) \\ & +(m_3 - f_3)(\phi^f_{j2} - \phi^f_{j1}) \\ & -A(\Gamma_{i2} - \Gamma_{i1}) - C(\tau_{j2} - \tau_{j1}). \end{aligned} \tag{2.11}$$

This expression makes it clear that spousal transfers in intra-household allocations can reduce the attractiveness of arrangement 2. Indeed, if men values their share of the non-labor income more than women do, i.e. $m_3 > f_3$, then less individuals would choose arrangement 2. Having said that, let us now turn to the consequences of commitment in household decisions in the arrangement choice. As discussed before, under full commitment, $\phi^f_{ja} = \overline{\phi}^f_j$ for all a. Hence, the third line of the right-hand side (R.H.S.) of expression (2.11) vanishes away. Thus, the sharing rules lose importance in determining arrangement choices. On the other hand, under limited commitment, $\phi_{ja}^{f} = \widetilde{\phi}_j^{af} + \overline{\phi}_j^{f}$, and then the third line of the R.H.S. of expression (2.11) becomes $(m_3 - f_3)(\widetilde{\phi}_j^{2f} - \widetilde{\phi}_j^{1f})$. As a result, differences in the sharing rule determining intra-household allocations also affect arrangement choices. Consequently, my test of full commitment in the household decisions examines the economic relevance of this last driving force in the spouse/location arrangement choices.

2.3.2.2 Three arrangements

Let the husband i's indirect utility of choosing arrangements 1, 2, and 3 be

$$\begin{aligned} V_{i1}^{m} &= e^{m_1 W_{i1}^{m}}(m_2 W_{i1}^{m} + m_3 \phi_{i1}^{m} + \eta_{i1}^{m}) + \Gamma_{i1} + \varepsilon_{i1}, \\ V_{i2}^{m} &= e^{m_1 W_{i2}^{m}}(m_2 W_{i2}^{m} + m_3 \phi_{i2}^{m} + \eta_{i2}^{m}) + \Gamma_{i2} + \varepsilon_{i2}, \\ V_{i3}^{m} &= e^{m_1 W_{i3}^{m}}(m_2 W_{i3}^{m} + m_3 \phi_{i3}^{m} + \eta_{i3}^{m}) + \Gamma_{i3} + \varepsilon_{i3}. \end{aligned}$$

Such man chooses arrangement 2 iff

$$V_{i2}^{m} \geq \mathrm{Max}(V_{i1}^{m}, V_{i3}^{m}).$$

Similarly, let the wife j's indirect utility of choosing arrangements 1, 2 and 3 be

$$\begin{aligned} V_{j1}^{f} &= e^{f_1 W_{j1}^{f}}(f_2 W_{j1}^{f} + f_3 \phi_{j1}^{f} + \eta_{j1}^{f}) + \tau_{j1} + \varepsilon_{j1}, \\ V_{j2}^{f} &= e^{f_1 W_{j2}^{f}}(f_2 W_{j2}^{f} + f_3 \phi_{j2}^{f} + \eta_{j2}^{f}) + \tau_{j2} + \varepsilon_{j2}, \\ V_{j3}^{f} &= e^{f_1 W_{j3}^{f}}(f_2 W_{j3}^{f} + f_3 \phi_{j3}^{f} + \eta_{j3}^{f}) + \tau_{j3} + \varepsilon_{j3}. \end{aligned}$$

Such woman chooses arrangement 2 iff

$$V_{j2}^{f} \geq \mathrm{Max}(V_{j1}^{f}, V_{j3}^{f}).$$

Assume both husband and wife live in the same location. Then, both must choose the same arrangement. Let us say that both choose arrangement 2. If the second-best arrangement is the same for both husband and wife, e.g. $\mathrm{Max}(V_{i1}^{m}, V_{i3}^{m}) = V_{i1}^{m}$ and $\mathrm{Max}(V_{j1}^{f}, V_{j3}^{f}) = V_{j1}^{f}$, then the decision-making process is identical to the one described in the previous section. If the second-best arrangement differs, e.g. $\mathrm{Max}(V_{i1}^{m}, V_{i3}^{m}) = V_{i1}^{m}$ and $\mathrm{Max}(V_{j1}^{f}, V_{j3}^{f}) = V_{j3}^{f}$, then the decision process is still similar to the previous one, but the expression representing it changes a little bit. To find out such new expression, notice again that if both husband and wife choose arrangement 2, then the following inequalities must be satisfied simultaneously:

$$\begin{aligned} A(\varepsilon_{i2}^{m} - \varepsilon_{i1}^{m}) + m_2(W_{i2}^{m} - BW_{i1}^{m}) + m_3(\phi_{i2}^{m} - B\phi_{i1}^{m}) + (\eta_{i2}^{m} - B\eta_{i1}^{m}) + A(\Gamma_{i2} - \Gamma_{i1}) &\geq 0 \\ C(\varepsilon_{j2}^{f} - \varepsilon_{j3}^{f}) + f_2(W_{j2}^{f} - DW_{j3}^{f}) + f_3(\phi_{j2}^{f} - D\phi_{j3}^{f}) + (\eta_{j2}^{f} - D\eta_{j3}^{f}) + C(\tau_{j2} - \tau_{j3}) &\geq 0, \end{aligned}$$

where $A = e^{-m_1 W_{i2}^{m}}$, $B = e^{-m_1(W_{i2}^{m} - W_{i1}^{m})}$, $C = e^{-f_1 W_{j2}^{f}}$ and $D = e^{-f_1(W_{j2}^{f} - W_{j3}^{f})}$.

Given that $\phi^m_{ia} = Y_{ija} - \phi^f_{ja}$, these inequalities imply that both husband and wife choose arrangement 2 iff

$$\begin{aligned} A(\varepsilon^m_{i2} - \varepsilon^m_{i1}) + C(\varepsilon^f_{j2} - \varepsilon^f_{j3}) \;\; \geq \;\; & -m_2(W^m_{i2} - BW^m_{i1}) - f_2(W^f_{j2} - DW^f_{j3}) \\ & -m_3(Y_{ij2} - BY_{ij1}) \\ & -(\eta^m_{i2} - B\eta^m_{i1}) - (\eta^f_{j2} - D\eta^f_{j3}) \\ & +m_3(\phi^f_{j2} - B\phi^f_{j1}) - f_3(\phi^f_{j2} - D\phi^f_{j3}) \\ & -A(\Gamma_{i2} - \Gamma_{i1}) - C(\tau_{j2} - \tau_{j3}). \end{aligned} \quad (2.12)$$

Notice that this expression is very similar to the corresponding one in the two-arrangement context, except that variables of three arrangements are now relevant to the arrangement choice. Consequently, all the results discussed before are valid here, and are extended to the five-arrangement case that is the focus of my study.

2.4 Empirical Strategy

As mentioned previously, my ultimate goals in this study are (i) to test full commitment in household decisions in the context of spouse/location arrangement choice, (ii) to provide evidence of transfers between spouses arising from that choice, and (iii) to examine some implications of commitment issues on the observed migration behavior of married individuals. To reach these goals, it is crucial to recover the preferences of men and women making those decisions. Here, I do so by assuming a functional form for the utility function and by estimating its key parameters. As will be clear soon, there are several empirical challenges to be surmounted in order to get reliable estimates of such parameters. The major one is the presence of important unobservable preference factors affecting the decision process. Here, I get over this unobservability problem by using a control-function approach à la Olley and Pakes (1996). Overcoming such problem turns out to be a new contribution to the literature of household behavior, and a fundamental step towards reaching my three final goals.

Before proceeding to the implementation, let me summarize the empirical strategy I use here. Basically, it is a novel, three-step econometric procedure that combines (i) the Olley and Pakes's (1996) approach of using a bijection between unobservables and observables to control for unobserved heterogeneity, (ii) the Willis and Rosen's (1979) idea of predicting some outcome variables through selected-corrected estimation to ultimately recover structural parameters, and (iii) the Hausman and Taylor's (1981) insight of constructing instrumental variables. The *first step* involves nonparametric estimation/prediction of conditional choice probabilities (CCP's), and semiparametric estimation/prediction of some outcome variables for all arrangements, à la Willis and Rosen (1979). I employ a sieves logit method to estimate/predict the CCP's, and develop a new approach to correct for sample selection bias in the estimation/prediction of outcome equations. The *second step* addresses estimation of some key parameters of the indirect utilities through likelihoods arising directly from my parametric assumption that individuals' behavior follows a multinomial logit model, conditional on *all* heterogeneity they observe. The control-function approach à la Olley and Pakes (1996) is crucial here. The *third and last step* deals with estimation of the remaining parameters of interest. I adapt the Hausman and Taylor's (1981) instrumental variable approach to cross-sectional data in order to get such parameters. Again, the bijection à la Olley and Pakes (1996) is fundamental in this final step. As we can see here, and in the sections to come, the one-to-one mapping between unobservables and observables à la Olley and Pakes (1996) plays an essential role in my empirical framework.

2.4.1 Specification of indirect utility

To start, suppose the indirect utility of a woman j living in a spouse/location arrangement a with spouse i is

$$\begin{aligned} V_{ja}^f &= F(W_{ja}^f, S_{ja}^f, X_{ja}, \eta_{ja}^f, \eta_{ja}^m) + \tau_{ja} + \varepsilon_{ja}^f \\ &= e^{f_1 W_{ja}^f}\left(f_2^a + f_3 W_{ja}^f + f_4 S_{ja}^f + \gamma_f^a X_{ja} + (f_5\eta_{ja}^f + f_6\eta_{ja}^m)\right) + \tau_{ja} + \varepsilon_{ja}^f \\ &= e^{f_1 W_{ja}^f} f_{ja} + \tau_{ja} + \varepsilon_{ja}^f \\ &= v_{ja}^f + \varepsilon_{ja}^f, \end{aligned} \tag{2.13}$$

where $S^f \equiv \left(\frac{W^f}{W^m + W^f}\right)$ is the share of earnings potential, $X \equiv (Y, Z, Q)$, and the other variables are defined as before. I use the share of earnings potential rather than the wage of the other spouse to express f_{ja} because, throughout the empirical implementation, I assume that the sharing rule is a function of that share instead of wages of both spouses directly, as in Browning et al. (1994) and Lise and Seitz (2011).

I choose this functional form because it is very convenient to illustrate the way I deal with the unobservability of η's. As shown in Appendix B, it arises from assuming linear labor supply (see Stern, 1986, Table 9.3) and linear sharing rule (à la Blundell et al., 2007) in the expression (2.3). Later on, the linear labor supply assumption is proved to be very useful to clarify the main issues of my methodology. Besides suitable for methodological purposes, this indirect utility captures factors driving worker mobility in Moretti's (2011) model of spatial equilibrium (wage, cost of living, amenities, and individual preferences), factors driving intra-household allocation in Chiappori's (1988, 1992) collective model (wage, spouse's wage, household nonlabor income, marriage market conditions, and individual preferences), as well as factors driving the equilibrium in Choo and Siow's (2006) marriage market model (intra-household utility transfers). Last, for the sake of completeness, let me make a notational clarification. When I put a subscript j in male's variables, it means that such variables convey information of the optimal spouse for the woman j. Since I assume below that the spouse/location arrangement market is in equilibrium, I use the actual spouse's variables for estimation purposes.

Now, similarly, suppose that a man i, who lives in a spouse/location arrangement a with spouse j, has indirect utility

$$\begin{aligned} V_{ia}^m &= M(W_{ia}^m, S_{ia}^m, X_{ia}, \eta_{ia}^m, \eta_{ia}^f) + \Gamma_{ia} + \varepsilon_{ia}^m \\ &= e^{m_1 W_{ia}^m}\left(m_2^a + m_3 W_{ia}^m + m_4 S_{ia}^m + \gamma_m^a X_{ia} + (m_5\eta_{ia}^m + m_6\eta_{ia}^f)\right) + \Gamma_{ia} + \varepsilon_{ia}^m \\ &= e^{m_1 W_{ia}^m} m_{ia} + \Gamma_{ia} + \varepsilon_{ia}^m \\ &= v_{ia}^m + \varepsilon_{ia}^m, \end{aligned} \tag{2.14}$$

where $S^m = 1 - S^f$.

2.4.2 Estimable equations

To estimate the parameters of the indirect utilities, I use the probability functions of my non-linear conditional logit model:

$$P_{ja} = \frac{\exp\left(e^{f_1 W_{ja}^f}\left(f_2^a + f_3 W_{ja}^f + f_4 S_{ja}^f + \gamma_f^a X_{ja} + (f_5\eta_{ja}^f + f_6\eta_{ja}^m)\right) + \tau_{ja}\right)}{\sum_r \exp\left(e^{f_1 W_{jr}^f}\left(f_2^r + f_3 W_{jr}^f + f_4 S_{jr}^f + \gamma_f^r X_{jr} + (f_5\eta_{jr}^f + f_6\eta_{jr}^m)\right) + \tau_{jr}\right)}, \tag{2.15}$$

$$P_{ia} = \frac{\exp\left(e^{m_1 W_{ia}^m}\left(m_2^a + m_3 W_{ia}^m + m_4 S_{ia}^m + \gamma_m^a X_{ia} + (m_5\eta_{ia}^m + m_6\eta_{ia}^f)\right) + \Gamma_{ia}\right)}{\sum_r \exp\left(e^{m_1 W_{ir}^m}\left(m_2^r + m_3 W_{ir}^m + m_4 S_{ir}^m + \gamma_m^r X_{ir} + (m_5\eta_{ir}^m + m_6\eta_{ir}^f)\right) + \Gamma_{ir}\right)}. \tag{2.16}$$

Since only differences in f_2, m_2, τ and Γ are identified in the model, then f_2^1, m_2^1, τ_{j1} and Γ_{i1} are normalized to zero. Recall that such normalizations are standard in multinomial choice settings, because only differences of parameters across alternatives are generally identified. For the same reason, the coefficients γ_f^1 and γ_m^1 associated with X-variables that are invariant across arrangements, such as education and age, are also normalized to zero.

As we can see, equations (2.15) and (2.16) include two distribution-free unobserved-heterogeneity components that greatly enrich the analysis, yet they have a very simple structure. Thus, the payoff for making the parametric assumption that individual behavior follows a multinomial logit model, conditional on *all* heterogeneity, is substantial. Notwithstanding, such equations have two issues that must be addressed before proceeding to the empirical implementation. First, the unobservability of some explanatory variables in all but one arrangements, such as wages. I circumvent this problem by estimating such variables semiparametrically, and by inputing them in the main analysis, à la Willis and Rosen (1979). The details are presented in subsections to come. Second, the presence of fully unobserved components (η^f, η^m) in their R.H.S. Since these components are very relevant for the agents' decision process, if we fail to incorporate them in the analysis, all the estimated coefficients are inconsistent. To get over such endogeneity problem, I make use of a bijection between unobservable η's and observable variables, à la Olley and Pakes (1996), as described right below.

2.4.3 One-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*})

As already briefly mentioned, if we try to estimate the parameters of equations (2.15) and (2.16), we face a major endogeneity problem arising from the unobservability of (η^f, η^m). One way to overcome such problem is to show that the optimal (H^f, H^m) maps to a unique value of (η^f, η^m) under plausible assumptions. Indeed, with such mapping in hand, I can associate a pair of observable equilibrium outcomes with a unique pair of unobserved components. As a result, I can use an approach à la Olley and Pakes (1996) to generate a control function that handles the unobserved heterogeneity.

Now, leading functional forms of labor supply generate such one-to-one mapping under the collective model. Examples include the linear supply function (Hausman, 1980), the log-linear function (Burtless and Hausman, 1978), and the semi-log function (Heckman, 1974). I discuss now why this is the case for the linear labor supply function. Recall that this functional form is the primitive for the indirect utilities that I have specified before. The mapping for the other functions and for the *general case* are presented in Appendix C. Throughout the discussion, keep in mind the structure of the labor supply functions derived from the collective model (equations (2.3) and (2.2)).

Following Stern (1986, Table 9.3), let the linear supply function be expressed as

$$h^k = \alpha W^k + \beta Y + \gamma, \tag{2.17}$$

where h is Marshallian labor supply, W is individual wage, Y is individual nonlabor income, and $k = \{f, m\}$. By the collective model, $Y \equiv \phi^k(W^k, S^k, X, \eta^f, \eta^m)$, with $\phi^f(.) \equiv \phi(.)$ and $\phi^m(.) \equiv Y - \phi(.)$, and $\gamma \equiv \gamma(Z, \eta^k)$. To simplify the exposition, let both spouses have linear supply function with identical parameters α and β, and with Y and γ linear in their arguments. Thus,

$$\begin{aligned} H^{f*} &= \alpha W^f + \beta(\delta S^f + \varphi_f X + \eta^f + \eta^m) + (\zeta Z + \eta^f) \\ &= \alpha W^f + \theta S^f + \rho_f X + (1+\beta)\eta^f + \beta\eta^m, \end{aligned}$$

and

$$\begin{aligned} H^{m*} &= \alpha W^m + \beta(\pi S^m + \varphi_m X + \eta^f + \eta^m) + (\xi Z + \eta^m) \\ &= \alpha W^m + \lambda S^m + \rho_m X + \beta\eta^f + (1+\beta)\eta^m. \end{aligned}$$

It can be shown that the system of these two equations can be rewritten as

$$\begin{aligned} \eta^f &= \left(\frac{1+\beta}{1+2\beta}\right) H^{f*} - \left(\frac{\beta}{1+2\beta}\right) H^{m*} + K^f(W^f, W^m, S^f, X) \\ \eta^m &= -\left(\frac{\beta}{1+2\beta}\right) H^{f*} + \left(\frac{1+\beta}{1+2\beta}\right) H^{m*} + K^m(W^f, W^m, S^f, X) \end{aligned}$$

iff $\beta \neq -\frac{1}{2}$, where $K^k(.)$'s are linear functions of their arguments. Therefore, (H^{f*}, H^{m*}) has an one-to-one mapping with (η^f, η^m) as long as $\text{Prob}\left(\beta \neq -\frac{1}{2}\right) = 1$, which is generally the case. Indeed, a labor supply model with $\beta = -\frac{1}{2}$ is a very particular case where half of any extra unearned dollar is spent reducing hours of men, and half is spent reducing hours of women, with no income effect on goods. At last, in order to get results consistent with utility maximization, we must add the Slutsky restrictions for the linear supply function: $\alpha - h^k\beta \geq 0$ or $(\alpha - \beta\gamma) - \alpha\beta W^k - \beta^2 Y \geq 0$ (see discussion in Stern (1986, Table 9.3)).

Notice that we can get the same result using the Inverse Function Theorem[6]. By this theorem, it suffices to show that the matrix

$$\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f,W^m,S^f,X)} \equiv \left.\begin{bmatrix} \frac{\partial H^{f*}}{\partial \eta^f} & \frac{\partial H^{f*}}{\partial \eta^m} \\ \frac{\partial H^{m*}}{\partial \eta^f} & \frac{\partial H^{m*}}{\partial \eta^m} \end{bmatrix}\right|_{(W^f,W^m,S^f,X)}$$

$$= \left.\begin{bmatrix} (1+\beta) & \beta \\ \beta & (1+\beta) \end{bmatrix}\right|_{(W^f,W^m,S^f,X)}$$

is invertible to check for the one-to-one mapping between (H^{f*}, H^{m*}) and (η^f, η^m). But this matrix is invertible iff

$$\det\left(\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f,W^m,S^f,X)}\right) = 1 + 2\beta \neq 0,$$

which also gives us $\beta \neq -\frac{1}{2}$.

2.4.4 Intermediate estimation

As discussed previously, before proceeding to the estimation of the parameters of interest, I must estimate/predict two sets of intermediate variables: (i) conditional choice probabilities (CCP's) for each spouse/location arrangement, and (ii) some outcomes for all arrangements, basically wage, non-labor income, and hours of work. This constitutes the *first step* of my three-step procedure outlined in the introduction of this section. It follows, in principle, the Willis and Rosen's (1979) idea of predicting some outcome variables through selected-corrected estimation to ultimately recover structural parameters. For CCP estimation, I use the nonparametric sieve logit method [see Newey and Powell (2003) and Ai and Chen(2003)]. This method models CCP's in such a flexible way that exhausts the information in the data through k-th order polynomials of the continuous explanatory variables [see Bajari, Hong and Nekipelov (2010)]. Now, for the outcome estimation, I develop a novel semiparametric approach to correct for sample selection bias. Basically, the selection correction term in the outcome equation is a nonparametric functional of a parametric function arising from the multinomial logit structure, whose main arguments are nonparametrically-estimated CCP's. Here, I use a power series approximation for the nonparametric functional à la Newey (2009).

[6]I include this second manner to get the same result here because it is the way I show the mapping for the other leading functional forms and for the general case in Appendix C.

Although it seems complicated, this estimation method follows the familiar two-step strategy proposed by Gronau (1973, 1974) and Heckman (1974, 1979) in a parametric setting, and by Ahn and Powell (1993) in a semiparametric one.

To make things clear, let us discuss the methodology for the outcome wage. Hence, assume the wage equation is

$$\log(W_{ia}) = X_{ia}\beta + D_{ia}\delta + \xi_{ia},$$

where W is wage, X represents explanatory variables such as education, experience, and place of birth, D_{ia} is a dummy variable equal to one when individual i chooses arrangement a, and ξ represents a distribution-free disturbance term with $E[\xi_{ia}] = 0$. (I simplify the exposition by assuming X non-stochastic.) Since individuals self-select themselves in the arrangement that maximizes their utility, say a, and we observe only the information associated with their choice, then the conditional expectation of observed wages is

$$E[\log(W_{ia})|D_{ia} = 1] = X_{ia}\beta + D_{ia}\delta + E[\xi|D_{ia} = 1].$$

One way to make the estimation of this conditional expectation feasible is to get a control function corresponding to $E[\xi|D_{ia} = 1]$. Given the empirical model specified previously,

$$\begin{aligned} E[\xi|D_{ia} = 1] &= E[\xi|V_{ia} > V_{is}] \\ &= E[\xi|(\varepsilon_{is} - \varepsilon_{ia}) < (v_{ia} - v_{is})] \\ &\equiv g(v_{ia} - v_{is}), \end{aligned}$$

where $V_{is} \equiv \text{Max}_{r\neq a}V_{ir}$ is the indirect utility of the second best arrangement[7] s, and $g(.)$ is assumed to be a nonparametric functional representing the relationship between ξ and $(\varepsilon_{is} - \varepsilon_{ia})$. Interestingly, under the standard random-utility setup with any distribution for ε's, there is a mapping between differences in conditional valuation functions v's and CCP's (Hotz and Miller, 1993). As a result, the argument of $g(.)$ can be expressed as a function of CCP's. In particular, under the multinomial logit structure of my empirical model, it is precisely

$$\begin{aligned} (v_{ia} - v_{is}) &= \log(P_{ia}) - \log(P_{is}) \\ &= \log\left(\frac{P_{ia}}{P_{is}}\right) \\ &\equiv l(P_{ia}, P_{is}) \end{aligned}$$

(Arcidiacono and Miller, forthcoming). Finally, as discussed above, the CCP's are estimated nonparametrically. Therefore, the selection correction function

$$E[\xi|D_{ia} = 1] = g(l(\widehat{P}_{ia}, \widehat{P}_{is}))$$

[7]Notice that I am using Lee's (1983) maximum order statistic approach to reduce the dimensionality of the relevant set of error terms.

is a nonparametric functional of the parametric function $l(.)$, arising from the multinomial logit structure, whose arguments are the nonparametrically-estimated CCP's of the first and the second best arrangements. Again, the parametric assumption that individual behavior follows a multinomial logit model, conditional on *all* heterogeneity, generates a considerable payoff.

Although derived in a different way, this method happens to be very similar to Dahl's (2002) approach to correct for sample selection bias in a multi-alternative setup. Even better, it connects directly with the random-utility setup to analyze discrete choices, which became standard since McFadden (1974), and overcomes a major Dahl's limitation when combined with the one-to-one mapping between unobservables and observables à la Olley and Pakes (1996). Dahl makes the assumption that the utility-maximizing choice is *sufficient* to describe the joint distribution of the relevant error terms. This *index sufficiency* assumption is, unfortunately, too restrictive. While a simple individual fixed effect (η_i) model satisfies it, slight modifications of it, such as the mere multiplication of the individual unobserved heterogeneity by an arrangement loading factor ($\kappa_a \eta_i$), do not so[8]. My (combined) approach, on the other hand, can deal even with individual-arrangement unobserved heterogeneity (η_{ia}).

Now, to estimate the coefficients of the wage equation consistently, we must have at least one exclusion restriction for the control function. I use spouse's place of birth, and individual's and spouse's ("unobserved") preferences for arrangements. In fact, my first *identification assumption* in that the state of birth of the spouse does not affect an individual's outcomes directly, but influences the location decision. In my sample, 13.41 percent of the husbands live in their wives' state of birth, and 13.87 percent of the wives live in their husbands' state of birth. Furthermore, I assume that preferences for spouse/location arrangements (η^f, η^m) affect the determination of wages only through the decision to get into a particular arrangement a. Given that such preferences are not supposed to be productive attributes of individuals, that seems a reasonable assumption. Since η's are not observed, I utilize labor supplies from the bijection between (η^f, η^m) and (H^{f*}, H^{m*}) in my empirical implementation.

To be precise about the specification of the outcome equations in this intermediate step, I now write them down explicitly. I estimate these equations separately for men and women, but I present only the specifications for men here. It is worthy mentioning that to get the "average" of these predicted outcomes across arrangements, I estimate such equations without arrangements and their interactions.

Wage equation. To predict the wage of each individual in each arrangement, I take an extended human capital approach. I allow (hourly) wages to vary with years of education, years of labor market experience, dummies for state of birth, dummies for (1-digit) occupation, dummies for (1-digit) industry, dummies for the arrangements individuals can choose from, and interactions between years of education and arrange-

[8]Dahl (2002) develops an approach to estimate returns to education when state of residence is treated as a choice variable. Although innovative, his methodology rules out interesting cases where unobserved ability is rewarded differently across states. Therefore, models based on comparative advantage, such as in Gibbons et al. (2005), cannot be studied under his setup.

ments. The dummies for state of birth basically controls for school quality (Card and Krueger, 1992) and for other productive attributes associated with different home states. The dummies for occupation and industry provides additional sources of variation under the assumption that individuals work in the same broad category of those variables regardless of the place of residence. The interactions between education and arrangements allow the return to education to vary across arrangements. Hence,

$$\begin{aligned}\log(W_{ia}^m) &= \alpha_0^m + \alpha_1^m \text{Educ}_i + \alpha_2^m \text{Exper}_i + \alpha_3^m \text{Exper}_i^2 + \alpha_4^m \text{D\_SOB}_i \\ &\quad + \alpha_5^m \text{D\_Occ}_i + \alpha_6^m \text{D\_Ind}_i + \alpha_7^m \text{D\_Arr}_{ia} + \alpha_8^m (\text{D\_Arr}_{ia} * \text{Educ}_i) + \xi_{ia}^m.\end{aligned}$$

Hours of work equation. To forecast the hours worked by each individual in each arrangement, I use a specification close to the right-hand side of the wage equation. I just allow (annual) hours of work to also vary with interactions between number of children and dummies for the five possible arrangements. Clearly, I am assuming that offspring affects labor supply directly and indirectly through the interaction with arrangement. I believe this make sense because raising children requires a lot of time that could be allocated to work. However, if a couple lives close to its extended family, for example, then it might have the availability of "unconstrained" child care and, consequently, more freedom to set hours of work. That said, the equation used for forecasting is,

$$\begin{aligned}\log(H_{ia}^m) &= \delta_0^m + \delta_3^m \text{Educ}_i + \delta_5^m \text{Exper}_i + \delta_6^m \text{Exper}_i^2 + \delta_7^m \text{D\_SOB}_i + \delta_8^m \text{D\_Occ}_i \\ &\quad + \delta_9^m \text{D\_Ind}_i + \delta_{10}^m \text{Offs}_i + \delta_{11}^m \text{D\_Arr}_{ia} + \delta_{12}^m (\text{D\_Arr}_{ia} * \text{Offs}_i) + \iota_{ia}^m.\end{aligned}$$

Nonlabor income equation. To predict the nonlabor income of each couple in each arrangement, I use a specification associated with an age profile of wealth accumulation. I allow the couple nonlabor income to vary with education, age, and state of birth of both spouses, but importantly I let the quadratic terms of age to interact with the five possible arrangements. Therefore, I am assuming that the unearned income arises from a nonlinear wealth accumulation process that varies across arrangements. For the sake of clarity, I am measuring nonlabor income as the sum of interest, dividends, net rental income, royalty income, income from estates and trusts, and any public assistance or welfare payments from the state or local welfare office. The equation used for prediction is

$$\begin{aligned}NLI_{ija}^c &= \gamma_0^c + \gamma_1^c \text{Educ}_i + \gamma_2^c \text{PEduc}_i + \gamma_3^c \text{Age}_i + \gamma_4^c \text{Age}_i^2 + \gamma_5^c \text{PAge}_i + \gamma_6^c \text{PAge}_i^2 \\ &\quad + \gamma_7^c \text{D\_SOB}_i + \gamma_8^c \text{D\_PSOB}_i + \gamma_9^c \text{D\_Arr}_{ia} + \gamma_{10}^c (\text{D\_Arr}_{ia} * \text{Age}_i) \\ &\quad + \gamma_{11}^c (\text{D\_Arr}_{ia} * \text{Age}_i^2) + \gamma_{12}^c (\text{D\_Arr}_{ia} * \text{PAge}_i) + \gamma_{13}^c (\text{D\_Arr}_{ia} * \text{PAge}_i^2) + \upsilon_{ia}^c.\end{aligned}$$

2.4.5 Estimation of indirect utility parameters

To carry on the estimation of my ultimate parameters of interest, f_4 and m_4, let us consider an "estimable" version of equations (2.15) and (2.16):

$$\begin{aligned} P_{ja} &= \frac{\exp\left(e^{f_1 \widehat{W}^f_{ja}} f_{ja} + \tau_{ja}\right)}{\sum_r \exp\left(e^{f_1 \widehat{W}^f_{jr}} f_{jr} + \tau_{jr}\right)}, \\ &= \frac{\exp\left(e^{f_1 \widehat{W}^f_{ja}}\left(f_2^a + f_3 \widehat{W}^f_{ja} + f_4 \widehat{S}^f_{ja} + \gamma^a_f X_{ja} + (f_5 \eta^f_{ja} + f_6 \eta^m_{ja})\right) + \tau_{ja}\right)}{\sum_r \exp\left(e^{f_1 \widehat{W}^f_{jr}}\left(f_2^r + f_3 \widehat{W}^f_{jr} + f_4 \widehat{S}^f_{ja} + \gamma^r_f X_{jr} + (f_5 \eta^f_{jr} + f_6 \eta^m_{jr})\right) + \tau_{jr}\right)}, \end{aligned} \tag{2.18}$$

$$\begin{aligned} P_{ia} &= \frac{\exp\left(e^{m_1 \widehat{W}^m_{ia}} m_{ia} + \Gamma_{ia}\right)}{\sum_r \exp\left(e^{m_1 \widehat{W}^m_{ir}} m_{ir} + \Gamma_{ir}\right)} \\ &= \frac{\exp\left(e^{m_1 \widehat{W}^m_{ia}}\left(m_2^a + m_3 \widehat{W}^m_{ia} + m_4 \widehat{S}^m_{ia} + \gamma^a_m X_{ia} + (m_5 \eta^m_{ia} + m_6 \eta^f_{ia})\right) + \Gamma_{ia}\right)}{\sum_r \exp\left(e^{m_1 \widehat{W}^m_{ir}}\left(m_2^r + m_3 \widehat{W}^m_{ir} + m_4 \widehat{S}^m_{ir} + \gamma^r_m X_{ir} + (m_5 \eta^m_{ir} + m_6 \eta^f_{ir})\right) + \Gamma_{ir}\right)} \end{aligned} \tag{2.19}$$

To proceed with the *second step* of my three-step methodology, and consequently to get consistent estimates for my key parameters, let us deal with the unobservability of η. As stressed several times, I use here the Olley and Pakes's (1996) approach, which consists in generating a control function from a bijection between unobserved heterogeneity and observable equilibrium outcomes. Given the one-to-one mapping between $\eta \equiv (\eta^f, \eta^m)$ and $H^* \equiv (H^{f*}, H^{m*})$ conditional on observed covariates, conditioning on η is equivalent to conditioning on H^*. As a result,

$$P_{ja}|\left[W^f, S^f, X, (\eta^f, \eta^m), \tau\right] = P_{ja}|\left[W^f, S^f, X, (H^{f*}, H^{m*}), \tau\right],$$

$$P_{ia}|\left[W^m, S^m, X, (\eta^m, \eta^f), \Gamma\right] = P_{ia}|\left[W^m, S^m, X, (H^{m*}, H^{f*}), \Gamma\right].$$

Notice, however, that the parameters inside f_{ja} and m_{ia} are not identified through the estimation of these conditional expectations. This non-identification result arises from the fact that the functions η are also linear in each variable of $(W^f, W^m, S^f, X, H^{f*}, H^{m*})$, as showed before. Therefore, when we estimate

$$P_{ja} = \frac{\exp\left(e^{f_1 \widehat{W}^f_{ja}}\left(f_2^a + f_3 \widehat{W}^f_{ja} + f_4 \widehat{S}^f_{ja} + \gamma^a_f X_{ja} + (f_5 \widehat{H}^{f*}_{ja} + f_6 \widehat{H}^{m*}_{ja})\right) + \tau_{ja}\right)}{\sum_r \exp\left(e^{f_1 \widehat{W}^f_{jr}}\left(f_2^r + f_3 \widehat{W}^f_{jr} + f_4 \widehat{S}^f_{jr} + \gamma^r_f X_{jr} + (f_5 \widehat{H}^{f*}_{jr} + f_6 \widehat{H}^{m*}_{jr})\right) + \tau_{jr}\right)}, \tag{2.20}$$

$$P_{ia} = \frac{\exp\left(e^{m_1 \widehat{W}^m_{ia}}\left(m_2^a + m_3 \widehat{W}^m_{ia} + m_4 \widehat{S}^m_{ia} + \gamma^a_m X_{ia} + (m_5 \widehat{H}^{m*}_{ia} + m_6 \widehat{H}^{f*}_{ia})\right) + \Gamma_{ia}\right)}{\sum_r \exp\left(e^{m_1 \widehat{W}^m_{ir}}\left(m_2^r + m_3 \widehat{W}^m_{ir} + m_4 \widehat{S}^m_{ir} + \gamma^r_m X_{ir} + (m_5 \widehat{H}^{m*}_{ir} + m_6 \widehat{H}^{f*}_{ir})\right) + \Gamma_{ir}\right)}, \tag{2.21}$$

all the coefficients but f_1, f_{ja}, τ_{ja}, m_1, m_{ia}, and Γ_{ia} are biased[9]. Such coefficients reflect not only their own effect on the arrangement choice, but also part of the impact of unobserved preferences on that choice. In fact, those equations do not allow us to separate the effect of each variable in $(W^f, W^m, S^f, X,)$ on the household's labor supplies (H^{f*}, H^{m*}) from their effect on the arrangement choice.

Since we still need to identify and to estimate the parameters inside f_{ja} and m_{ia}, let us proceed to the *last step* of my three-step procedure. To begin, let us rearrange the non-linear conditional logit probabilities (2.20) and (2.21) in order to obtain new estimable equations. Using the estimated coefficients $\widehat{f}_1$, $\widehat{f}_{ja}$, $\widehat{\tau}_{ja}$, $\widehat{m}_1$, $\widehat{m}_{ia}$ and $\widehat{\Gamma}_{ia}$, such rearranging yields

$$\frac{\left[\ln(\widehat{P}_{ja}) + \widehat{D}^f_{ja}\right] - \widehat{\tau}_{ja}}{e^{\widehat{f}_1 \widehat{W}^f_{ja}}} = f^a_2 + f_3 \widehat{W}^f_{ja} + f_4 \widehat{S}^f_{ja} + \gamma^a_f X_{ja} + (f_5 \eta^f_{ja} + f_6 \eta^m_{ja} + \xi^f_{ja}) \tag{2.22}$$

$$\frac{\left[\ln(\widehat{P}_{ia}) + \widehat{D}^m_{ia}\right] - \widehat{\Gamma}_{ia}}{e^{\widehat{m}_1 W^m_{ia}}} = m^a_2 + m_3 \widehat{W}^m_{ia} + m_4 \widehat{S}^m_{ia} + \gamma^a_m X_{ia} + (m_5 \eta^m_{ia} + m_6 \eta^f_{ia} + \xi^m_{ia}) \tag{2.23}$$

where $\widehat{D}^f_{ja} = \ln\left(\sum_r \exp\left(e^{\widehat{f}_1 \widehat{W}^f_{jr}} \widehat{f}_{jr} + \widehat{\tau}_{jr}\right)\right)$, $\widehat{D}^m_{ia} = \ln\left(\sum_r \exp\left(e^{\widehat{m}_1 \widehat{W}^m_{ir}} \widehat{m}_{ir} + \widehat{\Gamma}_{ir}\right)\right)$, and ξ's are measurement errors, probably arising from the estimated coefficients. Again, we face the problem of unobservability of η. Nevertheless, the only endogeneity left in those equations comes from the correlation between wage, share of earnings potential, and non-labor income with labor supplies. Indeed, labor supply is the only element of the control function representing unobserved preferences that is excluded from the R.H.S. of such equations. To surmount this endogeneity problem, I use an instrumental variable (IV) framework. I construct instruments à la Hausman and Taylor (1981) for each of those three variables using the bijection between H^* and η. Basically, I regress each of those three variables on individual's hours of work and spouse's hours of work, and take the residuals as instruments. That is, for each regressor $R_l = \{\widehat{W}_l, \widehat{S}_l, \widehat{Y}_l\}$, $l = \{i, j\}$, I run

$$R_l = r_1 \widehat{H}^{m*}_l + r_2 \widehat{H}^{f*}_l + \varrho_{Rl},$$

as a proxy for

$$R_l = r_1 \eta^m_l + r_2 \eta^f_l + \varrho_{Rl},$$

and take $\widehat{\varrho}_{Rl}$ as instruments. Since such residuals are unrelated to η by construction, the order condition is satisfied. Furthermore, since they are clearly correlated to the original variables, the rank condition is also satisfied. In the end, I use a standard IV estimator with those constructed instruments to get the remaining key parameters. As we can see, this approach is an adaptation of Hausman and Taylor (1981) to cross-sectional data. In fact, such authors use demeaned values of time-varying endogenous

[9] For the sake of clarity, in Appendix D I compare the log-likelihood function of the standard conditional logit model with the one estimated here.

variables as instruments for them in a panel data setting. The demeaned variables are, essentially, residuals from regressions of time-varying endogenous variables on individual effects, their unobserved heterogeneity components. To see the similarity more formally, suppose that some regressors R_{lt}'s are endogenous due to correlations with the individual fixed effects, represented here by the dummies L_l. Now, consider the linear projection of L onto R,

$$R_{lt} = rL_l + \varrho_{Rlt}, \tag{2.24}$$

where ϱ_{Rlt} is orthogonal to L_l by construction. Taking the average over time for each individual ($R_{l.} = rL_l + \varrho_{Rl.}$), and subtracting it from equation (2.24) gives

$$(R_{lt} - R_{l.}) = (\varrho_{Rlt} - \varrho_{Rl.}).$$

Hausman and Taylor (1981) use $(R_{lt} - R_{l.})$ as instrument for each endogenous regressor R_{lt}. Indeed, since ϱ_{Rlt} is unrelated to L_l by construction, the demeaned values of R_{lt} are also orthogonal to L_l, and, consequently, the order condition is satisfied. Moreover, since $(R_{lt} - R_{l.})$ is clearly correlated with R_{lt}, the rank condition is also satisfied. To see the connection with my approach, just notice that $(R_{lt} - rL_l)$ provides the same variation as $(R_{lt} - R_{l.})$ in the estimation of the coefficients of R_{lt}'s through fixed-effect methods, and that $(R_{lt} - rL_l)$ is the residual of equation (2.24). Hence, Hausman and Taylor's (1981) instruments can be easily found by regressing equation (2.24) and taking the residuals $\widehat{\varrho}_{Rlt}$, the same way my instruments are found.

Now, for the sake of completeness, I present the variables contained in X, τ and Γ. In X, I include:

- household non-labor income (average across arrangements, and arrangement-specific deviations from the average);

- preference shifters: indicator of college for both spouses, indicator of age range (20-25, 26-30, 31-35 years old) for both spouses, indicator for the presence of children (aged at most 5 years old) within the household, indicator of SOB for both spouses, housing costs (Albouy, 2010: more details in the data section), quality-of-life amenities (Albouy, 2010), and firm-productivity amenities (Albouy, 2010);

- distribution factors: difference of age between spouses, sex ratio, indicator of unilateral divorce (Voena, 2011: more details in the data section), indicator of community property regime (assets divided equally, under the presumption that they are jointly owned by the spouses) (Voena, 2011).

In τ and Γ, I include arrangement-specific intercepts, indicators for the educational composition of couples (husband: non-college/ wife: non-college, non-college/college, college/non-college, college/college), and difference of age between spouses.

2.4.6 Consistency of the model

One way to verify the internal consistency of my framework is to check the equilibrium condition in the marriage market, equation (2.25), which I reproduce here for convenience:

$$\ln\left(\frac{\mu_a}{\mu_1}\right) = \frac{[(M_a - M_1) + (F_a - F_1)] + [(\Gamma_a - \Gamma_1) + (\tau_a - \tau_1)]}{2}. \tag{2.25}$$

The L.H.S. of this marriage matching function is readily observed: it is the ratio of number of marriages in arrangement a and arrangement 1. The R.H.S., in turn, can be easily calculated as the average of the systematic part of the utilities of both spouses for each arrangement, across the entire sample. This will be the main check of internal consistency of my modelling strategy.

Another way to inspect if the model generates meaningful estimates is to compare some of its coefficients, or functions of them, with estimates well-established in the literature. One parameter that could be used here is the response of labor supply to non-labor income. In my model, it is the coefficient of wage in the exponential term of the utility functions. In order to make such comparison, I derive some useful expressions from the budget constraint and the labor supply under the collective model. For men, such budget constraint is $C^m = W^m H^m + (Y - \phi)$, where $\phi \equiv \phi(W^f, S^f, Y)$ is the sharing rule of intra-household allocations. Taking derivatives with respect to Y in both sides, and rearranging, gives

$$\begin{aligned} W^m \frac{\partial H^m}{\partial Y} &= -\left(1 - \frac{\partial C^m}{\partial Y}\right) + \frac{\partial \phi}{\partial Y} \\ &= -(1 - mpe) + \frac{\partial \phi}{\partial Y}, \end{aligned} \tag{2.26}$$

where mpe is the marginal increase in total spending on goods and services if non-labor income goes up by one dollar.

Also, the male labor supply under the collective model is $H^m = \alpha W^m + \beta(Y - \phi) + \gamma$ (see equations (2.2) and (2.17)). Hence,

$$\frac{\partial H^m}{\partial Y} = \beta\left(1 - \frac{\partial \phi}{\partial Y}\right). \tag{2.27}$$

Finally, equations (2.26) and (2.27) yields

$$\frac{\partial \phi}{\partial Y} = \frac{(1 - mpe) + \beta W^m}{1 + \beta W^m}. \tag{2.28}$$

Now, I have wages, the classic benchmark of $(1 - mpe) \in [0.1, 0.2]$ for American male workers, and an estimate of $\beta = \widehat{m}_1$. Therefore, I can compute the implied $\frac{\partial \phi}{\partial Y}$ using expression (2.28), and compare it with the Chiappori, Fortin and Lacroix's (2002) estimate of 0.7 (95 percent confidence interval equal to $[0.36, 1.03]$).

Similarly, for women, the budget constraint in the collective model is $C^f = W^f H^f + \phi$. Thus,

$$
\begin{aligned}
W^f \frac{\partial H^f}{\partial Y} &= \frac{\partial C^f}{\partial Y} - \frac{\partial \phi}{\partial Y} \\
&= mpe - \frac{\partial \phi}{\partial Y}.
\end{aligned} \tag{2.29}
$$

Also, the female labor supply under the collective model is $H^f = \alpha W^f + \beta\phi + \gamma$ (see equations (2.3) and (2.17)). Hence,

$$
\frac{\partial H^f}{\partial Y} = \beta \frac{\partial \phi}{\partial Y}. \tag{2.30}
$$

Likewise, equations (2.29) and (2.30) yields

$$
\frac{\partial \phi}{\partial Y} = \frac{mpe}{1 + \beta W^f}. \tag{2.31}
$$

Again, I can use wages, the classic benchmark of $mpe \in [0.8, 0.9]$ for American male workers, and an estimate of $\beta = \widehat{f_1}$, to compute the implied $\frac{\partial \phi}{\partial Y}$ and compare it with the Chiappori, Fortin and Lacroix's (2002) findings.

2.5 Data Description

The data I use come from the U.S. Census of 2000. These data are ideal for the study of choices of spouse/location arrangements for three reasons. First, the Census has information on state of birth for each household member, crucial to understand how individuals weight wages and preferences for location in their arrangement choice. Second, the Census has a more complete picture of the household structure. Indeed, after declaring marital status, married individuals are asked to inform if their spouses are actually living in the household. Third, the Census has a large sample size, providing enough variation to disentangle the effect of the variables of interest.

My sample includes only U.S.-born, white, non-hispanic, heterosexual couples, whose both spouses are present in a household of only one family, are not attending school anymore, are working, and are aged 20-35 years old. I exclude single individuals to abstract from the marriage decision by itself and to focus on broad locational choices (partner's birthplace and place of residence). Therefore, my analysis is conditional on marrying. I also leave out older couples to concentrate my analysis in agents with few years of marriage, whose arrangement choices have been recently made. Ideally, I would restrict my attention to newlywed individuals, with fresh arrangement choices, but unfortunately the Census does not report the date of marriage. I also exclude couples with at least one spouse not working because the methodology, as developed here, requires the observability of the labor supply of both spouses. This does not mean that labor force participation is infeasible within my framework or irrelevant in the analysis. In fact, future research can potentially extend my framework to encompass the participation decision through the discrete characterization of labor supply as used, for example, by Lise and Seitz (2011). Finally, I keep out couples containing immigrants, nonwhites, homosexuals, and students, to narrow down my analysis to a sample as homogenous as possible. Indeed, I believe the data generating process of arrangement choices for these groups might differ in ways not modeled in my framework.

My analysis also incorporates some variables (distribution factors, housing cost, and amenities) derived from other data sources. To construct two of distribution factors - unilateral divorce and community property regime (assets are divided equally, under the presumption that they are jointly owned by the spouses) -, I depend on information provided in the table 15 (divorce law reforms in the U.S.) of Voena (2011). To create the variables housing cost, quality of life and firm productivity for all arrangements, I use information provided in the table A2 (list of states ranked by total amenity value) of Albouy (2010).

At last, it is worth to point out again that I consider the choices of partner and location as if they were made joint and simultaneously. Since I do not observe the timing of those two decisions in the census data, I do not model it. I am aware though of the discussion about such timing in the literature. As mentioned before, Costa and Kahn (2000) find that couples whose both husband and wife have at least college education are increasingly, and disproportionately, located in large metropolitan areas. In 1970, 39% of these couples, called "power couples" by them, lived in metropolitan areas with a population of at least 2 million. In 1990, this number had jumped to 50%. They then argue that this comes basically from the growth of dual career households and the resulting severity of the "colocation problem". By contrast, Compton and Pollack (2007) argue that the empirical fact that power couples are increasingly likely to be located in large metropolitan areas is well explained by higher rates of power couple formation in such areas. To my analysis, it does not matter in which sequence the choices of partner and location happened. My interest resides in the final arrangement choice. The timing might reflect only stronger preferences toward either decision. Since I incorporate such preferences in my framework, I might be taking the timing into account implicitly.

2.6 Results

As mentioned throughout the paper, my ultimate goals in the present study are (i) to test full commitment in household decisions in the context of spouse/location arrangement choice, (ii) to provide evidence of transfers between spouses arising from that choice, and (iii) to examine some implications of commitment issues on the observed migration behavior of married individuals. In order to reach those objectives, I have developed an empirical strategy based on a collective marriage market model. I present the results in the following sequence. Firstly, I discuss some evidence supporting the framework adopted here. Secondly, I talk about the main results. Thirdly, and lastly, I present some interesting estimates from the intermediate step.

2.6.1 Consistency of the model

To verify the internal consistency of my empirical framework, I mainly use the restriction imposed by the equilibrium condition of the collective marriage market model, the marriage matching equation (2.25). As we can see in table 2.2, estimates of both sides of that equation are statistically identical. This finding seems to support my modelling choices, even though they are somewhat restrictive. Therefore, from now on, I interpret my results in light of that model.

To also check the suitableness of my methodology, I compare my estimates with some established results in the literature. Using expressions (2.28) and (2.31), I compute the implied response of my sharing rules to an one-dollar increase in non-labor income. For men, such response is in the range $[0.42, 0.48]$, depending on the value used to $(1 - mpe)$. Such range is completely inside the 95-percent confidence interval for $\frac{\partial \phi}{\partial Y}$ found by Chiappori, Fortin and Lacroix (2002): $[0.36, 1.03]$. For women, the implied response is in the range $[0.68, 0.77]$, exactly around the point estimate of 0.70 found by those researchers. Given that my results are in accord to the ones in the literature, I once more infer that my estimates look reliable to answer my main research questions.

2.6.2 Main results

To test full commitment in household behavior related to locational choices, I use the variable share of earnings potential within the household. As explained in the theoretical framework, I decompose it in two parts: the average across arrangements (share base), which represents the full-commitment share, and the deviation of the average (share deviation), which represents the limited commitment share. The marginal effect of these two components are presented in table 2.3, for men, and table 2.4, for women.

The first column of table 2.3 shows that, in the equilibrium of the collective marriage market model, increases in men's base share of earnings potential are associated with increases in SOB-endogamous marriages. This result is consistent with a marriage market favorable to men in their home location. Nevertheless, this does not seem the case in other places. The first column of table 2.4 provides evidence that such market looks more propitious to women in states which are neither their SOB nor their husbands' SOB. Indeed, increases in women's base share of earnings potential are related to increases in out-of-SOB residency. Given that the average base share is 43.91 percent for women, these findings lead to a simple conclusion: more equitable couples are formed by individuals from different SOB and live out of their SOB.

If there is full commitment in household behavior, the effects of the base shares of earnings potential in equilibrium are all we need to understand how such shares influence spouse/location arrangement choices. However, the significant impact of arrangement-specific deviations from the base share seems to demonstrate that full commitment is not the case here. Looking at the diagonal elements of the matrices generated by columns 2-6 of tables 2.3 and 2.4, I infer that indeed couples do not commit to the sharing rule negotiated at the ouset of marriage. In fact, table 2.3 shows that, in equilibrium, positive deviations of the men's share of earnings potential of arrangement a from the base share imply that husbands get a higher portion of the household resources when in such an arrangement. This is particularly true for arrangements 1, 3 and 4, which involve living in the SOB of at least one spouse. Complementarily, table 2.4 says that if women's share of earnings potential deviates positively from the base share in arrangement a, then wives get a lower percentage of the household resources in that arrangement. Therefore, the two pieces of evidence lead to the same direction: there appears to be no full commitment in household behavior related to broad locational choices, and such lacking of commitment is detrimental to women. The first result corroborates Mazzoco's (2007) main finding, that household members cannot commit to future plans, in the context of spouse/location choices. The second result confirms the "dampening" impact of migration decisions on wives' outcomes, as predicted by Mincer (1978).

Taken together, the results of both the base share of earnings potential within the household and the deviations of it tell us the same story in different acts. At first, the formation of households tends to be beneficial to women in out-of-SOB locations. At last, more equitable couples preserve their *status quo* by residing in states which are neither the husband's SOB nor the wife's SOB. Told from another angle, at first, both SOB-endogamous and SOB-exogamous couples favor the husbands in the division of resources within the household in their home states. At last, such couples become even more inequitable because of the limited commitment in household decisions associated with locations.

Given that there seems to be no full commitment in household behavior related to spouse/location choices, I now examine by how much this lack of commitment affects the observed migration rates of married people. To start, column 7 of tables 2.3 and 2.4 shows the percentage of spouses in each arrangement. Adding up the numbers associated with individual out-of-SOB residency yields migration rates of roughly 34 percent for men, and 34.4 percent for women. Shutting down the effect of the deviations of the base share of earnings potential - the variable representing limited commitment -, those rates grow to 47.5 and 42 percent, respectively. Thus, if there were no commitment issues within the household associated with broad locational decisions, the migration rate would be 39.7 percent larger for men, and 22.1 percent larger for women, approximately. Interestingly, these results are qualitatively very similar to the ones obtained by Gemici (2011) when she shuts down family ties in her empirical model. She finds out that without such ties, men would move 38.9 percent more, and women, 27.8 percent more[10].

In order to have a benchmark to compare those predicted full-commitment rates with, I report here the migration rates of singles with characteristics similar to the married individuals considered: [11]38.8 percent for single men, and 40.2 percent for single women, approximately. Although such predicted rates for married individuals are larger than the ones for singles, they are not unrealistic. Many married people are just moving from their SOB to their spouses's SOB. From a strict/puritan point of view, this would not be considered migration: individuals are still geographically close to part of their extended family. In any case, those two rates are really similar for women. I take such congruence of the results as a sign of the reliability of my estimates, and therefore I assert that limited commitment inhibits migration considerably. I go even further by infering that lack of commitment can explain the entire gap between migration rates of single and married individuals. Such empirical finding supports a theoretical result pointed out by Lundberg and Pollak (2003): when households bargain over locations without a commitment mechanism, potentially Pareto-improving moves not necessarily take place.

Perhaps, as I just mentioned, a more fair comparison of migration rates of married and single individuals occurs when we consider as migrants only spouses who live in neither their SOB nor their partners' SOB. I actually prefer this exercise, because here both singles and spouses have no ties with parents or other members of the relevant extended family. That said, in such situation, migration rates are 20.6 percent for men, and 21 for women, approximately, against 38.8 and 40.2 percent, respectively, for singles. Removing the lack-of-commitment effect now generates migration rates of 25.6 for husbands, and 26.8 for wives, roughly, still far away from the single rates. Anyway, migration rates would again increase in the absence of commitment issues. In fact, the husbands' rate would grow 24.3 percent, and the wives's, 27.6 percent, approximately, in that context. As we can see, both this and the previous comparison provide evidence that the economic effect of limited commitment in household behavior associated with broad locational choices is fairly large.

It is interesting to notice that the main impact of the shutdown of commitment issues is the increase in the proportion of individuals in arrangement 4 (SOB-exogamous couples living in the wife's SOB), as depicted by column 8 of tables 2.3 and 2.4. This

[10]As mentioned before, in the related literature section, the actual Gemici's (2011) results are the following: without family ties, 25 percent of men and 23 percent of women move, whereas when married only 18 percent move. Recall that she uses data from the PSID.

[11]My sample of singles then includes only U.S.-born, white, non-hispanic individuals, who are not attending school anymore, are working, and are 20-35 years old. I improve the comparability of this group relative to the married one by keeping in the sample only singles who are heads of household, housemates or roomers/boarders. Hence, singles living with their parents or other relatives are excluded from my computations.

finding might help us to understand the intriguing stylized fact that the percentage of SOB-exogamous couples living in the wife's SOB is almost identical to the percentage of such couples living in the husband's SOB. Ordinary people assume that women value the proximity to parents and other relatives more than men, and consequently SOB-exogamous couples are thought to reside more oftenly in the wife's SOB. My analysis offers some insights to explain why that is not the case: commitment issues within the household associated with spouse/location choices. Anticipating that their potential wives will have more bargaining power in their home locations, men move away from arrangements which include living in their wives' SOB.

Now, I discuss how some other variables contained only in the sharing rule behave in the equilibrium of the collective marriage market model. The estimated coefficients are depicted in table 2.5. Starting with sex ratio, the sign of its coefficient is negative in the utility function of both spouses. Since this congruence of signs is not consistent with transfers between spouses based on the scarcity of mates in the marriage market, then it seems that, in equilibrium, people just enjoy arrangements with gender-balanced population. Regarding the indicator for the presence of unilateral divorce law, the sign of its coefficient is also negative in both utility functions. This means that, in equilibrium, both spouses are willing to get smaller portions of the unearned household resources in arrangements with such law, indicating a more cooperative behavior within the household. On the other hand, the coefficient of the indicator for the presence of community property regime in case of divorce is positive in both utility functions, which suggests a behavior more egoistic inside the household. Nevertheless, the higher the shares of household resources the spouses demand under such regime, the fewer are the assets to be split in case of family dissolution. Therefore, at the end of day, both divorce laws seem to create incentive to maintain the household in equilibrium.

Finally, it is worth to discuss the sign of the estimated coefficients associated with the unobserved-preference terms in the utility function. Such coefficients are also displayed in table 2.5. Remember that the spouse's term enters the utility function only through the sharing rule. Also, recall that I replace such terms with labor supplies in my framework, using the one-to-one mapping à la Olley and Pakes (1996). That said, the coefficients of both labor supplies are positive in the utility function of both spouses, though they are very imprecisely estimated for wives. This finding suggests that unobserved preferences are indeed relevant for broad locational choices, confirming the need to incorporate them into the analysis. Even more important, the positiveness of both coefficients provides an empirical support for my control function approach to deal with the endogeneity arising from such unobservables. To see why, notice that if labor supply does represent preferences, then the sign of both coefficients must be nonnegative. The coefficient of the individual's own labor supply must be nonegative because stronger preferences for an arrangement increases the individual's utility. In addition, since there is a potential trade-off between taste for "hometown" kinships and share of household resources, the coefficient of the labor supply of the individual's spouse must be also positive: if the spouse enjoys an arrangement very much, the individual can demand more household resources to choose it. An alternative reason to include labor supply in the sharing rule is the one advanced by Basu (2006): labor supply as inducer of bargaining power within the household instead of proxy for unobserved preferences. In Basu's world, spouse's higher labor supply means smaller shares of household resources for the individual. Consequently, the sign of the coefficient of the spouse's labor supply in his setting is negative. This is not the case here.

2.6.3 Findings from the intermediate estimation

Having presented the main results of this study, I now turn to the findings of my intermediate step. Besides generating the variation needed to estimate the indirect utility parameters, such step produces interesting insights by itself. In fact, many of the sources of variation that I use to predict distinct wages, hours of work, and non-labor income across arrangements also shed light on some ideas informally discussed in the literature. Here I make an extra effort to correct for self-selection into arrangements in order to provide credible estimates. Recall that to estimate my coefficients of interest consistently, I estimate/predict conditional choice probabilities using a nonparametric sieve logit method with two exclusion restrictions: spouse's place of birth, and individual's and spouse's ("unobserved") preferences for arrangements. Table 2.6 shows the criteria I use to choose a third order polynomial approximation for my sieve logit. Furthermore, to guarantee that my findings hold under a fully flexible selection correction, I utilize up to the tenth order of the polynomials of the term $ln\left(\widehat{P}_{ia}/\widehat{P}_{is}\right)$ in the estimation of the outcome equations. Remember that such term is just the argument of the nonparametric selectivity regressor. All the results that follow are conditional on the tenth-order polynomial.

Starting with wages, I use differences in the return to education to get variation across arrangements. Tables 2.7 and 2.8 shows the primary results for males and females, respectively. For men, one additional year of schooling is associated with an increase of 7.8 percent in wages in arrangement 1 (SOB-endogamous couples living in their SOB). Surprisingly, such gain is 19.2 percent larger in arrangement 2 (SOB-endogamous couples living out-of-SOB), 25.6 percent larger in arrangement 4 (SOB-exogamous couples living in the wife's SOB), and 33.7 percent larger in arrangement 5 (SOB-exogamous couples living out of their SOBs). We all know that migrants have higher return to education, but here the evidence says that such return still varies with the origin and the migration status of the spouse. For women, however, there is much less variation in return to education. Although it is much higher than the men's counterpart - it is 10.4 percent, approximately -, the only dissonance occurs in arrangement 5, where it is 9.2 percent larger. At last, notice that my selection-correction approach looks effective to expurge the bias from the estimates. For men, selection bias is negative and sizable. In fact, the return to education across arrangements are much bigger after the correction, for example. Furthermore, given that the coefficient of the selectivity regressor is negative, it seems that men trade wage for their favorite arrangement. For women, the results are much weaker, but suggest that they have higher payoff when living in the arrangement they prefer. Indeed, the coefficient of the selectivity regressor is very imprecise, though positive.

Regarding hours of work, I utilize number of children to generate variation over arrangements. Tables 2.9 and 2.10 depicts the main results for men and women, respectively. As expected, I do not succeed in producing noticeable fluctuations of labor supply for husbands: there is virtually no variation arising from number of offspring. The only exception is an 1.7-percent increase in arrangement-2 hours of work associated with the presence of an additional child in the household. Still, such estimate is statistically significant only at 10 percent. On the other hand, number of children does create considerable variation in female labor supply across arrangements. It is long-familiar that motherhood has deleterious effects on women's outcomes in the labor market. Here, I provide the extra piece of evidence long supposed in the literature: those effects can be even worse when women live far away from their extended family. Indeed, in arrangement 1, an additional child is associated with a decrease of 25.7 percent in hours of work. In arrangements 3 and 4, with women enjoying proximity to only one side of the family - either their parents or their parents-in-law -, such decrease is 12.4 percent larger, on average. Yet, in arrangements 2 and 5, with couples living completely out of their SOB, that reduction is even larger: 31.3 percent, approximately. These impressive findings corroborate Compton and Pollak's (2011) preliminary results that close geographical proximity to mothers or mothers-in-law has a substantial positive effect on the labor supply of married women with young children. Curiously, I do not find any significant difference in that impact for arrangements 3 and 4. Perhaps, this just confirms Compton and Pollak's argument that the mechanism behind our results is the availability of childcare to meet irregular or unanticipated needs. Lastly, again I discuss how my selection-correction strategy improves the reliability of my estimates. Comparing the first column of tables 2.9 and 2.10 with the other columns, we can see, for example, that for both men and women the coefficients of the interactions between number of children and arrangements are larger in real terms, though very imprecise for males. Yet, the selection bias as a whole seems to be positive, as indicated by the coefficient of the selectivity regressor. This last finding suggests that individuals trade leisure for their preferred arrangement.

Finally, concerning the household non-labor income, I use the age profile of both spouses to produce variation across arrangements. Although my sample has only individuals aged 20-35 years old, I advance the idea that even in this narrow age interval, the dynamics of wealth accumulation may generate different unearned income levels in distinct arrangements. Since here I estimate only one equation for the couple, all the results are displayed in table 2.11. As we can see, it seems that the husband's age profile is the only one that matters in the determination of household non-labor income across arrangements. There is virtually no statistically significant estimates on the wife's side. Intriguingly, the shape of the age profile changes from convex, in arrangement 1 (SOB-endogamous couples living in their SOB), to concave, in arrangements 3 and 4 (SOB-exogamous couples living in the SOB of one of the spouses). The remaining age profiles are not distinguishable from the arrangement-1's. Taken together, these results appear to indicate a detrimental effect of the proximity to only one side of the family on the accumulation of wealth. Perhaps the help from both sides of the family is crucial to cross important thresholds in the direction of making more non-labor income, such as the acquisition of a real estate. Such help might happen much more often in the presence of frequent social interactions that the geographical proximity allows. If the help does not happen, maybe the best that a couple can do to generate higher levels of unearned income is to explore better oportunities far away. In any case, it is interesting to see so different dynamics across arrangements. At last, once more I want to point out the effect of my selection-corretion methodology on the estimates. As we can notice, the coefficients of the interactions between husband's age and arrangements are much larger after the correction. This seems to indicate the same impact discussed for male wages: again, the selection bias is negative. Consequently, couples appears to trade non-labor income for their favorite arrangement.

2.7 Concluding Remarks

In this paper, I have studied the joint choice of spouse and location ordinarily made by individuals at the ouset of their adult lives. I have assumed that agents are forward-looking and consider potential conflicts that might arise in future negotiations within the household regarding place of residence when they are searching for mates. I motivated this concern with the stylized fact that the vast majority of Americans lives in their SOB, and I have concluded that those worries are quite reasonable. Indeed, I have found that household members cannot commit to the intra-household allocations associated with broad locational choices that they agreed to in the beginning of their marriage. I have also showed that, in general, such lack of commitment is detrimental to women, in terms of the share of the household resources they end up getting. In light of these results, I have also provided evidence that limited commitment in household behavior can explain the entire gap between observed migration rates of single and married individuals in the U.S.

I have used a collective marriage market model as background for my empirical analysis. To build such theoretical framework, I brought together insights from the Chiappori's (1988, 1992) way of modelling household decisions, and the Choo and Siow's (2006) approach of matching people in the marriage market. I have allowed the individual choices to reflect all the information that spouses observe from each other in their frequent interactions. Although rich, the resulting framework imposed many challenges to the empirical implementation. Indeed, part of the information that spouses consider in their decisions are unobservable to the researchers. I have overcome such obstacles by using an one-to-one mapping between unobservable preferences and household labor supply, à la Olley and Pakes (1996). I have utilized such mapping to generate a control function that handles the unobserved heterogeneity. Finally, using data of young dual-career couples in the 2000 U.S. Census, I have estimated all the parameters of interest, from which I have derived all my findings.

Now, the results found in this paper might help to understand some mechanisms behind (at least) two recent empirical findings. The first is the decline in internal migration in the U.S. from the 1980s to the 2000s, richly documented by Molloy, Smith, and Wozniak (2011). Their results show that interstate migration rates differ a lot among married couples, depending on whether two, one or none of the spouses work. The decrease in migration rates is strongest for dual-career couples: while it has fallen approximately 38 percent for couples with just one working spouse, it has dropped by 46 percent for couples in which both spouses work. This piece of evidence might be consequence of the lack of commitment in household decisions related to locations, as indicated by my analysis.

The second finding that can be interpreted in light of my results is the high degree of marital sorting on the basis of parental wealth in the U.S. Charles, Hurst and Killewald (2011) show that men and women in the U.S. marry spouses whose parents have wealth similar to that of their own parents, and are very unlikely to marry persons from very different parental wealth backgrounds. Their preferred estimates indicate that the correlation in log wealth between own and spouse's parents wealth is around 0.4. Such finding might be rationalized, at least in part, by the prominent issues of household commitment that are likely to appear in this context as well. Indeed, like place of birth, parental traits are also exogenously given to individuals. Consequently, they can make little accomodations if their spouses cannot commit to future plans. As a result, individuals might induce a natural balance in the decision power within the household by sorting in the marriage market on the basis of parental wealth.

In the near future, I intend to use the framework I have developed in this paper to study the relationship between spouse/location choices and gender wage gap. Given that I have found deleterious effects of limited commitment on women's outcomes, I suppose it can also explain part of that observed gap. Also, since I have not considered the timing of marriage/migration here, it would be interesting to use longitudinal data to investigate potential actions agents take to avoid commitment issues regarding broad locational choices. Postponing marriage is one of those possible actions, for example. Indeed, many individuals might first settle down in their favorite location, and only then search for mates.

2.8 Appendix

2.8.1 Appendix A: Redistribution under NTU and TU

Before understanding why redistribution alters household behavior, first acknowledge the following general result in NTU models: total gains of marriage depend on Pareto weights. In fact, as discussed in Legros and Newman (2007), under NTU the division of the surplus bewteen partners cannot be separated from the level they generate. To illustrate the point, I present how this happens in my setting. It is a special case of Proposition 1 in Choo, Seitz and Siow (2008a). Suppose the household programme is

$$\max_{\{C^f,H^f,C^m,H^m\}} U^f(C^f,1-H^f)+\theta\left[U^m(C^m,1-H^m)\right] \tag{2.32}$$

$$\text{subject to } C^m+C^f \leq W^mH^m+W^fH^f+Y,$$

where $\theta \in \mathbb{R}^+$ is the husband's Pareto weight relative to his wife's, which is normalized to one. The first order conditions (F.O.C.) are:

$$\begin{aligned} U^f_{C^f} &= \lambda, \\ U^f_{H^f} &= \lambda W^f, \\ U^m_{C^m} &= \frac{\lambda}{\theta}, \\ U^m_{H^m} &= \frac{\lambda}{\theta}W^m. \end{aligned}$$

Using the F.O.C., as θ changes,

$$\begin{aligned} \frac{\partial V^f}{\partial \theta} &= \lambda(C^{f*}_\theta - W^fH^{f*}_\theta), \\ \frac{\partial V^m}{\partial \theta} &= \frac{\lambda}{\theta}(C^{m*}_\theta - W^mH^{m*}_\theta), \end{aligned}$$

which imply

$$\frac{1}{\theta}\frac{\partial V^f}{\partial \theta}+\frac{\partial V^m}{\partial \theta}=\frac{\lambda}{\theta}(C^{m*}_\theta + C^{f*}_\theta - W^mH^{m*}_\theta - W^fH^{f*}_\theta).$$

Since the budget constraint also holds at the optimum, then $C^{m*}_\theta + C^{f*}_\theta - W^mH^{m*}_\theta - W^fH^{f*}_\theta = 0$. Therefore,

$$\frac{\partial V^f}{\partial \theta} = -\theta\frac{\partial V^m}{\partial \theta} < 0.$$

In words, as θ increases, the wife's indirect utility V^f falls and the husband's indirect utility V^m increases. Thus, the total surplus of the household is indeed affected by redistribution. As a result, household decisions might change as well.

Now, consider the case where $U(.)$ is quasi-linear in consumption, say $U(C, 1-H) = C + G(1-H)$, with $G(.)$ denoting a function, as it would be under TU. Hence, the F.O.C. are:

$$\begin{aligned}
\lambda &= 1, \\
G^f_{H^f} &= \lambda W^f, \\
\theta &= \lambda, \\
G^m_{H^m} &= \frac{\lambda}{\theta} W^m.
\end{aligned}$$

Using the F.O.C., as θ changes,

$$\begin{aligned}
\frac{\partial V^f}{\partial \theta} &= 0, \\
\frac{\partial V^m}{\partial \theta} &= 0.
\end{aligned}$$

Therefore, under TU changes in Pareto weights cannot affect the total surplus of the household. Consequently, household behavior remains the same after redistributions.

2.8.2 Appendix B: Specification of the indirect utility

In this appendix, I show that the indirect utility function specified throughout the empirical strategy arises from assuming linear labor supply (see Stern, 1986, Table 9.3) and linear sharing rule (à la Blundell et al., 2007) in the expressions (2.3) and (2.2). Indeed, following Stern (1986, Table 9.3), the indirect utility associated with the linear labor supply function $h^k = \alpha W^k + \beta Y + \gamma$ is

$$U_k(W^k, Y) = e^{\beta W^k}\left(Y + \frac{\alpha}{\beta}W^k - \frac{\alpha}{\beta^2} + \frac{\gamma}{\beta}\right),$$

where W is individual wage, Y is individual nonlabor income, and $k = \{f, m\}$. By the collective model,$Y \equiv \phi^k(W^k, S^k, X, \eta^f, \eta^m)$, with $\phi^f(.) \equiv \phi(.)$, $\phi^m(.) \equiv Y - \phi(.)$ and $X \equiv (Y, Z, S)$, and $\gamma \equiv \gamma(Z, \eta^k)$. For simplicity, suppose that both spouses have linear supply function with identical parameters α and β, and with Y and γ linear in their arguments. Thus,

$$\begin{aligned}
F(.) &= e^{\beta W^f}\left(Y + \frac{\alpha}{\beta}W^f - \frac{\alpha}{\beta^2} + \frac{\gamma}{\beta}\right) \\
&= e^{\beta W^f}\left((\delta_1 S^f + \delta_2 Y + \delta_3 Z + \delta_4 Q + \eta^f + \eta^m) + \frac{\alpha}{\beta}W^f - \frac{\alpha}{\beta^2} + \frac{(\zeta Z + \eta^f)}{\beta}\right) \\
&= e^{\beta W^f}\left(-\frac{\alpha}{\beta^2} + \frac{\alpha}{\beta}W^f + \delta_1 S^f + \delta_2 Y + \left(\delta_3 + \frac{\zeta}{\beta}\right) Z + \delta_4 Q + \left(1 + \frac{1}{\beta}\right)\eta^f + \eta^m\right) \\
&= e^{f_1 W^f}\left(f_2 + f_3 W^f + f_4 S^f + \gamma_f X + (f_5\eta^f + f_6\eta^m)\right) \\
&= e^{f_1 W^f} f,
\end{aligned}$$

$$\begin{aligned}
M(.) &= e^{\beta W^m}\left(Y + \frac{\alpha}{\beta}W^m - \frac{\alpha}{\beta^2} + \frac{\gamma}{\beta}\right) \\
&= e^{\beta W^m}\left((\pi_1 S^m + \pi_2 Y + \pi_3 Z + \pi_4 Q + \eta^f + \eta^m) + \frac{\alpha}{\beta}W^m - \frac{\alpha}{\beta^2} + \frac{(\xi Z + \eta^m)}{\beta}\right) \\
&= e^{\beta W^m}\left(-\frac{\alpha}{\beta^2} + \frac{\alpha}{\beta}W^m + \pi_1 S^m + \pi_2 Y + \left(\pi_3 + \frac{\xi}{\beta}\right) Z + \pi_4 Q + \left(1 + \frac{1}{\beta}\right)\eta^m + \eta^f\right) \\
&= e^{m_1 W^m}\left(m_2 + m_3 W^m + m_4 S^m + \gamma_m X + (m_5\eta^m + m_6\eta^f)\right) \\
&= e^{m_1 W^m} m.
\end{aligned}$$

At last, recall that to get results consistent with utility maximization, the Slutsky conditions must be satisfied: $\alpha - H^k\beta \geq 0$ or $(\alpha - \beta\gamma) - \alpha\beta W^k - \beta^2 Y \geq 0$ (see discussion in Stern (1986, Table 9.3)).

2.8.3 Appendix C: One-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*})

Here, I first discuss the one-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*}) that leading functional forms of labor supply generate under the collective model. I focus on the log-linear function (Burtless and Hausman, 1978) and the semi-log function (Heckman, 1974). In the end, I consider the general case. Throughout the discussion, keep in mind the structure of the labor supply functions derived from the collective model (equations (2.3) and (2.2)).

C.1) The log-linear supply function

Following Stern (1986, Table 9.5), let the log-linear supply function be expressed as

$$\log(h^k) = \alpha\log(W^k) + \beta\log(Y) + \log(\gamma),$$

where h is Marshallian labor supply, W is individual wage, Y is individual nonlabor income, and $k = \{f, m\}$. By the collective model, $Y \equiv \phi^k(W^k, S^k, X, \eta^f, \eta^m)$, with $\phi^f(.) \equiv \phi(.)$ and $\phi^m(.) \equiv Y - \phi(.)$, and $\gamma \equiv \gamma(Z, \eta^k)$. As in the linear labor supply case, let us simplify the exposition by letting both spouses have log-linear supply function with identical parameters α and β, but making Y and γ multiplicative functions of their arguments. Thus,

$$\begin{aligned}
\log(H^{f*}) &= \alpha\log W^f + \beta\log((S^f)^\delta.X^{\varphi_f}.\eta^f.\eta^m) + \log(Z^\zeta.\eta^f) \\
&= \alpha\log W^f + \theta\log S^f + \rho_f\log X + (1+\beta)\log\eta^f + \beta\log\eta^m,
\end{aligned}$$

and

$$\begin{aligned}
\log(H^{m*}) &= \alpha W^m + \beta\log((S^m)^\pi.X^{\varphi_m}.\eta^f.\eta^m) + \log(Z^\xi.\eta^m) \\
&= \alpha\log W^m + \lambda\log S^m + \rho_m\log X + \beta\log\eta^f + (1+\beta)\log\eta^m.
\end{aligned}$$

We can see clearly that there exists an one-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*}) as long as the restriction of the linear case ($\beta \neq -\frac{1}{2}$) holds here. Indeed,

$$\begin{aligned}
\det\left(\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f, W^m, S^f, X)}\right) &= \det\left(\left.\begin{bmatrix} \frac{(1+\beta)}{\eta^f} & \frac{\beta}{\eta^m} \\ \frac{\beta}{\eta^f} & \frac{(1+\beta)}{\eta^m} \end{bmatrix}\right|_{(W^f, W^m, S^f, X)}\right) \\
&= \frac{1+2\beta}{\eta^f\eta^m},
\end{aligned}$$

and $\eta^f\eta^m \neq 0$ by assumption. To guarantee consistency with utility maximization, the Slutsky conditions also must be satisfied: $\frac{\beta W^k H^{k*}}{Y} \leq \alpha$ or $\beta\gamma(W^k)^{\alpha+1}Y^{\beta-1} \leq \alpha$ (see discussion in Stern (1986, Table 9.5)).

C.2) The semi-log supply function

Following Stern (1986, Table 9.6), let the semi-log supply function be expressed as

$$h^k = \alpha \log(W^k) + \beta Y + \gamma.$$

Let us examine the same simple example as in the linear function. Thus,

$$\begin{aligned} H^{f*} &= \alpha\log(W^f) + \beta(\delta S^f + \varphi_f X + \eta^f + \eta^m) + (\zeta Z + \eta^f) \\ &= \alpha\log(W^f) + \theta S^f + \rho_f X + (1+\beta)\eta^f + \beta\eta^m, \end{aligned}$$

and

$$\begin{aligned} H^{m*} &= \alpha\log(W^m) + \beta(\pi S^m + \varphi_m X + \eta^f + \eta^m) + (\xi Z + \eta^m) \\ &= \alpha\log(W^m) + \lambda S^m + \rho_m X + \beta\eta^f + (1+\beta)\eta^m. \end{aligned}$$

Again, we can see clearly that there exists an one-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*}) as long as the restriction for the linear case ($\beta \neq -\frac{1}{2}$) holds here. The only change is the condition to make this supply function consistent with utility maximization: now it is $\alpha \leq \beta W^k H^{k*}$ (see discussion in Stern (1986, Table 9.6)).

C.3) General case

To prove that there exists an one-to-one mapping between (η^f, η^m) and (H^{f*}, H^{m*}) in the general case, I apply the Inverse Function Theorem to the function

$$\begin{aligned} H^*(\eta^f, \eta^m, W^f, W^m, X) &\equiv \left(H^{f*}(\eta^f, \eta^m, W^f, S^f, X),\, H^{m*}(\eta^f, \eta^m, W^m, S^m, X)\right) \qquad (2.33) \\ &= \left(h^f(W^f, \phi^f(W^f, S^f, X, \eta^f, \eta^m), Z, \eta^f),\right. \\ &\qquad \left. h^m(W^m, \phi^m(W^m, S^m, X, \eta^f, \eta^m), Z, \eta^m)\right), \end{aligned}$$

where $\phi^f(.) = \phi(.)$ and $\phi^m(.) = Y - \phi(.)$. Then, it suffices to show that the matrix

$$\begin{aligned} \left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f, W^m, S^f, X)} &\equiv \left.\begin{bmatrix} \frac{\partial H^{f*}}{\partial \eta^f} & \frac{\partial H^{f*}}{\partial \eta^m} \\ \frac{\partial H^{m*}}{\partial \eta^f} & \frac{\partial H^{m*}}{\partial \eta^m} \end{bmatrix}\right|_{(W^f, W^m, S^f, X)} \\ &= \left.\begin{bmatrix} \left(\frac{\partial h^f}{\partial \phi^f}\frac{\partial \phi^f}{\partial \phi}\frac{\partial \phi}{\partial \eta^f} + \frac{\partial h^f}{\partial \eta^f}\right) & \frac{\partial h^f}{\partial \phi^f}\frac{\partial \phi^f}{\partial \phi}\frac{\partial \phi}{\partial \eta^m} \\ \frac{\partial h^m}{\partial \phi^m}\frac{\partial \phi^m}{\partial \phi}\frac{\partial \phi}{\partial \eta^f} & \left(\frac{\partial h^m}{\partial \phi^m}\frac{\partial \phi^m}{\partial \phi}\frac{\partial \phi}{\partial \eta^m} + \frac{\partial h^m}{\partial \eta^m}\right) \end{bmatrix}\right|_{(W^f, W^m, S^f, X)} \\ &= \left.\begin{bmatrix} \left(\frac{\partial h^f}{\partial \phi}\frac{\partial \phi}{\partial \eta^f} + \frac{\partial h^f}{\partial \eta^f}\right) & \frac{\partial h^f}{\partial \phi}\frac{\partial \phi}{\partial \eta^m} \\ -\frac{\partial h^m}{\partial \phi}\frac{\partial \phi}{\partial \eta^f} & \left(-\frac{\partial h^m}{\partial \phi}\frac{\partial \phi}{\partial \eta^m} + \frac{\partial h^m}{\partial \eta^m}\right) \end{bmatrix}\right|_{(W^f, W^m, S^f, X)} \end{aligned}$$

is invertible. We know that this is equivalent to show that

$$\begin{aligned} \det\left(\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f, W^m, S^f, X)}\right) &= \left(\frac{\partial h^f}{\partial \phi}\frac{\partial \phi}{\partial \eta^f}\frac{\partial h^m}{\partial \eta^m}\right) - \left(\frac{\partial h^m}{\partial \phi}\frac{\partial \phi}{\partial \eta^m}\frac{\partial h^f}{\partial \eta^f}\right) + \left(\frac{\partial h^f}{\partial \eta^f}\frac{\partial h^m}{\partial \eta^m}\right) \\ &\neq 0. \end{aligned}$$

Now, the equation $\det\left(\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f,W^m,S^f,X)}\right) = 0$ describes a measure-zero subspace of the parameter space. In practice, such equation can be assumed to fail unless it is known to hold identically. Therefore, there exists a one-to-one mapping between (H^{f*}, H^{m*}) and (η^f, η^m) except on a set of measure zero.

Finally, since $\left.\frac{\partial H^*}{\partial \eta}\right|_{(W^f,W^m,S^f,X)}$ has full rank, then $H^*(.)$ has an inverse $(H^*)^{-1}(.)$ defined as

$$(H^*)^{-1}(H^{f*}, H^{m*}, W^f, W^m, S^f, X) \equiv \left(\eta^f(H^{f*}, H^{m*}, W^f, W^m, S^f, X),\, \eta^m(H^{f*}, H^{m*}, W^f, W^m, S^f, X)\right).$$

2.8.4 Appendix D: Log-likelihood function

The log-likelihood function of the conditional logit model associated with the indirect utility $V_{ia}^{m} = m_{2a} + m_3 W_{ia}^{m} + m_4 S_{ia}^{m} + \gamma_m X_{ia} + (m_5 H_{ia}^{m*} + m_6 H_{ia}^{f*}) + \varepsilon_{ia}^{m}$ is

$$LL(\theta) = \sum_{i=1}^{N} \sum_{a=1}^{A} y_{ia} \ln P_{ia},$$

where

$$P_{ia} = \frac{\exp(m_{2a} + m_3 W_{ia}^{m} + m_4 S_{ia}^{m} + \gamma_m X_{ia} + (m_5 H_{ia}^{m*} + m_6 H_{ia}^{f*}))}{\sum_{r=1}^{A} \exp(m_{2r} + m_3 W_{ir}^{m} + m_4 S_{ir}^{m} + \gamma_m X_{ir} + (m_5 H_{ir}^{m*} + m_6 H_{ir}^{f*}))}.$$

In this study, however, $V_{ia}^{m} = e^{m_1 W_{ia}^{m}} \left(m_{2a} + m_3 W_{ia}^{m} + m_4 S_{ia}^{m} + \gamma_m X_{ia} + (m_5 H_{ia}^{m*} + m_6 H_{ia}^{f*}) \right) + \Gamma_{ia} + \varepsilon_{ia}^{m}$. Then,

$$P_{ia} = \frac{\exp(e^{m_1 W_{ia}^{m}} \left(m_{2a} + m_3 W_{ia}^{m} + m_4 S_{ia}^{m} + \gamma_m X_{ia} + (m_5 H_{ia}^{m*} + m_6 H_{ia}^{f*}) \right) + \Gamma_{ia})}{\sum_{r=1}^{A} \exp(e^{m_1 W_{ir}^{m}} \left(m_{2r} + m_3 W_{ir}^{m} + m_4 S_{ir}^{m} + \gamma_m X_{ir} + (m_5 H_{ir}^{m*} + m_6 H_{ir}^{f*}) \right) + \Gamma_{ir})}.$$

Chapter 3

A Note on the Trade-off between Ecosystem Preservation and Air Quality: Evidence from Hydroelectric Licensing Rules

3.1 Introduction

Land regulations have been long enacted in the U.S. to preserve the wilderness and the wildlife. As a result, the natural habitat of many threatened/endangered species has been protected. Despite of this invaluable benefit, such regulations might have an unintended/unexpected consequence: more air pollution and more global warming. Indeed, land regulations restrict the development of new hydroelectric dams, which are renewable, non-emitting sources of energy, and might induce electricity generation by highly polluting firms: the conventional fossil-fuel power plants[1]. As a matter of fact, conventional electricity generation is responsible for 40 percent of the U.S. greenhouse gas emissions, and is loosely regulated[2]. In this paper, I study the trade-off between land conservation and air quality, both theoretically and empirically.

I motivate my empirical analysis on the trade-off between land conservation and air quality using a simple general equilibrium model for the electricity industry. I assume that consumers value eletricity, land conservation and air quality, but electricity generation damages the environment either through construction of hydroeletric dams or greenhouse gas emissions. The trade-off is clear in the theoretical model. More importantly, empirical evidence suggests its existence in the U.S. Each megawatt of potential hydropower that is not developed because of land conservation regulations produces roughly the carbon dioxide emissions per megawatt of an average coal-fired

[1]The fossil fuels most used by power plants in the U.S. are coal (49 percent of total electricity generation) and natural gas (22 percent of total electricity generation).

[2]Even a draft of new rules limiting carbon dioxide emissions by new power plants, recently proposed by the U.S. Environmental Protection Agency (EPA), has faced sharp resistance.

plant (1768 pounds) in the U.S. The substitution between hydropower plants and fossil-fuel power plants appears to be clearer for counties more affected by the regulations.

The data I use in this paper comes from two sources. The first is a unique report prepared in the 1990s for the U.S. Department of Energy (DOE), to determine the undeveloped potential hydropower resources in the U.S. It contains site characteristics such as exact location and potential generation capacity, and, crucially, the list of all land regulations that reduce the viability of each site, as well as the probability of development of each site discounted by each regulation. I focus only on the regulations meant to preserve the wilderness and the wildlife. The second source of data is "The Emissions & Generation Resource Integrated Database" (eGRID), produced by the U.S. Environmental Protection Agency (EPA). It is a comprehensive database on the environmental characteristics of almost all electric power generated in the U.S., including air emissions for carbon dioxide, nitrogen oxides, sulfur dioxide, methane, and nitrous oxide.

This study might have at least two relevant contributions to the design of environmental policies in the U.S. and abroad. First, it highlights the pernicious incentives that incomplete environmental regulation generates[3], and points to an integrated regulatory framework which includes both land conservation and air quality. If the government wants to preseve nature, it should restrict land use and emissions simultaneously. Hence, the recent push by the U.S. Environmental Protection Agency (EPA) to limit greenhouse gas emissions goes in the expected direction. (The cost, however, might be higher relative prices for electricity, as predicted by my simple theoretical model.) Also, such regulatory framework may be useful to guide the debate on the development of other renewable energy sources, such as wind and solar energy. Studies have identified enough sites in the U.S. that, if developed, could make these technologies the dominant electricity sources in the country[4]. Nevertheless, large-scale wind and solar projects might create major alterations to the landscape and would not be seen as environmentally friendly, as in the hydroelectricity case. Indeed, wind turbines may harm many species of birds, and large-scale solar projects in the desert may endanger the habitat for native animals. Therefore, the trade-off between land conservation and air quality might be as fundamental here as in the hydroelectricity setting.

Second, it indicates that the heated debate sparked by hydropower projects in developing and underdeveloped countries might be misguided. The Three Gorges Dam in China, the world's largest hydroelectric project, for example, has raised international concerns on environmental damages, but few organizations recognize the sizeable amount of pollution-free electric power generated, which would be mainly produced by the most-polluting power plants: coal-fired power plants[5]. Also, the historical involve-

[3]Fowlie (2009) also provides evidence of emissions leakage when industrial pollution is incompletely regulated. She argues that if unregulated production can be easily substituted for production at regulated firms, emissions can even exceed the level of emissions that would have occurred in the absence of regulation.

[4]See a recent discussion about it on Borenstein (2012)

[5]In China, 80% of the electricity is produced by coal-fired power plants, the highest rate in the

ment of the World Bank with the construction of large hydro dams in Asia, Africa and Latin America has been severely criticized by environmentalists. It is likely that the opportunity cost that such criticisms implied has been more air pollution and, potentially, more global warming. Again, bidimensional negotiations, integrating both land conservation and air quality concerns, would have been more effective in preserving our environment.

The remainder of the paper is organized as follows. Section 3.2 presents a simple theoretical framework to illustrate the trade-off between land conservation and air quality. Section 3.3 describes the databases used in this study. Section 3.4 outlines the methodology for the empirical analysis. Section 3.5 reports and discusses results. Section 3.6 provides some concluding remarks.

3.2 Theoretical Framework

To examine the trade-off between land conservation and air quality, let us work with a simple general equilibrium model for eletricity generation. Let us assume that consumers value eletricity, land conservation and air quality, but electricity generation damages the environment either through construction of hydroeletric dams or greenhouse gas emissions.

3.2.1 Set-up

In the simplest-possible setting, suppose that there are two price-taking economic agents, a single consumer and a single firm, and three goods, land, clean air, and eletricity produced by the firm.

The consumer has a strictly concave utility function $U(T, C, A)$, defined over his consumption of eletricity T, land for conservation C, and clean air A. He has an endowment of $\overline{L}$ units of land, an endowment of $\overline{E}$ units of emission permits, but no endowment of eletricity.

The firm uses inputs land L (to construct hydroelectric dams) and carbon dioxide emissions E to produce eletricity according to the increasing and strictly concave production function $F(L, E)$. Thus, to produce the output, the firm must buy land and emission permits from the consumer. Assume that the firm seeks to maximize its profits taking market prices as given. Letting p_T be the price of its output, p_L be the price of land, and p_E the price of emission permits, the firm solves

$$\mathrm{Max}_{L,E\in\mathbb{R}^2_+} p_T F(L, E) - p_L L - p_E E. \tag{3.1}$$

Given prices (p_T, p_L, p_E), the firm's optimal demands are $L(p_T, p_L, p_E)$ and $E(p_T, p_L, p_E)$, its output is $Q(p_T, p_L, p_E)$, and its profits are $\pi(p_T, p_L, p_E)$.

world.

Firms are owned by consumers. Thus, assume that the consumer is the sole owner of the firm and receives the profits earned by the firm $\pi(p_T, p_L, p_E)$. Therefore, the consumer's problem given prices (p_T, p_L, p_E) is

$$\begin{aligned} &\mathrm{Max}_{T,L,E\in\mathbb{R}^3_+} U(T,C,A) \\ &\qquad \text{s.t. } p_T T \leq p_L(\overline{L}-C)+p_E(\overline{E}-A)+\pi(p_T,p_L,p_E). \end{aligned} \tag{3.2}$$

The budget constraint in (3.2) reflects the three sources of the consumer's purchasing power. If the consumer supplies $(\overline{L}-C)$ units of land for the construction of hydro-electric dams, and $(\overline{E}-A)$ units of emission permits when prices are (p_T, p_L, p_E), then the total amount he can spend on eletricity is $p_L(\overline{L}-C)+p_E(\overline{E}-A)$ plus the profit distribution from the firm $\pi(p_T, p_L, p_E)$. The consumer's optimal demands in problem (3.2) for prices (p_T, p_L, p_E) are denoted by $(T(p_T, p_L, p_E),\ C(p_T, p_L, p_E),\ A(p_T, p_L, p_E))$.

A Walrasian equilibrium in this economy involves a price vector (p_T^*, p_L^*, p_E^*) at which the eletricity, the land and the permit markets clear; that is, at which

$$\begin{aligned} Q(p_T^*, p_L^*, p_E^*) &= T(p_T^*, p_L^*, p_E^*), \\ L(p_T^*, p_L^*, p_E^*) &= \overline{L}-C(p_T^*, p_L^*, p_E^*), \\ E(p_T^*, p_L^*, p_E^*) &= \overline{E}-A(p_T^*, p_L^*, p_E^*). \end{aligned}$$

As well-known[6], *a particular eletricity-land-permit combination can arise in a competitive equilibrium if and only if it maximizes the consumer's utility subject to the economy's technological and endowment constraints.* Indeed, the Walrasian equilibrium allocation is the same allocation that would be obtained if a planner ran the economy in a manner that maximized the consumer's well-being. Therefore, the competitive equilibrium is also Pareto optimal. The equilibrium problem is

$$\begin{aligned} &\mathrm{Max}_{T,L,E\in\mathbb{R}^3_+} U(T,C,A) \\ &\qquad \text{s.t. } T = F(L,E), \\ &\qquad\qquad C = \overline{L}-L, \\ &\qquad\qquad A = \overline{E}-E, \end{aligned}$$

which is equivalent to

$$\mathrm{Max}_{L,E\in\mathbb{R}^2_+} U(F(L,E),(\overline{L}-L),(\overline{E}-E)). \tag{3.3}$$

The first-order conditions for this problem are

$$\begin{aligned} U_T F_L - U_C &= 0, \\ U_T F_E - U_A &= 0, \end{aligned}$$

[6]See, for example, Mas-Collel, Whinston and Green (1995), chapter 15.

from which we can define $L^*(\overline{L}, \overline{E})$ and $E^*(\overline{L}, \overline{E})$. To check for a trade-off between optimal emissions (E^*) and land regulation (change in $\overline{L}$), we use the implicit function theorem and find

$$\begin{aligned}\frac{\partial E^*}{\partial \overline{L}} \quad = \quad & \frac{(U_T U_{TC} F_L F_{LE} - U_T U_{TC} F_E F_{LL} + U_T U_{CC} F_{LE} + U_T U_{CA} F_{LL})}{(-U_T U_{TA} F_L F_{LE} - U_{TA} U_{CA} F_L - U_T U_{TC} F_E F_{LE} + U_T^2 F_{LE}^2} \\ & ... + U_T U_{CA} F_{LE} - U_{TC} U_{CA} F_E + U_T U_{CA} F_{LE} + U_{CA}^2 \\ & ... + U_T U_{TC} F_L F_{EE} - U_{TC} U_{AA} F_L + U_T U_{TA} F_E F_{LL} - U_T^2 F_{EE} F_{LL} \\ & ... + U_T U_{AA} F_{LL} - U_{TA} U_{CC} F_E + U_T U_{CC} F_{EE} - U_{CC} U_{AA}).\end{aligned}$$

As we can see, the sign of $\frac{\partial E^*}{\partial \overline{L}}$ is ambiguous under mild assumptions on both the utility and the production functions, so we now turn to some special cases.

3.2.2 Case 1: Cobb-Douglas Production and Cobb-Douglas Utility

To illustrate the trade-off between land conservation and air quality, let us find the competitive equilibrium for eletricity generation using a Cobb-Douglas functional form for both the production function and the utility function. Let us get the equilibrium allocations (T^*, L^*, E^*) first, and then compute the equilibrium prices (p_T^*, p_L^*, p_E^*). The competitive equilibrium problem is

$$\begin{aligned} \text{Max}_{T,L,E \in \mathbb{R}_+^3} T^\alpha C^\beta A^\gamma, \qquad & \{\alpha, \beta, \gamma\} \in (0,1), \\ \text{s.t. } T \;=\; & L^l E^e, \quad \{l, e\} \in (0,1), \\ C \;=\; & \overline{L} - L, \\ A \;=\; & \overline{E} - E, \end{aligned}$$

which is equivalent to

$$\text{Max}_{L,E \in \mathbb{R}_+^2} (L^l E^e)^\alpha (\overline{L} - L)^\beta (\overline{E} - E)^\gamma. \tag{3.4}$$

Solving problem (3.4) yields optimal allocations

$$L^* = \left(\frac{1}{1 + \frac{\beta}{\alpha l}}\right) \overline{L} \in (0, \overline{L}), \tag{3.5}$$

$$E^* = \left(\frac{1}{1 + \frac{\gamma}{\alpha e}}\right) \overline{E} \in (0, \overline{E}), \tag{3.6}$$

$$T^* = (L^*)^l (E^*)^e. \tag{3.7}$$

Now, let (p_T^*, p_L^*, p_E^*) be a supporting price vector of the Pareto optimal allocations just identified. As a normalization, put $p_T^* = 1$. The zero-profit condition and the cost minimization condition of the eletricity production imply that

$$p_L^* = \frac{(E^*)^e}{\left(1+\frac{e}{l}\right)(L^*)^{1-l}}, \tag{3.8}$$

$$p_E^* = \frac{e}{l}\frac{(L^*)^l}{\left(1+\frac{e}{l}\right)(E^*)^{1-e}}, \tag{3.9}$$

$$\frac{p_E^*}{p_L^*} = \frac{e}{l}\frac{L^*}{E^*}. \tag{3.10}$$

To make the trade-off between land conservation and gas emissions clear, let us write E^* as a function of L^* (and, consequently, $\overline{L}$). Hence,

$$E^* = \left(\frac{1}{1+\frac{\gamma}{\frac{e\beta}{l}\left(\frac{L^*}{(\overline{L}-L^*)}\right)}}\right)\overline{E}. \tag{3.11}$$

Now, it is evident that optimal emissions E^* increase when governmental regulations restrict the number of developable sites for hydroelectric dams, that is, when government reduces $\overline{L}$. *Therefore, nature is being damaged one way or the other: conservation of land is being offset with emission of greenhouse gases.* (Notice that the relative price of emissions with respect to land, $\frac{p_E^*}{p_L^*}$, goes down with the land regulations. This is the way the market accommodates the presence of such regulations.)

If the government really wants to implement an eco-friendly policy, it should impose both land and emission regulations, that is, it should bring both $\overline{L}$ and $\overline{E}$ down. Indeed, equation (3.11) says that the increase in optimal emissions arising from a lower $\overline{L}$ might be offset with a reduction in $\overline{E}$. The consequence of such policy, however, is less eletricity generation (see equations (3.5), (3.6), and (3.7)). As a result, the relative price of eletricity might go up (see equations (3.8) and (3.17) and recall the normalization $p_T^* = 1$). Land regulations have existed for a long time in the U.S. On the other hand, emissions of greenhouse gases have yet to be regulated. Interestingly, the U.S. Environmental Protection Agency (EPA) has recently proposed a rule to control greenhouse gas emissions from new power plants.

3.2.3 Case 2: Perfect Substitutes Production and Cobb-Douglas Utility

The competitive equilibrium problem in this case is

$$\begin{aligned} \mathrm{Max}_{T,L,E\in\mathbb{R}^3_+} T^\alpha C^\beta A^\gamma, \qquad & \{\alpha,\beta,\gamma\}\in(0,1), \\ \text{s.t. } T &= lL+eE, \quad \{l,e\}\in\mathbb{R}_+, \\ C &= \overline{L}-L, \\ A &= \overline{E}-E, \end{aligned}$$

which is equivalent to

$$\mathrm{Max}_{L,E\in\mathbb{R}^2_+}(lL+eE)^\alpha(\overline{L}-L)^\beta(\overline{E}-E)^\gamma. \tag{3.12}$$

Solving problem (3.12) yields optimal allocations

$$L^* = \frac{(\alpha+\gamma)l\overline{L}-\beta e\overline{E}}{(\alpha+\beta+\gamma)l} \in (0,\overline{L}), \tag{3.13}$$

$$E^* = \frac{(\alpha+\beta)e\overline{E}-\gamma l\overline{L}}{(\alpha+\beta+\gamma)e} \in (0,\overline{E}), \tag{3.14}$$

$$T^* = lL^*+eE^*. \tag{3.15}$$

Now, let (p_T^*, p_L^*, p_E^*) be a supporting price vector of the Pareto optimal allocations just identified. As a normalization, put $p_T^*=1$. Also, due to the perfect substitutibility of inputs in the production function, and the non-zero optimal allocations for both of them, $p_E^* = \frac{e}{l}p_L^*$. The zero-profit condition of the eletricity generation then implies that

$$p_L^* = l, \tag{3.16}$$

$$p_E^* = e. \tag{3.17}$$

Notice that the trade-off between land conservation and gas emissions is again evident in equation (3.14).

3.3 Data Description

To proceed with the empirical analysis, I use two sources of data. The first is a unique report prepared in the 1990s for the U.S. Department of Energy (DOE), to determine the undeveloped potential hydropower resources in the U.S. It is the 1998 U.S. Hydropower Resource Assessment, prepared by the Idaho National Engineering and Environmental Laboratory (INL) (Conner, Francfort, and Rinehart, 1998; INL, 1998). It contains site characteristics such as exact location and potential generation capacity, and, crucially, the list of all land regulations that reduce the viability of each site, as well as the probability of development of each site based on each regulation. Such information allows me to compute the hydropower potential that cannot be developed due to regulations meant to preserve the wilderness and the wildlife. The second source of data is "The Emissions & Generation Resource Integrated Database" (eGRID) for 2007 (eGRID, 2010), produced by the U.S. Environmental Protection Agency (EPA). It is a comprehensive database on the characteristics of almost all electric power generated in the U.S., including capacity installed in power plants, and air emissions for carbon dioxide, nitrogen oxides, sulfur dioxide, methane, and nitrous oxide.

3.3.1 Hydropower Assessment

The INL report presents DOE's efforts to produce a more definitive assessment of undeveloped hydropower resources within the U.S. No agency had previously estimated the undeveloped hydropower capacity based on site characteristics, stream flow data, and available hydraulic heads. Initial efforts began in 1989 and information from the last state was received in 1998. State agencies such as departments of dam safety, water resources, environmental quality, fish and game, history, and commerce, contributed information about hydropower resources within their states. The report summarizes and discusses the undeveloped *conventional* hydropower capacity for the 5,677 sites within the country. It does not include the capacity produced by pumped storage sites. However, for conventional hydropower, the resource assessment contains site identification information, geographic coordinates, and crucially the estimated nameplate capacity[7].

3.3.1.1 Suitability Factor Determination and Undevelopable Hydropower Potential

A key element of my analysis here is the suitability factor of a potential hydropower site. Such a factor reflects the probability that environmental considerations might make a project site unacceptable, prohibiting its development. Suitability factors were developed by the INL, in conjunction with Oak Ridge National Laboratory staff who are experienced in hydropower licensing cases. Five potential values were selected, as shown in table 3.1. (The discussion that follows is heavily based on Conner, Francfort, and Rinehart [1998].)

The crucial step in evaluating the environmental suitability of each project site is to combine the suitability factors for the individual environmental attributes into a single factor for each project site. This overall suitability factor is an estimate of the probability of a project's successful development, considering all the attributes described in Appendix B. The presence of more than one environmental attribute means that more than one environmental concern affects a project. The overall suitability factor should obviously be no greater than the lowest factor for individual attributes, and it should be less than the lowest factor if multiple significant environmental constraints are present. For example, if an undeveloped project has both fish values (suitability factor = 0.25) and wildlife values (suitability factor = 0.25), the cumulative effects of these two concerns will make its overall suitability even less than 0.25, so an overall suitability factor of 0.1 is assigned.

If the environmental suitability factors for individual attributes were truly the probability of the project's being developed, then the overall probability of development could be mathematically calculated. And, if the individual suitability factors were true and independent probabilities, then the probability of developing the project site because of environmental concerns would be equal to the product of all the individual factors. However, the Federal Energy Regulatory Commission's (FERC's) licensing process is

[7] Nameplate capacity refers to the intended technical full-load sustained output of a facility.

not a statistical probability function, and it cannot be assumed that suitability factors can be handled as independent probabilities (for example, there is a strong correlation between the scenic, recreational, and fishing values of a stream). The procedure outlined in table 3.2 is used for assigning overall suitability factors. It was developed by the laboratories mentioned above and assumes that the lowest suitability factor dominates the likelihood of a project's development. However, it also considers the reduced likelihood of development resulting from the occurrence of multiple low suitability factors.

After finding the overall suitability factor for each potential hydropower site, I obtain the probability of development at the county level. First, I weight the potential capacity of each site with its own probability, and sum the weighted capacities over all sites in the county. Then, I divide this weighted sum by the total potential capacity. This quotient is my county suitability factor.

To obtain a crucial variable in my analysis - the hydropower potential that cannot be developed because of environmental regulations in each county -, I use the probability that some hydroelectric projects will not be carried out, which is one minus the county suitability factor. This probability of non-development is then multiplied by the hydropower potential at the county level.

3.3.1.2 Environmental, Legal, and Institutional Attributes

The INL defined the following environmental, legal, and institutional attributes. I use only the ones marked with (*) in my empirical analysis. The corresponding suitability factors are fully explained in the Suitability Factor Determination section above.

Wild/Scenic Protection (*). This attribute identifies project sites that are included in the federal wild and scenic rivers system, under consideration for inclusion in the federal system, included in a state river protection program, in a designated wilderness area, or protected from development under another program. Relatively few sites have this status, but those that do are highly unlikely to be developed. Projects at undeveloped sites on state or federally protected wild and scenic rivers, or in wilderness areas, must be assumed to be legally protected from hydropower development. Also, projects at sites under consideration for protection are highly likely to be opposed by state and federal resource agencies, and protection will be approved at many such sites before hydropower development could occur. Since it is possible, but highly unlikely, that development could occur at a site with wild and scenic river protection, the suitability factor assigned to all such projects at undeveloped sites is 0.1. It is highly unlikely that a project at an existing dam would be on a wild and scenic river since rivers are usually designated as wild and scenic only if they are free of developments such as dams. A suitability factor of 0.5 is assigned for such unusual cases.

Wild and Scenic Tributary or Upstream or Downstream of a Wild and Scenic Location (*). This attribute is assigned to a project if it is at the upstream or downstream end of a wild and scenic river reach or is on a tributary of a wild and scenic river. A project at a developed site would affect a downstream wild and scenic river if additional alterations to the flow regime resulted. A suitability factor of 0.75 is assigned for such projects. Projects at undeveloped sites are highly likely to alter the flow regime and may cause changes in downstream water quality, so a suitability factor of 0.5 is assigned to undeveloped sites.

Cultural and Historic Values. Project impacts on cultural and historic resources can often be mitigated (for example, by excavating archeological sites or relocating historic structures). Projects at existing dams are unlikely to affect such resources unless an increase in reservoir pool elevation occurs or major new structures are built. A suitability factor of 0.75 is assigned to such projects. Development of undeveloped sites is more likely to affect cultural and historic resources, so a suitability factor of 0.5 is assigned.

Fish Presence Value (*). A stream reach may or may not have legally protected fisheries. In either case, however, strong state opposition to new development must be expected if a valuable fishery resource exists. Relatively high instream flow release requirements can mitigate the impact on fisheries, but a high instream flow release would reduce the economic viability of the project. Projects at developed sites could have some impact, such as increased turbine mortality. A suitability factor of 0.75 is assigned to projects at developed sites. Development at undeveloped sites could have a major impact on aquatic habitat through inundation, migration blockage, turbine mortality, water quality, and altered flows. Some of these can be mitigated, but such mitigation could be expensive. A suitability factor of 0.25 is assigned to undeveloped sites.

Geologic Value. Geologic values such as rock formations are rarely protected legally and are not generally affected by small projects. Development at existing sites is not affected by geologic resources, so a suitability factor of 0.9 is assigned. Development at undeveloped sites may inundate geologic features, so a suitability factor of 0.5 is assigned.

Recreation Value. River recreation users tend to be effective opponents of hydropower development. Development at any storage dam would affect recreation by altering flow releases; mitigation typically includes higher flow releases during periods of high recreation use. Such releases can be made through turbines, but higher flow releases tend to occur when power demands are low. Projects at existing dams would have little effect on recreation besides flow alterations, so they are assigned a suitability factor of 0.75. Projects at undeveloped sites would inundate reaches, block the passage of boats, and reduce aesthetics. Because projects at undeveloped sites are likely to be strongly opposed, a suitability factor of 0.25 is assigned.

Scenic Value. Scenic values are not legally protected but must be considered in assessing the impact of a project. Scenic values are also important to recreational river users. The addition of power to existing dams would alter scenic values only through the addition of new structures and perhaps by reducing visually attractive spillage, so a suitability factor of 0.9 is assigned. New projects at undeveloped sites would have important effects on scenic resources because views would be altered by the project. Undeveloped projects are assigned a suitability factor of 0.5.

Wildlife Value (*). Terrestrial wildlife and wildlife habit are protected by fish and game agencies that are influential in determining mitigation requirements for hydropower projects. Development at existing sites would have little effect on wildlife unless reservoir pool elevations are altered or construction of major facilities is required. A suitability factor of 0.75 is assigned for projects at existing sites. Development at undeveloped sites could inundate wildlife habitat, and construction would cause a great deal of disturbance. It is difficult to mitigate for such impacts, so opposition to such a project could be strong. Undeveloped projects are assigned a suitability factor of 0.25.

Other Value. The effects of other values, such as the presence of rare wetland communities or consideration for wilderness designation, are assigned by using the most commonly assigned suitability factor for the other values. For projects at developed sites, the suitability factor is 0.75. For projects at undeveloped sites, the suitability factor is 0.5.

Threatened and Endangered Fish or Wildlife (*). The presence of threatened and endangered species near a project site requires additional consultations with wildlife agencies and can result in additional studies and mitigation requirements. The presence of threatened and endangered fish species may preclude development of new storage projects because new projects can involve the greatest alteration of aquatic habitat. Terrestrial threatened and endangered species are unlikely to be highly affected by run-rivers projects, but storage reservoirs could affect terrestrial habitat. For existing sites, a suitability factor of 0.75 is assigned when threatened and endangered species are present. For projects at undeveloped sites, a suitability factor of 0.5 is assigned when threatened and endangered species are present.

Federal Land Code 103: National Park, Monument, Lakeshore, Parkway, Battlefield, Or Recreation Area. These lands are legally protected from development. A suitability factor of 0.1 is assigned for such projects.

Federal Land Code 104 (*): National Forest or Grassland. These lands are not legally protected from development, but the managing agency has the right to impose additional mitigation requirements on projects. A suitability factor of 0.75 is assigned to projects at existing sites, since these projects typically have fewer impacts. A suitability factor of 0.5 is assigned for undeveloped sites.

Federal Land Code 105 (*): National Wildlife Refuge, Game Preserve, or Fish Hatchery. These lands are managed for fish and wildlife habitats, and hydropower development would almost always be incompatible. A suitability factor of 0.1 is assigned for such projects.

Federal Land Code 106 (*): National Scenic Waterway or Wilderness Area. These lands are legally protected from development. A suitability factor of 0.1 is assigned for such projects.

Federal Land Code 107: Indian Reservation. These lands are not legally protected from development, but Indian tribes have the right to impose additional mitigation requirements on projects. A suitability factor of 0.75 is assigned for projects at developed sites, and a suitability factor of 0.5 is assigned for projects at undeveloped sites.

Federal Land Code 108: Military Reservation. These lands are not legally protected from development, but the managing agency has the right to impose additional mitigation requirements on projects. A suitability factor of 0.75 is assigned for projects at developed sites, and a suitability factor of 0.5 is assigned for projects at undeveloped sites.

Federal Land Code 198: Not on Federal Land. This variable indicates that the project is not on federal land, so there are not any development constraints based on Federal Land Codes. The value for this variable is 0.9.

3.3.2 Emissions-eGRID Database

Emissions and power plant information comes from the U.S. Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID) for 2007. This database is a comprehensive inventory of the generation and environmental attributes of all power plants in the United States. Much of the information in eGRID, including plant opening years, comes from the U.S. Department of Energy's Annual Electric Generator Report compiled from responses to the EIA-860, a form completed annually by all electric-generating plants. In addition, eGRID includes plant identification information, geographic coordinates, number of generators, primary fuel, plant nameplate capacity, plant annual net generation, whether the plant is a cogeneration facility, and air emissions for nitrogen oxides, sulfur dioxide, carbon dioxide, methane, and nitrous oxide.

3.4 Empirical Strategy

In order to test for the existence and economic relevance of the trade-off between land conservation and air quality empirically, I use ideas advanced in the conceptual framework. Basically, I regress variation in carbon dioxide emissions for the period 1998-2007 ($\triangle E$) on the thermal (fossil-fuel) power capacity built during the same time ($\triangle ThermDev$), controlling for variation in population (ΔPop) and per capita income ($\Delta PCInc$),

$$\triangle E_c = \beta_0 + \beta_1 \triangle ThermDev_c + \beta_2 \triangle Pop_c + \beta_3 \Delta PCInc_c + \varepsilon_c, \tag{3.18}$$

and use an instrumental variable (IV) strategy to identify the response of emissions to thermal power capacity induced by potential hydropower capacity that cannot be developed due to land conservation regulations ($HydroNotDev$). The first stage is then

$$\triangle ThermDev_c = \gamma_0 + \gamma_1 HydroNotDev + \gamma_2 \triangle Pop_c + \gamma_3 \Delta PCInc_c + \nu_c. \tag{3.19}$$

Notice that the coefficient β_1 in equation (3.18) reflects just the average mechanical effect of new thermal power capacity on carbon dioxide emissions. The behavioral response, my object of interest, comes from the IV approach. Since $HydroNotDev$ represents how much land availability for the development of new hydro dams ($\overline{L}$ in the theoretical model) has dropped because of land conservation regulations, coefficient β_1^{IV} captures the increase in emissions arising from the potential substitution of hydropower plants with fossil-fuel power plants in the generation of electricity. Therefore, it tells us the relevance of the aforementioned trade-off between land conservation and air quality. Recall either equation (3.11) or equation (3.14) to understand the link between the conceptual framework and the empirical strategy here.

My unit of observation is county (c), and I focus on the period 1998-2007 because the final DOE's hydropower assessment report was released in 1998, and the latest emissions eGRID data is for 2007. I restrict my sample for counties that have high hydropower potential (above 100 megawatts[8]), and that have developed any power plants in the period of analysis. My sample turns out to be really small: 32 counties, in 17 states.

Major threats to identification are changes in preferences towards environmental amenities and in access to coal versus natural gas at a local level. Because my analysis focus on a short period of time, the domestic production of natural gas started to climb only in 2006, and I take away county fixed effects with the differencing strategy, those concerns might be of second order.

3.5 Results

The trade-off between land conservation and air quality is estimated through an instrumental variable approach. Results are presented in table 3.3. Initially, equation (3.18) is estimated by OLS. Then, IV estimates are found using potential hydropower not developed due to environmental regulations as exogenous shifter in the thermal power capacity built in the period 1998-2007.

The OLS estimate indicates that each new megawatt installed in fossil-fuel power plants generates 832 pounds of carbon dioxide emissions on average. This suggests that large power plants built recently might be driven by natural gas, since natural gas plants emit 800 to 850 pounds of carbon dioxide per megawatt. However, the preferred IV estimate reveals that counties with larger hydropower potential not exploited because of strict hydroelectric licensing rules emit 77 percent more of carbon dioxide per megawatt (approximately 1476 pounds per megawatt). Since coal plants emit an average of 1,768 pounds of carbon dioxide per megawatt, those environmental regulations seem to induce dirtier choices in electricity generation.

The first stage regression also brings insights on the impact of environmental regulations on the energy mix. It sheds some light on how restricting construction of hydro dams affects the development of new thermal power plants. When I use the

[8]Plants smaller than 100 megawatts are not considered here because they tend to be built simultaneously with existing or expanding facilities such as industrial plants. Since the objective of the study is to provide evidence of substitution among difference types of power plants, and hydroelectric dams tend to be large, independend projects, it makes sense to concentrate on large plants. Davis (2011) uses the same cut-off in his study of the effect of power plants on local housing values and rents.

number of megawatts of hydropower that cannot be developed because of environmental regulations ($HydroNotDev$) as instrument, the coefficient is approximately 0.25, although not statistically significant. Taken at face value, that number means that for each megawatt of hydropower potential not allowed to be developed due to regulations induces an increase of 0.25 megawatt of thermal power developed in that county. As we can see, the substitution does not seem to be one-to-one. This may be rationalized by the fact that electric utilities might build power plants in other counties within their service area, or buy electricity from other regions. Also, such environmental restrictions might stifle local developement generally, or trigger efforts towards energy efficiency policies.

Because the F-statistic of the first stage with $HydroNotDev$ suggests only very weak identification, I exploit some nonlinearities to improve it. I use a quartic function of $HydroNotDev$ instead. The IV estimate bounces around as I increase the order of the polynomial, but stabilizes at the fourth order. Interestingly, it stabilizes on a value very close to the one found using only the linear function of $HydroNotDev$. Knowing that just-identified IV estimate is median-unbiased, such finding provides support for my identification strategy. Furthermore, the Hansen's J-test for overidentifying restrictions reveals that the model is "valid", that is, the data come close to meeting the restrictions.

The non-linear first stage reveals an interesting pattern in the relationship between hydropower not developed due to environmental regulations and development of thermal power capacity. Figure 3.1 shows that for low levels of $HydroNotDev$, increases in constraints are associated with decreases in the number of megawatts developed in fossil-fuel power plants. However, for higher levels of $HydroNotDev$, a positive relationship seems to emerge. Figure 3.2, zoomed in around the sample average (between 10th and 90th percentiles), displays the pattern even more clearly. This suggests that after a certain threshold, restrictions imposed by hydroelectric licensing rules may be used as leverage by electric utilities to get permits to build new thermal power plants. Indeed, one of the biggest challenges in siting new plants is resistance from local communities. Citizen groups argue that power plants are a source of numerous negative local externalities, including visual disamenities and noise. Davis (2011) provides empirical evidence suggesting that such claims might be well-founded. Examining housing values and rents for neighborhoods in the U.S. where power plants were opened during the 1990s, he find that neighborhoods within 2 miles of plants experienced 3%-7% decreases in housing values and rents, with some evidence of larger decreases within 1 mile and for large-capacity plants.

Weak identification. There may be some weak identification issues here. The F-statistic for the first stage with instrument $HydroNotDev$ is below the "safe threshold" of 10 suggested by Stock, Wright and Yogo (2002). The F-statistic for the non-linear first stage is larger than 10, but individual coefficients are not statistically significant. When instruments are only weakly correlated with the endogenous explanatory variable, two problems might emerge: (i) biased parameter estimates and (ii) biased standard errors. Stock and Yogo (2005) provide a formal test for when an IV is "too weak" to be trustworthy. The null hypothesis in this test is that bias of IV is some fraction of the bias of OLS. In my overidentified model, the one with a quartic function on $HydroNotDev$, the Kleibergen-Paap rk Wald F-statistic is above the Stock-Yogo 10-percent maximal IV relative bias critical value, suggesting that the bias of IV is less than 10 percent the bias of OLS. Stock and Yogo (2005) also propose a test of the null hypothesis that the true significance of hypothesis tests about the endogenous regressor coefficient is smaller than 10, 15, 20, or 25 percent when the usually stated significance level is 5 percent. In my model, the test statistic is slightly lower than the Stock-Yogo 15-percent maximal IV size critical value, then standard errors are not strongly downward biased.

I also estimate the model with a quartic function on $HydroNotDev$ by continuously-updated GMM, known to perform better than two-step feasible GMM in small samples, and by limited-information maximum likelihood (LIML), known to be less precise but also less biased than IV. As shown in table 3.3, in both cases the coefficient of interest increases, suggesting that the IV estimate might be just a lower bound of the effect of the environmental regulations on carbon dioxide emissions. An average of the coefficients estimated by the three procedures is approximately 1768 pounds of carbon dioxide per megawatt, exactly the average emissions of coal-fired power plants in the U.S.

3.6 Concluding Remarks

Do environmental regulations aimed to preserve natural ecosystems really protect nature? The answer seems to be not really. I present evidence that while hydroelectric licensing rules conserve the wilderness and the wildlife by restricting the development of hydro projects, they lead to more greenhouse gas emissions. Basically, the land conservation regulations give rise to a replacement of hydropower, which is a renewable, non-emitting source of energy, with conventional fossil-fuel power, which is highly pollutant. Restrictions imposed by hydroelectric licensing rules might be used as leverage by electric utilities to get permits to expand thermal power generation. Each megawatt of hydropower potential that is not developed because of those regulations induces the generation of the average emissions of carbon dioxide per megawatt of U.S. coal-fired power plants. Environmental regulations focusing only on the preservation of ecosystems appears to stimulate dirty substitutions within electric utilities regarding electricity generation.

Such finding highlights the pernicious incentives of incomplete environmental regulations, and points to an integrated regulatory framework that includes both land conservation and air quality. If the government wants to preseve nature, it should restrict land use and emissions simultaneously. Hence, the recent push by the U.S. Environmental Protection Agency (EPA) to limit greenhouse gas emissions goes in the expected direction. Similar regulatory framework may be useful to guide the debate on the development of other renewable energy sources, such as wind and solar energy. Also, my empirical evidence of such unintended consequence of land conservation regulations provides guidelines for a more balanced cost-benefit analysis of hydroelectric dams. The Three Gorges Dam in China, the world's largest hydroelectric project, for example, has raised international concerns on environmental damages, but few organizations recognize the sizeable amount of pollution-free electric power generated, which would be mainly produced by the most-polluting power plants: coal-fired power plants.

Bibliography

- Abadie, Alberto, and Gardeazabal, Javier. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country, *American Economic Review*, 93(1): 112-132.
- Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program, *Journal of the American Statistical Association*, 105(490): 493-505.
- Ahn, Hyungtaik, and James L. Powell. (1993). Semiparametric Estimation of Censored Selection Models with a Nonparametric Selection Mechanism, *Journal of Econometrics*, 58(1-2): 3-29.
- Ai, Chunrong, and Xiaohong Chen. (2003). Efficient Estimation of Models with Conditional Moment Restrictions Containing Unknown Functions, *Econometrica*, 71(6): 1795-1843.
- Albouy, David. (2010). What Are Cities Worth? Land Rents, Local Productivity, and the Capitalization of Amenity Values, *Working Paper - University of Michigan.*
- Arcidiacono, Peter, and Robert A. Miller. (forthcoming). CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity, *Econometrica.*
- Bajari, Patrick, Han Hong, and Denis Nekipelov. (2010). Game Theory and Econometrics: A Survey of Some Recent Research, *Working Paper - University of California at Berkeley.*
- Basu, Kaushik. (2006). Gender and Say: A Model of Household Behaviour with Endogenously Determined Balance of Power, *The Economic Journal*, 116(511): 558-580.
- Becker, Gary. (1973). A Theory of Marriage: Part I, *Journal of Political Economy*, 81(4): 813-846.
- Becker, Gary. (1974). A Theory of Marriage: Part II, *Journal of Political Economy*, 82(2): S11-S26, Part 2.
- Becker, Gary. (1991). *A Treatise on the Family.* Harvard University Press, Cambridge, MA, Second Edition.
- Becker, Gary, and Kevin Murphy. (2000). *Social Economics.* Harvard University Press, Cambridge, MA.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. (2004). How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics*, 119(1): 249-275.
- Billington, David P., Donald C. Jackson, and Martin V. Melosi. (2005). *The History*

of Large Federal Dams: Planning, Design, and Construction in the Era of Big Dams. Denver: U.S. Department of the Interior/ Bureau of Reclamation.
- Black, Dan A., Natalia Kolesnikova and Lowell J. Taylor. (2010). Why Do So Few Women Work in New York (And So Many in Minneapolis)? Labor Supply of Married Women across U.S. Cities, *Working Paper - Federal Reserve Bank of St. Louis*.
- Blanchard, Olivier J., and Lawrence F. Katz. (1992). Regional Evolutions, *Brookings Papers on Economic Activity*, 23(1): 1-76.
- Bleakley, Hoyt, and Jeffrey Lin. (2010). Portage and Path Dependence, *Quarterly Journal of Economics*, 127(2): 587-644.
- Blundell, Richard, Pierre-Andre Chiappori, Thierry Magnac and Costas Meghir. (2007). Collective Labour Supply: Heterogeneity and Non-Participation, *Review of Economic Studies*, 74(2): 417–445.
- Borenstein, Severin. (2012). The Private and Public Economics of Renewable Electricity Generation, *Journal of Economic Perspectives*, 26(1): 67-92.
- BPA - Bonneville Power Administration. (n.d.). *History*. Portland, OR: BPA, bpa.gov/news/AboutUs/Pages/History.aspx.
- Brakman, Steven, Harry Garretsen, and Marc Schramm. (2004). The Strategic Bombing of German Cities during WWII and its Impact on City Growth, *Journal of Economic Geography*, 4(2): 201-218.
- Brown, Matthew H., and Richard P. Sedano. (2004). *Electricity Transmission: A Primer*. Denver/Washington D.C.: National Council on Electricity Policy.
- Browning, Martin, François Bourguignon, Pierre-Andre Chiappori, and Valerie Lechene. (1994). Income and Outcomes: A Structural Model of Intrahousehold Allocation, *Journal of Political Economy*, 102(6): 1067-1096.
- Browning, Martin, Pierre-Andre Chiappori, and Valerie Lechene. (2006). Collective and Unitary Models: A Clarification, *Review of Economics of the Household*, 4(1): 5-14.
- Bureau of the Census. (1949). *Census of Manufactures 1947: Fuels and Electric Energy Consumed*. Washington, DC: U.S. Department of Commerce.
- Burtless, G., and Jerry A. Hausman. (1978). The Effect of Taxation on Labor Supply: Evaluating the Gary Negative Income Tax Experiment, *Journal of Political Economy*, 86(6): 1103-1130.
- Card, David, and Alan B. Krueger. (1992). Does School Quality Matter? Returns to Education and the Characteristics of Public Schools in the United States, *Journal of Political Economy*, 100(1): 1-40.
- Charles, Kerwin Kofi, Erik Hurst, and Alexandra Killewald. (2011). Marital Sorting and Parental Wealth, *Working Paper - University of Chicago*.
- Chiappori, Pierre-Andre. (1988). Rational Household Labor Supply, *Econometrica*, 56(1): 63-90.
- Chiappori, Pierre-Andre. (1992). Collective Labor Supply and Welfare, *Journal of Political Economy*, 100(3): 437-467.
- Chiappori, Pierre-Andre, Bernard Fortin, and Guy Lacroix. (2002). Household Labor Supply, Sharing Rule, and the Marriage Market, *Journal of Political Economy*, 110(1): 37-72.

- Chiappori, Pierre-Andre, Bernard Salanie, and Yoram Weiss. (2010). Partner Choice and the Marital College Premium, *Working Paper - Columbia University.*
- Choo, Eugene, and Aloysius Siow. (2006). Who Marries Whom and Why, *Journal of Political Economy*, 114(1): 175-201.
- Choo, Eugene, Shannon Seitz and Aloysius Siow. (2008). The Collective Marriage Matching Model: Identification, Estimation and Testing, *Working Paper - University of Toronto.*
- Cintrón, Lizette (ed.). (1995). *Historical Statistics of the Electric Utility Industry through 1992.* Washington D.C.: Edison Electric Institute.
- Compton, Janice, and Robert A. Pollak. (2007). Why Are Power Couples Increasingly Concentrated in Large Metropolitan Areas? *Journal of Labor Economics*, 25(3): 475-512.
- Compton, Janice, and Robert A. Pollak. (2011). Family Proximity, Childcare, and Women's Labor Force Attachment, *Working Paper - Institute for Research on Poverty, University of Wisconsin - Madison.*
- Conner, Alison M., James E. Francfort, and Ben N. Rinehart. (1998). *U.S. Hydropower Resource Assessment - Final Report.* Idaho Falls, ID: Idaho National Engineering and Environmental Laboratory (INL), hydropower.inel.gov/resourceassessment.
- Costa, Dora L., and Matthew E. Kahn. (2000). Power couples: Changes in the Locational Choice of the College Educated, 1940-1990, *Quarterly Journal of Economics*, 115(4): 1287-1315.
- Dahl, Gordon B. (2002). Mobility and the Return to Education: Testing a Roy Model with Multiple Markets, *Econometrica*, 70(6): 2367-2420.
- Davis, Donald, and David Weinstein. (2002). Bones, Bombs, and Break Points: The Geography of Economic Activity, *American Economic Review*, 92(5): 1269-1289.
- Davis, Donald, and David Weinstein. (2008). A Search for Multiple Equilibria in Urban Industrial Structure, *Journal of Regional Science*, 48(1): 29-65.
- Davis, Lucas W. (2011). The Effect of Power Plants on Local Housing Values and Rents, *Review of Economics and Statistics*, 93(4): 1391-1402.
- Davis, Steven J., Cheryl Grim, John Haltiwanger, and Mary Streitwieser. (Forthcoming). Electricity Unit Value Prices and Purchase Quantities: U.S. Manufacturing Plants, 1963-2000, *Review of Economics and Statistics.*
- Devine, Warren D. (1983). From Shafts to Wires: Historical Perspective on Electrification, *Journal of Economic History*, 43(2): 347-372.
- Donaldson, Dave, and Richard Hornbeck. (2012). Railroads and American Economic Growth: A "Market Access" Approach, *Working Paper - Harvard University.*
- DuBoff, Richard B. (1979). *Electric Power in American Manufacturing, 1889-1958*, University of Pennsylvania Dissertation, (1964), New York: Arno Press.
- Duflo, Esther, and Rohini Pande. (2007). Dams, *Quarterly Journal of Economics*, 122(2): 601-646.
- Duranton, Gilles, and Henry G. Overman. (2005). Testing for Localization Using Microgeographic Data, *Review of Economic Studies*, 72(4): 1077-1106.

- Duranton, Gilles, and Henry G. Overman. (2008). Exploring the Detailed Location Patterns of U.K. Manufacturing Industries Using Microgeographic Data, *Journal of Regional Science*, 48(1): 213-43.
- EIA - U.S. Energy Information Administration. (n.d.). *History of the U.S. Electric Power Industry, 1882-1991.* Washington, DC: U.S. Department of Energy, eia.gov/cneaf/electricity/page
- Ellison, Glenn, and Edward L. Glaeser. (1997). Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach, *Journal of Political Economy*, 105(5): 889-927.
- Ellison, Glenn, and Edward L. Glaeser. (1999). The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? *American Economic Review Papers and Proceedings*, 89(2): 311-316.
- Ellison, Glenn, Edward L. Glaeser, and William R. Kerr. (2010). What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns, *American Economic Review*, 100(3): 1195-1213.
- Emissions and Generation Resource Integrated Database (eGRID). (2010). *eGRID2010: Version 1.1.* Washington, DC: U.S. Environmental Protection Agency, epa.gov/cleanenergy/energy-resources/egrid.
- Fowlie, Meredith L. (2009). Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage, *American Economic Journal: Economic Policy*, 1(2): 72-112.
- Galichon, Alfred, and Bernard Salanie. (2010). Matching with Trade-offs: Revealed Preferences over Competing Characteristics, *Working Paper - Columbia University.*
- Galichon, Alfred, and Bernard Salanie. (2011). Cupid's Invisible Hand: Social Surplus and Identification in Matching Models, *Working Paper - Columbia University.*
- Gemici, Ahu. (2011). Family Migration and Labor Market Outcomes, *Working Paper - New York University.*
- Gibbons, Robert, Lawrence F. Katz, Thomas Lemieux, and Daniel Parent. (2005). Comparative advantage, Learning, and Sectoral Wage Determination, *Journal of Labor Economics*, 23(4): 681-723.
- Greenstone, Michael, Hornbeck, Richard, and Enrico Moretti. (2010). Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Opnenings, *Journal of Political Economy*, 118(3): 536-598.
- Greenstone, Michael, John A. List, and Chad Syverson. (2012). The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing, *Working Paper - University of Chicago.*
- Gronau, Reuben. (1973). The Effect of Children on the Housewife's Value of Time, *Journal of Political Economy*, 81(2): S168-S199.
- Gronau, Reuben. (1974). Wage Comparisons-A Selectivity Bias, *Journal of Political Economy*, 82(6): 1119-1143.
- Grossbard-Schectman, Amyra. (1984). A Theory of Allocation of Time in Markets for Labour and Marriage, *The Economic Journal*, 94(376): 863-882.
- Haines, Michael R., and Inter-university Consortium for Political and Social Research (ICPSR). (2010). *Historical, Demographic, Economic, and Social Data: The United*

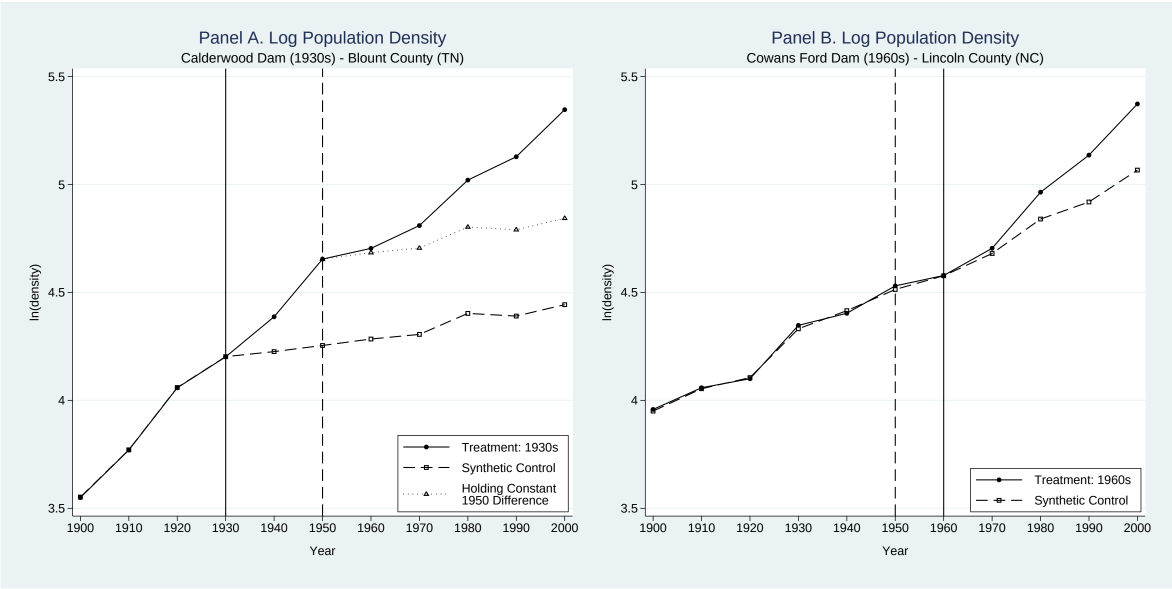
States, 1790-2002. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, icpsr.org.
- Hausman, Jerry A. (1980). The Effect of Wages, Taxes, and Fixed Costs on Women's Labor Force Participation, *Journal of Public Economics*, 14(2): 161-194.
- Hausman, Jerry A., and William E. Taylor. (1981). Panel Data and Unobservable Individual Effects, *Econometrica*, 49(6): 1377-1398.
- Heckman, James J. (1974). Shadow Prices, Market Wages and Labor Supply, *Econometrica*, 42(4): 679-694.
- Heckman, James J. (1979). Sample Selection Bias as a Specification Error, *Econometrica*, 47(1): 153-161.
- Heckman, James J., and V. Joseph Hotz. (1989). Choosing Among Alternatives Nonexperimental Methods for Estimating the Impact of Social Programs, *Journal of the American Statistical Association*, 84(408): 862-874.
- Hornbeck, Richard. (2010). Barbed Wire: Property Rights and Agricultural Development, *Quarterly Journal of Economics*, 125(2): 767-810.
- Hornbeck, Richard. (2012). The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe, *American Economic Review*, 102(4): 1477-1507.
- Hornbeck, Richard, and Pinar Keskin. (2012). Does Agriculture Generate Local Economic Spillovers? Short-run and Long-run Evidence from the Ogallala Aquifer, *NBER Working Paper* No. 18416.
- Hotz, V. Joseph, and Robert A. Miller. (1993). Conditional Choice Probabilities and the Estimation of Dynamic Models, *Review of Economic Studies*, 60(3): 497-529.
- Idaho National Engineering and Environmental Laboratory (INL). (1998). *U.S. Hydropower Resource Assessment*. Idaho Falls, ID: hydropower.inel.gov/resourceassessment.
- Iyigun, Murat, and Randall P. Walsh. (2007). Building the Family Nest: Premarital Investments, Marriage Markets, and Spousal Allocations, *Review of Economic Studies*, 74(2): 507-535.
- Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. (1993). Earnings Losses of Displaced Workers, *American Economic Review*, 83(4): 685-709.
- Jollata, Pat. (2004). *Images of America: Downtown Vancouver*. Arcadia Publishing.
- Killingsworth, Mark R., and James J. Heckman. (1986). Female Labor Supply: A Survey. In: *Handbook of Labor Economics, Volume 1*, edited by Orley Ashenfelter, and Richard Layard, North Holland: Amsterdam, Chapter 2, pp. 103-204.
- Kline, Patrick. (2010). Place Based Policies, Heterogeneity, and Agglomeration, *American Economic Review Papers and Proceedings*, 100(2): 383-387.
- Kline, Patrick. (2012). The Impact of Juvenile Curfew Laws on Arrests of Youth and Adults, *American Law and Economics Review*, 14(1): 44-67.
- Kline, Patrick, and Enrico Moretti. (2011). Local Economic Development, Agglomeration Economies and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority, *Working Paper - University of California at Berkeley*.
- Lee, Lung-Fei. (1983). Generalized Econometric Models with Selectivity, *Econometrica*, 51(2): 507-512.

- Legros, Patrick, and Andrew F. Newman. (2007). Beauty Is a Beast, Frog Is a Prince: Assortative Matching with Nontransferabilities, *Econometrica*, 75(4): 1073-1102.
- Lich-Tyler, Stephen. (2004). Negotiations and Love Songs: The Dynamics of Bargained Household Decisions, *Working Paper - University of Michigan at Ann Arbor*.
- Lise, Jeremy, and Shannon Seitz. (2011). Consumption Inequality and Intra-Household Allocations, *Review of Economic Studies*, 78(1): 328-355.
- Lundberg, Shelly J., and Robert A. Pollak. (2003). Efficiency in Marriage, *Review of Economics of the Household*, 1(3): 153-167.
- Manser, Marilyn, and Murray Brown. (1980). Marriage and Household Decision-Making: A Bargaining Analysis, *International Economic Review*, 21(1): 31-44.
- Mansur, Erin T., and Matthew E. Kahn. (2012). Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment? A Border Pairs Approach, *Working Paper - Dartmouth College*.
- Mas-Colell, Andreu, Michael D. Whinston, and Jerry R. Green. (1995). *Microeconomic Theory*, New York: Oxford University Press.
- Mazzocco, Maurizio. (2007). Household Intertemporal Behaviour: A Collective Characterization and a Test of Commitment, *Review of Economic Studies*, 74(3): 857-895.
- McClary, Daryl C. (2008). Longview - Thumbnail History, *HistoryLink.org Essay 8560*, historylink.org/index.cfm?DisplayPage=output.cfm&file_id=8560.
- McCrary, Justin. (2007). The Effect of Court Ordered Hiring Quotas on the Composition and Quality of Police, *American Economic Review*, 97(1): 318-53.
- McElroy, Marjorie. (1990). The Empirical Content of Nash-Bargained Household Behavior, *Journal of Human Resources*, 25(4): 559-583.
- McElroy, Marjorie, and Mary-Jean Horney. (1981). Nash-Bargained Household Decisions: Toward a Generalization of the Theory of Demand, *International Economic Review*, 22(2): 333-349.
- McFadden, Daniel L. (1974). Conditional Logit Analysis of Qualitative Choice Behavior, In: *Frontiers in Econometrics*, edited by Paul Zarembka, Academic Press: New York, Chapter 4, pp. 105-142.
- McNerneya, James, J. Doyne Farmer, and Jessika E. Trancik. (2011). Historical Costs of Coal-fired Electricity and Implications for the Future, *Energy Policy*, 39(6): 3042-3054.
- Miguel, Edward, and Gérard Roland. (2011). The Long-Run Impact of Bombing Vietnam, *Journal of Development Economics*, 96(1): 1-15.
- Mincer, Jacob. (1978). Family Migration Decisions, *Journal of Political Economy*, 86(5): 749-773.
- Minnesota Population Center. (2011). *National Historical Geographic Information System (NHGIS): Version 2.0.* Minneapolis, MN: University of Minnesota, nhgis.org.
- Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. (2011). Internal Migration in the United States, *Journal of Economic Perspectives*, 25(3): 173-196.
- Moretti, Enrico. (2011). Local Labor Markets. In: *Handbook of Labor Economics, Volume 4B*, edited by Orley Ashenfelter, and David Card, North Holland: Amsterdam, Chapter 14, pp. 1237-1313.

- Newey, Whitney K. (2009). Two-step Series Estimation of Sample Selection Models, *Econometrics Journal*, 12(S1): S217-S229.
- Newey, Whitney K., and James L. Powell. (2003). Instrumental Variable Estimation of Nonparametric Models, *Econometrica*, 71(5): 1565-1578.
- Olley, G. Steven, and Ariel Pakes. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica*, 64(6): 1263-1297.
- Pencavel, John. (1986). Labor Supply of Men: A Survey. In: *Handbook of Labor Economics, Volume 1*, edited by Orley Ashenfelter, and Richard Layard, North Holland: Amsterdam, Chapter 1, pp. 3-102.
- Redding, Stephen J., and Daniel M. Sturm. (2008). The Costs of Remoteness: Evidence from German Division and Reunification, *American Economic Review*, 98(5): 1766-97.
- Redding, Stephen J., Daniel M. Sturm, and Nikolaus Wolf. (2011). History and Industry Location: Evidence from German Airports, *Review of Economics and Statistics*, 93(3): 814-831.
- Schlenker, Wolfram, and Michael J. Roberts. (2009). *Nonlinear Temperature Effects indicate Severe Damages to U.S. Crop Yields under Climate Change*, Proceedings of the National Academy of Sciences, 106(37): 15594-15598.
- Schramm, Gunter. (1969). The Effects of Low-Cost Hydro Power on Industrial Location, *Canadian Journal of Economics*, 2(2): 210-229.
- Shimer, Robert, and Lones Smith. (2000). Assortative Matching and Search, *Econometrica*, 68(2): 343-369.
- Stern, Nicholas. (1986). On the Specification of Labour Supply Functions. In: *Unemployment, Search and Labour Supply*, edited by Richard Blundell, and Ian Walker, Cambridge University Press: Cambridge, Chapter 9, pp. 141-189.
- U.S. Department of the Interior. (2011). *The National Parks: Index 2009-2011*. Washington, DC: nps.gov/history/history/online_books/nps/index2009_11.pdf.
- Voena, Alessandra. (2011). Yours, Mine and Ours: Do Divorce Laws Affect the Intertemporal Behavior of Married Couples?, *Working Paper - Stanford University*.
- Voller, Bob. (2010). Early Aluminum Production in the Pacific Northwest, *IEEE Industry Applications Magazine*, 16(3): 10-12.
- Walker, James R. (2006). Economic Perspectives on Family and Migration, *Working Paper - University of Wisconsin-Madison*.
- Willis, Robert J., and Sherwin Rosen. (1979). Education and Self-Selection, *Journal of Political Economy*, 87(5): S7-S36, Part 2.
- World Comission on Dams. (2000). *Dams and Development: A New Framework for Decision-Making*. London and Sterling, VA: Earthscan Publications Ltd.

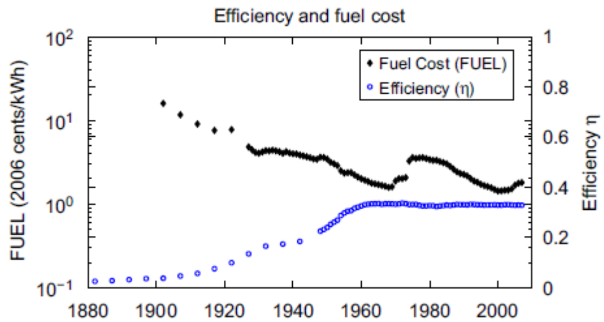
Figures and Tables

Figure 1.1: Impact of Hydro Dams on Population Density: Pre-1950 Dams vs. Post-1950 Dams



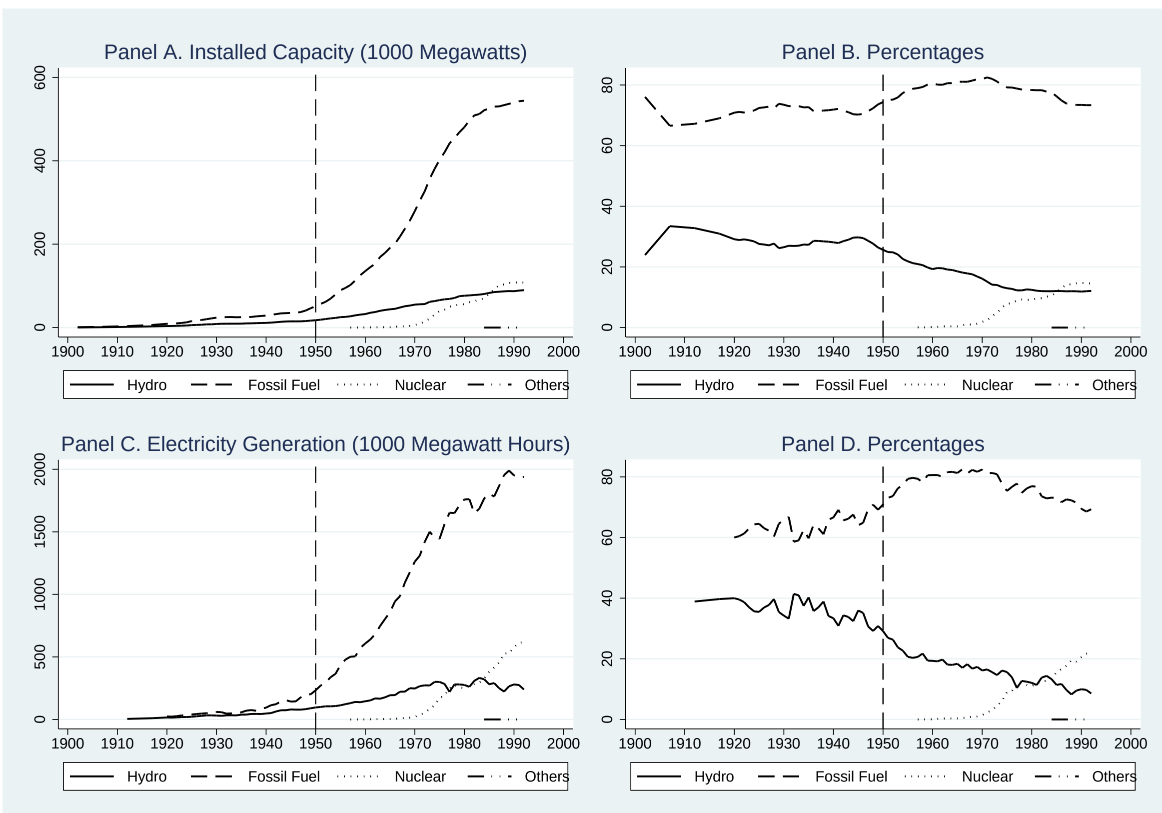
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with a hydroelectric dam built before 1950 (panel A), and the other with a dam built after 1950 (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The dotted line with hollow triangles in panel A displays the simulated times series of the treated county if growth in population density had stopped in 1950.

Figure 1.2: Average efficiency of coal plants and the cost of the fuel component, 1882-2006



Source: McNerneya, Farmer and Trancik (2011, p. 3045).

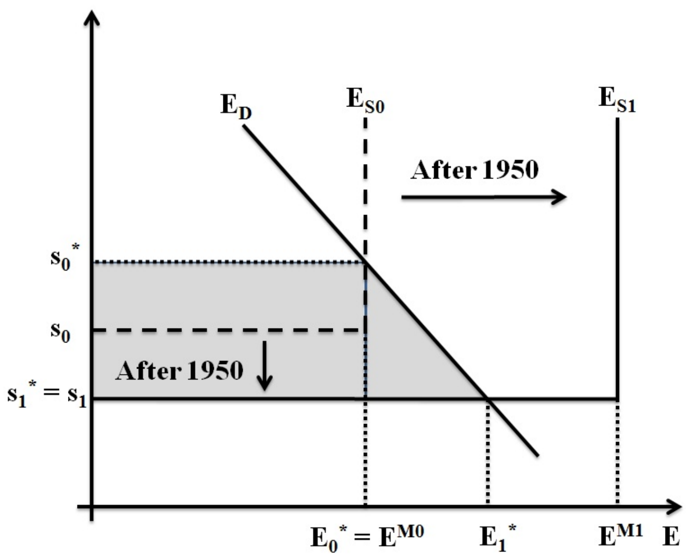
Figure 1.3: Installed Capacity and Electricity Generation in the U.S.



Notes: This figure displays the evolution of installed capacity and electricity generation by source in the U.S. throughout the twentieth century. Panel A depicts installed capacity in thousands of megawatts. Panel B shows corresponding percentages. Panel C displays electricity generation in thousands of megawatt hours. Panel D shows corresponding percentages. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. "Hydro" includes conventional hydroelectricity and pumped storage. "Fossil Fuel" includes coal, natural gas, petroleum, geothermal, other gases, and wood and wood derived fuels. "Others" includes solar and wind.

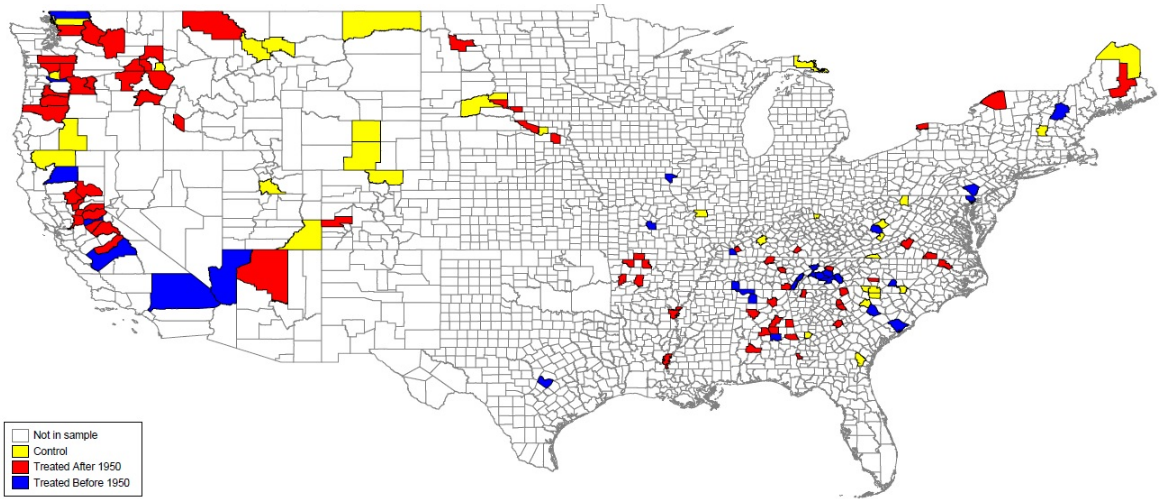
Source: *Historical Statistics of the Electric Utility Industry through 1992,* edited by Lizette Cintrón, 1995.

Figure 1.4: Hydro Dams and Electricity Markets



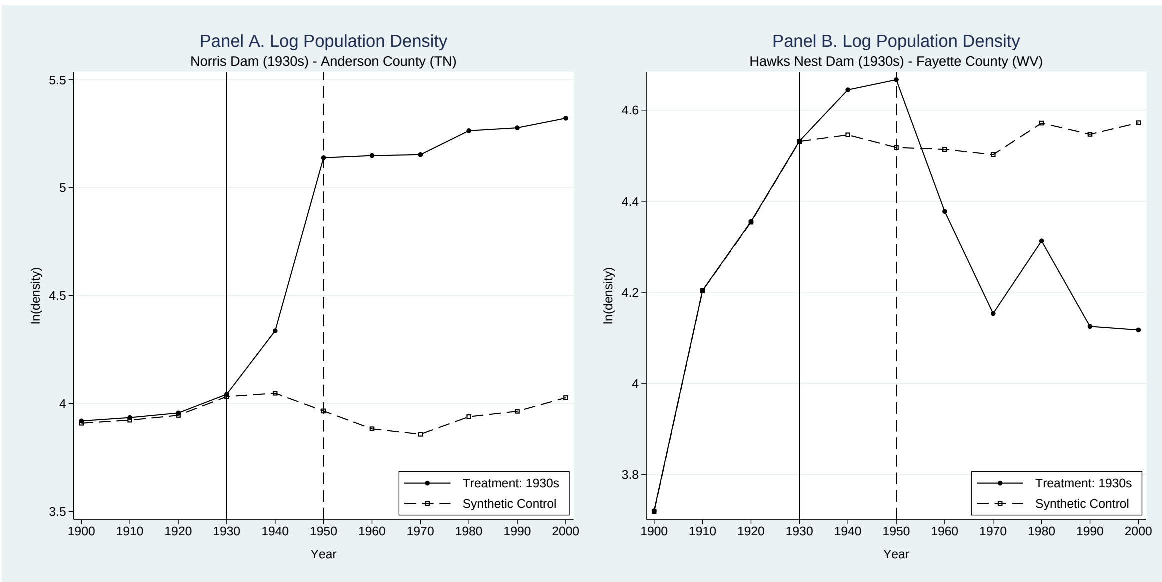
Notes: This schematic diagram represents the impact of hydro dams, and of the attenuation of the appeal of cheap local hydroelectricity in the second half of the twentieth century, on electricity markets. E denotes electricity quantity, and s electricity price. The dashed curve E_{S0} represents electricity supply in a county with no hydro dams, and the solid curve E_{S1} the supply in a county with dams. The solid line E_D represents electricity demand of a particular firm. E^M denotes the maximum amount of electricity that each county can generate with its installed capacity. E^* denotes the optimal electricity quantity. The shaded trapezoid represents rents that firms can exploit by moving to counties with large hydropower facilities, with cheap and abundant electricity. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. After 1950, E_{S0} and E_{S1} become just one curve within a grid area, which is much larger than counties. This reduces local rents considerably.

Figure 1.5: Sample Counties: Treatment vs. Control



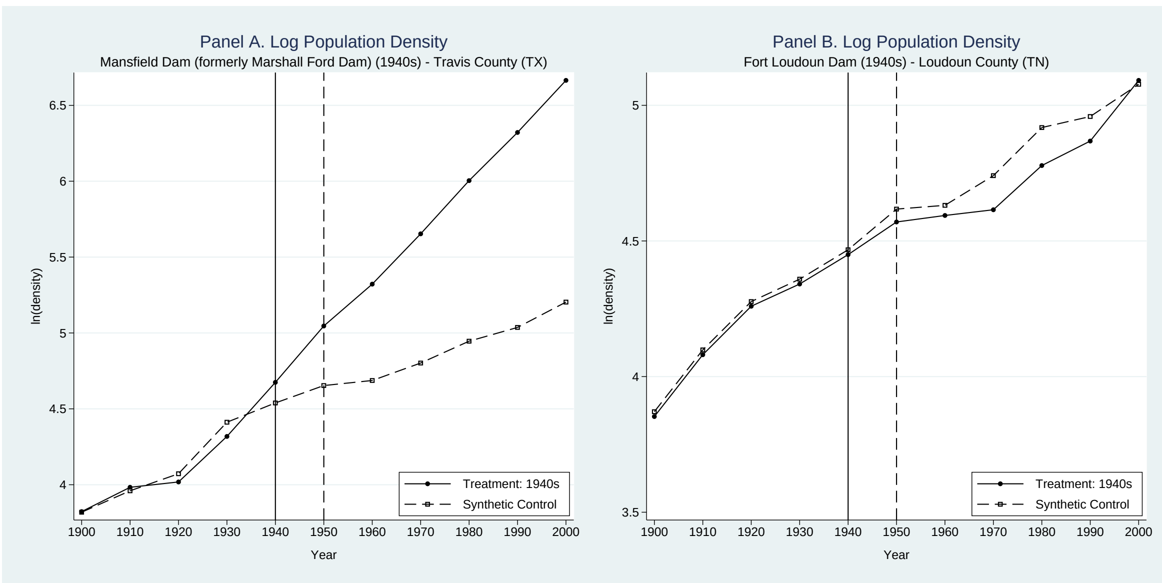
Notes: This figure displays the counties included in my sample. "Treated Before 1950" are indicated in blue and have hydroelectric dams built in the first half of the twentieth century. "Treated After 1950" are indicated in green and have hydroelectric dams built in the second half of the century. "Control" are indicated in yellow and have hydropower potential comparable to the capacity installed in treated counties, but have no hydroelectric facilities. Counties left blank are not in my sample. Thin gray lines denote 1900 county borders, which are held constant throughout my analysis.

Figure 1.6: Impact of Hydro Dams on Population Density: Pre-1950 Dams



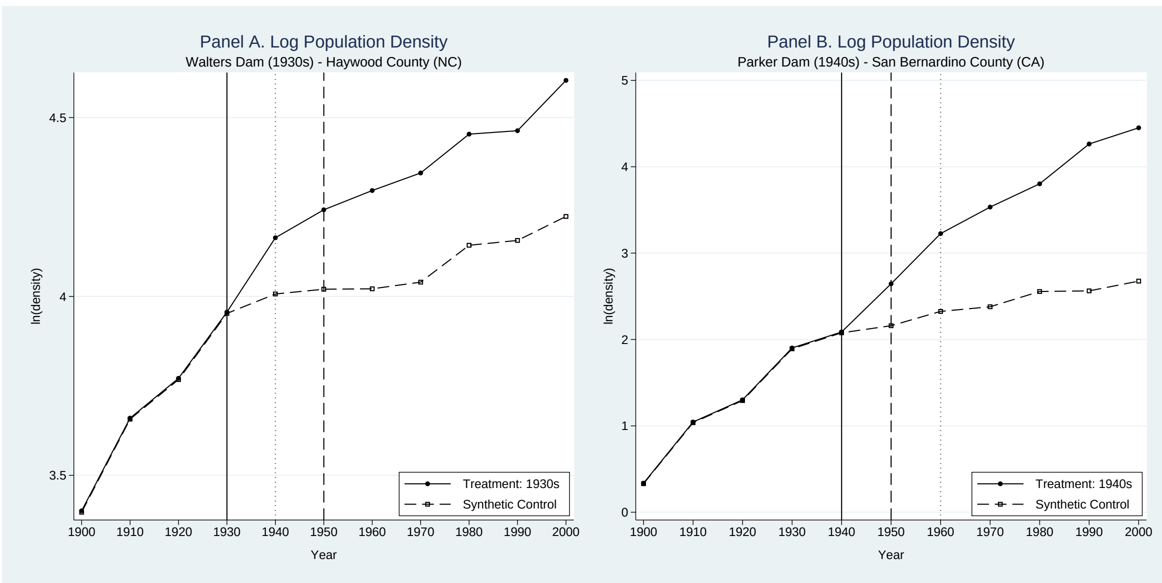
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with virtually no agglomeration effects after 1950 (panel A), and the other with negative growth after 1950 (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams.

Figure 1.7: Impact of Hydro Dams on Population Density: Pre-1950 Dams



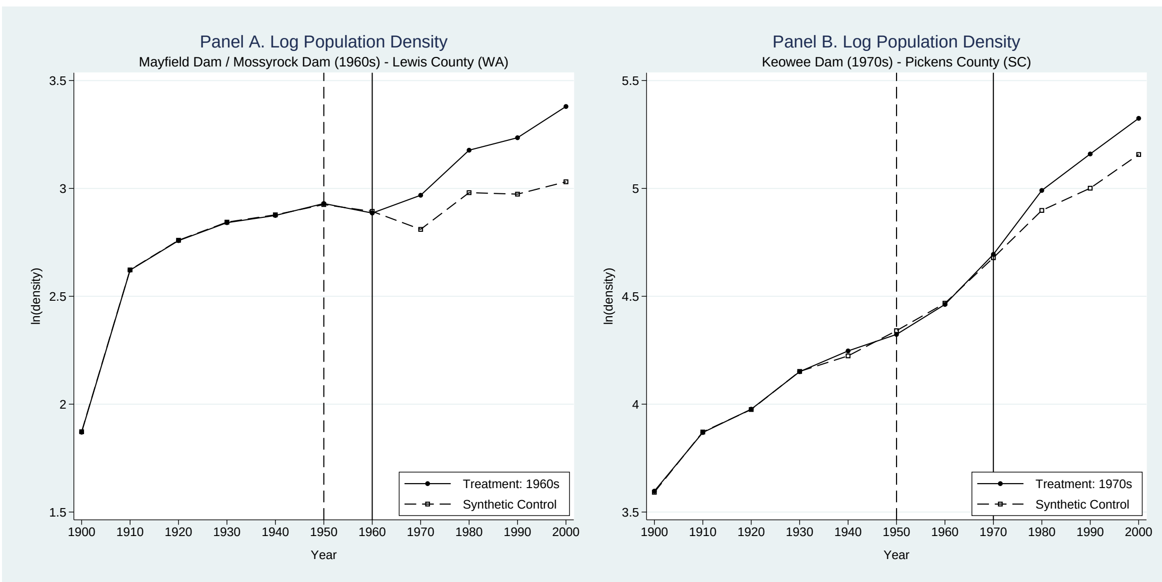
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with constant growth after dam completion (panel A), and the other with virtually no difference relative to the counterfactual of no dams (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams.

Figure 1.8: Impact of Hydro Dams on Population Density: Pre-1950 Dams



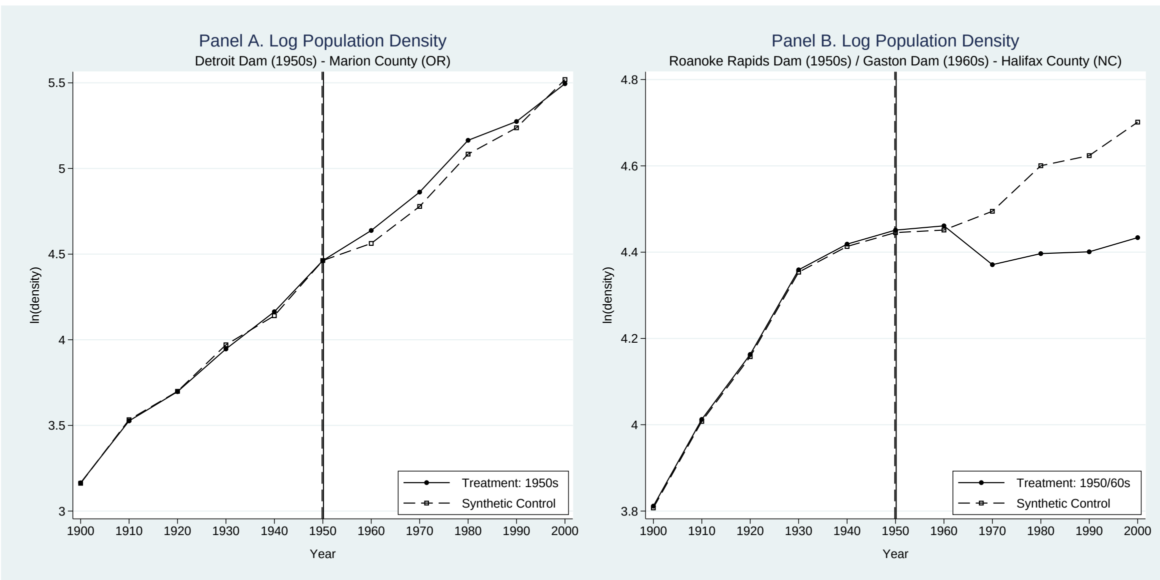
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with growth flattening before 1950 (panel A), and the other with growth flattening after 1950 (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The dotted vertical line shows a cutoff that might be a more accurate turning point for the county in question. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams.

Figure 1.9: Impact of Hydro Dams on Population Density: Post-1950 Dams



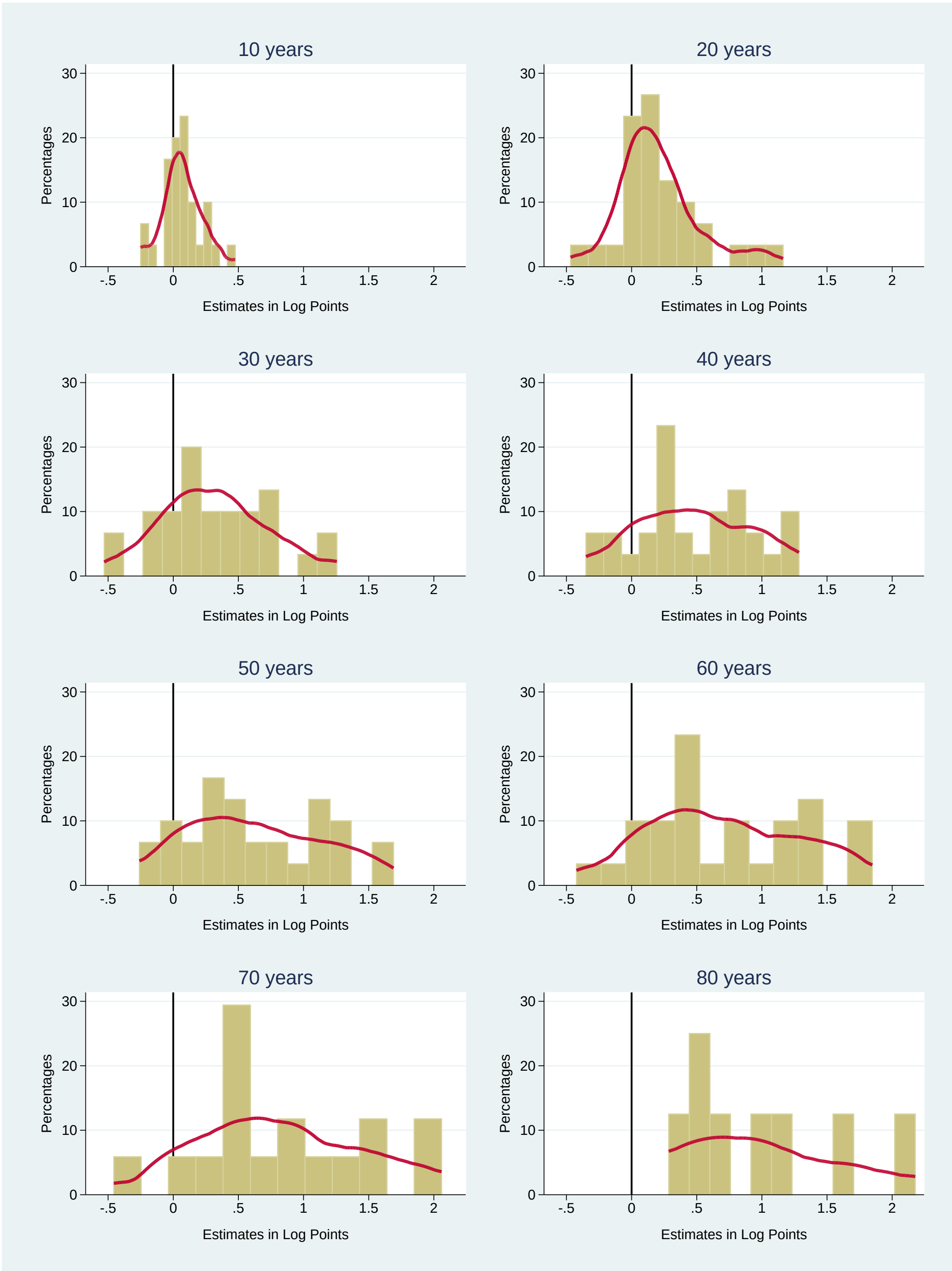
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with moderately positive effects of dams (panel A), and the other with small but positive dam effects (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams.

Figure 1.10: Impact of Hydro Dams on Population Density: Post-1950 Dams



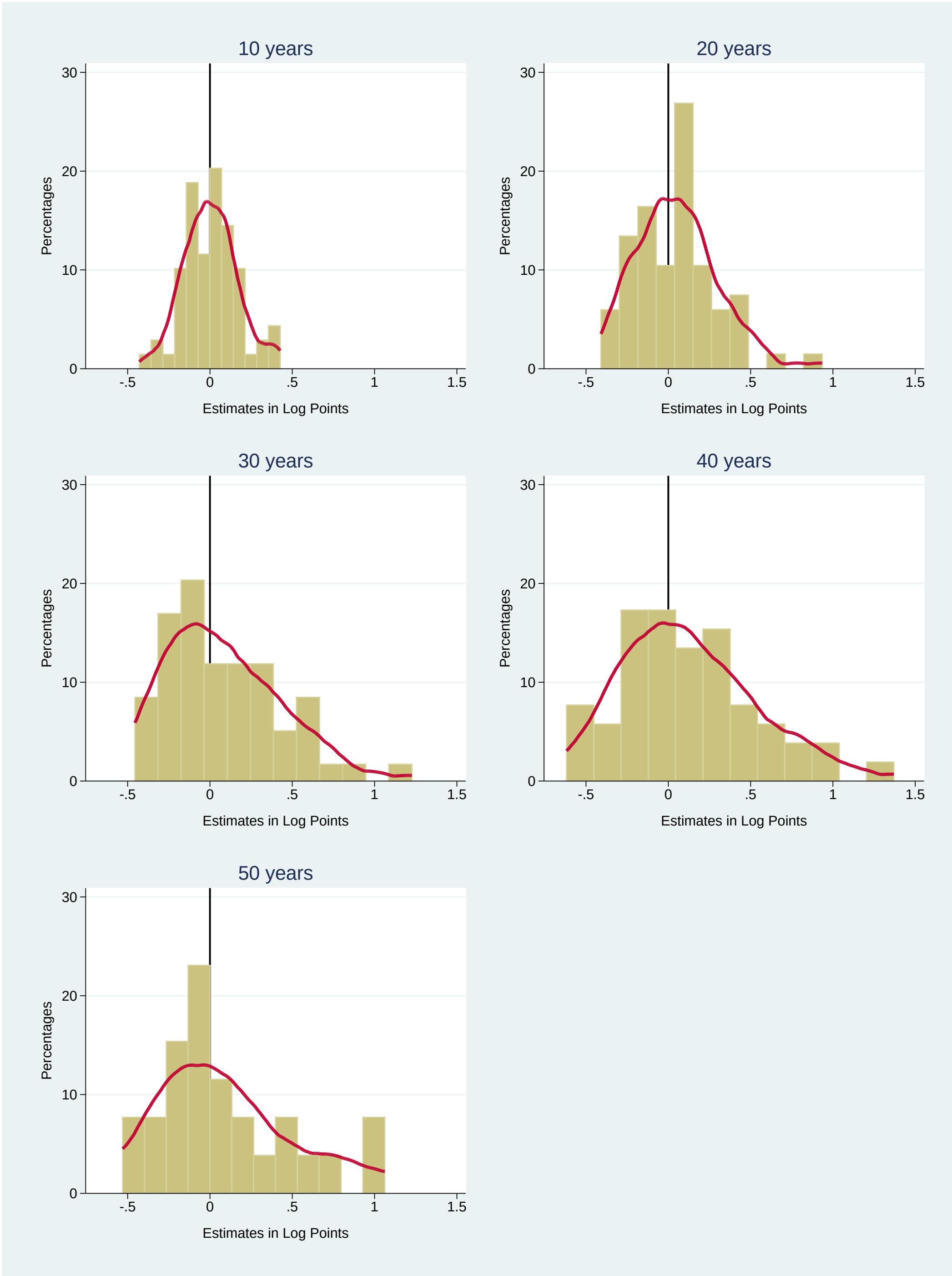
Notes: This figure plots the log population density from 1900 to 2000 for two counties: one with virtually no dam effects (panel A), and the other with somewhat negative effects of dams (panel B). The solid vertical line shows the decade in which the dam was completed. The dashed vertical line simply separates the twentieth century into pre-1950 and post-1950. The cutoff 1950 is my assumed turning point for the attenuation of the advantage of cheap local hydroelectricity. The solid line with solid circles displays the observed time series of log population density for each county, and the dashed line with hollow squares depicts the predicted time series of a corresponding synthetic control county. The synthetic control is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams.

Figure 1.11: Impact of Hydro Dams on Population Density: Distribution of County Estimates by Years Since Dam Completion (Pre-1950 Dams)



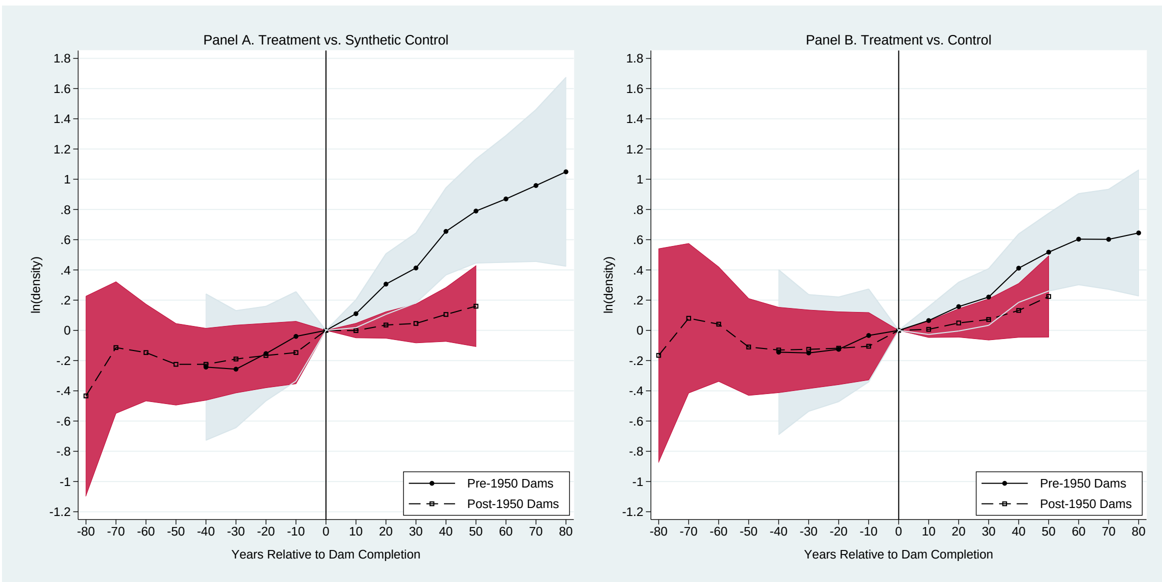
Notes: This figure plots the distribution of county-specific estimates of the impact of pre-1950 hydro dams on the log of population density. The estimates are found by using the synthetic control estimator for each treated county. The solid vertical line at zero just emphasizes the point of no effects of dams. Each vertical bar in each histogram shows the percentage of counties with effects of dams in a particular bin. The thick solid curved line just smoothes the distribution of effects using a kernel density estimator.

Figure 1.12: Impact of Hydro Dams on Population Density: Distribution of County Estimates by Years Since Dam Completion (Post-1950 Dams)



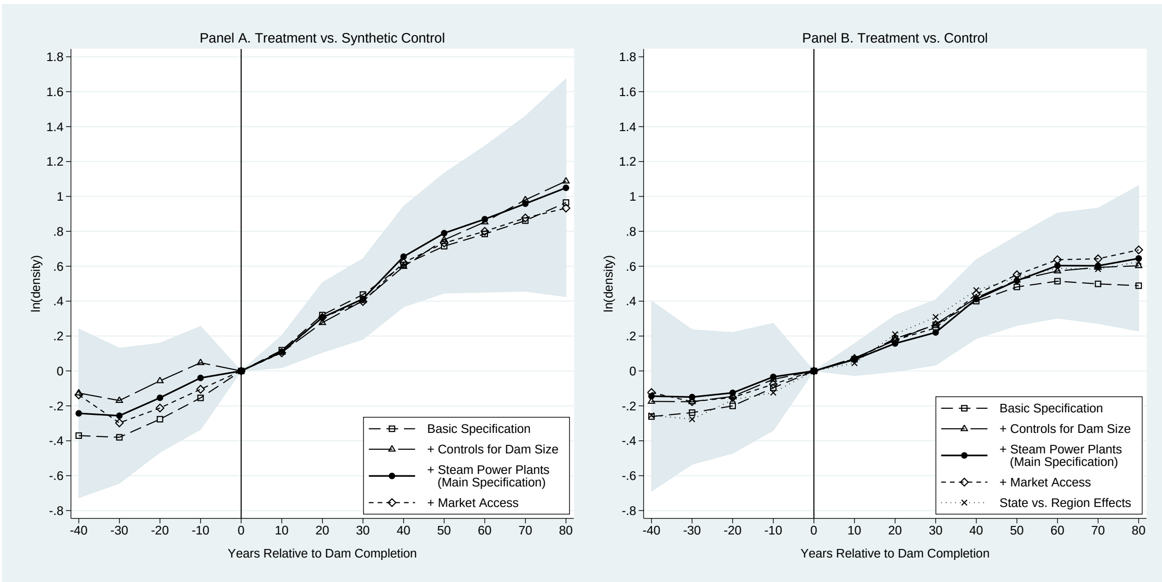
Notes: This figure plots the distribution of county-specific estimates of the impact of post-1950 hydro dams on the log of population density. The estimates are found by using the synthetic control estimator for each treated county. The solid vertical line at zero just emphasizes the point of no effects of dams. Each vertical bar in each histogram shows the percentage of counties with effects of dams in a particular bin. The thick solid curved line just smoothes the distribution of effects using a kernel density estimator.

Figure 1.13: Impact of Hydro Dams on Population Density: Short- and Long-Run Estimates



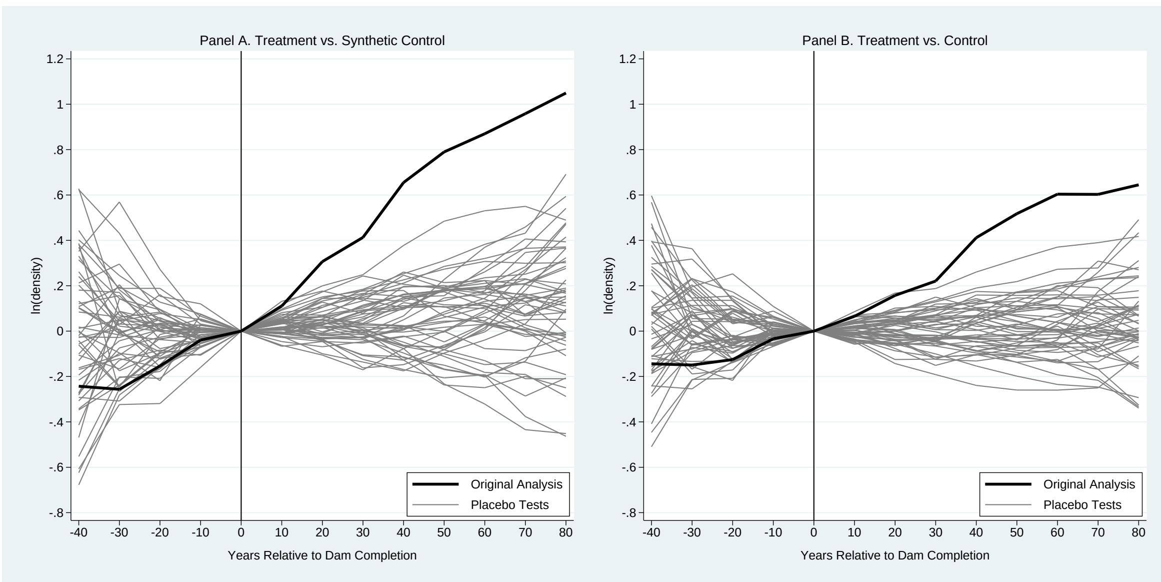
Notes: This figure presents the short- and long-run effects of large hydroelectric dams on population density. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The solid lines with solid circles report differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The light (bluish gray) shade around the solid line depicts the 95% confidence interval for the coefficients represented by solid circles. The dashed lines with hollow squares report similar differences for counties that had dams installed after 1950. The dark (cranberry) shade around the dashed line depicts the 95% confidence interval for the coefficients represented by hollow squares. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.14: Impact of Hydro Dams on Population Density: Specification Checks - Pre-1950 Dams



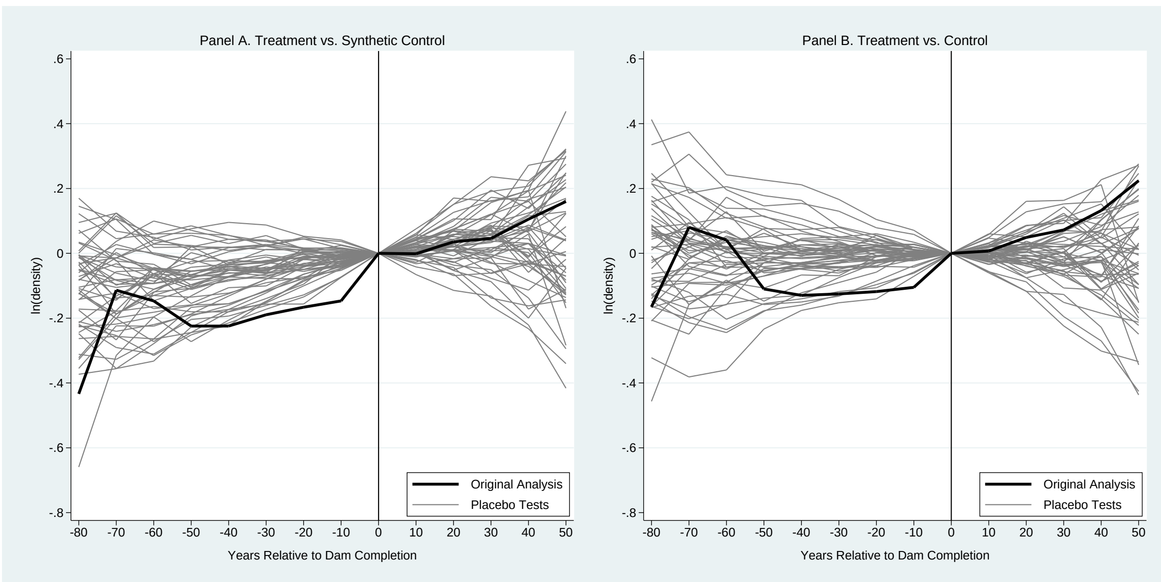
Notes: This figure presents some robustness checks regarding the specification used in the estimation of equation (1.5) in the text. Each panel graphs the estimated coefficients β's of event-time dummies from equations like that one. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. Each line reports differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The dashed lines with hollow squares display estimates related to the basic specification. Such specification includes event-time dummies, county effects, region-by-year fixed effects, and time-invariant county characteristics (cubic function in latitute and longitude, and 50-year average rainfall and 50-year average temperature for each season of the year) interacted with year effects. The long-dashed lines with hollow triangles show estimates associated with the basic specification plus a cubic function in dam capacity. The solid lines with solid circles report the estimates related to the main specification, which is basic specification plus controls for dam size plus a cubic function in thermal power plant capacity. The short-dashed lines with hollow diamonds display estimates related to the main specification plus controls for the interaction of year effects with three county-specific measures of market access: mileage of railroad tracks, distance to closest waterway, and log of market access as estimated by Donaldson and Hornbeck (2012). The light (bluish gray) shade around the solid line depicts the 95% confidence interval for the coefficients of the main specification, represented by solid circles. In panel B, the dotted line with little crosses displays estimates associated with the main specification, but replacing region-by-year fixed effects with state-by-year fixed effects. This line does not appear in panel A because the sample size was insufficient to estimate all the parameters. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.15: Impact of Hydro Dams on Population Density: Placebo - Pre-1950 Dams



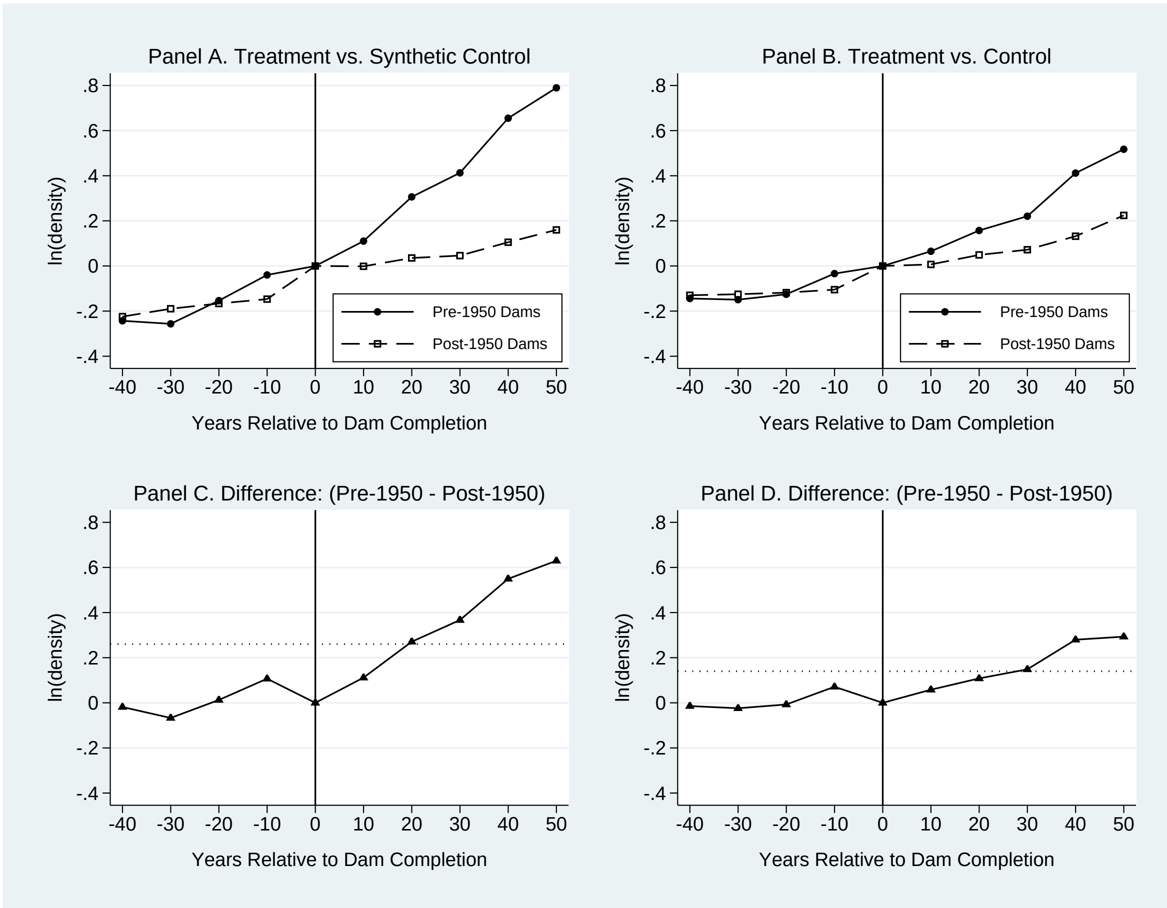
Notes: This figure plots estimates of placebo tests with pre-1950 dams. Each panel graphs estimated coefficients β's of event-time dummies from equation (1.5) in the text for actual and artificially assigned treatments. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The thick solid black line displays the effects of actual dams. The thin solid gray lines show the effects of artificially treated counties. Artificial treatment is assigned through a two-step procedure. First, counties are drawn randomly from the pool of originally treated and control counties. The number of selected counties is identical to the number of originally treated counties. Second, for each artificially treated county, the date of dam completion is set at random as well. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.16: Impact of Hydro Dams on Population Density: Placebo - Post-1950 Dams



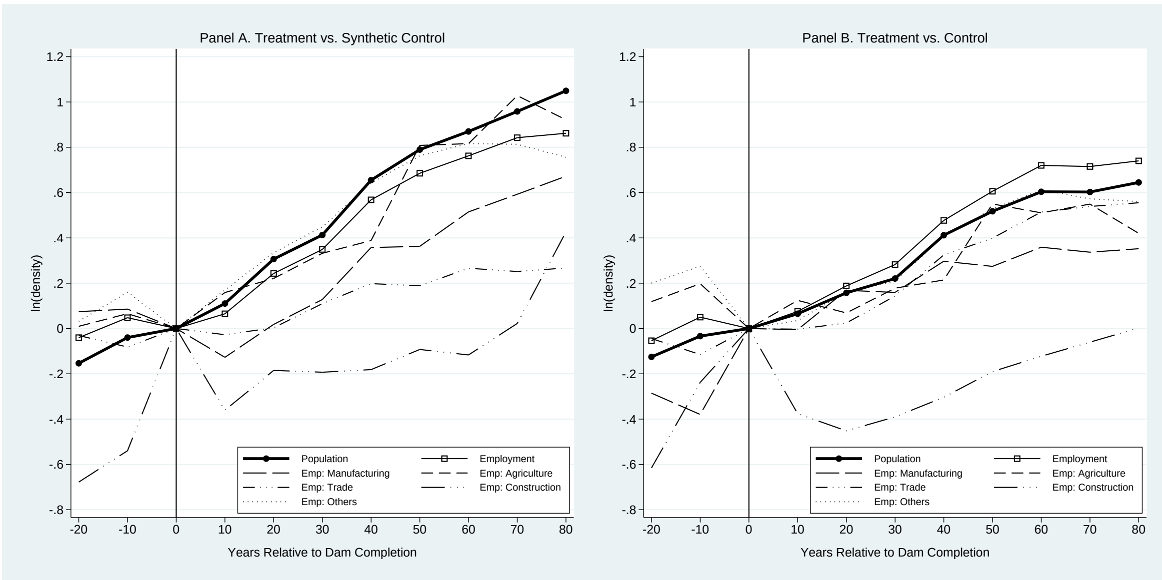
Notes: This figure plots estimates of placebo tests with post-1950 dams. Each panel graphs estimated coefficients β's of event-time dummies from equation (1.5) in the text for actual and artificially assigned treatments. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The thick solid black line displays the effects of actual dams. The thin solid gray lines show the effects of artificially treated counties. Artificial treatment is assigned through a two-step procedure. First, counties are drawn randomly from the pool of originally treated and control counties. The number of selected counties is identical to the number of originally treated counties. Second, for each artificially treated county, the date of dam completion is set at random as well. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.17: Impact of Hydro Dams on Population Density: Agglomeration Spillovers



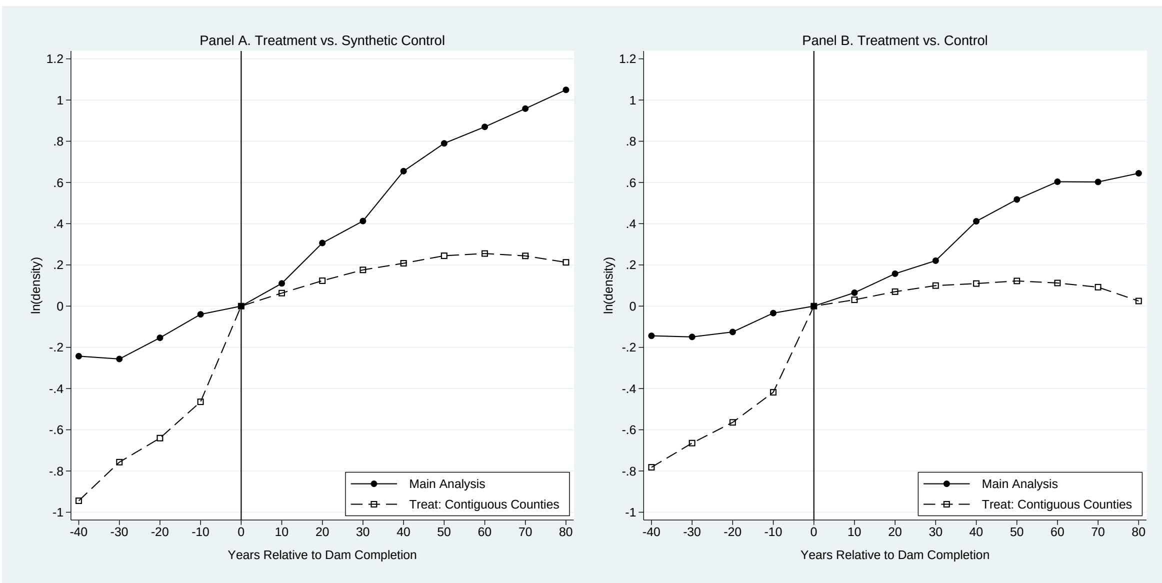
Notes: This figure presents my estimates of agglomeration spillovers. The top panels plot the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The bottom panels plot the differences between coefficients associated with pre-1950 dams and post-1950 dams. Each panel shows estimates from 40 years before dam installation until 50 years after the dam: the differences in the bottom charts can be computed only for this range. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation of the coefficients. The solid lines with solid circles in the top panels report differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The dashed lines with hollow squares in the top panels report similar differences for counties that had dams installed after 1950. The solid lines with solid triangles in the bottom panels report the difference between the solid line with solid circles and the dashed line with hollow squares of the corresponding top panel. The dotted lines in the bottom panels report the effect of dams attributable to the advantage of cheap local hydroelectricity until 1950. My (lower bound) estimates of agglomeration spillovers consist of the differences between the solid line with solid triangles and the dotted line, in the bottom panels. In panels A and C, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panels B and D, the control set contains the originally defined control counties.

Figure 1.18: Impact of Hydro Dams on Population/Employment Density: Employment by Sector - Pre-1950 Dams



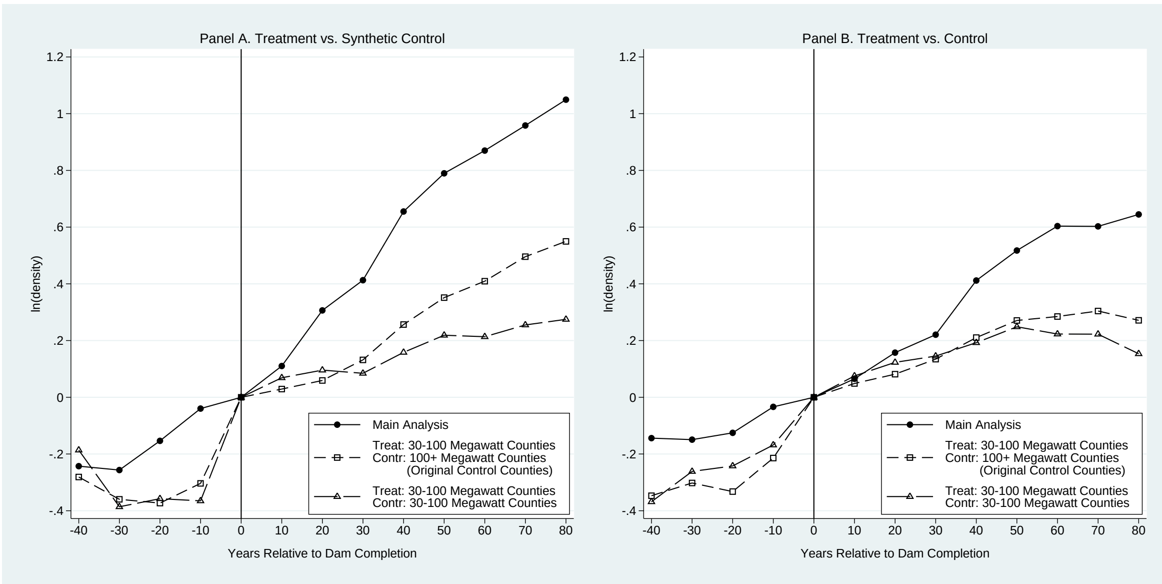
Notes: This figure presents the impact of pre-1950 dams on population and employment by sector. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text, for the log density of each outcome mentioned in the legend. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The thick solid lines with solid circles report differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The thin solid lines with hollow squares report similar estimates, but for log of employment density. More specifically, the long-dashed lines display similar estimates for log of employment in manufacturing, the dashed lines for log of employment in agriculture, the dash-3dotted lines for log of employment in trade (wholesale plus retail), the long-dash-3dotted lines for log of employment in construction, and the dotted lines for log of employment in other sectors. "Other sectors" includes employment in industries that provide local goods and services such as real estate, cleaning services, legal services, medical services, and personal services. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.19: Impact of Hydro Dams on Population Density: Analysis with Contiguous Counties - Pre-1950 Dams



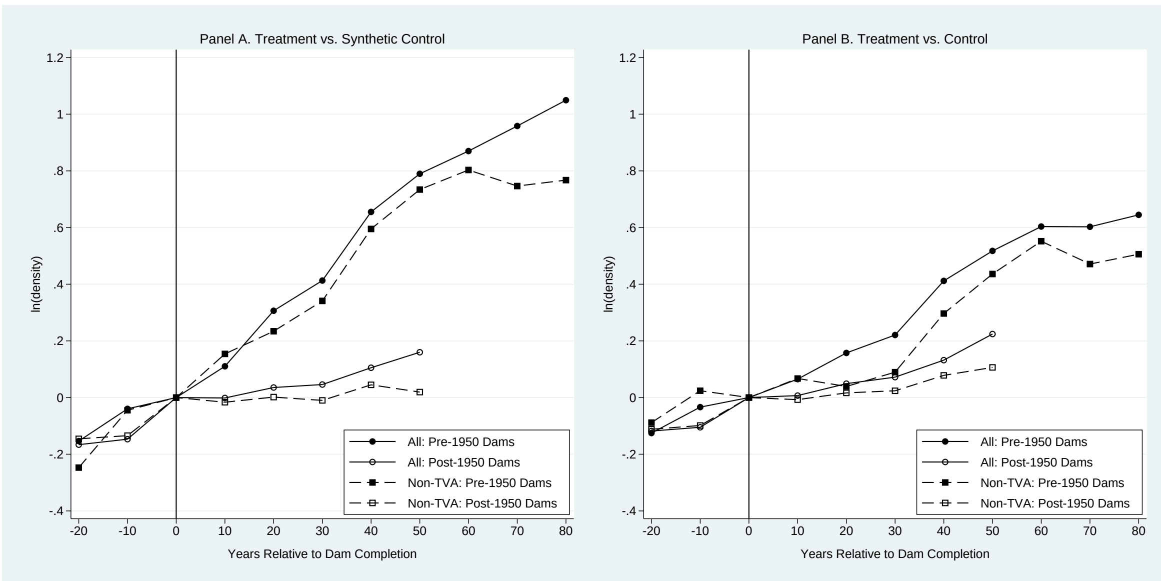
Notes: This figure presents potential externalities of pre-1950 dams on population density of neighboring counties. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The solid lines with solid circles report differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The dashed lines with hollow squares report similar estimates, but with counties contiguous to the treated ones as the treatment. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.20: Impact of Hydro Dams on Population Density: Analysis with Counties with Capacity of 30-100 Megawatts - Pre-1950 Dams



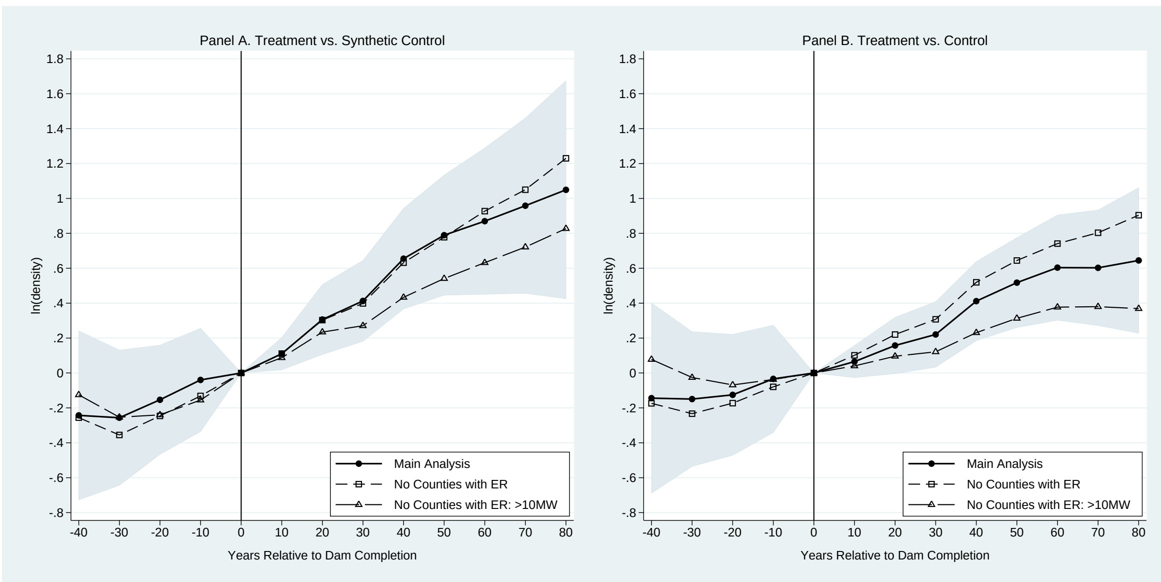
Notes: This figure presents effects of smaller pre-1950 dams on population density. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The solid lines with solid circles report differences in the log of population density relative to year of dam completion, for counties that had hydroelectric dams installed before 1950. The dashed lines with hollow squares report similar estimates, but with treated counties with hydropower capacity in the range of 30-100 megawatts. The long-dashed lines with hollow triangles report comparable estimates, but with treated and control counties with hydropower capacity in the range 30-100 megawatts. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.21: Impact of Hydro Dams on Population Density: All vs. Non-TVA Counties



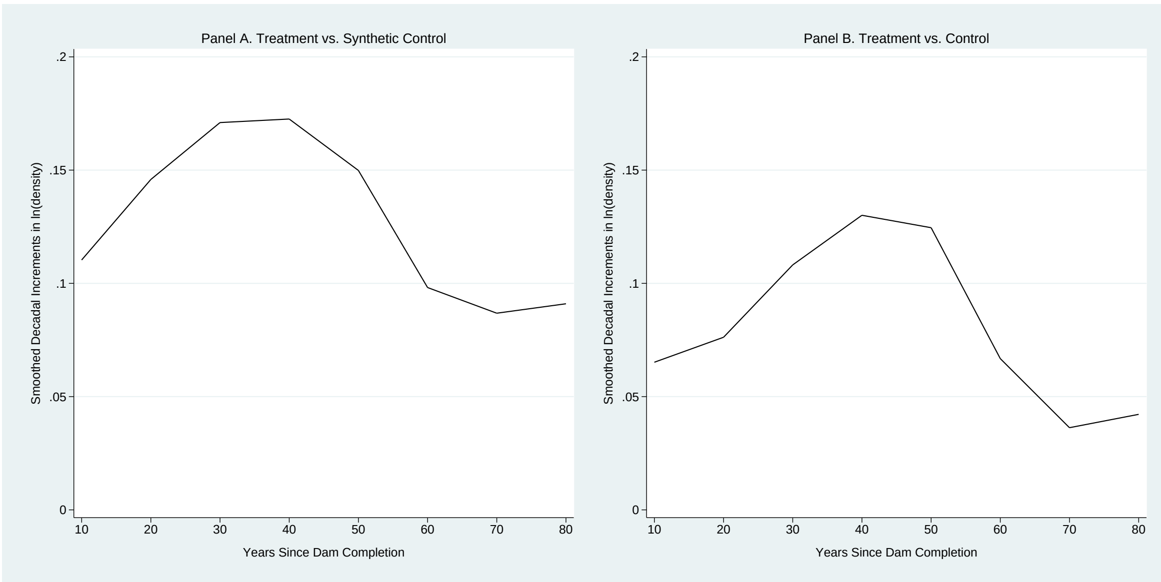
Notes: This figure presents the effects of dams estimated with all counties in my sample versus with only counties outside the Tennessee Valley Authority (TVA) region. The TVA was one of the most ambitious place based economic development policies in the history of the U.S. Besides hydroelectric dams, it included construction of an extensive network of new roads, canals, and flood control systems. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The solid lines with solid circles report differences in the log of population density relative to year of dam completion, for all sample counties that had hydroelectric dams installed before 1950. The solid lines with hollow circles report similar differences for all sample counties that had dams installed after 1950. The dashed lines with solid squares report differences in the log of population density relative to year of dam completion, for non-TVA counties that had hydroelectric dams installed before 1950. The dashed lines with hollow squares report similar differences for non-TVA counties that had dams installed after 1950. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.22: Impact of Hydro Dams on Population Density: All vs. No Control Counties With Environmental Regulations (ER) - Pre-1950 Dams



Notes: This figure presents the short- and long-run effects of hydroelectric dams on population density, with and without control counties subject to land regulations aimed at preserving wilderness and wildlife. Such environmental regulations could restrict population growth in those locations. Each panel graphs the estimated coefficients β's of event-time dummies from equation (1.5) in the text. The vertical solid line at zero facilitates the comparison of the dynamics before and after the treatment. It also points out that the dummy for event time zero is omitted in the estimation. The solid lines with solid circles report differences in the log of population density relative to year of dam completion, for all sample counties that had hydroelectric dams installed before 1950. These are the estimates from the main analysis. The dashed lines with hollow squares report similar differences, but excluding any control counties with environmental regulations from the analysis. The long-dashed lines with hollow triangles also report similar differences as in the main analysis, but redefining the original control group to include all counties without environmental regulations but with hydropower potential starting at 10 megawatts (instead of 100 megawatts, as in the main analysis). In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 1.23: Impact of Pre-1950 Hydro Dams on Population Density: Non-Structural Shape of Agglomeration Function



Notes: This figure presents the shape of the agglomeration function based on the estimates from equation (1.5). Each panel displays the decadal increments of log of population density after dam installation for counties treated before 1950, smoothed out by locally weighted regressions (lowess). Each decadal increment is the difference between the estimated coefficient of an event-time dummy and the estimated coefficient of the event-time dummy a decade before. In panel A, the control group used in the estimation consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. In panel B, the control set contains the originally defined control counties.

Figure 2.1: Broad Locational Choice

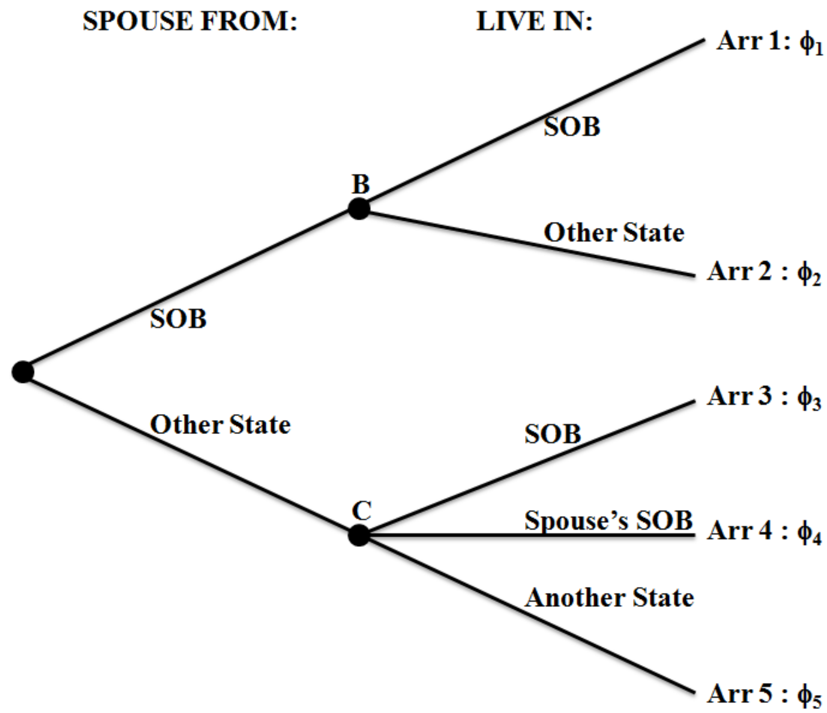
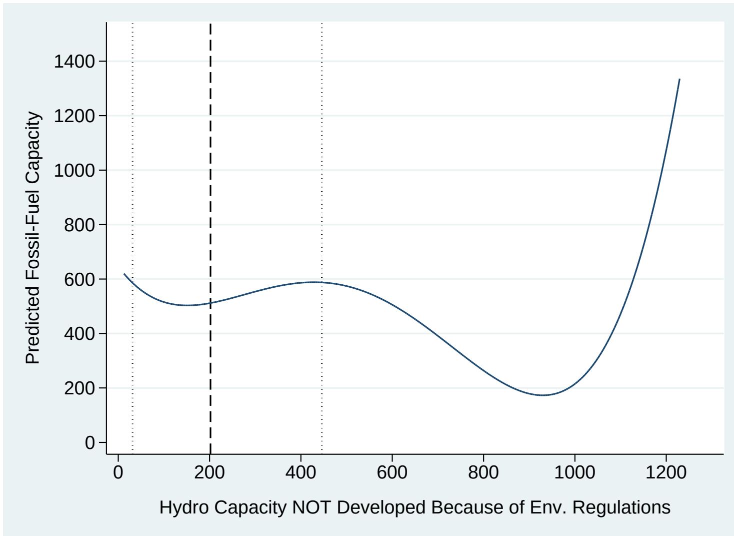
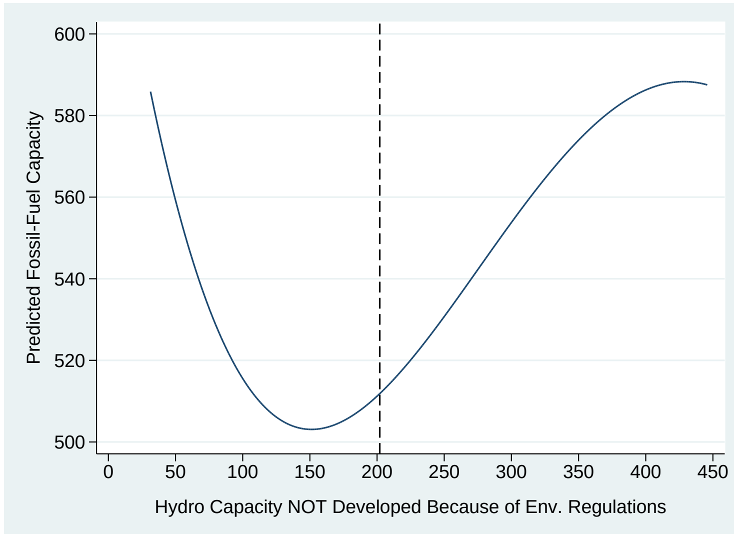


Figure 3.1: Predicted Fossil-Fuel Capacity: 1998-2007



Notes: This figure presents effects of hydropower potential restricted from development because of environmental regulations on the thermal (fossil-fuel) power capacity developed in the period 1998-2007. Both variables are measure in megawatts. The dashed vertical line represents the average of hydro not developed in my sample, and the dotted vertical lines the 10th and the 90th percentiles of such variable.

Figure 3.2: Predicted Fossil-Fuel Capacity: 1998-2007 (Between 10th and 90th Percentiles of Hydro NOT Developed)



Notes: This figure presents effects of hydropower potential restricted from development because of environmental regulations on the thermal (fossil-fuel) power capacity developed in the period 1998-2007, zoomed in around the sample average of hydro not developed, represented by the dashed vertical line. Both variables are measure in megawatts.

Table 1.1: Chronology of Electrification of Industry and History of the U.S. Electric Power Industry

1870: D.C. Electric Generator

__73: Motors Driven by a Generator

__81: Hydroelectric Dam Built Near Niagara Falls

__82: Modern Electric Utility Industry Launched

__83: Motors Used in Manufacturing

__88: A.C. Motor Developed

__91: A.C. Power Transmission for Industrial Use

__92: A.C. Polyphase Induction Motor Marketed

__95: A.C. Generation at Niagara Falls

1900: A.C. Generator

__01: Right-of-Way Act: Federal Govt. Entitled the Authority to Grant Permits for Hydro Projects

__02: Reclamation Act: Federal Water Development Projects Initiated

__06: General Dam Act: Private Owners Must Build and Operate Navigation Facilities W/O Compensation

__07: State Regulation of Electric Utilities Started (Georgia, New York, and Wisconsin)

__14-18: World War I

__17: Capacity and Generation of Utilities Exceeded That of Industrial Establishments

__20: Federal Water Power Act: Hydroelectric Licenses Revocable After Fifty Years

__27: Supreme Court Ruling: Only Federal Govt. Can Regulate Interstate Wholesale Power Transactions

__29: Wall Street Crash

__33: Tennessee Valley Authority (TVA) Act: Local Development Fostered by Hydroelectricity

__35: Federal Power Act: Interstate Wholesale Power Transactions Regulated

__39-45: World War II

__49: TVA authorized to construct thermal-electric power plants for commercial electricity sale

__50s: Construction of High-Voltage (230kV or more) Transmission Lines Began

__54: Atomic Energy Act: Private Development of Commercial Nuclear Power Allowed

__60: Current Level of Thermal Efficiency of Fossil-Steam Plants Reached

__63: Clean Air Act (Amendments in 1970, 1977, and 1990): Pollution Regulation Initiated

__64: Wilderness Act: Land Preservation Efforts Became Official

Sources: Devine (1983), Brown and Sedano (2004), Billington, Jackson and Melosi (2005), McNerneya, Farmer and Trancik (2011), and EIA (n.d.).

Table 1.2: Domestic Economy: Percentage distribution of total installed electric generating capacity by producer, 1889-1961

Year	Total Capacity	Industrial Establishments	Electric Utilities
1889	100.0	55.6	44.4
1899	100.0	53.4	46.6
1902	100.0	59.6	40.6
1907	100.0	60.2	39.8
1912	100.0	53.0	47.0
1917	100.0	42.0	58.0
1920	100.0	34.6	65.4
1925	100.0	28.6	71.4
1929	100.0	22.9	77.1
1935	100.0	19.6	80.4
1939	100.0	21.4	78.6
1947	100.0	19.7	80.3
1954	100.0	13.7	86.3
1958	100.0	11.0	89.0
1961	100.0	9.0	91.0

Source: DuBoff (1979, p.39).

Table 1.3: Summary Statistics

		All Counties		Treated - Before 1950		Treated - After 1950		Control	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Outcomes and Hydroelectricity		Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
Log of Population Density	1900	2.66	*1.52*	3.28	*1.34*	2.57	*1.29*	2.43	*1.80*
	1950	3.26	*1.32*	3.94	*1.31*	3.13	*1.10*	3.04	*1.48*
	2000	3.80	*1.40*	4.74	*1.06*	3.70	*1.27*	3.41	*1.49*
Log of Employment Density	1900	1.60	*1.49*	2.17	*1.37*	1.51	*1.31*	1.41	*1.71*
	1950	2.19	*1.32*	2.85	*1.34*	2.07	*1.10*	1.99	*1.47*
	2000	2.96	*1.45*	3.94	*1.13*	2.84	*1.34*	2.58	*1.52*
Hydroelectric Capacity	1910s			1.25	.				
at Dam Completion	1920s			1.85	*0.75*				
(in 100's of megawatts)	1930s			1.48	*0.69*				
	1940s			2.05	*2.18*				
	1950s					3.21	*3.34*		
	1960s					4.45	*5.25*		
	1970s					3.43	*3.23*		
	1980s					1.70	*0.72*		
	1990s					1.47	*0.63*	Potential Capacity	
	All Years	2.97	*3.53*	1.81	*1.51*	3.48	*4.01*	2.28	*1.97*
Average Hydroelectric	1910	0.78	*0.47*	0.99	*0.23*	0.14	.		
Installed Capacity	1920	1.49	*0.87*	1.77	*0.73*	0.39	*0.09*		
Over time	1930	1.48	*0.86*	1.71	*0.81*	0.58	*0.23*		
(in 100's of megawatts)	1940	1.98	*1.83*	2.29	*1.90*	0.65	*0.25*		
	1950	2.95	*3.05*	2.96	*2.89*	2.94	*3.26*		
	1960	3.99	*4.49*	3.41	*3.66*	4.30	*4.89*		
	1970	4.49	*5.64*	3.47	*3.63*	4.99	*6.37*		
	1980	4.48	*5.54*	3.84	*3.93*	4.76	*6.13*		
	1990	4.43	*5.50*	3.89	*3.92*	4.67	*6.07*		
	2000	4.43	*5.50*	3.89	*3.92*	4.67	*6.07*		
	All Years	3.90	*4.93*	3.18	*3.31*	4.38	*5.71*		
Sample Counties		154		30		69		55	
Panel B. Dam Completion by Decade		Obs.	*Percent*	Obs.	*Percent*	Obs.	*Percent*	Obs.	*Percent*
Dam Completion Date	1910s	1	*1.01*	1	*3.33*				
	1920s	7	*7.07*	7	*23.33*				
	1930s	9	*9.09*	9	*30.00*				
	1940s	13	*13.13*	13	*43.33*				
	1950s	26	*26.26*			26	*37.68*		
	1960s	26	*26.26*			26	*37.68*		
	1970s	7	*7.07*			7	*10.14*		
	1980s	8	*8.08*			8	*11.59*		
	1990s	2	*2.02*			2	*2.90*		
	All Years	99	*100.00*	30	*100.00*	69	*100.00*		

Notes: Panel A reports mean and standard deviation (SD) for my main outcomes - population density and employment density - for selected years (see Figures A1 and A2 for more details), and for hydroelectricity-related variables throughout the twentieth century. Standard deviations are shown in italic. That panel also provides the sample size for each group of counties: all counties in the sample ("All Counties"), counties that have dams built before 1950 ("Treated - Before 1950"), counties that have dams built after 1950 ("Treated - After 1950"), and counties that have hydropower potential but no hydroelectric facilities ("Control"). Panel B presents the distribution of dam completion by decade. For each group of counties, the first column reports the number of counties ("Obs."), and the second column the corresponding percentage ("Percent").

Table 1.4: Short- and Long-Run Effects of Hydro Dams on Population Density

ln(Pop Density)	TS_b1950	TC_b1950	TS_a1950	TC_a1950	Diff. (TS)	Diff. (TC)
	(1)	(2)	(3)	(4)	(5) = (1) - (3)	(6) = (2) - (4)
80 years before dam			-0.4335	-0.1652		
			(0.3306)	(0.3564)		
70 years before dam			-0.1137	0.0802		
			(0.2182)	(0.2500)		
60 years before dam			-0.1468	0.0411		
			(0.1605)	(0.1914)		
50 years before dam			-0.2245	-0.1100		
			(0.1353)	(0.1620)		
40 years before dam	-0.2428	-0.1441	-0.2243*	-0.1298	-0.0185	-0.0143
	(0.2365)	(0.2740)	(0.1193)	(0.1428)	(0.2061)	(0.2523)
30 years before dam	-0.2564	-0.1493	-0.1895*	-0.1252	-0.0670	-0.0240
	(0.1893)	(0.1941)	(0.1124)	(0.1315)	(0.1743)	(0.1936)
20 years before dam	-0.1536	-0.1253	-0.1663	-0.1180	0.0126	-0.0073
	(0.1528)	(0.1740)	(0.1070)	(0.1218)	(0.1510)	(0.1778)
10 years before dam	-0.0398	-0.0337	-0.1468	-0.1049	0.1070	0.0712
	(0.1445)	(0.1544)	(0.1036)	(0.1126)	(0.1459)	(0.1617)
10 years after dam	0.1103**	0.0652	-0.0014	0.0070	0.1117***	(0.0582)
	(0.0451)	(0.0461)	(0.0241)	(0.0273)	(0.0390)	(0.0443)
20 years after dam	0.3063***	0.1574*	0.0355	0.0491	0.2708***	0.1083
	(0.0979)	(0.0811)	(0.0439)	(0.0475)	(0.0831)	(0.0783)
30 years after dam	0.4129***	0.2207**	0.0460	0.0721	0.3670***	0.1485
	(0.1131)	(0.0942)	(0.0646)	(0.0688)	(0.1021)	(0.0968)
40 years after dam	0.6551***	0.4118***	0.1053	0.1320	0.5497***	0.2798**
	(0.1408)	(0.1138)	(0.0893)	(0.0900)	(0.1382)	(0.1193)
50 years after dam	0.7897***	0.5176***	0.1600	0.2242	0.6298***	0.2934*
	(0.1681)	(0.1293)	(0.1340)	(0.1358)	(0.1845)	(0.1554)
60 years after dam	0.8699***	0.6036***				
	(0.2047)	(0.1514)				
70 years after dam	0.9584***	0.6026***				
	(0.2454)	(0.1663)				
80 years after dam	1.0494***	0.6448***				
	(0.3052)	(0.2094)				
Cheap Local Hydroelectricity Effect					0.2579	0.1407
Observations	660	935	1518	1364		
R-squared	0.9837	0.9781	0.9634	0.9634		

Notes: This table presents the short- and long-run effects of hydroelectric dams on population density. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, "b1950" before 1950, and "a1950" after 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. The cheap local hydroelectricity effects displayed at the bottom of columns 5 and 6 represent average growth of population density from the time of dam installation until 1950, as expressed in equation (7) in the text. Therefore, to obtain the estimates of agglomeration spillovers, simply subtract the cheap local hydroelectricity effect from the post-dam effects in columns 5 and 6, as expressed in equation (6) in the text. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 1.5: The Impact of Hydro Dams on Population Density - Specification Checks

ln(Pop Density)	Treatment vs. Synthetic Control				Treatment vs. Control				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
40 years before dam	-0.3703	-0.1265	-0.2428	-0.1369	-0.2610	-0.1744	-0.1441	-0.1235	-0.2542
	(0.2624)	(0.2346)	(0.2365)	(0.1784)	(0.2091)	(0.2911)	(0.2740)	(0.2556)	(0.4039)
30 years before dam	-0.3802**	-0.1692	-0.2564	-0.2974*	-0.2387**	-0.1763	-0.1493	-0.1758	-0.2761
	(0.1521)	(0.2003)	(0.1893)	(0.1459)	(0.1136)	(0.2129)	(0.1941)	(0.1921)	(0.2927)
20 years before dam	-0.2764***	-0.0565	-0.1536	-0.2122	-0.2001***	-0.1457	-0.1253	-0.1516	-0.1652
	(0.0934)	(0.1785)	(0.1528)	(0.1275)	(0.0684)	(0.2005)	(0.1740)	(0.1772)	(0.2679)
10 years before dam	-0.1542***	0.0471	-0.0398	-0.1048	-0.0964**	-0.0482	-0.0337	-0.0758	-0.1240
	(0.0472)	(0.1778)	(0.1445)	(0.1208)	(0.0409)	(0.1799)	(0.1544)	(0.1634)	(0.2220)
10 years after dam	0.1193**	0.1062**	0.1103**	0.1041**	0.0675*	0.0744	0.0652	0.0702	0.0448
	(0.0482)	(0.0471)	(0.0451)	(0.0451)	(0.0363)	(0.0502)	(0.0461)	(0.0456)	(0.0655)
20 years after dam	0.3206***	0.2770***	0.3063***	0.3070***	0.1854***	0.1757*	0.1574*	0.1772**	0.2106*
	(0.0905)	(0.0918)	(0.0979)	(0.1016)	(0.0664)	(0.0887)	(0.0811)	(0.0831)	(0.1194)
30 years after dam	0.4380***	0.4022***	0.4129***	0.3978***	0.2644***	0.2682**	0.2207**	0.2467***	0.3093*
	(0.1264)	(0.1206)	(0.1131)	(0.1044)	(0.0905)	(0.1129)	(0.0942)	(0.0934)	(0.1592)
40 years after dam	0.6079***	0.5985***	0.6551***	0.6209***	0.4000***	0.4197***	0.4118***	0.4409***	0.4628**
	(0.1595)	(0.1557)	(0.1408)	(0.1292)	(0.1104)	(0.1364)	(0.1138)	(0.1131)	(0.1770)
50 years after dam	0.7150***	0.7512***	0.7897***	0.7335***	0.4815***	0.5210***	0.5176***	0.5514***	0.5331***
	(0.1899)	(0.1862)	(0.1681)	(0.1509)	(0.1309)	(0.1518)	(0.1293)	(0.1272)	(0.2016)
60 years after dam	0.7850***	0.8535***	0.8699***	0.7999***	0.5142***	0.5726***	0.6036***	0.6374***	0.5882**
	(0.2245)	(0.2272)	(0.2047)	(0.1858)	(0.1467)	(0.1718)	(0.1514)	(0.1477)	(0.2312)
70 years after dam	0.8614***	0.9804***	0.9584***	0.8767***	0.4990***	0.5936***	0.6026***	0.6427***	0.5839**
	(0.2737)	(0.2823)	(0.2454)	(0.2145)	(0.1783)	(0.1997)	(0.1663)	(0.1681)	(0.2674)
80 years after dam	0.9652***	1.0877***	1.0494***	0.9330***	0.4886**	0.6030**	0.6448***	0.6937***	0.6253**
	(0.3293)	(0.3398)	(0.3052)	(0.3371)	(0.2227)	(0.2562)	(0.2094)	(0.2089)	(0.2983)
Hydro Dam Size		0.2180	0.1263	0.0442		0.0754	0.0807	0.0420	0.0002
		(0.1572)	(0.1217)	(0.1138)		(0.1416)	(0.1193)	(0.1314)	(0.1942)
Hydro Dam Size^2		-0.0443*	-0.0260	-0.0097		-0.0221	-0.0210	-0.0160	-0.0071
		(0.0217)	(0.0167)	(0.0158)		(0.0185)	(0.0153)	(0.0174)	(0.0273)
Hydro Dam Size^3		0.0019**	0.0011*	0.0004		0.0011	0.0010*	0.0008	0.0005
		(0.0008)	(0.0006)	(0.0006)		(0.0007)	(0.0006)	(0.0006)	(0.0010)
Thermal Plant Size			0.1936***	0.1826***			0.1297***	0.1154***	0.1185***
			(0.0401)	(0.0386)			(0.0273)	(0.0284)	(0.0417)
Thermal Plant Size^2			-0.0154***	-0.0146***			-0.0088***	-0.0078***	-0.0078**
			(0.0029)	(0.0031)			(0.0021)	(0.0023)	(0.0032)
Thermal Plant Size^3			0.0003***	0.0003***			0.0001***	0.0001***	0.0001**
			(0.0001)	(0.0001)			(0.0000)	(0.0000)	(0.0001)
Market Access-by-Year	No	No	No	Yes	No	No	No	Yes	No
Region-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
State-by-Year FE	No	No	No	No	No	No	No	No	Yes
Observations	660	660	660	660	935	935	935	913	935
R-squared	0.9787	0.9801	0.9837	0.9875	0.9745	0.9751	0.9781	0.9796	0.9872

Notes : This table presents some robustness checks regarding the specification used in the estimation of the effects of pre-1950 hydroelectric dams on population density. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Columns 1 and 5 display estimates related to the basic specification. Such specification includes event-time dummies, county effects, region-by-year fixed effects, and time-invariant county characteristics (cubic function in latitute and longitude, and 50-year average rainfall and 50-year average temperature for each season of the year) interacted with year effects. Columns 2 and 6 show estimates associated with the basic specification plus a cubic function in dam capacity. Columns 3 and 7 report the estimates related to the main specification, which is basic specification plus controls for dam size plus a cubic function in thermal power plant capacity. Columns 4 and 8 report the estimates related to the main specification plus controls for the interaction of year effects with three county-specific measures of market access: mileage of railroad tracks, distance to closest waterway, and log of market access as estimated by Donaldson and Hornbeck (2012). Column 9 displays estimates associated with the main specification, but replacing region-by-year fixed effects with state-by-year fixed effects. A similar column does not appear under the label "Treatment vs. Synthetic Control" because the sample size was insufficient to estimate all the parameters. Standard errors are shown in parentheses. In columns 1 through 4, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In columns 5 through 9, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 1.6: Short- and Long-Run Effects of Hydro Dams on Employment Density

ln(Pop Density)	TS_b1950	TC_b1950	TS_a1950	TC_a1950
	(1)	(2)	(3)	(4)
80 years before dam			-0.3185	-0.1612
			(0.3929)	(0.3784)
70 years before dam			-0.2408	-0.1090
			(0.2599)	(0.2778)
60 years before dam			-0.1482	0.0001
			(0.1934)	(0.2223)
50 years before dam			-0.2665	-0.1751
			(0.1626)	(0.1941)
40 years before dam	-0.0411	-0.0150	-0.2800*	-0.1905
	(0.2235)	(0.3112)	(0.1443)	(0.1706)
30 years before dam	-0.1079	-0.0682	-0.2628*	-0.1758
	(0.1788)	(0.2291)	(0.1338)	(0.1579)
20 years before dam	-0.0402	-0.0538	-0.2515*	-0.1605
	(0.1593)	(0.2221)	(0.1302)	(0.1494)
10 years before dam	0.0478	0.0502	-0.2377*	-0.1343
	(0.1459)	(0.1903)	(0.1199)	(0.1355)
10 years after dam	0.0650	0.0754	0.0145	0.0184
	(0.0466)	(0.0568)	(0.0291)	(0.0306)
20 years after dam	0.2430**	0.1881*	0.0395	0.0552
	(0.0992)	(0.0995)	(0.0526)	(0.0571)
30 years after dam	0.3491***	0.2824**	0.0606	0.0897
	(0.1116)	(0.1212)	(0.0764)	(0.0823)
40 years after dam	0.5681***	0.4770***	0.1188	0.1593
	(0.1230)	(0.1480)	(0.1022)	(0.1075)
50 years after dam	0.6854***	0.6059***	0.1840	0.2710
	(0.1375)	(0.1664)	(0.1729)	(0.1645)
60 years after dam	0.7624***	0.7200***		
	(0.1592)	(0.1931)		
70 years after dam	0.8425***	0.7152***		
	(0.1885)	(0.2127)		
80 years after dam	0.8619***	0.7401***		
	(0.2580)	(0.2613)		
Observations	660	935	1496	1353
R-squared	0.9865	0.9677	0.9554	0.9509

Notes : This table presents the short- and long-run effects of hydroelectric dams on employment density. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, "b1950" before 1950, and "a1950" after 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 1.7: The Impact of Hydro Dams on Employment Density - Sectoral Decomposition

ln(density)	Total		Manufacturing		Agriculture		Trade		Construction		Other Sectors	
	TS_b1950	TC_b1950	TS_b1950	TC_b1950	TS_b1950	TC_b1950	TS_b1950	TC_b1950	TS_b1950	TC_b1950	TS_b1950	TC_b1950
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
40 years before dam	-0.0411	-0.0150	0.2843	-0.3996	0.2905	0.4334*	0.8197	0.0939	-1.2201**	-1.0967**	-0.3724	-0.1949
	(0.2235)	(0.3112)	(0.5156)	(0.4122)	(0.2412)	(0.2285)	(0.8111)	(0.5670)	(0.4166)	(0.4404)	(0.3732)	(0.4240)
30 years before dam	-0.1079	-0.0682	0.3037	-0.2043	0.0111	0.1761	0.0924	-0.2169	-1.0684**	-0.7967	-0.1229	0.1461
	(0.1788)	(0.2291)	(0.4676)	(0.3264)	(0.1888)	(0.1552)	(0.4330)	(0.4236)	(0.4097)	(0.4836)	(0.3364)	(0.3350)
20 years before dam	-0.0402	-0.0538	0.0744	-0.2853	0.0096	0.1189	-0.0308	-0.0443	-0.6780*	-0.6156*	0.0320	0.2003
	(0.1593)	(0.2221)	(0.4837)	(0.4319)	(0.2291)	(0.1645)	(0.5193)	(0.4480)	(0.3693)	(0.3556)	(0.3015)	(0.3257)
10 years before dam	0.0478	0.0502	0.0858	-0.3795	0.0655	0.1977	-0.0817	-0.1150	-0.5398*	-0.2376	0.1602	0.2753
	(0.1459)	(0.1903)	(0.4006)	(0.3589)	(0.1941)	(0.1564)	(0.3564)	(0.3820)	(0.2545)	(0.3344)	(0.3035)	(0.2792)
10 years after dam	0.0650	0.0754	-0.1271	-0.0049	0.1588***	0.1242**	-0.0275	-0.0031	-0.3605	-0.3758	0.1697**	0.0352
	(0.0466)	(0.0568)	(0.1474)	(0.1562)	(0.0525)	(0.0495)	(0.2096)	(0.1341)	(0.5112)	(0.3130)	(0.0736)	(0.0834)
20 years after dam	0.2430**	0.1881*	0.0180	0.1685	0.2210***	0.0687	0.0034	0.0243	-0.1851	-0.4518	0.3346**	0.1611
	(0.0992)	(0.0995)	(0.1706)	(0.1501)	(0.0799)	(0.0865)	(0.2335)	(0.1695)	(0.5102)	(0.3347)	(0.1247)	(0.1256)
30 years after dam	0.3491***	0.2824**	0.1280	0.1595	0.3322**	0.1780	0.1099	0.1435	-0.1930	-0.3900	0.4488**	0.2096
	(0.1116)	(0.1212)	(0.1902)	(0.1655)	(0.1248)	(0.1149)	(0.2518)	(0.2101)	(0.5476)	(0.3751)	(0.1860)	(0.1654)
40 years after dam	0.5681***	0.4770***	0.3574	0.2970	0.3883**	0.2144	0.1982	0.3247	-0.1815	-0.3033	0.6422**	0.4088*
	(0.1230)	(0.1480)	(0.2083)	(0.1989)	(0.1727)	(0.1344)	(0.2423)	(0.2362)	(0.5997)	(0.3790)	(0.2387)	(0.2056)
50 years after dam	0.6854***	0.6059***	0.3629	0.2743	0.8084***	0.5501***	0.1887	0.3993	-0.0926	-0.1901	0.7627**	0.5287**
	(0.1375)	(0.1664)	(0.2185)	(0.2161)	(0.1822)	(0.1736)	(0.2772)	(0.2618)	(0.5904)	(0.3994)	(0.3152)	(0.2329)
60 years after dam	0.7624***	0.7200***	0.5148**	0.3589	0.8164***	0.5106***	0.2661	0.5141*	-0.1168	-0.1226	0.8168**	0.6122**
	(0.1592)	(0.1931)	(0.2384)	(0.2269)	(0.2003)	(0.1482)	(0.3186)	(0.2911)	(0.6536)	(0.4566)	(0.3698)	(0.2583)
70 years after dam	0.8425***	0.7152***	0.5927**	0.3369	1.0279***	0.5492***	0.2516	0.5389*	0.0223	-0.0603	0.8134*	0.5726*
	(0.1885)	(0.2127)	(0.2660)	(0.2350)	(0.2035)	(0.2002)	(0.3357)	(0.2967)	(0.6954)	(0.4838)	(0.4597)	(0.3047)
80 years after dam	0.8619***	0.7401***	0.6723**	0.3523	0.9216***	0.4202**	0.2674	0.5552	0.4266	0.0024	0.7560	0.5604
	(0.2580)	(0.2613)	(0.2973)	(0.2714)	(0.2086)	(0.2103)	(0.3856)	(0.4014)	(0.6146)	(0.4821)	(0.4635)	(0.3488)
Observations	660	935	506	638	638	924	440	682	352	528	660	902
R-squared	0.9865	0.9677	0.9715	0.9471	0.9664	0.9525	0.9803	0.9536	0.9817	0.9526	0.9693	0.9387

Notes : This table presents the effects of pre-1950 hydroelectric dams on employment density by sector. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "Other sectors" includes employment in industries that provide local goods and services like real estate, cleaning services, legal services, medical services, and personal services. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, and "b1950" before 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 1.8: The Impact of Hydro Dams on Population Density of Contiguous Counties

ln(Pop Density)	Main Analysis		Treatment: Contiguous Counties	
	TS_b1950	TC_b1950	TS_b1950	TC_b1950
	(1)	(2)	(3)	(4)
40 years before dam	-0.2428	-0.1441	-0.9443***	-0.7819***
	(0.2365)	(0.2740)	(0.1826)	(0.1803)
30 years before dam	-0.2564	-0.1493	-0.7571***	-0.6644***
	(0.1893)	(0.1941)	(0.1597)	(0.1537)
20 years before dam	-0.1536	-0.1253	-0.6404***	-0.5639***
	(0.1528)	(0.1740)	(0.1294)	(0.1282)
10 years before dam	-0.0398	-0.0337	-0.4642***	-0.4180***
	(0.1445)	(0.1544)	(0.1011)	(0.1015)
10 years after dam	0.1103**	0.0652	0.0633*	0.0307
	(0.0451)	(0.0461)	(0.0322)	(0.0288)
20 years after dam	0.3063***	0.1574*	0.1234***	0.0702
	(0.0979)	(0.0811)	(0.0463)	(0.0426)
30 years after dam	0.4129***	0.2207**	0.1759***	0.0996*
	(0.1131)	(0.0942)	(0.0591)	(0.0548)
40 years after dam	0.6551***	0.4118***	0.2080***	0.1096*
	(0.1408)	(0.1138)	(0.0669)	(0.0619)
50 years after dam	0.7897***	0.5176***	0.2444***	0.1222*
	(0.1681)	(0.1293)	(0.0734)	(0.0671)
60 years after dam	0.8699***	0.6036***	0.2552***	0.1123
	(0.2047)	(0.1514)	(0.0765)	(0.0735)
70 years after dam	0.9584***	0.6026***	0.2439***	0.0919
	(0.2454)	(0.1663)	(0.0795)	(0.0798)
80 years after dam	1.0494***	0.6448***	0.2127**	0.0249
	(0.3052)	(0.2094)	(0.0973)	(0.1118)
Observations	660	935	2222	1430
R-squared	0.9837	0.9781	0.9697	0.9656

Notes: This table presents the effects of pre-1950 hydroelectric dams on population density of neighboring counties. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, and "b1950" before 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 1.9: The Impact of Smaller (30-100MW) Hydro Dams on Population Density

ln(Pop Density)	Main Analysis		Treatment:		Treatment:	
	TS_b1950	TC_b1950	TS_b1950	TC_b1950	TS_b1950	TC_b1950
	(1)	(2)	(3)	(4)	(5)	(6)
40 years before dam	-0.2428	-0.1441	-0.1861	-0.3683*	-0.2811	-0.3470
	(0.2365)	(0.2740)	(0.2068)	(0.2185)	(0.2680)	(0.2700)
30 years before dam	-0.2564	-0.1493	-0.3860*	-0.2614	-0.3597*	-0.3021
	(0.1893)	(0.1941)	(0.1935)	(0.2057)	(0.2056)	(0.2317)
20 years before dam	-0.1536	-0.1253	-0.3576**	-0.2421	-0.3729**	-0.3324
	(0.1528)	(0.1740)	(0.1624)	(0.1849)	(0.1836)	(0.2016)
10 years before dam	-0.0398	-0.0337	-0.3651**	-0.1681	-0.3035*	-0.2142
	(0.1445)	(0.1544)	(0.1489)	(0.1687)	(0.1654)	(0.1794)
10 years after dam	0.1103**	0.0652	0.0689**	0.0753**	0.0290	0.0488
	(0.0451)	(0.0461)	(0.0328)	(0.0289)	(0.0302)	(0.0315)
20 years after dam	0.3063***	0.1574*	0.0959	0.1232**	0.0593	0.0816*
	(0.0979)	(0.0811)	(0.0577)	(0.0475)	(0.0440)	(0.0476)
30 years after dam	0.4129***	0.2207**	0.0847	0.1453**	0.1319**	0.1345**
	(0.1131)	(0.0942)	(0.0691)	(0.0614)	(0.0590)	(0.0635)
40 years after dam	0.6551***	0.4118***	0.1584*	0.1925**	0.2565***	0.2105***
	(0.1408)	(0.1138)	(0.0809)	(0.0744)	(0.0728)	(0.0794)
50 years after dam	0.7897***	0.5176***	0.2189**	0.2487***	0.3514***	0.2709***
	(0.1681)	(0.1293)	(0.0882)	(0.0838)	(0.0819)	(0.0921)
60 years after dam	0.8699***	0.6036***	0.2136**	0.2231**	0.4093***	0.2848**
	(0.2047)	(0.1514)	(0.0971)	(0.0941)	(0.0956)	(0.1082)
70 years after dam	0.9584***	0.6026***	0.2552**	0.2226**	0.4958***	0.3042**
	(0.2454)	(0.1663)	(0.1050)	(0.1106)	(0.1106)	(0.1233)
80 years after dam	1.0494***	0.6448***	0.2748**	0.1535	0.5497***	0.2714*
	(0.3052)	(0.2094)	(0.1337)	(0.1341)	(0.1317)	(0.1445)
Observations	660	935	968	1584	968	946
R-squared	0.9837	0.9781	0.9880	0.9651	0.9869	0.9833

Notes: This table presents the effects of smaller pre-1950 hydroelectric dams on population density. Small dams refers to dams with hydropower capacity between 30 and 100 megawatts (MW). The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, and "b1950" before 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 1.10: The Impact of Hydro Dams on Population Density - All vs. Non-TVA Counties

ln(Pop Density)	*With* TVA Counties				*Without* TVA Counties			
	TS_b1950	TC_b1950	TS_a1950	TC_a1950	TS_b1950	TC_b1950	TS_a1950	TC_a1950
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
80 years before dam			-0.4335	-0.1652			-0.3578	-0.1590
			(0.3306)	(0.3564)			(0.3508)	(0.3778)
70 years before dam			-0.1137	0.0802			-0.0214	0.1115
			(0.2182)	(0.2500)			(0.2374)	(0.2708)
60 years before dam			-0.1468	0.0411			-0.0880	0.0520
			(0.1605)	(0.1914)			(0.1753)	(0.2093)
50 years before dam			-0.2245	-0.1100			-0.1780	-0.1062
			(0.1353)	(0.1620)			(0.1490)	(0.1786)
40 years before dam	-0.2428	-0.1441	-0.2243*	-0.1298	-0.6014	-0.1867	-0.1838	-0.1197
	(0.2365)	(0.2740)	(0.1193)	(0.1428)	(0.3714)	(0.4076)	(0.1330)	(0.1588)
30 years before dam	-0.2564	-0.1493	-0.1895*	-0.1252	-0.5027*	-0.1490	-0.1616	-0.1176
	(0.1893)	(0.1941)	(0.1124)	(0.1315)	(0.2690)	(0.2313)	(0.1273)	(0.1475)
20 years before dam	-0.1536	-0.1253	-0.1663	-0.1180	-0.2473	-0.0883	-0.1457	-0.1119
	(0.1528)	(0.1740)	(0.1070)	(0.1218)	(0.1884)	(0.2034)	(0.1250)	(0.1383)
10 years before dam	-0.0398	-0.0337	-0.1468	-0.1049	-0.0446	0.0242	-0.1343	-0.0986
	(0.1445)	(0.1544)	(0.1036)	(0.1126)	(0.1632)	(0.1784)	(0.1214)	(0.1296)
10 years after dam	0.1103**	0.0652	-0.0014	0.0070	0.1540**	0.0673	-0.0164	-0.0073
	(0.0451)	(0.0461)	(0.0241)	(0.0273)	(0.0716)	(0.0594)	(0.0268)	(0.0297)
20 years after dam	0.3063***	0.1574*	0.0355	0.0491	0.2341**	0.0393	0.0017	0.0166
	(0.0979)	(0.0811)	(0.0439)	(0.0475)	(0.1040)	(0.0868)	(0.0502)	(0.0509)
30 years after dam	0.4129***	0.2207**	0.0460	0.0721	0.3411**	0.0896	-0.0099	0.0239
	(0.1131)	(0.0942)	(0.0646)	(0.0688)	(0.1386)	(0.1153)	(0.0730)	(0.0734)
40 years after dam	0.6551***	0.4118***	0.1053	0.1320	0.5950***	0.2966**	0.0450	0.0782
	(0.1408)	(0.1138)	(0.0893)	(0.0900)	(0.1788)	(0.1411)	(0.0965)	(0.0943)
50 years after dam	0.7897***	0.5176***	0.1600	0.2242	0.7340***	0.4361***	0.0194	0.1065
	(0.1681)	(0.1293)	(0.1340)	(0.1358)	(0.2331)	(0.1571)	(0.1350)	(0.1391)
60 years after dam	0.8699***	0.6036***			0.8031**	0.5518***		
	(0.2047)	(0.1514)			(0.2824)	(0.1831)		
70 years after dam	0.9584***	0.6026***			0.7464**	0.4712**		
	(0.2454)	(0.1663)			(0.3142)	(0.1880)		
80 years after dam	1.0494***	0.6448***			0.7673*	0.5060**		
	(0.3052)	(0.2094)			(0.4040)	(0.2337)		
Observations	660	935	1518	1364	440	792	1364	1254
R-squared	0.9837	0.9781	0.9634	0.9634	0.9914	0.9798	0.9637	0.9638

Notes: This table presents the short- and long-run effects of hydroelectric dams on population density, with and without counties of the Tennessee Valley Authority (TVA) region. The TVA was one of the most ambitious place based economic development policies in the history of the U.S. Besides hydroelectric dams, it included construction of an extensive network of new roads, canals, and flood control systems. The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, "b1950" before 1950, and "a1950" after 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 1.11: The Impact of Hydro Dams on Population Density - All vs. No Control Counties With Environmental Regulations

ln(Pop Density)	Treatment vs. Synthetic Control			Treatment vs. Control		
	(1)	(2)	(3)	(4)	(5)	(6)
40 years before dam	-0.2428	-0.2557	-0.1249	-0.1441	-0.1739	0.0777
	(0.2365)	(0.4924)	(0.4001)	(0.2740)	(0.4194)	(0.2881)
30 years before dam	-0.2564	-0.3550	-0.2534	-0.1493	-0.2331	-0.0257
	(0.1893)	(0.3492)	(0.3044)	(0.1941)	(0.3100)	(0.2075)
20 years before dam	-0.1536	-0.2459	-0.2398	-0.1253	-0.1729	-0.0685
	(0.1528)	(0.2585)	(0.2512)	(0.1740)	(0.2502)	(0.1929)
10 years before dam	-0.0398	-0.1315	-0.1552	-0.0337	-0.0794	-0.0370
	(0.1445)	(0.1887)	(0.2004)	(0.1544)	(0.2004)	(0.1669)
10 years after dam	0.1103**	0.1112	0.0877	0.0652	0.1013	0.0406
	(0.0451)	(0.0852)	(0.0605)	(0.0461)	(0.0838)	(0.0526)
20 years after dam	0.3063***	0.3030	0.2345*	0.1574*	0.2202	0.0960
	(0.0979)	(0.1792)	(0.1219)	(0.0811)	(0.1551)	(0.0882)
30 years after dam	0.4129***	0.3987*	0.2708*	0.2207**	0.3076	0.1214
	(0.1131)	(0.2282)	(0.1445)	(0.0942)	(0.2139)	(0.1026)
40 years after dam	0.6551***	0.6321**	0.4334**	0.4118***	0.5196*	0.2309*
	(0.1408)	(0.2705)	(0.1728)	(0.1138)	(0.2690)	(0.1172)
50 years after dam	0.7897***	0.7780**	0.5411**	0.5176***	0.6443**	0.3132**
	(0.1681)	(0.3182)	(0.1964)	(0.1293)	(0.3183)	(0.1258)
60 years after dam	0.8699***	0.9274**	0.6321***	0.6036***	0.7415*	0.3773***
	(0.2047)	(0.3709)	(0.2262)	(0.1514)	(0.3698)	(0.1430)
70 years after dam	0.9584***	1.0502**	0.7215***	0.6026***	0.8035*	0.3799**
	(0.2454)	(0.4392)	(0.2424)	(0.1663)	(0.4110)	(0.1673)
80 years after dam	1.0494***	1.2300**	0.8273***	0.6448***	0.9041*	0.3691
	(0.3052)	(0.5057)	(0.2766)	(0.2094)	(0.4583)	(0.2468)
Observations	660	660	660	935	462	1892
R-squared	0.9837	0.9858	0.9818	0.9781	0.9861	0.9559

Notes: This table presents the short- and long-run effects of hydroelectric dams on population density, with and without control counties subject to land regulations aimed at preserving wilderness and wildlife. Such environmental regulations could restrict population growth in those locations. The estimated coefficients are the β's in equation (5) in the text. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Columns 1 and 4 display the estimates of the main analysis, which includes control counties subject to environmental regulations. Columns 2 and 5 show estimates associated with synthetic control and control counties, respectively, without environmental regulations. Columns 3 and 6 report estimates related to synthetic control and control counties, respectively, without environmental regulations but with hydropower potential starting at 10 megawatts (instead of 100 megawatts, as in the main analysis). Standard errors are shown in parentheses. In columns 1 through 3, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In columns 4 through 6, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 1.12: Short- and Long-Run Effects of Hydro Dams on Average Value of Farmland

ln(Average Value of Farmland)	TS_b1950	TC_b1950	TS_a1950	TC_a1950
	(1)	(2)	(3)	(4)
80 years before dam			0.1887	0.1267
			(0.1341)	(0.1528)
70 years before dam			0.1425	0.0892
			(0.1140)	(0.1377)
60 years before dam			0.0800	-0.0153
			(0.1030)	(0.1244)
50 years before dam			0.0607	-0.0536
			(0.0858)	(0.1040)
40 years before dam	-0.1932	-0.2882	-0.0113	-0.0972
	(0.3165)	(0.3087)	(0.0771)	(0.0889)
30 years before dam	-0.1767	-0.1984	-0.0031	-0.0610
	(0.2652)	(0.2618)	(0.0717)	(0.0839)
20 years before dam	-0.2911	-0.2825	-0.0015	-0.0390
	(0.2850)	(0.2924)	(0.0705)	(0.0795)
10 years before dam	-0.3019	-0.2482	0.0046	-0.0177
	(0.2262)	(0.2341)	(0.0666)	(0.0733)
10 years after dam	0.0881	0.0689	0.0213	0.0141
	(0.0523)	(0.0551)	(0.0304)	(0.0352)
20 years after dam	0.1678**	0.1554**	0.0824*	0.0432
	(0.0719)	(0.0686)	(0.0417)	(0.0536)
30 years after dam	0.1721*	0.1461*	0.1109**	0.0464
	(0.0976)	(0.0859)	(0.0540)	(0.0709)
40 years after dam	0.1449	0.1786	0.0890	0.0213
	(0.1437)	(0.1224)	(0.0721)	(0.0923)
50 years after dam	0.1916	0.2652**	0.0658	0.0153
	(0.1405)	(0.1328)	(0.1008)	(0.1313)
60 years after dam	0.1789	0.2937*		
	(0.1626)	(0.1508)		
70 years after dam	0.0932	0.3108*		
	(0.1750)	(0.1797)		
80 years after dam	-0.0088	0.1949		
	(0.1398)	(0.1640)		
Observations	660	902	1518	1331
R-squared	0.9685	0.9451	0.9653	0.9452

Notes: This table presents the short- and long-run effects of hydroelectric dams on the average value of farmland ($/acre). The estimated coefficients are the β's in equation (5) in the text. They are coefficients of event-time dummies. "TS" in the labels of the columns represents treatment vs. synthetic control, "TC" treatment vs. control, "b1950" before 1950, and "a1950" after 1950. The synthetic control group consists of synthetic control counties. Each synthetic control county is a weighted average of the originally defined control counties that reproduces more closely the counterfactual outcome trajectory that the affected county would have experienced in the absence of hydro dams. The control group contains the originally defined control counties. Standard errors are shown in parentheses. In "TS" columns, they are clustered at a case level. A case is a pair of a treated county and its corresponding synthetic control. In "TC" columns, they are clustered at the county level. "Observations" reports the number of county-year observations.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 1.13: Valuation of Environmental Attributes

Effect of Environmental Attribute	Value of Suitability Factor
Least impediment to development	0.90
Minor reduction in likelihood of development	0.75
Likelihood of development reduced by half	0.50
Major reduction in likelihood of development	0.25
Development prohibited or highly unlikely	0.10

Source: Conner, Francfort, and Rinehart (1998, p.11).

Table 1.14: Overall Project Suitability Factor Computation

No environmental attributes assigned	0.90
Lowest individual factor(s) = 0.90	0.90
Lowest individual factor = 0.75	0.75
Two or more lowest individual factors = 0.75	0.50
Lowest individual factor = 0.50	0.50
Two or more lowest individual factors = 0.50	0.25
Lowest individual factor = 0.25	0.25
Two or more lowest individual factors = 0.25	0.10
Lowest individual factor(s) = 0.10	0.10

Source: Conner, Francfort, and Rinehart (1998, p.13).

Table 2.1: Distribution of Couples across Spouse/Location Arrangements

Spouses from/Live in	None has college degree	Wife has college degree	Husband has college degree	Both have college degree	*Both have PhD degree*	All Couples
Same SOB/SOB	58.20	58.53	50.13	41.60	*12.03*	52.16
Same SOB/Other State	6.35	6.11	7.68	9.92	*12.86*	7.59
Different SOB/Husband's SOB	13.23	13.52	13.93	14.84	*13.69*	13.87
Different SOB/Wife's SOB	13.14	12.14	14.86	14.05	*7.88*	13.41
Different SOB/Neither SOB	9.08	9.70	13.40	19.58	*53.33*	12.98
Live in SOB of any spouse	84.57	84.19	78.92	70.50	*33.60*	79.43
Percentage of couples	41.31	17.50	8.63	32.55	*0.23*	100.00

Source: U.S. Census Data - 2000. Sample includes only U.S.-born, white, non-hispanic, heterosexual couples, whose both spouses are present in a household of only one family, are not attending school anymore, are working, and are 20-35 years old. This is the sample I use in my empirical analysis. In the column for PhD couples, sample includes individuals 20-65 years old.

Table 2.2: Marriage Matching Equation

	L.H.S.	R.H.S.	SE(R.H.S.)	95% CI(R.H.S.) Lower Bound	95% CI(R.H.S.) Upper Bound
Arrangement 1	0	0	0	0	0
Arrangement 2	-1.9280	-1.9996	0.4232	-2.8291	-1.1701
Arrangement 3	-1.3248	-1.3766	0.3986	-2.1578	-0.5953
Arrangement 4	-1.3585	-1.4323	0.3940	-2.2045	-0.6601
Arrangement 5	-1.3911	-1.5376	0.4421	-2.4041	-0.6711

Notes: Standard errors computed through the Delta Method.

Table 2.3: Main Results - Males

	Marginal effects						Prob(Arr)	Prob(Arr) w/o Share Dev	Variables	
	Share Base	Share Dev Arr1	Share Dev Arr2	Share Dev Arr3	Share Dev Arr4	Share Dev Arr5			Share Base	Share Dev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Arr1	3.69	7.14	-1.18	-2.17	-2.08	-1.71	52.16	37.21		1.48
	(0.95)	(1.69)	(0.78)	(1.02)	(1.05)	(0.92)				(3.98)
Arr2	0.41	-1.14	2.04	-0.31	-0.30	-0.30	7.59	11.28		-0.66
	(0.37)	(0.75)	(1.30)	(0.29)	(0.29)	(0.38)				(3.93)
Arr3	-1.92	-2.09	-0.31	3.50	-0.54	-0.56	13.87	15.28	56.09	0.25
	(0.84)	(0.99)	(0.29)	(1.61)	(0.46)	(0.67)			(5.29)	(3.92)
Arr4	-1.50	-1.97	-0.29	-0.53	3.34	-0.54	13.41	21.94		-0.97
	(0.73)	(1.00)	(0.28)	(0.45)	(1.65)	(0.69)				(3.93)
Arr5	-0.52	-1.65	-0.30	-0.56	-0.55	3.06	12.98	14.30		0.02
	(0.41)	(0.92)	(0.39)	(0.68)	(0.71)	(1.95)				(3.92)

Notes: Standard *deviations* of the marginal effects over my sample in parentheses. "Dev" stands for deviation, and "Arr" for arrangement.

Table 2.4: Main Results - Females

	Marginal effects						Prob(Arr)	Prob(Arr) w/o Share Dev	Variables	
	Share Base	Share Dev Arr1	Share Dev Arr2	Share Dev Arr3	Share Dev Arr4	Share Dev Arr5			Share Base	Share Dev
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Arr1	0.26	-10.48	1.72	3.20	3.06	2.50	52.16	33.09		-1.48
	(0.29)	(2.08)	(1.08)	(1.51)	(1.50)	(1.29)				(3.98)
Arr2	0.18	1.72	-3.08	0.46	0.45	0.45	7.59	12.26		0.66
	(0.11)	(1.08)	(1.82)	(0.41)	(0.40)	(0.53)				(3.93)
Arr3	-0.66	3.19	0.46	-5.29	0.81	0.83	13.87	15.20	43.91	-0.25
	(0.32)	(1.50)	(0.41)	(2.28)	(0.65)	(0.93)			(5.29)	(3.92)
Arr4	-0.49	3.05	0.45	0.81	-5.12	0.81	13.41	24.91		0.97
	(0.27)	(1.50)	(0.40)	(0.65)	(2.35)	(0.97)				(3.93)
Arr5	0.71	2.49	0.44	0.83	0.81	-4.58	12.98	14.54		-0.02
	(0.46)	(1.29)	(0.53)	(0.93)	(0.97)	(2.69)				(3.92)

Notes: Standard *deviations* of the marginal effects over my sample in parentheses. "Dev" stands for deviation, and "Arr" for arrangement.

Table 2.5: Indirect Utility Parameters

Non-Linear Conditional Logit: Arr Choice	Males				Females			
	Coef.	**Std. Err.**	**Z**	**P-Value**	**Coef.**	**Std. Err.**	**Z**	**P-Value**
Wage - Exponential Term	0.031				0.012			
Wage	0.2593	0.0764	3.39	0.0010	-0.2195	0.2074	-1.06	0.2900
Sharing rule								
Share of Earnings Potential - Base - Arr 2	0.0006	0.0070	0.09	0.9300	0.0373	0.0135	2.77	0.0060
Share of Earnings Potential - Base - Arr 3	-0.0153	0.0051	-3.00	0.0030	0.0389	0.0087	4.47	0.0000
Share of Earnings Potential - Base - Arr 4	-0.0122	0.0071	-1.73	0.0840	0.0426	0.0114	3.75	0.0000
Share of Earnings Potential - Base - Arr 5	-0.0267	0.0090	-2.96	0.0030	0.0927	0.0185	5.00	0.0000
Share of Earnings Potential - Deviations	0.2227	0.0446	4.99	0.0000	-0.4023	0.0715	-5.62	0.0000
Couple Non-Labor Income - Base - Arr 2	0.2081	0.0498	4.18	0.0000	0.2580	0.0686	3.76	0.0000
Couple Non-Labor Income - Base - Arr 3	0.1153	0.0461	2.50	0.0120	0.0571	0.0596	0.96	0.3380
Couple Non-Labor Income - Base - Arr 4	0.0916	0.0566	1.62	0.1060	-0.0494	0.0769	-0.64	0.5210
Couple Non-Labor Income - Base - Arr 5	0.3816	0.0647	5.90	0.0000	0.4312	0.0944	4.57	0.0000
Couple Non-Labor Income - Deviations	0.0270	0.0304	0.89	0.3740	0.0510	0.0465	1.10	0.2730
Difference of Age Between Spouses - Arr 2	0.0372	0.0483	0.77	0.4410	-0.3707	0.1673	-2.22	0.0270
Difference of Age Between Spouses - Arr 3	0.0966	0.0416	2.32	0.0200	-0.0686	0.1502	-0.46	0.6480
Difference of Age Between Spouses - Arr 4	0.0473	0.0450	1.05	0.2930	0.1549	0.1578	0.98	0.3260
Difference of Age Between Spouses - Arr 5	0.1272	0.0383	3.32	0.0010	0.0206	0.1581	0.13	0.8970
Sex Ratio	-23.1422	3.9589	-5.85	0.0000	-33.4639	5.6576	-5.91	0.0000
Unilateral Divorce	-0.3469	0.2101	-1.65	0.0990	-0.5201	0.3149	-1.65	0.0990
Community Property	1.2855	0.2206	5.83	0.0000	1.8519	0.3129	5.92	0.0000
Hours of Work	0.1077	0.0692	1.56	0.1200	0.0442	0.0498	0.89	0.3740
Hours of Work - Spouse	0.0831	0.0418	1.99	0.0470	0.0825	0.1063	0.78	0.4380
Preference Shifters								
Housing Cost	-0.1109	0.0970	-1.14	0.2530	-0.1759	0.1398	-1.26	0.2080
Amenity - Quality of Life	0.2765	0.2428	1.14	0.2550	0.4394	0.3500	1.26	0.2090
Amenity - Firm Productivity	0.1864	0.1598	1.17	0.2430	0.2946	0.2303	1.28	0.2010
College Dummy - Arr 2	-0.1052	0.8006	-0.13	0.8950	4.1345	2.8824	1.43	0.1510
College Dummy - Arr 3	0.3607	0.3430	1.05	0.2930	2.8073	2.1137	1.33	0.1840
College Dummy - Arr 4	0.1582	0.6422	0.25	0.8050	0.7303	1.4069	0.52	0.6040
College Dummy - Arr 5	-0.6487	0.7788	-0.83	0.4050	3.3691	2.9836	1.13	0.2590
College Dummy - Spouse - Arr 2	-0.0644	0.3197	-0.20	0.8400	-0.8619	1.1890	-0.72	0.4690
College Dummy - Spouse - Arr 3	0.5084	0.2522	2.02	0.0440	1.0516	1.0675	0.99	0.3250
College Dummy - Spouse - Arr 4	0.3703	0.2597	1.43	0.1540	2.6848	1.0963	2.45	0.0140
College Dummy - Spouse - Arr 5	-0.0384	0.2605	-0.15	0.8830	-0.4676	1.0113	-0.46	0.6440
Children Dummy - Arr 2	-0.1562	0.0601	-2.60	0.0090	-0.2715	0.0857	-3.17	0.0020
Children Dummy - Arr 3	0.0455	0.0424	1.07	0.2840	0.0026	0.0596	0.04	0.9650
Children Dummy - Arr 4	0.0346	0.0372	0.93	0.3520	0.0260	0.0539	0.48	0.6300
Children Dummy - Arr 5	-0.0617	0.0538	-1.15	0.2520	-0.1594	0.0699	-2.28	0.0230
Age Range Dummies		Yes				Yes		
Age Range Dummies - Spouse		Yes				Yes		
SOB Dummies		Yes				Yes		
SOB Dummies - Spouse		Yes				Yes		
Intercepts		Yes				Yes		
Γ (males) or τ (females)								
Col x NoColSpouse Dummy - Arr 2	-0.0980	1.2290	-0.08	0.9360	-4.9319	3.2709	-1.51	0.1320
Col x NoColSpouse Dummy - Arr 3	-0.5787	0.5498	-1.05	0.2930	-3.3217	2.4020	-1.38	0.1670
Col x NoColSpouse Dummy - Arr 4	-0.2862	0.9937	-0.29	0.7730	-0.9772	1.6155	-0.60	0.5450
Col x NoColSpouse Dummy - Arr 5	0.8472	1.1991	0.71	0.4800	-4.4034	3.3859	-1.30	0.1930
NoCol x ColSpouse Dummy - Arr 2	-0.0584	0.4876	-0.12	0.9050	0.7149	1.3417	0.53	0.5940
NoCol x ColSpouse Dummy - Arr 3	-0.9479	0.3849	-2.46	0.0140	-1.2705	1.2018	-1.06	0.2900
NoCol x ColSpouse Dummy - Arr 4	-0.7876	0.3974	-1.98	0.0470	-3.1599	1.2349	-2.56	0.0110
NoCol x ColSpouse Dummy - Arr 5	-0.3969	0.3965	-1.00	0.3170	0.2349	1.1377	0.21	0.8360
Col x ColSpouse Dummy - Arr 2	0.2448	1.2423	0.20	0.8440	-3.8157	3.4421	-1.11	0.2680
Col x ColSpouse Dummy - Arr 3	-1.5559	0.6086	-2.56	0.0110	-4.5740	2.4478	-1.87	0.0620
Col x ColSpouse Dummy - Arr 4	-1.0303	1.0139	-1.02	0.3100	-4.1780	1.5507	-2.69	0.0070
Col x ColSpouse Dummy - Arr 5	0.6897	1.2522	0.55	0.5820	-3.9013	3.5380	-1.10	0.2700
Difference of Age Between Spouses - Arr 2	-0.0993	0.0780	-1.27	0.2030	0.4380	0.1954	2.24	0.0250
Difference of Age Between Spouses - Arr 3	-0.1441	0.0652	-2.21	0.0270	0.0547	0.1735	0.32	0.7530
Difference of Age Between Spouses - Arr 4	-0.0631	0.0685	-0.92	0.3570	-0.2191	0.1783	-1.23	0.2190
Difference of Age Between Spouses - Arr 5	-0.1875	0.0628	-2.99	0.0030	-0.1015	0.1829	-0.55	0.5790
Intercepts		Yes				Yes		
Log-likelihood		-36779.65				-36841.90		
N		154685				154685		

Notes: Std. Err. defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old).

Table 2.6: Choice of the Polynomial Order for the Nonparametric Sieve Logit

p^{th} polynomial	# of parameters (q)	N	ln(L)	LR	DoF (LR)	P-Value Chi2 (LR)	AIC	Consistent AIC	BIC
1	468	30937	-38203.60				77343.20	81714.18	81246.18
2	524	30937	-37512.46	1382.28	56	0.000	76072.92	80966.93	80442.93
3	580	30937	-37276.49	471.94	56	0.000	75712.98	81130.01	80550.01

Notes: LR (Likelihood Ratio) $= -2[\ln(L_{restricted}) - \ln(L_{unrestricted})]$
AIC (Akaike Information Criterion) $= -2\ln(L) + 2q$
Consistent AIC $= -2\ln(L) + [1+\ln(N)]q$
BIC (Bayesian information criterion) $= -2\ln(L) + [\ln(N)]q$

Table 2.7: Intermediate Estimation - Male Wages

Dep Var: ln(wage)	**No SC**	**SC-PO1**	**SC-PO2**	**SC-PO3**	**SC-PO4**	**SC-PO5**	**SC-PO6**	**SC-PO7**	**SC-PO8**	**SC-PO9**	**SC-PO10**
Years of Schooling	0.0861**	0.0835**	0.0786**	0.0780**	0.0781**	0.0781**	0.0779**	0.0779**	0.0779**	0.0780**	0.0780**
	(0.0034)	(0.0035)	(0.0034)	(0.0035)	(0.0035)	(0.0035)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Arrangement 2	-0.1050	-0.2127*	-0.2722**	-0.2810**	-0.2792**	-0.2814**	-0.2867**	-0.2864**	-0.2888**	-0.2877**	-0.2882**
	(0.0852)	(0.0943)	(0.0949)	(0.0959)	(0.0963)	(0.0960)	(0.0968)	(0.0966)	(0.0969)	(0.0968)	(0.0970)
Arrangement 3	-0.0692	-0.1617*	-0.2611**	-0.2657**	-0.2663**	-0.2676**	-0.2700**	-0.2698**	-0.2703**	-0.2692**	-0.2692**
	(0.0733)	(0.0771)	(0.0843)	(0.0853)	(0.0855)	(0.0858)	(0.0861)	(0.0860)	(0.0861)	(0.0861)	(0.0861)
Arrangement 4	-0.1887**	-0.2842**	-0.3816**	-0.3865**	-0.3867**	-0.3878**	-0.3908**	-0.3906**	-0.3914**	-0.3904**	-0.3906**
	(0.0680)	(0.0709)	(0.0758)	(0.0765)	(0.0765)	(0.0767)	(0.0771)	(0.0771)	(0.0771)	(0.0771)	(0.0772)
Arrangement 5	-0.2133**	-0.3378**	-0.4321**	-0.4372**	-0.4377**	-0.4403**	-0.4454**	-0.4461**	-0.4488**	-0.4493**	-0.4502**
	(0.0708)	(0.0772)	(0.0795)	(0.0805)	(0.0804)	(0.0808)	(0.0816)	(0.0816)	(0.0822)	(0.0821)	(0.0823)
Yrs of Sch * Arr 2	0.0083	0.0121+	0.0144*	0.0150*	0.0148*	0.0148*	0.0151*	0.0150*	0.0151*	0.0150*	0.0150*
	(0.0062)	(0.0066)	(0.0066)	(0.0066)	(0.0067)	(0.0067)	(0.0068)	(0.0068)	(0.0068)	(0.0067)	(0.0067)
Yrs of Sch * Arr 3	0.0055	0.0091+	0.0134*	0.0138*	0.0137*	0.0136*	0.0138*	0.0137*	0.0137*	0.0136*	0.0135*
	(0.0053)	(0.0054)	(0.0056)	(0.0057)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Yrs of Sch * Arr 4	0.0119*	0.0156**	0.0198**	0.0202**	0.0201**	0.0200**	0.0202**	0.0202**	0.0201**	0.0200**	0.0200**
	(0.0050)	(0.0050)	(0.0051)	(0.0051)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Yrs of Sch * Arr 5	0.0149**	0.0210**	0.0255**	0.0259**	0.0258**	0.0259**	0.0261**	0.0261**	0.0262**	0.0263**	0.0263**
	(0.0050)	(0.0052)	(0.0052)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
ln(ccp1/ccp2)		-0.0176**	-0.0325**	-0.0304**	-0.0328**	-0.0343**	-0.0315**	-0.0329**	-0.0344**	-0.0389**	-0.0406**
		(0.0052)	(0.0068)	(0.0069)	(0.0091)	(0.0102)	(0.0107)	(0.0125)	(0.0130)	(0.0139)	(0.0156)
[ln(ccp1/ccp2)]^2			-0.0084**	-0.0098**	-0.0100**	-0.0113*	-0.0155**	-0.0157*	-0.0195+	-0.0166	-0.0184
			(0.0019)	(0.0027)	(0.0028)	(0.0049)	(0.0059)	(0.0067)	(0.0106)	(0.0122)	(0.0154)
[ln(ccp1/ccp2)]^3				-0.0005	0.0000	0.0002	-0.0016	-0.0009	-0.0004	0.0036	0.0049
				(0.0005)	(0.0012)	(0.0014)	(0.0025)	(0.0042)	(0.0045)	(0.0072)	(0.0098)
[ln(ccp1/ccp2)]^4					0.0001	0.0003	0.0009	0.0010	0.0023	0.0015	0.0025
					(0.0002)	(0.0006)	(0.0007)	(0.0015)	(0.0032)	(0.0040)	(0.0067)
[ln(ccp1/ccp2)]^5						0.0000	0.0003	0.0002	0.0003	-0.0007	-0.0009
						(0.0001)	(0.0003)	(0.0004)	(0.0007)	(0.0017)	(0.0024)
[ln(ccp1/ccp2)]^6							0.0000	-0.0000	-0.0001	-0.0002	-0.0003
							(0.0000)	(0.0002)	(0.0003)	(0.0004)	(0.0012)
[ln(ccp1/ccp2)]^7								-0.0000	-0.0000	0.0000	0.0000
								(0.0000)	(0.0001)	(0.0002)	(0.0002)
[ln(ccp1/ccp2)]^8									-0.0000	0.0000	0.0000
									(0.0000)	(0.0000)	(0.0001)
[ln(ccp1/ccp2)]^9										0.0000	0.0000
										(0.0000)	(0.0000)
[ln(ccp1/ccp2)]^{10}											0.0000
											(0.0000)
R^2	0.2185	0.2191	0.2199	0.2199	0.2199	0.2199	0.2200	0.2200	0.2200	0.2200	0.2200
N	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937

Notes: Clustered standard errors in parentheses. They are all based on 400 bootstrap replications. Bootstrap replications are based on 1886 clusters defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old). "SC" stands for selection correction, "PO" for polynomial order, and "ccp" for conditional choice probability.
** significant at 1%; * significant at 5%; + significant at 10%.

Table 2.8: Intermediate Estimation - Female Wages

Dep Var: ln(wage)	**No SC**	**SC-PO1**	**SC-PO2**	**SC-PO3**	**SC-PO4**	**SC-PO5**	**SC-PO6**	**SC-PO7**	**SC-PO8**	**SC-PO9**	**SC-PO10**
Years of Schooling	0.1022**	0.1027**	0.1027**	0.1034**	0.1040**	0.1041**	0.1038**	0.1038**	0.1038**	0.1038**	0.1037**
	(0.0028)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Arrangement 2	-0.1088	-0.0851	-0.0850	-0.0754	-0.0652	-0.0730	-0.0822	-0.0819	-0.0791	-0.0799	-0.0795
	(0.0988)	(0.1027)	(0.1023)	(0.1018)	(0.1018)	(0.1019)	(0.1019)	(0.1017)	(0.1017)	(0.1018)	(0.1015)
Arrangement 3	-0.0676	-0.0465	-0.0462	-0.0432	-0.0513	-0.0558	-0.0576	-0.0574	-0.0564	-0.0571	-0.0569
	(0.0726)	(0.0721)	(0.0731)	(0.0729)	(0.0727)	(0.0730)	(0.0732)	(0.0733)	(0.0732)	(0.0732)	(0.0732)
Arrangement 4	-0.0635	-0.0432	-0.0429	-0.0386	-0.0446	-0.0497	-0.0529	-0.0526	-0.0512	-0.0518	-0.0515
	(0.0683)	(0.0708)	(0.0729)	(0.0727)	(0.0728)	(0.0730)	(0.0730)	(0.0729)	(0.0730)	(0.0731)	(0.0732)
Arrangement 5	-0.1799*	-0.1502*	-0.1500*	-0.1475+	-0.1546*	-0.1638*	-0.1695*	-0.1663*	-0.1627*	-0.1623*	-0.1615*
	(0.0700)	(0.0740)	(0.0756)	(0.0755)	(0.0754)	(0.0755)	(0.0755)	(0.0754)	(0.0753)	(0.0754)	(0.0755)
Yrs of Sch * Arr 2	0.0084	0.0077	0.0077	0.0070	0.0055	0.0054	0.0059	0.0061	0.0060	0.0061	0.0061
	(0.0068)	(0.0069)	(0.0068)	(0.0068)	(0.0068)	(0.0067)	(0.0067)	(0.0068)	(0.0068)	(0.0068)	(0.0067)
Yrs of Sch * Arr 3	0.0033	0.0027	0.0027	0.0023	0.0017	0.0014	0.0016	0.0017	0.0018	0.0018	0.0018
	(0.0050)	(0.0049)	(0.0049)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Yrs of Sch * Arr 4	0.0044	0.0038	0.0038	0.0033	0.0026	0.0023	0.0025	0.0027	0.0027	0.0028	0.0028
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Yrs of Sch * Arr 5	0.0112*	0.0099*	0.0099*	0.0097*	0.0095+	0.0096*	0.0098*	0.0097*	0.0096*	0.0096*	0.0095*
	(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)
ln(ccp1/ccp2)		0.0046	0.0047	0.0009	-0.0155*	-0.0221*	-0.0167+	-0.0114	-0.0093	-0.0060	-0.0046
		(0.0045)	(0.0058)	(0.0065)	(0.0079)	(0.0086)	(0.0096)	(0.0117)	(0.0121)	(0.0136)	(0.0149)
$[\ln(ccp1/ccp2)]^2$			0.0000	0.0021	0.0002	-0.0058	-0.0134*	-0.0127+	-0.0072	-0.0095	-0.0079
			(0.0019)	(0.0027)	(0.0028)	(0.0052)	(0.0061)	(0.0069)	(0.0105)	(0.0116)	(0.0154)
$[\ln(ccp1/ccp2)]^3$				0.0008	0.0041**	0.0051**	0.0017	-0.0010	-0.0016	-0.0046	-0.0057
				(0.0007)	(0.0013)	(0.0015)	(0.0026)	(0.0042)	(0.0046)	(0.0071)	(0.0091)
$[\ln(ccp1/ccp2)]^4$					0.0006**	0.0015*	0.0025**	0.0020	0.0001	0.0007	-0.0001
					(0.0002)	(0.0007)	(0.0008)	(0.0015)	(0.0030)	(0.0035)	(0.0064)
$[\ln(ccp1/ccp2)]^5$						0.0001	0.0006+	0.0008+	0.0007	0.0014	0.0016
						(0.0001)	(0.0003)	(0.0004)	(0.0007)	(0.0016)	(0.0021)
$[\ln(ccp1/ccp2)]^6$							0.0000	0.0001	0.0003	0.0003	0.0005
							(0.0000)	(0.0001)	(0.0003)	(0.0003)	(0.0011)
$[\ln(ccp1/ccp2)]^7$								0.0000	0.0000	-0.0000	-0.0000
								(0.0000)	(0.0001)	(0.0001)	(0.0002)
$[\ln(ccp1/ccp2)]^8$									0.0000	-0.0000	-0.0000
									(0.0000)	(0.0000)	(0.0001)
$[\ln(ccp1/ccp2)]^9$										-0.0000	-0.0000
										(0.0000)	(0.0000)
$[\ln(ccp1/ccp2)]^{10}$											-0.0000
											(0.0000)
R^2	0.2711	0.2711	0.2711	0.2712	0.2715	0.2715	0.2716	0.2717	0.2717	0.2717	0.2717
N	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937

Notes: Clustered standard errors in parentheses. They are all based on 400 bootstrap replications. Bootstrap replications are based on 1928 clusters defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old). "SC" stands for selection correction, "PO" for polynomial order, and "ccp" for conditional choice probability.
** significant at 1%; * significant at 5%; + significant at 10%.

Table 2.9: Intermediate Estimation - Male Hours of Work

Dep Var: ln(hours)	**No SC**	**SC-PO1**	**SC-PO2**	**SC-PO3**	**SC-PO4**	**SC-PO5**	**SC-PO6**	**SC-PO7**	**SC-PO8**	**SC-PO9**	**SC-PO10**
Number of Children	-0.0003	-0.0005	-0.0004	-0.0003	-0.0004	-0.0005	-0.0005	-0.0004	-0.0003	-0.0003	-0.0004
	(0.0040)	(0.0042)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Arrangement 2	-0.0045	0.0052	0.0029	0.0031	0.0009	-0.0009	-0.0012	-0.0031	-0.0059	-0.0059	-0.0079
	(0.0115)	(0.0148)	(0.0155)	(0.0155)	(0.0160)	(0.0168)	(0.0168)	(0.0171)	(0.0173)	(0.0173)	(0.0173)
Arrangement 3	0.0041	0.0123	0.0091	0.0095	0.0062	0.0047	0.0047	0.0030	0.0011	0.0010	-0.0004
	(0.0078)	(0.0105)	(0.0121)	(0.0120)	(0.0127)	(0.0133)	(0.0133)	(0.0135)	(0.0137)	(0.0137)	(0.0137)
Arrangement 4	-0.0027	0.0056	0.0025	0.0029	-0.0002	-0.0018	-0.0018	-0.0034	-0.0056	-0.0057	-0.0073
	(0.0086)	(0.0106)	(0.0120)	(0.0119)	(0.0124)	(0.0129)	(0.0129)	(0.0131)	(0.0132)	(0.0132)	(0.0132)
Arrangement 5	0.0030	0.0096	0.0073	0.0074	0.0056	0.0043	0.0037	0.0029	0.0005	0.0006	-0.0008
	(0.0093)	(0.0109)	(0.0116)	(0.0116)	(0.0119)	(0.0122)	(0.0123)	(0.0125)	(0.0127)	(0.0127)	(0.0128)
No of Child * Arr 2	0.0164+	0.0170+	0.0170+	0.0170+	0.0172+	0.0173+	0.0173+	0.0174+	0.0173+	0.0173+	0.0175+
	(0.0093)	(0.0098)	(0.0097)	(0.0097)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)
No of Child * Arr 3	-0.0047	-0.0045	-0.0047	-0.0048	-0.0046	-0.0045	-0.0045	-0.0045	-0.0047	-0.0047	-0.0046
	(0.0076)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)
No of Child * Arr 4	0.0067	0.0069	0.0067	0.0067	0.0069	0.0069	0.0069	0.0070	0.0068	0.0068	0.0069
	(0.0077)	(0.0083)	(0.0083)	(0.0083)	(0.0083)	(0.0083)	(0.0083)	(0.0083)	(0.0083)	(0.0082)	(0.0082)
No of Child * Arr 5	0.0020	0.0028	0.0027	0.0027	0.0028	0.0028	0.0028	0.0026	0.0025	0.0025	0.0026
	(0.0091)	(0.0091)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
ln(ccp1/ccp2)		0.0033	0.0021	0.0026	-0.0004	-0.0017	-0.0007	-0.0049	-0.0076	-0.0080	-0.0130
		(0.0024)	(0.0032)	(0.0034)	(0.0051)	(0.0058)	(0.0061)	(0.0078)	(0.0078)	(0.0093)	(0.0102)
$[\ln(ccp1/ccp2)]^2$			-0.0008	-0.0011	-0.0014	-0.0025	-0.0038	-0.0044	-0.0113+	-0.0110+	-0.0165*
			(0.0011)	(0.0016)	(0.0016)	(0.0030)	(0.0040)	(0.0044)	(0.0060)	(0.0066)	(0.0080)
$[\ln(ccp1/ccp2)]^3$				-0.0001	0.0005	0.0007	0.0001	0.0022	0.0030	0.0034	0.0073
				(0.0004)	(0.0008)	(0.0009)	(0.0016)	(0.0031)	(0.0029)	(0.0054)	(0.0066)
$[\ln(ccp1/ccp2)]^4$					0.0001	0.0003	0.0005	0.0009	0.0033+	0.0032	0.0062+
					(0.0001)	(0.0004)	(0.0006)	(0.0011)	(0.0019)	(0.0021)	(0.0036)
$[\ln(ccp1/ccp2)]^5$						0.0000	0.0001	-0.0001	0.0001	-0.0000	-0.0007
						(0.0000)	(0.0002)	(0.0003)	(0.0004)	(0.0012)	(0.0015)
$[\ln(ccp1/ccp2)]^6$							0.0000	-0.0001	-0.0003	-0.0003	-0.0008
							(0.0000)	(0.0001)	(0.0002)	(0.0002)	(0.0007)
$[\ln(ccp1/ccp2)]^7$								-0.0000	-0.0001	-0.0000	-0.0001
								(0.0000)	(0.0000)	(0.0001)	(0.0001)
$[\ln(ccp1/ccp2)]^8$									-0.0000	-0.0000	0.0000
									(0.0000)	(0.0000)	(0.0000)
$[\ln(ccp1/ccp2)]^9$										0.0000	0.0000
										(0.0000)	(0.0000)
$[\ln(ccp1/ccp2)]^{10}$											0.0000
											(0.0000)
R^2	0.0355	0.0355	0.0355	0.0355	0.0356	0.0356	0.0356	0.0356	0.0357	0.0357	0.0358
N	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937

Notes: Clustered standard errors in parentheses. They are all based on 400 bootstrap replications. Bootstrap replications are based on 1886 clusters defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old). "SC" stands for selection correction, "PO" for polynomial order, and "ccp" for conditional choice probability.
** significant at 1%; * significant at 5%; + significant at 10%.

Table 2.10: Intermediate Estimation - Female Hours of Work

Dep Var: ln(hours)	**No SC**	**SC-PO1**	**SC-PO2**	**SC-PO3**	**SC-PO4**	**SC-PO5**	**SC-PO6**	**SC-PO7**	**SC-PO8**	**SC-PO9**	**SC-PO10**
Number of Children	-0.2447**	-0.2455**	-0.2514**	-0.2547**	-0.2566**	-0.2566**	-0.2565**	-0.2565**	-0.2565**	-0.2569**	-0.2570**
	(0.0083)	(0.0083)	(0.0084)	(0.0085)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)
Arrangement 2	-0.0589**	-0.0122	0.1017**	0.0844**	0.0511	0.0514	0.0514	0.0493	0.0500	0.0485	0.0461
	(0.0193)	(0.0299)	(0.0328)	(0.0322)	(0.0325)	(0.0345)	(0.0344)	(0.0342)	(0.0342)	(0.0340)	(0.0342)
Arrangement 3	-0.0053	0.0348	0.1938**	0.1487**	0.1006**	0.1009**	0.1009**	0.0989**	0.0995**	0.0983**	0.0965**
	(0.0137)	(0.0226)	(0.0282)	(0.0275)	(0.0268)	(0.0281)	(0.0279)	(0.0280)	(0.0282)	(0.0280)	(0.0280)
Arrangement 4	-0.0084	0.0313	0.1845**	0.1391**	0.0917**	0.0920**	0.0920**	0.0901**	0.0907**	0.0896**	0.0877**
	(0.0149)	(0.0245)	(0.0302)	(0.0302)	(0.0290)	(0.0306)	(0.0305)	(0.0301)	(0.0302)	(0.0301)	(0.0301)
Arrangement 5	-0.0460**	-0.0144	0.1077**	0.0960**	0.0695**	0.0698*	0.0698*	0.0688*	0.0694*	0.0701*	0.0685*
	(0.0152)	(0.0212)	(0.0258)	(0.0257)	(0.0258)	(0.0272)	(0.0275)	(0.0272)	(0.0274)	(0.0272)	(0.0270)
No of Child * Arr 2	-0.0945**	-0.0917**	-0.0958**	-0.0918**	-0.0880**	-0.0880**	-0.0880**	-0.0880**	-0.0879**	-0.0877**	-0.0874**
	(0.0247)	(0.0237)	(0.0244)	(0.0241)	(0.0241)	(0.0242)	(0.0242)	(0.0242)	(0.0242)	(0.0241)	(0.0242)
No of Child * Arr 3	-0.0531**	-0.0524**	-0.0438*	-0.0375*	-0.0344*	-0.0344*	-0.0344*	-0.0344*	-0.0343*	-0.0338+	-0.0337+
	(0.0174)	(0.0173)	(0.0173)	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0175)	(0.0175)
No of Child * Arr 4	-0.0517**	-0.0504**	-0.0403*	-0.0341*	-0.0308+	-0.0309+	-0.0309+	-0.0308+	-0.0308+	-0.0302+	-0.0300+
	(0.0162)	(0.0159)	(0.0159)	(0.0161)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)
No of Child * Arr 5	-0.0804**	-0.0767**	-0.0731**	-0.0742**	-0.0733**	-0.0733**	-0.0733**	-0.0736**	-0.0736**	-0.0735**	-0.0734**
	(0.0186)	(0.0183)	(0.0183)	(0.0184)	(0.0185)	(0.0185)	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0186)
ln(ccp1/ccp2)		0.0159*	0.0757**	0.0234+	-0.0216+	-0.0214	-0.0215	-0.0266	-0.0259	-0.0389+	-0.0452
		(0.0066)	(0.0085)	(0.0120)	(0.0117)	(0.0136)	(0.0140)	(0.0196)	(0.0208)	(0.0225)	(0.0291)
[ln(ccp1/ccp2)]^2			0.0392**	0.0662**	0.0607**	0.0609**	0.0611**	0.0604**	0.0623**	0.0711**	0.0642*
			(0.0033)	(0.0049)	(0.0045)	(0.0083)	(0.0119)	(0.0124)	(0.0181)	(0.0205)	(0.0294)
[ln(ccp1/ccp2)]^3				0.0107**	0.0196**	0.0196**	0.0196**	0.0223*	0.0220*	0.0336*	0.0386+
				(0.0019)	(0.0020)	(0.0022)	(0.0047)	(0.0092)	(0.0100)	(0.0141)	(0.0233)
[ln(ccp1/ccp2)]^4					0.0015**	0.0015	0.0015	0.0020	0.0013	-0.0011	0.0027
					(0.0003)	(0.0010)	(0.0015)	(0.0026)	(0.0056)	(0.0069)	(0.0151)
[ln(ccp1/ccp2)]^5						-0.0000	-0.0000	-0.0003	-0.0003	-0.0032	-0.0041
						(0.0001)	(0.0006)	(0.0010)	(0.0014)	(0.0033)	(0.0056)
[ln(ccp1/ccp2)]^6							-0.0000	-0.0001	-0.0000	-0.0001	-0.0008
							(0.0001)	(0.0003)	(0.0005)	(0.0008)	(0.0032)
[ln(ccp1/ccp2)]^7								-0.0000	0.0000	0.0002	0.0002
								(0.0000)	(0.0001)	(0.0003)	(0.0005)
[ln(ccp1/ccp2)]^8									0.0000	0.0000	0.0001
									(0.0000)	(0.0001)	(0.0002)
[ln(ccp1/ccp2)]^9										0.0000	0.0000
										(0.0000)	(0.0000)
[ln(ccp1/ccp2)]^{10}											0.0000
											(0.0000)
R^2	0.1330	0.1333	0.1435	0.1496	0.1511	0.1511	0.1511	0.1511	0.1511	0.1512	0.1512
N	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937

Notes: Clustered standard errors in parentheses. They are all based on 400 bootstrap replications. Bootstrap replications are based on 1928 clusters defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old). "SC" stands for selection correction, "PO" for polynomial order, and "ccp" for conditional choice probability.
** significant at 1%; * significant at 5%; + significant at 10%.

Table 2.11: Intermediate Estimation - Couple Non-Labor Income

Dep Var: CNLInc	No SC	SC-PO1	SC-PO2	SC-PO3	SC-PO4	SC-PO5	SC-PO6	SC-PO7	SC-PO8	SC-PO9	SC-PO10
Husband's Age	-610.27**	-610.88*	-607.34*	-604.48*	-604.41*	-601.67*	-600.66*	-600.66*	-600.67*	-601.60*	-601.84*
	(220.38)	(242.30)	(241.92)	(245.33)	(244.97)	(242.89)	(243.86)	(243.17)	(241.42)	(241.11)	(240.01)
Husband's Age^2	11.32**	11.33*	11.26*	11.20*	11.20*	11.14*	11.12*	11.12*	11.10*	11.11*	11.12*
	(4.05)	(4.45)	(4.44)	(4.51)	(4.50)	(4.46)	(4.47)	(4.46)	(4.42)	(4.41)	(4.40)
Wife's Age	-317.30	-310.66	-245.73	-182.45	-177.51	-207.27	-219.99	-220.00	-216.42	-219.57	-210.90
	(211.68)	(215.42)	(215.44)	(217.42)	(217.36)	(216.27)	(214.68)	(214.92)	(215.53)	(216.21)	(216.02)
Wife's Age^2	5.83	5.70	4.47	3.27	3.18	3.73	3.94	3.94	3.89	3.95	3.79
	(3.93)	(3.99)	(4.00)	(4.04)	(4.04)	(4.02)	(3.99)	(4.00)	(4.01)	(4.02)	(4.01)
Arrangement 2	-10014.52	-10107.35	-9856.49	-9514.79	-9482.83	-9957.11	-10502.67	-10502.77	-10405.12	-10640.81	-10269.43
	(8424.96)	(8586.74)	(8578.51)	(8642.24)	(8633.46)	(8598.39)	(8692.83)	(8675.73)	(8679.06)	(8658.80)	(8646.67)
Arrangement 3	-17871.49*	-17895.02*	-17950.23*	-17576.93*	-17477.08*	-18422.87*	-18756.88*	-18756.89*	-18810.44*	-18838.21*	-18789.73*
	(8267.64)	(8622.94)	(8600.75)	(8648.18)	(8669.59)	(8634.56)	(8609.25)	(8618.02)	(8623.39)	(8615.54)	(8620.44)
Arrangement 4	1357.36	1347.30	1279.33	1459.36	1525.32	634.19	159.89	159.88	-39.78	-52.70	-133.37
	(8527.97)	(8692.72)	(8770.05)	(8846.61)	(8864.62)	(8815.72)	(8774.72)	(8780.64)	(8751.75)	(8757.72)	(8750.34)
Arrangement 5	-2536.42	-2644.49	-2555.73	-1599.61	-1485.94	-1888.07	-1902.01	-1902.06	-1943.03	-1952.47	-2032.90
	(10380.90)	(11444.65)	(11457.08)	(11436.27)	(11425.57)	(11450.60)	(11456.75)	(11474.33)	(11475.17)	(11467.27)	(11482.58)
HAge * Arr 2	789.42	778.79	856.80+	849.50+	849.09+	817.04	846.70+	846.69+	837.89+	842.48+	817.86
	(496.74)	(489.21)	(496.80)	(502.74)	(501.63)	(506.12)	(506.66)	(507.09)	(506.79)	(505.01)	(504.46)
HAge * Arr 3	1450.33**	1450.09*	1454.50*	1466.64*	1466.79*	1478.14*	1487.59*	1487.59*	1493.47*	1488.13*	1494.61*
	(527.99)	(579.40)	(577.86)	(582.05)	(582.40)	(584.14)	(584.19)	(584.49)	(585.46)	(584.43)	(584.61)
HAge * Arr 4	1417.05+	1422.24+	1421.26+	1421.15+	1423.01+	1412.30+	1420.78+	1420.78+	1430.85+	1428.55+	1438.94+
	(751.89)	(783.80)	(786.82)	(790.95)	(791.48)	(790.01)	(788.91)	(788.58)	(786.53)	(786.03)	(785.59)
HAge * Arr 5	412.00	415.27	417.79	385.09	384.33	353.23	350.83	350.83	356.30	354.03	353.97
	(709.64)	(723.85)	(724.45)	(725.64)	(725.82)	(727.33)	(728.80)	(729.64)	(728.29)	(727.31)	(728.14)
HAge^2 * Arr 2	-15.13	-14.96	-16.32+	-16.15+	-16.14+	-15.59	-16.07+	-16.07+	-15.84+	-15.90+	-15.45
	(9.38)	(9.23)	(9.36)	(9.47)	(9.45)	(9.51)	(9.52)	(9.53)	(9.52)	(9.49)	(9.48)
HAge^2 * Arr 3	-24.12*	-24.11*	-24.16*	-24.36*	-24.37*	-24.57*	-24.72*	-24.72*	-24.81*	-24.69*	-24.82*
	(9.59)	(10.52)	(10.49)	(10.57)	(10.57)	(10.60)	(10.60)	(10.60)	(10.62)	(10.60)	(10.61)
HAge^2 * Arr 4	-25.65+	-25.72+	-25.71+	-25.75+	-25.78+	-25.63+	-25.78+	-25.78+	-25.94+	-25.88+	-26.06+
	(13.39)	(13.99)	(14.04)	(14.11)	(14.13)	(14.10)	(14.08)	(14.08)	(14.04)	(14.03)	(14.02)
HAge^2 * Arr 5	-7.71	-7.75	-7.73	-7.16	-7.15	-6.59	-6.54	-6.54	-6.63	-6.57	-6.58
	(12.72)	(12.95)	(12.96)	(12.98)	(12.99)	(13.01)	(13.03)	(13.04)	(13.02)	(13.00)	(13.01)
WAge * Arr 2	-123.08	-117.91	-232.76	-259.42	-260.40	-222.42	-221.36	-221.34	-228.19	-215.13	-221.63
	(496.20)	(488.26)	(493.40)	(494.50)	(493.50)	(493.16)	(492.70)	(493.59)	(490.60)	(490.41)	(490.21)
WAge * Arr 3	-175.09	-183.88	-218.13	-256.44	-260.99	-224.65	-211.44	-211.43	-217.97	-211.81	-224.95
	(528.86)	(547.04)	(552.77)	(555.48)	(555.18)	(551.60)	(550.18)	(549.65)	(549.91)	(550.08)	(549.81)
WAge * Arr 4	-1559.13	-1574.74	-1600.67+	-1612.52+	-1616.58+	-1561.73	-1538.81	-1538.81	-1540.81	-1538.06	-1547.65
	(963.36)	(970.47)	(969.80)	(969.86)	(971.06)	(970.21)	(968.47)	(968.31)	(967.19)	(966.78)	(966.83)
WAge * Arr 5	-351.23	-359.33	-396.81	-434.17	-439.43	-402.15	-403.88	-403.87	-413.57	-410.86	-410.37
	(726.44)	(777.93)	(773.40)	(774.56)	(775.54)	(780.64)	(781.00)	(781.64)	(782.08)	(782.37)	(783.52)
WAge^2 * Arr 2	4.42	4.37	6.39	6.99	7.03	6.40	6.43	6.43	6.48	6.25	6.32
	(9.03)	(8.81)	(8.90)	(8.93)	(8.91)	(8.89)	(8.88)	(8.90)	(8.85)	(8.84)	(8.83)
WAge^2 * Arr 3	2.21	2.39	3.11	3.87	3.95	3.26	3.02	3.02	3.11	3.01	3.23
	(9.91)	(10.19)	(10.31)	(10.37)	(10.36)	(10.29)	(10.27)	(10.26)	(10.27)	(10.27)	(10.27)
WAge^2 * Arr 4	29.24+	29.53+	30.12+	30.46+	30.54+	29.55+	29.18+	29.18+	29.20+	29.15+	29.31+
	(17.48)	(17.57)	(17.56)	(17.56)	(17.58)	(17.56)	(17.53)	(17.53)	(17.51)	(17.50)	(17.50)
WAge^2 * Arr 5	9.38	9.59	10.35	11.06	11.16	10.53	10.56	10.56	10.74	10.66	10.69
	(13.54)	(14.51)	(14.41)	(14.43)	(14.45)	(14.55)	(14.55)	(14.56)	(14.57)	(14.58)	(14.60)
ln(ccp1/ccp2)		-48.13	-184.67	-48.51	-4.53	-262.63	-152.82	-152.72	-247.15	-54.35	-277.61
		(96.73)	(146.63)	(154.65)	(217.13)	(250.15)	(265.89)	(306.84)	(322.54)	(354.14)	(379.21)
[ln(ccp1/ccp2)]^2			-82.89+	-172.17**	-167.67*	-390.93**	-561.84**	-561.82**	-797.14**	-927.79**	-1166.84**
			(46.62)	(60.41)	(75.29)	(148.03)	(171.59)	(193.81)	(288.48)	(309.62)	(344.36)
[ln(ccp1/ccp2)]^3				-31.90*	-40.80	-3.11	-74.35	-74.40	-47.35	-219.14	-44.11
				(14.84)	(27.29)	(28.44)	(61.13)	(86.64)	(108.71)	(187.13)	(198.42)
[ln(ccp1/ccp2)]^4					-1.51	31.78+	55.29**	55.28	136.52+	171.68*	301.72*
					(6.24)	(17.36)	(19.13)	(35.94)	(75.99)	(82.44)	(122.97)
[ln(ccp1/ccp2)]^5						3.28	13.30+	13.31	19.68	62.28	31.11
						(2.29)	(6.97)	(8.70)	(21.51)	(45.23)	(43.77)
[ln(ccp1/ccp2)]^6							0.77	0.77	-6.32	-4.94	-29.49
							(0.67)	(3.11)	(5.74)	(8.40)	(19.67)
[ln(ccp1/ccp2)]^7								0.00	-1.57	-4.66	-5.07
								(0.31)	(2.01)	(3.52)	(4.01)
[ln(ccp1/ccp2)]^8									-0.09	-0.67	0.75
									(0.17)	(0.78)	(1.21)
[ln(ccp1/ccp2)]^9										-0.03	0.21
										(0.05)	(0.27)
[ln(ccp1/ccp2)]^{10}											0.01
											(0.02)
R^2	0.0181	0.0182	0.0185	0.0189	0.0189	0.0194	0.0196	0.0196	0.0198	0.0199	0.0201
N	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937	30937

Notes: Clustered standard errors in parentheses. They are all based on 400 bootstrap replications. Bootstrap replications are based on 1886 clusters defined by division of birth, state of residence, education category (college degree, no-college degree), and age range (20-25, 25-30, 31-35 years old). "SC" stands for selection correction, "PO" for polynomial order, and "ccp" for conditional choice probability.

** significant at 1%; * significant at 5%; + significant at 10%.

Table 3.1: Valuation of Environmental Attributes

Effect of Environmental Attribute	Value of Suitability Factor
Least impediment to development	0.90
Minor reduction in likelihood of development	0.75
Likelihood of development reduced by half	0.50
Major reduction in likelihood of development	0.25
Development prohibited or highly unlikely	0.10

Source: Conner, Francfort, and Rinehart (1998, p.11).

Table 3.2: Overall Project Suitability Factor Computation

No environmental attributes assigned	0.90
Lowest individual factor(s) = 0.90	0.90
Lowest individual factor = 0.75	0.75
Two or more lowest individual factors = 0.75	0.50
Lowest individual factor = 0.50	0.50
Two or more lowest individual factors = 0.50	0.25
Lowest individual factor = 0.25	0.25
Two or more lowest individual factors = 0.25	0.10
Lowest individual factor(s) = 0.10	0.10

Source: Conner, Francfort, and Rinehart (1998, p.13).

Table 3.3: Effects of Environmental Regulations on Carbon Dioxide Emissions

DepVar: ΔEmissions	**OLS**	**First Stage - Linear**	**First Stage - Non-Linear**	**IV: 2SLS**	**IV: GMM**	**IV: LIML**
	(1)	(2)	(3)	(4)	(5)	(6)
ΔThermDev	832.10***			1,475.82***	1,539.64***	2,290.27*
	(274.15)			(303.63)	(236.81)	(1,226.15)
Excluded Instruments						
HydroNotDev		0.25384	-2.25912			
		(0.34863)	(3.07407)			
HydroNotDev^2			0.01132			
			(0.01147)			
HydroNotDev^3			-0.00002			
			(0.00001)			
HydroNotDev^4			0.00000			
			(0.00000)			
F-statistic		0.53	32.82			
(Excluded Instruments)						
Controls						
ΔPop	1.60	-0.00213	-0.00235	2.86	2.23	4.45
	(1.60)	(0.00128)	(0.00144)	(1.75)	(1.67)	(3.53)
ΔPCIn	-19.10	-0.10745***	-0.09688**	47.58	65.84	131.95
	(32.01)	(0.03505)	(0.03722)	(56.32)	(51.13)	(154.12)
Sample Counties	32	32	32	32	32	32
R^2	0.41	0.30	0.38			
Kleibergen-Paap rk Wald F-statistic				13.08	13.08	13.08
Stock-Yogo Critical Values						
10% maximal IV relative bias				10.27		
20% maximal IV relative bias				6.71		
30% maximal IV relative bias				5.34		
10% maximal IV size				24.58	5.44	5.44
15% maximal IV size				13.96	3.87	3.87
20% maximal IV size				10.26	3.30	3.30
25% maximal IV size				8.31	2.98	2.98
Hansen J-statistic				2.143	2.884	1.330
P-value				0.5433	0.4098	0.7219

Notes: This table presents results of regressions of variation in emissions in the period 1998-2007, measured in pounds, on variation in thermal (fossil-fuel) power capacity, measured in megawatts, controlling for variation in population and per capita income.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.